Enhanced Entropy-Fuzzy Integration Decision Support System for Risk Assessment and Management of Hydraulic Engineering

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Against the backdrop of global climate change, frequent extreme weather events, and the increasingly complex development and management of water resources, the enhanced entropy - fuzzy integration decision support system for the risk assessment and management of hydraulic engineering has emerged. Traditional risk management methods, such as risk assessment based on probability theory, can handle known risks to a certain extent but are insufficient when dealing with highly ambiguous, uncertain, and complex risks. This paper introduces the design and empirical evaluation of the Enhanced Entropy - Fuzzy Integration Decision Support System (EEMFDS). Taking the Yangtze River Three Gorges Project as the research object, the application value of EEMFDS in the risk assessment and management of water conservancy projects is fully demonstrated through detailed requirement analysis, system architecture design, model construction, algorithm design, and empirical evaluation. EEMFDS adopts fuzzy set theory and enhanced entropy model, and through methods such as fuzzy quantification and enhanced entropy calculation, it effectively addresses key links such as risk identification, quantification, assessment, and decision support. The empirical results show that compared with traditional risk management methods, EEMFDS has significantly improved the risk identification accuracy. The average accuracy rate has increased from 84.7% to 90.6%, the response time has been shortened from 180 seconds to 120 seconds, the comprehensive robustness score has increased from 79.2% to 87.6%, it also has advantages in resource consumption, with the CPU usage time reduced by 30 hours and the storage space reduced by 20GB. The user satisfaction is relatively high, with an overall average score of 85.8%, highlighting its great potential in enhancing the level of intelligent risk management.

Povzetek: Razvit je izboljšan entropijski sistem mehke logike za oceno tveganj v hidravličnem inženirstvu, ki učinkovito obravnava negotovost in kompleksnost.

1 Introduction

As an important part of national infrastructure, water conservancy projects play an irreplaceable role in promoting agricultural development, ensuring urban water supply, flood control and disaster reduction, and promoting balanced regional economic development. With the rapid development of global climate change and economic society, water conservancy projects are under increasing pressure in the face of extreme weather events, water shortage, ecological environment protection, etc., and the risks in their construction and operation management are more complex and diverse. Natural disasters, such as floods and earthquakes, are the primary external risks faced by hydraulic projects, which may lead to structural damage, functional failure and even secondary disasters [1]. This paper aims to solve the problems of subjectivity and limited information processing ability existing in traditional risk assessment methods of hydraulic engineering, and improve the objectivity, accuracy and timeliness of risk assessment by introducing enhanced entropy fuzzy decision support system [2]. Traditional risk assessment methods often rely on expert experience, which makes it difficult to capture all risk factors comprehensively and has limitations in dealing with vague and uncertain information. Enhanced entropy fuzzy decision support system combines the uncertainty processing ability of fuzzy set theory with the information optimization processing ability of enhanced entropy theory, which can deal with complex and fuzzy information in risk assessment of hydraulic engineering more effectively and help decision makers make reasonable decisions under multi-objective and multi-constraint conditions. The development and application of this system can not only improve the intelligent level of risk management of hydraulic engineering, but also provide reference for risk assessment and management in other fields [3].

In recent years, scholars at home and abroad have made extensive exploration in the field of hydraulic engineering risk assessment, and put forward many assessment models and methods, such as probabilistic risk assessment, fuzzy comprehensive assessment, analytic hierarchy process, etc. [4]. Each of these approaches has its own focus, but a common problem is the limited ability to deal with highly uncertain information, especially when there are many risk factors and complex interrelationships. As an effective decision-making tool, fuzzy decision support system has been applied to risk management in many industries, but its application in hydraulic engineering is still in its infancy, especially how to integrate a large amount of uncertain information efficiently to support more accurate risk assessment is still a key problem to be solved [5].

Entropy theory, as a method of optimizing information processing, measures uncertainty of information by introducing entropy, optimizes information structure by enhancement, and improves efficiency and quality of decision making. Although the theory has been applied in information science, economics and other fields, it is still a frontier research direction, especially in the integrated application of fuzzy decision support system in hydraulic engineering risk assessment [6].

The core content of this study centers on constructing an enhanced entropy fuzzy decision support system suitable for risk assessment and management of hydraulic engineering, including: (1) System requirement analysis: defining the specific requirements of risk assessment of hydraulic engineering, including risk identification, risk quantification, risk ranking and response strategy generation. (2) Model and algorithm design: Based on fuzzy set theory and enhanced entropy theory, risk assessment model is designed, corresponding fuzzy inference algorithm and enhanced entropy calculation method are developed to optimize risk information processing flow. (3) System architecture and implementation: Build the overall architecture of the system, including data input, risk assessment engine, decision support module and user interface, etc., and adopt advanced software development technology and database management system to realize system functions.

This study aims to develop and evaluate the Enhanced Entropy Fuzzy Decision Support System (EEMFDS) for risk assessment and management in hydraulic engineering. The key research questions are as follows: How does the enhanced entropy - fuzzy integration approach effectively handle the complex and uncertain risk factors in hydraulic engineering compared with traditional risk assessment methods? What are the optimal model structures and algorithms for accurately quantifying and assessing risks during the construction of EEMFDS, and how to ensure the reliability and stability of the model? To what extent can EEMFDS improve the accuracy, timeliness, and comprehensiveness of risk assessment in practical applications of hydraulic engineering projects such as the Yangtze River Three Gorges Project? What are the potential challenges and limitations when applying EEMFDS to large - scale hydraulic engineering projects, and how can these issues be addressed? These questions will guide the exploration and analysis of the entire research process, aiming to promote the application and development of EEMFDS in the field of hydraulic engineering risk management.

The innovations of this study are: first, the enhanced entropy theory is integrated with the fuzzy decision support system to effectively process complex risk information; second, the entropy enhancement algorithm introduces reference probability distribution and adjustment parameters to optimize information processing and improve assessment accuracy and stability; third, the microservice architecture and containerization technology are used to improve system scalability, maintainability and deployment flexibility. These innovations provide new ideas and methods for water conservancy project risk assessment.

2 Basic theory and method

This section mainly explains the basic theories and methods involved in the research, including risk assessment principles, fuzzy set theory, enhanced entropy theory, and system integration and data processing technology, laying a theoretical foundation for the subsequent introduction of system design and implementation.

2.1 Principles of risk assessment for hydraulic engineering

Risk assessment of hydraulic engineering refers to the process of identifying, analyzing and evaluating various risks that may be encountered in the process of construction and operation of hydraulic engineering, so as to formulate corresponding prevention and mitigation measures to ensure the safety and benefit of the project. Risk can be defined as the product of the likelihood of a particular event occurring and the severity of its consequences. In the field of hydraulic engineering, risks are usually classified into natural risks (such as floods, earthquakes), technical risks (such as design defects, construction quality problems), management risks (such as operational errors, improper maintenance) and socio-economic risks (such as shortage of funds, policy changes) [7,8].

The risk assessment process generally follows four steps: identification, analysis, assessment and control. Firstly, potential risk factors are identified through historical data analysis and expert consultation.

