

Article

Evolutionary Modeling of Risk Transfer for Safe Operation of Inter-Basin Water Transfer Projects Using Dempster–Shafer and Bayesian Network

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Abstract

Inter-basin water transfer projects (IBWTPs) play a crucial role in addressing the uneven spatial and temporal distribution of water resources and ensuring water security in the receiving areas. However, these projects are subject to various risk factors during their operation. While risk management is critical, current research in this field lacks a systematic and dynamic approach. A three-dimensional measurement model for probability, loss, and risk value, based on Dempster–Shafer (DS) evidence theory, Bayesian networks, and the equivalence method, was established in this study and, in consideration of the engineering characteristics of the IBWTP, a dynamic transmission evolution model for risk is constructed. The applicability and effectiveness of the model are demonstrated through a case study of the Central Line Project of South-to-North Water Diversion (CLPSNWD). The results indicate that the system risk of the CLPSNWD is in an unstable state, with the key influencing factors being channel engineering risk, flood disaster risk, pipeline engineering risk, and water transfer (discharge) cross-structure risk. The research findings offer a novel approach to the quantitative analysis and evolution of risk and contribute to the further development of engineering risk management theory.

Keywords: inter-basin water transfer project (IBWTP); risk; bayesian networks; DS evidence theory



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1. Introduction

Since the beginning of the twenty-first century, water resources have become a critical factor for the sustainable economic and social development of countries worldwide, driven by economic growth, population expansion, and climate change [1–3]. Precipitation is the primary source of global water resources; however, due to variations in climatic factors and natural geographical conditions, the distribution of water resources across time and space is highly uneven. In China, in particular, there are more water resources in the summer and fewer in the winter, more in the southeast and fewer in the northwest, with a clear trend of decreasing water resources from the southeast to the northwest. This leads to a significant disparity between the supply and demand for water resources [3–5]. The inter-basin water transfer project (IBWTP) typically refers to large-scale, long-distance, and long-duration water transfer projects that serve as critical infrastructure. These projects effectively alleviate the spatial and temporal disparities in water distribution and optimize the allocation of

water resources [6,7]. Currently, IBWTPs are widely implemented worldwide. Examples of such projects include the Central Valley Project in the United States [8], the Great Lakes Basin Water Diversion [9], the Snowy Mountains Water Transfer Project in Australia [10], and the South-to-North Water Diversion Project (SNWDP) in China [11]. As the IBWTP operates, the receiving areas, while benefiting from the project, are becoming increasingly dependent on the transferred water. For instance, in recent years, more than 20% of Beijing's water consumption has been sourced from the water transfer project, with approximately 80% of the water used in the main urban area coming from the SNWDP. Additionally, nearly all of Tianjin's water in its main urban area is transferred via the SNWDP. This increasing reliance underscores the growing importance of ensuring the safe operation of the project [12]. However, due to the long distance and large scale of the IBWTP, along with complex geological conditions and variable climatic factors along its route, numerous risk factors affect the safe operation of the project. For example, a circuit failure at the 21st mouth gate pumping station of the SNWDP in China led to the shutdown of the water plant, resulting in a widespread water supply outage. Additionally, extraordinarily heavy rainfall on 20 July in Zhengzhou, China, led to large landslides along the Wenxian section of the Central Line Project of South-to-North Water Diversion (CLPSNWD), the collapse of channel inverted siphon embankment slopes, and disruption of water transmission.

Managing the risk associated with the safe operation of IBWTPs is crucial for ensuring the effective utilization of project benefits and the sustainable development of the projects. The purpose of an IBWTP is to transfer water of adequate quality and quantity from the water source to the receiving area. In terms of water quantity, risks such as water shortages at the source [13], severe water shortages in the receiving area, and the simultaneous occurrence of water shortage events in both the supplying and receiving areas may lead to insufficient water supply [14], adversely impacting the lives of people in the receiving area. The water conveyance infrastructure is fundamental to the water transfer process. If the project suffers damage [15], such as blockage or destruction of the water transfer channels or control buildings [4,16], or encounters other risks [17], it can result in a complete disruption of water transfer. Regarding water quality, if the water source becomes polluted [18–20] or a pollution incident occurs during the transmission process [2,21–23], and the degree of pollution exceeds the self-purification capacity of the water body, the transferred water may become unusable, thereby seriously jeopardizing the project's benefits. Currently, many scholars have studied the risks associated with the safe operation of IBWTPs from various perspectives, providing valuable insights for risk management during the operational phase. However, most studies are limited to specific types of risks and lack a systematic approach [23–25]. Although some scholars have examined the risk of safe operation of IBWTPs from a systematic perspective [12], their findings tend to be relatively simplistic, primarily offering static overall risk evaluations without delving into the development and dynamic nature of these risks. However, the occurrence of risk events often involves a series of successive triggers in a chain transmission process, which, over time, exhibits dynamic transmission characteristics [26].