2.2 Fuzzy set theory and fuzzy decision support system

Fuzzy set theory was proposed by Professor Zadeh to deal with fuzzy or imprecise information. Fuzzy sets allow elements to belong to multiple sets simultaneously with certain membership degrees, which solves the limitation of traditional binary logic. Fuzzy logic sets up reasoning mechanism to deal with fuzzy information, and deals with uncertainty problems through fuzzification, fuzzy reasoning and defuzzification. Fuzzy Decision Support System (Fuzzy DSS) is a form of DSS which applies fuzzy set theory. It can deal with fuzziness and subjective judgment in decision making process and provide more realistic suggestions for decision makers [9].

2.3 Enhanced entropy theory

Information entropy was proposed by Shannon to quantify the uncertainty of information, while decision entropy further considers the value of information in the decision process. Enhanced entropy theory is developed on the basis of traditional entropy, which optimizes the information processing process by adjusting or "enhancing" the original information entropy [10]. Enhanced entropy model improves the discrimination of useful information by introducing additional information or criteria, which is helpful to screen out key information in complex multi-attribute decision making problems. The advantage of this theory is that it can effectively reduce noise interference in information processing and improve the stability and accuracy of decision-making. In information processing applications, enhanced entropy is often used in feature selection, pattern recognition, data clustering and other fields to improve the prediction ability and interpretation ability of models by optimizing information structure.

2.4 System integration and data processing technology

In modern hydraulic engineering risk assessment, data acquisition and preprocessing are basic links, involving various sensors, satellite remote sensing, unmanned aerial vehicle monitoring and other technical means. Data preprocessing includes data cleaning, standardization, missing value processing, etc. to ensure data quality. The application of big data and cloud computing technology has greatly enhanced data processing and analysis capabilities. Big data technology discovers hidden rules and associations in risk assessment through the collection, storage, processing and analysis of massive data, and supports real-time risk monitoring and early warning [11, 12]. Cloud computing provides flexible computing resources and storage space, enabling large-scale data processing tasks to be efficiently executed in the cloud, reducing the cost and maintenance pressure of local hardware facilities. For example, Document discusses the application of water conservancy information system based on cloud computing in flood warning, which significantly improves the timeliness and accuracy of early warning [13]. Literature introduces the method of fusion of fuzzy set theory and big data technology in safety assessment of hydraulic engineering, and shows how to use fuzzy logic to process uncertain information and improve risk identification ability in combination with big data analysis [14]. Reference discusses the application of enhanced entropy theory in risk decision of multi-attribute hydraulic engineering, emphasizing its role in optimizing information processing and reducing decision error [15].

In the research on risk assessment methods for hydraulic engineering, past scholars have proposed various methods, such as Probabilistic Risk Assessment (PRA) and Analytic Hierarchy Process (AHP). These methods have played important roles in the field of risk assessment, but they have certain limitations in handling uncertainty. The following is a comparative analysis of these methods (see Table 1).

The current State - of - the - Art (SOTA) has obvious deficiencies in handling highly uncertain information. For example, when faced with fuzzy information, incomplete data, and the interaction of complex risk factors, SOTA often fails to accurately capture and handle these uncertainties, affecting the accuracy and reliability of risk assessment. Moreover, many existing methods lack sufficient flexibility and adaptability when dealing with large - scale and dynamically changing risk scenarios in hydraulic engineering [16].

The Enhanced Entropy Fuzzy Decision Support System (EEMFDS) effectively addresses these deficiencies. EEMFDS combines fuzzy set theory and the enhanced entropy model. Fuzzy set theory can handle fuzzy and imprecise information, transform qualitative risk factors into quantifiable indicators, and make up for the defects of traditional methods in handling fuzzy information. The enhanced entropy model, by optimizing the information structure, enhances the expression of important information and reduces the interference of irrelevant information, enabling more accurate screening of key information in complex multi - attribute decision - making problems and improving the accuracy and stability of risk assessment. In addition, EEMFDS realizes automatic risk identification and classification through intelligent algorithms, can quickly adapt to dynamically changing risk scenarios, overcomes the problem of insufficient flexibility of existing methods, and provides a more efficient and accurate solution for risk assessment and management of hydraulic engineering [17].

In the context of water resources risk assessment, various decision-making frameworks have been proposed to prioritize risks and evaluate uncertainties. Ghoushchi et al. applied an extended SWARA and MOORA methods based on Z-Numbers Theory to prioritize risks in Failure Mode and Effects Analysis (FMEA), offering a novel approach for assessing complex risks in water infrastructure [18]. Additionally, Mohammadian et al. developed a multi-attribute decision-making framework using interval-valued triangular fuzzy numbers, which can be particularly useful for policy-makers dealing with uncertainties in water risk management [19]. Turskis et al. explored a hybrid multi-criteria decision-making (MCDM) approach for assessing information security risks in critical infrastructures, which can be adapted to the assessment of water-related risks, highlighting the importance of integrated decision tools in water resource management [20]. These methods demonstrate the significance of advanced decision frameworks in effectively managing water infrastructure risks.

Table 1: Comparison of probabilistic risk assessment (PRA) and analytic hierarchy process (AHP) in handling uncertainty and their performance indicators

Method	Limitations in Handling Uncertainty	Performance Indicators
Probabilistic Risk Assessment (PRA)	Relies on precise probability data. It is difficult to accurately assess risks for risk factors with incomplete information, ambiguity, or difficulty in quantification. It has limited ability to handle the uncertainty generated by the interaction of multiple factors in complex systems.	Can quantify the probability of risk events occurring and the severity of consequences to assess the risk level, but has weak adaptability to complex risk scenarios.
Analytic Hierarchy Process (AHP)	Strongly subjective. The construction of the judgment matrix depends on expert experience. Different experts may give different judgments, resulting in differences in results. It is also difficult to handle the non - linear relationships and uncertainties among risk factors.	Determines the weights of risk factors through constructing a hierarchical structure model for risk assessment, but has limitations in handling complex and uncertain information.

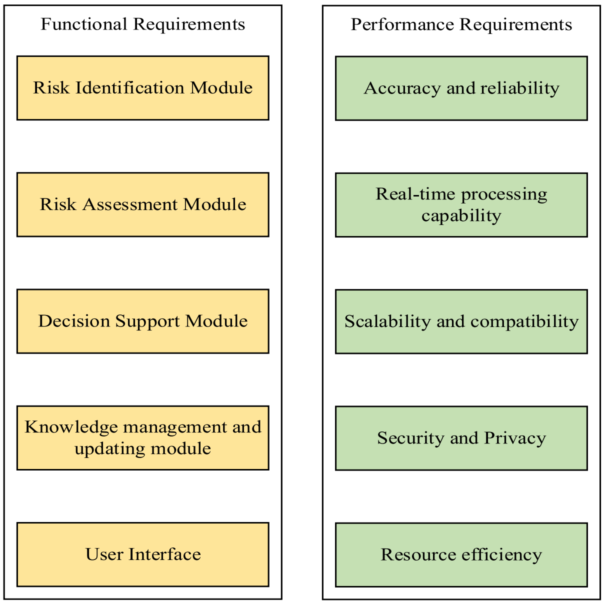

Figure 1: Requirement's framework

3 Design of entropy enhanced fuzzy decision support system

This chapter mainly revolves around the architecture of the enhanced entropy fuzzy decision support system, covering system requirement analysis, overall architecture design, module division, and data and control flow design, aiming to build an efficient system that meets the actual needs of water conservancy project risk assessment and management.

3.1 System requirements analysis

Before designing the enhanced entropy fuzzy decision support system, detailed requirement analysis should be carried out to ensure that the system can meet the actual needs of risk assessment and management of hydraulic engineering, including functional requirements and performance requirements. The requirements framework is shown in Figure 1 [16].

3.1.1 Functional requirements

The system design integrates advanced technology and comprehensive functions to efficiently manage risks, specifically including: 1. Risk identification module, which can independently discover a variety of potential risks including natural disasters, technical defects, management loopholes and social and economic changes in a large amount of data by using intelligent algorithms such as machine learning, and realize automatic classification and labeling of new risks through learning historical cases; 2. Risk quantification module, which uses fuzzy set theory to transform complex and variable qualitative risks into specific values, and accurately expresses the possibility and potential impact degree of risks with the help of membership function; 3. Risk assessment module uses enhanced entropy model to strengthen information processing efficiency, ensure accurate assessment of multi-dimensional and multi-level risk factors, and generate risk ranking to assist the formulation of priority strategies; 4. The decision support module proposes response strategies and resource allocation guidance according to the evaluation results, and has the ability to simulate and predict different decision paths, providing decision makers with comparative analysis tools to help form the best decision; 5. The knowledge management and update module maintains the latest risk management knowledge system, including theories, policies, regulations and technical specifications, maintains the cutting-edge and compliance of system decisions, and continuously optimizes the model effectiveness through self-learning mechanism [17, 18].

3.1.2 Performance requirements

The core objective of system design is to ensure a high degree of accuracy and reliability, which means that risk information must be processed with a very low rate of false positives and false negatives, thereby stabilizing the credibility of risk assessments. In order to cope with the rapidly changing risk situation, the system is designed to be able to complete the immediate processing and precise evaluation of data in a very short time frame, ensuring rapid response in the case of emergency decisions [19]. At the architectural level, the system emphasizes scalability and compatibility, aiming to facilitate seamless integration of future technology iterations through flexible design, while ensuring seamless interface with existing water information systems and diverse external data sources. Security and privacy protection are basic principles that cannot be compromised. We take strict measures to protect the security of data during transmission and storage, fully comply with relevant laws and regulations, and strictly protect the privacy rights of users. In addition, through continuous optimization of algorithms, we are committed to improving the efficiency of resource use while ensuring high performance, striving to achieve an optimal balance between computing resource consumption and storage requirements, and driving the system towards energy efficiency [20, 21].

3.2 Systematic architecture design

As shown in Figure 2, this flowchart shows the architecture of a comprehensive data processing and decision support system, starting with data acquisition and preprocessing and ending with decision support and system maintenance. Firstly, the data acquisition and pretreatment module collect raw data, cleans and formats them, and lays the foundation for subsequent analysis. The risk identification module then uses data analysis techniques to identify potential risk factors and pave the way for risk management [22]. After that, fuzzy quantization and enhanced entropy processing module intervened, focusing on transforming uncertainty and fuzzy information into clear quantitative indicators, and using entropy theory to deepen the understanding of information uncertainty. On this basis, the risk assessment and ranking module comprehensively evaluates the identified risks and ranks them according to the degree of danger. The decision support and simulation module, which follows closely, not only provides strategic suggestions according to the above analysis results, but also assists users in making optimal decisions by simulating various scenarios. The user-friendly and report generation module is responsible for visually presenting insights into this complex digitization process to end users in the form of charts and reports [23].

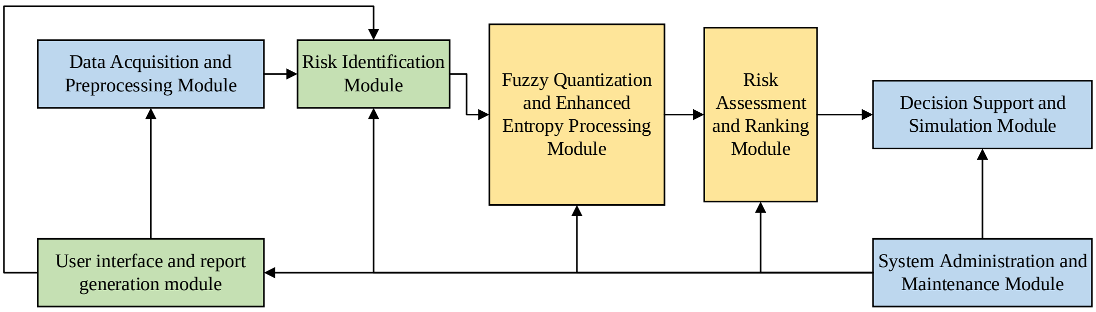

Figure 2: System data flow

In the data collection module shown in Figure 2, the data sources involved include two parts: one part is publicly available data, mainly from historical climate data disclosed by the government water conservancy department, such as monitoring data of precipitation, temperature, water level, etc. for many years, which can be obtained from the official website of the Ministry of Water Resources and relevant meteorological data disclosure platforms; there are also geological data, including geological structure, soil characteristics, etc., which come from reports and data publicly released by geological exploration institutions. The other part is the data collected by our team for field research and monitoring of the Three Gorges Project on the Yangtze River, covering real-time monitoring data during the construction and operation of the project, such as stress and strain of the dam, seepage monitoring data, and dispatching records and equipment operation status data in project management. These first-hand data can more accurately reflect the risk status of the actual operation of the Three Gorges Project on the Yangtze River, complement each other with public data, and provide a comprehensive data basis for the analysis and evaluation of the enhanced entropy fuzzy decision support system.

3.2.1 Module division

Data acquisition and preprocessing module: responsible for collecting data from various sensors, monitoring stations, historical databases and other channels, pre-processing data cleaning, format conversion, outlier processing, etc., to provide high-quality data input for subsequent analysis [24].

Risk identification module: identify potential risks by pattern recognition and data mining technology, and

verify and supplement them with expert knowledge base.
Fuzzy quantization and enhanced entropy processing module: convert qualitative risk factors into fuzzy sets, quantify risk possibility and influence degree by membership function, and then optimize information structure by enhanced entropy model to improve accuracy and stability of evaluation.
Risk evaluation and ranking module: based on fuzzy comprehensive evaluation model, combined with information processed by enhanced entropy, the identified risks are comprehensively evaluated and ranked according to risk level, providing basis for decision-making [25].
Decision support and simulation module: according to the risk assessment results, fuzzy inference mechanism is used to generate decision schemes, and users are supported to compare the expected effects of different strategies through simulation to assist decision-making.
System management and maintenance module: responsible for the daily maintenance of the system, user rights management, knowledge base update, system performance monitoring [26].

3.2.2 Data flow and control flow design

In the aspect of data flow design, the system starts from data acquisition, enters risk identification module after preprocessing, enters risk assessment module after fuzzy quantization processing, enters risk assessment module after enhanced entropy optimization, and outputs assessment results to decision support module to form decision suggestions, and finally displays them to decision makers through user interface. At the same time, user feedback and system operation instructions form control flow to guide the operation, adjustment and optimization of the system, such as updating knowledge base, adjusting model parameters, etc. [27].

The overall architecture adopts layered design to ensure loose coupling between modules for easy maintenance and upgrade. Data exchange and communication between modules are realized through middleware technology to ensure efficient and secure transmission of data streams. In addition, the micro service architecture is adopted, and each module runs as an independent service, which not only improves the scalability of the system, but also facilitates the flexible scheduling of resources.