In summary, an analysis of existing studies reveals two main deficiencies in the research on the safe operation risk of IBWTPs: a lack of systematic approaches and a lack of investigation into the risk's change patterns. To address these deficiencies, this paper takes a holistic approach, systematically identifies the risks, integrates DS evidence theory with Bayesian networks, establishes both a risk measurement model and a dynamic transfer evolution model, and analyzes the dynamic evolution of the risk, verifying the models through case studies.

The findings of this paper offer a novel approach to the quantitative analysis and evolutionary study of risk, enrich the theory of risk management, and provide theoretical support for the operational and management units of IBWTPs in risk control.

The rest of the paper is organized as follows: Section 2 reviews the studies related to risk management of IBWTPs, and the studies related to risk transfer evolution. Section 3 gives the risk indicator system, risk measurement model and risk transfer evolution model. Section 4 validates the model through example analysis. Finally, Sections 5 and 6 summarize the discussion and conclusions of this study.

2. Literature Review

2.1. Risks of IBWTPs

The IBWTP consists of a water storage system at the source, a water transmission system, a dispatching system, and a water distribution system. Numerous studies have investigated the risk of failure associated with various infrastructure components within each system, such as structural damage to channels, aqueducts, inverted siphons, culverts, pipelines, sluices, pumping stations, and cross-channel bridges [15]. The factors contributing to infrastructure failure include human factors (e.g., operational errors by schedulers and deliberate sabotage), management factors (e.g., errors in scheduling instructions), and environmental factors (e.g., geological hazards).

Due to the complexity and uncertainty of hydrological factors, such as rainfall, floods, and droughts, the normal operation of IBWTPs is often constrained, which not only impedes the realization of the project's benefits but also increases the difficulty of its operation and management. Wenquan Gu et al. [13] investigated the risk of water shortage in the water source area of IBWTPs, introducing risk indicators such as reliability, resilience, vulnerability, and consistency, and proposed a quantitative framework that included incoming water volume, water demand, reservoir operation simulation, and a risk evaluation model. Additionally, Xiaomang Liu et al. [14] examined the probability of simultaneous droughts in both the water source and receiving areas of China's CLPSNWD and predicted an increased risk of simultaneous droughts in these areas from 2020 to 2050 using a global climate model. WANG Xiaohong et al. [27] investigated the probability of drought in both the water supply and receiving areas of the Hanjiang-to-Weihe River Diversion Project from 1969 to 2018. Their findings revealed an increase in drought probability in both areas. They also predicted, based on CMIP6 projections, that the increase in precipitation from 2019 to 2050 may alleviate drought conditions, though the high variability in precipitation increases the uncertainty of concurrent droughts in the future.

The safety of water quality in IBWTPs is related to the water security of the receiving areas. Pollution of water sources [18–20], including illegal industrial wastewater discharge, the inflow of pesticide and fertilizer residues from agricultural non-point source pollution, and the intrusion of exogenous pollutants along with algae proliferation during water conveyance [2,21–23,28], can result in the degradation of water quality. Caihong Tang et al. [22] analyzed the risk of water pollution accidents caused by traffic accidents on bridges across the main canals of an IBWTP. They investigated pollution sources and identified pollution factors using Bayesian networks, and examined the transfer process of pollutants using hydrodynamic and water quality models. Xizhi Nong et al. [28] developed a risk analysis model using the Vine Copula function to examine the effects of various hydrological and environmental factors on algal proliferation in an IBWTP. Libin Chen, Chunhui Li, Wenwen Gao, and others focused on the water source, investigating the spatial and temporal patterns of eutrophication in the reservoirs and the overall risk of water pollution in the IBWTP's source area [18–20]. In contrast, Xizhi Nong and colleagues [21,23] took a holistic approach to evaluate the water quality of the IBWTP by analyzing seasonal

and spatial patterns using the Water Quality Indicator method. Yao Yang et al. [23] analyzed the environmental factors influencing the growth of golden mussels and developed a framework for assessing the risk of biological invasion in IBWTPs, considering the potential damage golden mussels pose to channel structures and water quality.

Existing studies have examined the risks related to the safe operation of IBWTPs in terms of engineering safety, water quality, and water quantity, significantly contributing to the safe and sustainable operation of these projects. However, systematic studies are lacking, and dynamic risk assessments have yet to be conducted.