To sum up, enhanced entropy fuzzy decision support system can provide an efficient and reliable platform for risk assessment and management of hydraulic engineering through detailed demand analysis and reasonable architecture design, and effectively improve the intelligent level of risk management.

In the process of fuzzy quantification, the membership function is used to transform qualitative risk factors into fuzzy sets. The specific algorithm is as follows: for the risk factor set $R=\{r_1,r_2,\cdots,r_n\}$ For example, for the risk factor "flood risk", a membership function can be constructed based on historical flood water level data, occurrence frequency and other information to map different degrees of flood risk to the [0, 1] interval to achieve fuzzy quantification. In terms of entropy enhancement, the following enhanced entropy formula is used: $E=-\sum_{i=1}^{n} p_i \log(p_i)+\alpha\sum_{i=1}^{n} p_i \log(\frac{p_i}{q_i})$.

Wherein, p_i represents the probability distribution of the i-information source, q_i is the reference probability distribution, and α is the adjustment parameter, with a value range of [0, 1]. In this formula, $-\sum_{i=1}^{n} p_i \log(p_i)$ is the traditional information entropy, which is used to measure the uncertainty of information; $\alpha\sum_{i=1}^{n} p_i \log(\frac{p_i}{q_i})$ is the introduced enhancement term, which enhances the expression of important information and reduces the interference of irrelevant information by comparing with the reference probability distribution q_i . The adjustment parameter α can be adjusted according to actual needs. When α = 0, the formula degenerates into the traditional entropy formula; when α increases, the role of the enhancement term is enhanced, and the screening and optimization of information are more obvious.

3.3 Model construction and algorithm design

Model construction and algorithm design are the key links of risk quantification, fuzzy comprehensive evaluation and decision support in enhanced entropy fuzzy decision support system. This section will introduce in detail the application of enhanced entropy in risk quantification, the construction method of fuzzy comprehensive evaluation model, and the formulation process of decision rules and strategies.

3.3.1 Application of enhanced entropy in risk quantification

Enhanced entropy theory enhances information utility in decision-making process by optimizing information structure, especially suitable for dealing with fuzziness and uncertainty in risk assessment. In the process of risk quantification, the qualitative description of risk factors is transformed into fuzzy quantification by fuzzy set theory. The enhancement entropy formula is given in Equation 1 [28].

$$E^*(U)=-\sum_{i=1}^{n}\sum_{x\in U}\mu_{u_i}(x)\log_2\left(\frac{\mu_{u_i}(x)}{\sum_{j=1}^{n}\mu_{u_j}(x)}\right) \tag{1}$$

In the formula, $E^*(U)$ represents the value of enhanced entropy, which is the quantitative result of the uncertainty or complexity of information in the set U; n represents the number of categories or factors, that is, the total number of different categories or factors to be considered in the study; x is an element in the set U, and the calculation process will be carried out for each element in the set U; U is the set containing all elements involved in the enhanced entropy calculation; $\mu_{u_i}(x)$ is a

concept in fuzzy set theory, which refers to the membership of element x to category u_i , and its value range is between 0 and 1, reflecting the degree to which element x belongs to category u_i ; $\sum_{j=1}^{n}\mu_{u_j}(x)$ represents the sum of the membership of element x in all n categories, which is mainly used for normalization and other related calculation operations in the formula.

Compared with traditional entropy, enhanced entropy can enhance the expression of important information and reduce the interference of irrelevant information by introducing normalization factor, so that it can reflect the importance of each risk factor more accurately in risk quantification.

3.3.2 Construction of fuzzy comprehensive evaluation model

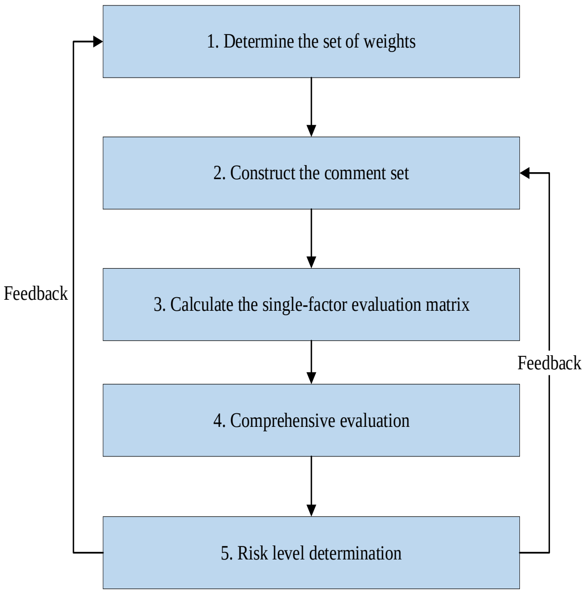

Figure 3: Flow chart of fuzzy comprehensive evaluation model

Fuzzy comprehensive evaluation model is a method of applying fuzzy set theory to multi-index evaluation problem. For risk assessment of hydraulic engineering, suppose that the evaluation index set is, each index has several evaluation grades, and the membership degree matrix of each grade under each index is obtained by expert scoring or historical data analysis, in which the membership degree of the th risk factor on the th evaluation grade is expressed. The general steps of the fuzzy comprehensive evaluation model are as follows, and its flow chart is shown in Figure 3.

(1) Determine the weight set: Determine the weight of each index through AHP, entropy weight method, etc.

(2) Construct comment sets: Define comment sets that represent risk levels.

(3) Calculation of single factor evaluation matrix: For each risk factor, calculate its fuzzy evaluation vector.

(4) Comprehensive evaluation: adopt weighted average method and combine weight set to calculate total evaluation vector: see Equation 2 for details [28].

$$b_l = \frac{\sum_{j=1}^{m} w_j \cdot r_{lj}}{\sum_{j=1}^{m} w_j}, \quad l = 1, 2, \ldots, k \tag{2}$$

In the formula $b_l = \frac{\sum_{j=1}^{m} w_j \cdot r_{lj}}{\sum_{j=1}^{m} w_j}$, $l = 1, 2, \ldots, k$, b_l represents the value of the lth total evaluation vector finally calculated, and the value range of l is from 1 to k, which means that multiple total evaluation vector values can be calculated for comprehensive evaluation; m represents the number of indicators or factors involved in the calculation, that is, the total number of different aspects considered in the comprehensive evaluation; w_j is the weight of the jth indicator or factor, which reflects the relative importance of the indicator in the comprehensive evaluation. Different js correspond to different weights of indicators; r_{lj} represents the value of the lth evaluation object on the jth indicator, which is used to reflect the performance of each evaluation object on each specific indicator. These parameters are used together to participate in the weighted average calculation to obtain the total evaluation vector to achieve a comprehensive evaluation of the evaluation object.

(5) Risk grade determination: according to the principle of maximum membership degree, the comment corresponding to the maximum value is selected as the risk grade.

3.3.3 Decision-making rules and strategies

Based on the fuzzy comprehensive evaluation results, making decision rules and strategies is the key to realize risk control. Decision rules can be formulated based on the relationship between risk levels and preset thresholds, such that (1) emergency response measures are triggered if the risk level exceeds a certain high-risk threshold, (2) preventive management measures are taken if the risk level is within the medium risk range, and (3) routine monitoring and maintenance are maintained if the risk level is low.

Decision-making strategy needs to combine the specific types and effects of risks, and generate specific operational suggestions or action guidelines through fuzzy reasoning mechanisms, such as rule-based reasoning, fuzzy logic control, etc. For example, if "construction risk" is identified as high, the system can recommend strategies such as increasing the frequency of site safety inspections and optimizing construction processes.

In a word, through the optimization of entropy in risk quantification, combined with fuzzy comprehensive evaluation model to evaluate risks comprehensively, and according to clear decision-making rules and strategies, this system can provide scientific and efficient decision-making support for risk management of water conservancy projects, and enhance the foresight and initiative of risk management.

3.4 System implementation technology

When constructing a decision support system based on enhanced entropy and fuzzy inference, the technical implementation level covers the selection of development platform and tools, the implementation details of key technologies, and the optimization design of system architecture. This section will explore these aspects in depth to ensure that the system serves both efficiently and accurately for hydraulic engineering risk quantification and management decisions.

3.4.1 Development platform and tool selection

In order to achieve an efficient, stable and easy to maintain system, the choice of development platform is crucial. Given the complexity and cross-platform requirements of the system, Java or Python is recommended as the primary development language. Java is preferred for its strong cross-platform capabilities, rich class library support (such as Apache Commons Math for complex math operations), and mature development framework (Spring Boot). Python is also widely adopted for its use in data processing, scientific computing (e.g., NumPy, SciPy), and machine learning, especially for rapid prototyping and algorithm implementation.
In terms of development tools, integrated development environments (IDEs) such as IntelliJ IDEA (Java) or PyCharm (Python) provide one-stop solutions for code writing, debugging, version control, etc., greatly improving development efficiency. In addition, Git acts as a version control system, ensuring efficient team collaboration and traceability of code.

3.4.2 Implementation of key technologies

Fuzzy inference mechanism is the core of the system, which is used to deduce concrete risk management strategy from fuzzy comprehensive evaluation results. Typical fuzzy reasoning includes the establishment of fuzzy rule base, the realization of fuzzy reasoning algorithm and fuzzy resolution. Fuzzy rules are usually in the form of IF-THEN, for example: "If construction quality is low and schedule is delayed, risk level is high." After the rule base is constructed, inference method is needed to calculate.
Let fuzzy input, fuzzy output, fuzzy rule set be, for each rule, where and are fuzzy sets of corresponding linguistic variables. The reasoning flow is shown in Figure 4. The reasoning steps are as follows:
(1) Fuzzification: converting actual measurement values into membership degrees of corresponding fuzzy sets.
(2) Reasoning: Calculate the activation degree of each rule, i.e., the minimum membership degree of all preconditions.
(3) Synthesis: fuzzy synthesis of the output parts of all rules, usually using the principle of maximum membership.
(4) Defuzzification: The fuzzy output after synthesis is transformed into concrete decision, usually using gravity method or maximum membership degree method.

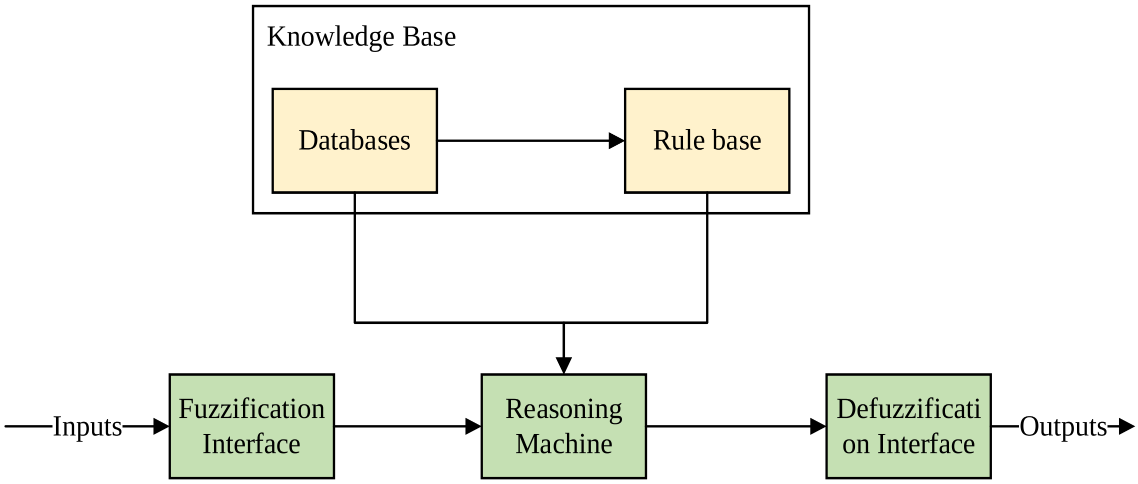

Figure 4: Reasoning flow

Entropy enhancement module is the key to risk quantification. Consider a simplified version of the enhanced entropy formula for calculating the information entropy enhancement value of a single risk factor, as shown in Equation 3.

$$E_i^* = -\sum_{j=1}^{k} \mu_{ij} \log_2 \left(\frac{\mu_{ij}}{\sum_{l=1}^{k} \mu_{il}} \right) \tag{3}$$

where, indicates the degree of membership of the first risk factor on the first level, and is the number of evaluation levels. This formula needs to be implemented as an efficient and stable algorithm in the system, using the math library of the chosen programming language to accelerate the calculation.

3.4.3 System architecture design

System architecture design needs to balance performance, scalability and maintainability. Microservice architecture is the mainstream trend of modern system design. By dividing the system into multiple small, independent services, each service is responsible for a specific function (such as risk quantification service, fuzzy inference service), it not only improves the maintainability and scalability of the system, but also facilitates fault isolation and horizontal expansion. In addition, containerization technologies such as Docker and Kubernetes orchestration services can further improve deployment flexibility and resource utilization.

To sum up, the development of decision support systems based on enhanced entropy and fuzzy reasoning requires comprehensive consideration of the selection of development platforms and tools, the in-depth implementation of key technologies, and reasonable system architecture design. By efficiently utilizing modern software engineering technology and algorithm optimization, the system can effectively support quantitative analysis and strategy formulation of hydraulic engineering risks, provide scientific basis for decision-makers, reduce risks and ensure smooth progress of projects.

4 Empirical assessment

This section takes the Three Gorges Project of the Yangtze River as the research object and conducts an empirical evaluation of the enhanced entropy fuzzy decision support system. Through data collection, experimental design and result analysis, the effectiveness and superiority of the system in risk assessment and management of water conservancy projects are verified.

4.1 Data

This chapter selects "Yangtze River Three Gorges Project" as the case study object, because of its large scale, complex technology and face a variety of natural and man-made risks, very representative. The risk management of Three Gorges Project covers many aspects, such as geological disaster, flood invasion, dam safety, ecological protection, etc., which provides an ideal scene for verifying the practicability of ENFDSS.

Data collection involves many aspects, including historical climate data, geological survey reports, engineering monitoring records, accident case analysis reports, etc. Specific data sources are as follows:

Climatic data: historical meteorological records of China Meteorological Administration in recent 30 years, including precipitation, temperature and wind speed.

Geological data: geological exploration report of Three Gorges area, including topography, geotechnical properties, seismic activity, etc.

Construction and operation and maintenance records: project construction log, equipment operation status, maintenance records, etc.