2.2. Evolution of Risk Transmission

Current research on the evolution of risk transmission can be categorized into two types: qualitative and quantitative. Qualitative research focuses on the causal relationships and transmission pathways of risk [29]. This approach primarily identifies and classifies risk factors through case studies, expert interviews, questionnaires, and literature reviews [30–33], aiming to construct a causal network structure [34] of risks and analyze the underlying causal links between them. For instance, Xiaobo Shi et al. [33] examine the causal relationship between safety risks in coal mine construction and identify 12 pathways of risk propagation. Similarly, Kai Zhang et al. [25] investigate the transmission pathways of international interest rate fluctuations on the bankruptcy risk of China's construction industry, which include the commodity price effect and exchange rate effect. The primary transmission pathways are the commodity price effect and exchange rate effect. In addition, qualitative research also examines the mediating variables in the risk transmission process, which elucidate the transmission mechanism of risk from the initial factors to the final outcome. For instance, it investigates the mediating role of international interest rates in the bankruptcy risk of China's construction industry [25].

In quantitative research on risk transfer, the focus is primarily on the transfer of probability [35]. This type of research leverages a wide range of mathematical models and statistical methods to accurately quantify the probability of risk transfer between different systems or entities and analyze its dynamic evolution [36]. Common quantitative models include the Markov chain model and the complex network model. The Markov chain model predicts the probability distribution of future states based on the current state of the system, and is useful for describing the probability patterns of risk transfer across different stages or states [37]. The complex network model constructs a risk transfer network, where each risk entity is treated as a node and the risk transfer relationship as a network edge, with corresponding weights or probability values. This model allows for the visualization of risk propagation within a complex network system [36].

Qualitative and quantitative research complement each other in the study of risk transfer evolution. Qualitative research offers a robust theoretical foundation and empirical evidence to deepen the understanding of the intrinsic mechanisms and logical relationships of risk transfer. In contrast, quantitative research supports the precise assessment, prediction, and management decision-making of risk transfer through advanced mathematical models and statistical methods. The integration of both approaches fosters the continued advancement of risk transfer evolution research and provides more scientifically grounded and effective theoretical guidance and practical strategies for addressing various complex risk challenges.

The definition of risk primarily involves two dimensions: the probability of occurrence and the potential loss associated with the risk. Most existing research quantifies risk by the product of probability and consequence. However, Williams argues that relying solely on this product to express and rank risk is inadequate, as it neglects to consider both factors simultaneously [38]. Some scholars have refined the risk measurement model by

incorporating additional indicators, such as predictability, exposure, manageability, and controllability, thus advancing from a two-dimensional to a three-dimensional approach with promising results [39]. Risk predictability refers to the understanding and awareness of risk event patterns; exposure represents the frequency of risk events [40]; risk controllability is the ratio of the impact of risk before and after implementing countermeasures [41]; and risk manageability, similar to controllability, reflects the ease with which a risk can be reduced through management efforts [42]. These indicators are intrinsically related to the likelihood and consequences of a risk's occurrence, and the traditional indicators of probability and risk loss effectively encompass the meanings expressed by these additional factors. Therefore, this paper measures risk by considering both the probability of occurrence and the associated risk loss, along with their product.

3. Model Construction

3.1. Research Methodology

A Bayesian network is a directed acyclic graph that describes probabilistic relationships, effectively representing the causal and dependency relationships between nodes in the analysis of uncertainty problems [43]. However, traditional Bayesian networks do not account for the dynamics of real-world situations and are unable to capture the evolving nature of variables over time. Dynamic Bayesian networks, in contrast, extend traditional Bayesian networks by incorporating a time component, allowing them to better align with real-world situations. These networks are particularly useful for analyzing complex problems through logical inference based on incomplete, imprecise, or uncertain knowledge, making them well-suited for probability estimation in stochastic processes [44]. However, due to limitations in available knowledge and data, obtaining accurate probability estimates remains challenging [45]. DS evidence theory is an uncertainty reasoning method that effectively expresses the concepts of “uncertainty” and “ignorance,” making it well-suited for handling uncertain information. It employs likelihood and trust probabilities from evidence theory to describe the failure probability interval of the root node, addressing the challenge of estimating the root node's risk probability when it is uncertain or difficult to obtain precisely [46]. By synthesizing the advantages of DS evidence theory and Bayesian networks, this paper proposes a novel risk probability estimation method that combines DS evidence inference with dynamic Bayesian networks. A risk probability estimation model for the safe operation of the IBWTP is developed by constructing the trust function, likelihood function, and the structural model of the risk relationship. Additionally, a dynamic evolution model of risk is developed using the dynamic Bayesian network.