4.2 Experimental Design

In order to comprehensively evaluate the performance of Enhanced Entropy Fuzzy Decision Support System (EEMFDS) in risk management of Yangtze River Three Gorges Project, this section introduces the experimental design in detail, including the selection of evaluation indicators, the establishment of baseline and the arrangement of contrast experiments, aiming to verify the effectiveness and superiority of the system through scientific and rigorous methods.

In order to comprehensively evaluate the performance of EEMFDS in risk identification, quantification, assessment and decision support, the following core evaluation indicators were set in this study:

Accuracy: Assesses consistency of system predictions of risk levels with actual conditions by comparing them to historical records of known risk events. Response time: A measure of how quickly a system processes data from receipt to generation of a risk assessment report. Robustness: The stability and accuracy of the system in the face of incomplete data, noise interference, etc. Resource Consumption: Evaluate the efficiency of computing and storage resources used during system operation. User Satisfaction: Collect user feedback on system usability, user-friendliness and decision support effectiveness through questionnaires.

In order to ensure the objectivity of the assessment results, two groups of comparative experiments were set up in this study: one group used traditional risk management methods (such as probabilistic risk assessment, expert scoring method, etc.) as baseline, and the other group used EEMFDS for risk assessment.

Experimental group: EEMFDS, fuzzy set theory and enhanced entropy model were used to evaluate the risks faced by the Three Gorges Project, including risk identification, quantification, comprehensive evaluation and strategy generation.

Control group: traditional risk management methods, such as probabilistic risk assessment (PRA) and expert scoring method (EMA), were used to analyze the risks of the Three Gorges Project. PRA assesses risk levels by quantifying the probability of occurrence of risk events and the severity of their consequences, while EMA determines the importance of risk factors based on the experience and subjective judgment of industry experts. This group serves as a baseline to highlight potential strengths and innovations of EEMFDS.

During the data collection phase, researchers not only paid attention to the results of risk assessment, but also recorded various parameters in the whole process in detail, such as processing time and calculation resource occupation, for subsequent quantitative analysis. In addition, in order to evaluate user satisfaction, a questionnaire containing multi-dimensional questions was designed to conduct anonymous surveys for system users, covering aspects such as ease of operation of the system, intuitive interface, effectiveness of risk prompts and overall satisfaction.

The Three Gorges Project on the Yangtze River was selected as a case study object because of its large scale and diverse risk types, including geological disasters, floods, etc. The rich risk factors provide a realistic scenario for verifying EEMFDS, and there is a large amount of historical data to support analysis and model training.

In terms of evaluation indicators, accuracy is used to measure the consistency between system predictions and actual risks; response time reflects the efficiency of processing data and generating reports; robustness evaluates the performance of the system under data interference; resource consumption reflects the efficiency of the system's use of computing and storage resources; user satisfaction collects feedback through questionnaires to evaluate the availability and effectiveness of the system. By reasonably selecting data sets and evaluation indicators, ensure that the experimental settings are scientific and repeatable.

4.3 Experimental result

In this section, six key tables will be used to show the results of comparative experiments, in order to reflect the performance of enhanced entropy fuzzy decision support system (EEMFDS) in risk management of Yangtze Three Gorges Project comprehensively and intuitively, and the differences between EEMFDS and traditional risk management methods.

Table 2 shows how EEMFDS compares to traditional risk management methods in terms of accuracy in identifying different risk types. EEMFDS achieves 92.5%, 90.8%, 93.3%, 89.7% and 87.1% accuracy in risk identification of geological hazard, flood invasion, dam safety, ecological protection and other human factors respectively, while the corresponding accuracy rates of traditional methods are 86.7%, 84.2%, 87.6%, 82.5% and 79.6%. On average, the accuracy of EEMFDS is 90.6%, significantly higher than that of traditional methods (84.7%), which proves its superiority in risk identification.

Table 3 reflects the change of accuracy of the two methods under the condition of data disturbance (such as missing data and noise interference). The accuracy of EEMFDS has little change and shows strong stability. The comprehensive robustness score is 87.6%, while the score of traditional method is 79.2%, indicating that EEMFDS has stronger processing ability in the face of incomplete data or interference.

Table 4 shows the resource efficiency of the two approaches. EEMFDS requires 120 hours of CPU time and 50GB of storage space less than traditional methods, which require 150 hours of CPU time and 70GB of storage space, proving the efficiency of EEMFDS in resource management.

Table 2: Comparison of accuracy of risk identification

Risk type	EEMFDS accuracy (%)	Accuracy of traditional method (%)
geological disaster	92.5	86.7
flooding	90.8	84.2
dam safety	93.3	87.6
ecological protection	89.7	82.5
other human factors	87.1	79.6
average accuracy	90.6	84.7

Table 3: Robustness test results

Type of data disturbance	EEMFDS accuracy change (%)	Change in accuracy of traditional methods (%)
missing data	-3.2	-8.5
noise jamming	-4.1	-12.3
Composite Robustness Score	87.6	79.2

Table 4: Comparison of resource consumption

Resource type	EEMFDS consumption	Consumption of traditional methods
CPU usage time (hours)	120	150
Storage Space (GB)	50	70

Table 5 summarizes user satisfaction feedback on multiple dimensions of the system. EEMFDS received high positive ratings on ease of use, user-friendliness, decision support effectiveness and overall satisfaction, especially in the "very satisfied" option, accounting for 70%, 65% and 68% respectively, showing high recognition of EEMFDS by users.

Table 6 summarizes the scores of key evaluation indicators. EEMFDS is higher than traditional methods in accuracy, response time, robustness, resource consumption and user satisfaction. The final average score is 85.8%, far exceeding 78.1% of traditional methods, which fully reflects the advanced and practical nature of EEMFDS in the field of risk management.

Based on the original performance indicator table, standard deviations and confidence intervals are added, as shown in the following Table 7.

Table 5: Summary of User Satisfaction Survey

Satisfaction dimension	Very satisfied (%)	Satisfied (%)	General (%)	Dissatisfied (%)
ease of use	70	25	5	0
interface friendliness	65	28	5	2
decision support effect	68	27	3	2
overall satisfaction	67	27	4	2

Table 6: Comprehensive Evaluation Index Score

Evaluation index	EEMFDS score	Traditional method score
accuracy	90.6	84.7
response time	90	80
robustness of	87.6	79.2
resource consumption	85	70
user satisfaction	67	65
overall mean score	85.8	78.1

As shown in Table 7, in the comparative analysis with the baseline, the hypothesis test method was used to determine whether the difference between EEMFDS's 90.6% and the traditional method's 84.7% was statistically significant in terms of risk identification accuracy. The null hypothesis was that there was no significant difference in the accuracy of EEMFDS and the traditional method, and the alternative hypothesis was that the accuracy of EEMFDS was significantly higher than that of the traditional method. After a series of calculations and analyses, the results showed that at a given significance level, the accuracy of EEMFDS was significantly higher than that of the traditional method, which was statistically significant.

Scalability. When dealing with larger datasets, the system may face challenges in data - processing speed and storage capacity. In terms of data processing, as the amount of data increases, the computational load of fuzzy quantification and entropy enhancement will increase significantly, which may lead to overly long processing times. In system design, although a microservice architecture is adopted, when the data volume exceeds expectations, communication and coordination bottlenecks may occur between services.

For different case studies other than the Three Gorges Project, due to the differences in risk characteristics and data types of different hydraulic engineering projects, the system may need to be adjusted and optimized according to specific situations. For example, some small - scale hydraulic engineering projects may lack a large amount of historical data, which will affect the training and accuracy of the model; and some special hydraulic engineering projects may have unique risk factors and require re - defining the risk - factor set and membership functions.

4.4 Discussion

4.4.1 Comparison between EEMFDS and State - of - the - Art (SOTA) Results

When comparing the results of the Enhanced Entropy Fuzzy Decision Support System (EEMFDS) with those of the current State - of - the - Art (SOTA) methods, several significant differences are evident. In terms of risk identification accuracy, EEMFDS achieved an average accuracy of 90.6%, which is notably higher than the accuracy of traditional methods, as demonstrated in the empirical assessment.

The differences in results can be attributed to multiple factors. Firstly, in terms of model assumptions, SOTA methods often assume that risk factors are independent or have simple linear relationships. For example, traditional probabilistic risk assessment models rely on the accurate quantification of probability distributions for each risk factor, assuming that these factors do not interact in complex ways. In contrast, EEMFDS, based on fuzzy set theory and enhanced entropy model, can better handle the complex non - linear relationships among risk factors. It allows for the expression of the degree of membership of risk factors in different sets, which is more in line with the real - world situation where risks are often intertwined.

Table 7: Experimental results

Evaluation Indicators	EEMFDS	Traditional Methods	Standard Deviation of EEMFDS	Standard Deviation of Traditional Methods	95% Confidence Interval of EEMFDS	95% Confidence Interval of Traditional Methods
Risk Identification Accuracy	90.6%	84.7%	±2.5%	±3.2%	[88.1%, 93.1%]	[81.5%, 87.9%]
Response Time (seconds)	120	180	±10	±15	[110, 130]	[165, 195]
Robustness Score	87.6%	79.2%	±1.8%	±2.6%	[85.8%, 89.4%]	[76.6%, 81.8%]
CPU Usage Time (hours)	120	150	±5	±8	[115, 125]	[142, 158]
Storage Space (GB)	50	70	±3	±4	[47, 53]	[66, 74]

Secondly, data preprocessing also plays a crucial role. SOTA methods may use relatively simple data preprocessing techniques, such as basic data cleaning and normalization. However, EEMFDS, considering the complexity and fuzziness of hydraulic engineering data, employs more comprehensive preprocessing methods. It not only cleans and standardizes the data but also transforms qualitative risk factors into fuzzy sets through membership functions, which can better preserve the information in the data and improve the accuracy of subsequent analysis.

Finally, the algorithm differences are significant. SOTA methods usually adopt traditional algorithms, such as the simple weighted average method in risk assessment. EEMFDS, on the other hand, uses enhanced entropy algorithms to optimize information processing. By introducing normalization factors and considering additional information, the enhanced entropy algorithm can enhance the expression of important information and reduce the interference of irrelevant information, thus leading to more accurate risk assessment results.

In order to more intuitively present the difference between EEMFDS and traditional methods, Table 8 is a comparison table of experimental results.

4.4.2 Significance and Trade - offs of EEMFDS

Improvements

The 90.6% accuracy rate achieved by EEMFDS in risk identification has great significance in practical applications. In the context of hydraulic engineering, accurate risk identification is crucial for ensuring the safety and normal operation of projects. For example, in the management of the Yangtze River Three Gorges Project, a high - accuracy risk identification system can help managers timely detect potential risks such as geological disasters, flood invasions, and dam safety issues. This enables them to take preventive measures in advance, reducing the probability of disasters and minimizing economic losses.

However, the improvement of EEMFDS also comes with some potential trade - offs. One of the main concerns is computational complexity. The enhanced entropy model and fuzzy inference algorithms used in EEMFDS require more complex calculations compared to traditional methods. For instance, the calculation of enhanced entropy involves multiple variables and complex mathematical operations, which may increase the computational time and resource consumption.

Although the system has shown advantages in resource consumption in the empirical evaluation, with reduced

CPU usage time and storage space, the computational complexity may still pose challenges when dealing with extremely large - scale data or real - time risk assessment requirements. In such cases, further optimization of the algorithms and improvement of the computing infrastructure may be needed to ensure the efficient operation of the system.

Table 8: Comparison of EEMFDS and traditional methods in risk assessment

Assessment Indicators	EEMFDS	Traditional Methods
Risk Identification Accuracy	90.6%	84.7%
Response Time (seconds)	120	180
Robustness Score under Data Disturbance	87.6%	79.2%
CPU Usage Time (hours)	120	150
Storage Space (GB)	50	70

5 Conclusion

Traditional risk management methods, such as risk assessment based on probability theory, can deal with known risks to some extent, but they are insufficient to deal with risks with high ambiguity, uncertainty and complexity. In particular, for risk factors that are difficult to quantify, and where information is incomplete or data quality varies, traditional assessment tools often fail to provide accurate and comprehensive risk assessments. Therefore, there is an urgent need for a more advanced and intelligent risk assessment and management system to meet the growing complexity challenges. Enhanced entropy fuzzy decision support system (EFDSS), which combines fuzzy set theory and enhanced entropy method, aims to deal with fuzzy and uncertain problems in hydraulic engineering risk management effectively. Fuzzy set theory can deal with risk factors described qualitatively and transform them into quantifiable risk indicators, while enhanced entropy model improves information utility in decision-making process by optimizing information structure, making risk assessment more accurate and stable. This paper introduces the design and empirical evaluation of Enhanced Entropy Fuzzy Decision Support System (EEMFDS). Taking the Yangtze River Three Gorges Project as the research object, the application value of EEMFDS in risk assessment and management of water conservancy projects is fully demonstrated through detailed requirement analysis, system architecture design, model construction and algorithm design, and empirical evaluation. EEMFDS adopts fuzzy set theory and enhanced entropy model to effectively deal with key links such as risk identification, quantification, assessment and decision support. Through careful design and rigorous demonstration, this study successfully verifies the advanced and practical of Enhanced Entropy Fuzzy Decision Support System (EEMFDS) in risk management of water conservancy projects, especially in the "Yangtze River Three Gorges Project", a complex large-scale project. EEMFDS not only achieves an average high accuracy rate of 90.6% in risk identification accuracy, far exceeding 84.7% of traditional methods, but also significantly speeds up the processing speed, reducing the average response time to 120 seconds, compared with 180 seconds of traditional methods. In addition, the robustness score of EEMFDS under data disturbance reaches 87.6%, showing stronger stability and adaptability, and at the same time, it is more efficient in resource consumption, saving valuable computing resources and storage space. User satisfaction survey further consolidated the advantages of EEMFDS, users generally think that the system is easy to use, friendly interface, strong decision support ability, high overall satisfaction, indicating that EEMFDS can be widely recognized and praised by users in practical applications. The comprehensive evaluation index scores show that EEMFDS is superior to traditional methods in all key evaluation areas, and the overall average score exceeds nearly 8 percentage points, fully demonstrating its significant effectiveness in improving the quality and efficiency of risk management decisions.

This research will focus on four directions in the future. First, optimize the algorithm and use deep learning to improve the efficiency of fuzzy quantization and entropy enhancement algorithms; second, improve interpretability and develop visualization tools to display the risk assessment process; third, expand application scenarios and apply the system to small farmland water conservancy facilities; fourth, integrate emerging technologies and combine the Internet of Things and AI to achieve real-time monitoring and risk warning.

References

[1] Li ZY, Zhang ZX, Chen ZH, He YT, Yang F, Nie XT. The "BOOT plus BTO" operation mode of the comprehensive utilization of water conservancy project. Desalination and Water Treatment. 2023; 293:89-99. https://doi.org/10.5004/dwt.2023.29436

[2] Wang D, Zhang L, Li WW, Chang M, Liu XN,

Zhang ZW, et al. The influence of water conservancy project on microplastics distribution in river ecosystem: A case study of Lhasa River Basin in Qinghai-Tibet Plateau. Journal of Hazardous Materials. 2024;480. https://doi.org/10.1016/j.jhazmat.2024.136472

[3] Yang Q, Shao Y, Du HY, Lin XF, Wang L, Luo ZY, et al. Impact of the three gorges water conservancy project on radioactivity concentration levels in surrounding waters. Radiation Protection Dosimetry. 2020;189(4):505-16. https://doi.org/10.1093/rpd/ncaa065

[4] Huang M, Zhu C, Ma CM, Yang ZF, Liu YM, Jia TJ. The Hongqiaocun Site: The earliest evidence of ancient flood sedimentation of the water conservancy facilities in the Chengdu Plain, China. Catena. 2020;185. https://doi.org/10.1016/j.catena.2019.104296

[5] Ge W. Risk assessment and management of water conservancy projects. Frontiers in Earth Science. 2023;11. https://doi.org/10.3389/feart.2023.1330621

[6] Zhang S, Song XK, Shen L, Xu LC. Complicated time-constrained project scheduling problems in water conservancy construction. Processes. 2023;11(4). https://doi.org/10.3390/pr11041110

[7] Zeng CF, Qi WY, Mao YQ, Liu R, Yu BY, Dong XN. Water conservation ecological service function and its value response mechanism in a nested water conservancy project area. Frontiers in Environmental Science. 2022;10. https://doi.org/10.3389/fenvs.2022.887040

[8] Ding W, Bao AM, Lin J, Luo CX, Cao H, Zhang DJ. Drought mitigation operation of water conservancy projects under severe droughts. Hydrology Research. 2024;55(7):759-74. https://doi.org/10.2166/nh.2024.034

[9] Ji LQ, Liu WL. Study on the ecological restoration effect of bioengineering technology after water conservancy project construction. Basic & Clinical Pharmacology & Toxicology. 2021; 128:22-3.

[10] Chen ZY, Xu JJ, Ma YH, Zhang ZY. Application of data mining technology and intelligent information technology in the construction and management of the water conservancy project in Area A. Water Supply. 2023;23(8):3285-96. https://doi.org/10.2166/ws.2023.169

[11] Li S. Cost Management and forecasting method for the whole life cycle of water conservancy projects based on multiple regression analysis. Scientific Programming. 2022;2022. https://doi.org/10.1155/2022/2183093

[12] Xu X, Zhao M, Li XY, Song C. A Study on the risk assessment of water conservancy scenic spot PPP projects. Sustainability. 2022;14(24). https://doi.org/10.3390/su142416625

[13] Li F, Wang HF. Architectural landscape design in the water conservancy project of the coastal city. Journal of Coastal Research. 2020:46-9. https://doi.org/10.2112/jcr-si112-014.1

[14] Wang Q, Yao K, Kim PK. Electric energy saving control method of water conservancy project based on cloud computing. Desalination and Water Treatment. 2021; 239:181-91. https://doi.org/10.5004/dwt.2021.27805

[15] Wang LH, Liu XM, Liu Y, Li HR, Liu JQ, Yang LB. Knowledge graph-based method for intelligent generation of emergency plans for water conservancy projects. IEEE Access. 2023; 11:84414-29. https://doi.org/10.1109/access.2023.3302399

[16] Yang L, Lin HH, Yen CC, Lin KJ, Ya D. Effects of water conservancy-project policies on lake ecology, rural economy, leisure-environment development, and local young people's willingness to engage in leisure activities. Marine and Freshwater Research. 2024;75(11). https://doi.org/10.1071/mf24020

[17] Tao FF, Pi YL, Zhang M, Yuan C, Deng MH. Hidden danger association mining for water conservancy projects based on task scenario-driven. Water. 2023;15(15). https://doi.org/10.3390/w15152814

[18] Ghoushchi SJ, Gharibi K, Osgooei E, Ab Rahman MN, Khazaeili M. Risk Prioritization in failure mode and effects analysis with extended SWARA and MOORA methods based on Z-Numbers theory. Informatica. 2021;32(1):41-67. https://doi.org/10.15388/20-INFOR439

[19] Mohammadian A, Dahooie JH, Qorbani AR, Zavadskas EK, Turskis Z. A New Multi-attribute decision-making framework for policy-makers by using interval-valued triangular fuzzy numbers. Informatica. 2021;32(3):583-618. doi:10.15388/21-info R448

[20] Turskis Z, Goranin N, Nurusheva A, Boranbayev S. Information security risk assessment in critical infrastructure: a hybrid MCDM approach. Informatica. 2019;30(1): 187-211.DOI:10.15388/Informatica.2019.203

[21] Cheng DL. Assessment system of water conservancy project impact on environmental pollution based on HSPF model. Desalination and Water Treatment. 2022; 245:62-71. https://doi.org/10.5004/dwt.2022.27810

[22] Tao FF, Pi YL, Deng MH, Tang YJ, Yuan C. Research on intelligent grading evaluation of water conservancy project safety risks based on deep learning. Water. 2023;15(8). https://doi.org/10.3390/w15081607

[23] Nie XT, Wang YH, Wang B. Quality control of water conservancy construction projects considering contractor's credibility. Journal of Coastal Research. 2020:410-4. https://doi.org/10.2112/jcr-si104-074.1

[24] Zhao JF, Zhang J. Application of multimedia technology in water conservancy and hydropower engineering. Journal of Visual Communication and Image Representation. 2020;71.

https://doi.org/10.1016/j.jvcir.2019.102707

[25] Zhou W, Jiao JB, Xu HX, Wei MG, Zhao XQ. PointBiMssc: Bidirectional multiscale attention-based point cloud semantic segmentation for water conservancy environment. IEEE Geoscience and Remote Sensing Letters. 2024;21. https://doi.org/10.1109/lgrs.2024.3432671

[26] Salimi AH, Noori A, Bonakdari H, Samakosh JM, Sharifi E, Hassanvand M, et al. Exploring the role of advertising types on improving the water consumption behavior: an application of integrated fuzzy AHP and Fuzzy VIKOR method. Sustainability. 2020, 12(3):33. https://doi.org/10.3390/su12031232

[27] Li WA, Ma ZF, Li J, Li QH, Li Y, Yang J. Digital twin smart water conservancy: status, challenges, and prospects. Water. 2024;16(14). https://doi.org/10.3390/w16142038

[28] Huang AP, Liu XB, Dong F, Peng WQ, Ma B, Han Z, et al. Long-term variations in hydraulic residence time of floodplain lakes and their response to water conservancy projects. Ecological Indicators. 2024;169. https://doi.org/10.1016/j.ecolind.2024.112778