3.2. Risk Indicators for the Safe Operation of IBWTPs

The primary objective of the IBWTP is to transfer water from water-abundant areas to water-scarce regions. However, several factors can hinder the achievement of this goal, which constitute the risk factors for its safe operation. These include engineering failures, issues with the scheduling system, water quality and quantity problems, as well as challenges arising from increased operational costs and decreased revenues, all of which can disrupt the normal functioning of the project [12]. Based on a literature review and data analysis, the risks associated with the safe operation of IBWTPs are categorized into six main types: engineering risks, natural risks, water quality pollution risks, operational risks, social risks, and economic risks, as illustrated in Table 1.

Table 1. Risk Framework for the Safe Operation of IBWTPs.

Second-Level Risk	Third-Level Risk	Fourth-Level Risk	Source
Engineering risks X_1	Channel engineering risk X_{11}	Channel water overflow X_{111} Uneven settlement of channel foundation X_{112} Uplift and cracking of channel bottom plate X_{113} Damage to channel slope protection measures X_{114} Channel slope instability and failure X_{115}	Bo Wang et al. [1] Xiangtian NIE et al. [12] Jin S et al. [17] Wang X et al. [47] Nie X et al. [48]
	Pipeline engineering risk X_{12}	Prestressed Concrete Cylinder Pipe(PCCP) pipe burst X_{121} Pipe crack damage X_{122} Pipe anti-floating instability X_{123} Pipe anti-sliding instability X_{124} Uneven settlement of pipe foundation X_{125} Seal failure of pipe X_{126}	
	Risks in cross-buildings for water conveyance (drainage) X_{13}	Surface erosion of concrete and corrosion of reinforcement in buildings X_{131} Cracks in concrete building structures X_{132} Uneven settlement of building substructure X_{133} Seal damage and leakage in aqueducts X_{134} Leakage at the joint of siphon (culvert) pipes X_{135}	
	Risks in cross-buildings for water conveyance (culverts) X_{14}	Rupture and Leakage of Cross-Channel Pipes X_{141} Leakage and Collapse of Cross-Channel Tunnels X_{142} Rupture and Fall into Channel of Cross-Channel Pipes X_{143} Collapse of power and communication line towers X_{144} Uneven settlement of piers in cross-channel bridges X_{145} Vehicle plunge in traffic bridge into the channel X_{146} Structural damage of cross-channel bridges X_{147}	
	Control building risk X_{15}	Malfunction of metal structures and electromechanical equipment X_{151} Instability of dam gate structures X_{152} Instability of pump station structures X_{153}	
Natural risks X_2	Flood disasters X_{21}	Flooding overflow X_{211} Building instability and damage by flood erosion X_{212}	Xiangtian NIE et al. [12] Gu W et al. [13] Liu X et al. [14] Liu M et al. [4] Liu M et al. [16]
	Drought disasters X_{22}	Insufficient water supply capacity in water source areas due to drought X_{221} Severe water shortage in receiving areas due to drought X_{222}	
	Freezing disasters X_{23}	Risk of ice jam and ice dam X_{231} Low-temperature damage to concrete structures X_{232} Equipment malfunction due to low temperatures X_{233}	
	Geological disasters X_{24}	Earthquake damage X_{241} Landslide and debris flow in mountainous areas X_{242} Foundation collapse X_{243}	
Water quality pollution risks X_3	Water quality pollution in water source areas X_{31}	Excessive levels of pollutants in inflowing water from the upstream area of water source X_{311} Excessive discharge of pollutants near the water source X_{312}	Nong X et al. [2] Chen L et al. [18] Li C et al. [20] Gao et al. [19] Zhang X et al. [49]
	Water quality pollution in the conveyance process X_{32}	Infiltration of underground sewage into channel X_{321} Infiltration of surface sewage into channel X_{322} Traffic accidents of hazardous material transport vehicles on cross-channel bridges X_{323} Abnormal proliferation of algae X_{324}	

Table 1. Cont.

Second-Level Risk	Third-Level Risk	Fourth-Level Risk	Source
Operational risks X_4	Internal failures or human operational errors in the scheduling system X_{41}	Remote control system malfunction X_{411} Abnormalities in data collection systems X_{412} Human operational errors X_{413}	Xiangtian NIE et al. [12]
	External impairment of the safeguarding capability of the scheduling system X_{42}	External power and communication system failures X_{421} Insufficient water supply capacity due to water source scheduling X_{422}	
Social risks X_5	Risks of sudden mass events X_{51}	Water disputes caused by unreasonable distribution in water conveyance and distribution process X_{511} Social conflicts arising from inadequate resettlement and post-aid for immigrants X_{512} Social conflicts arising from insufficient environmental and ecological protection and compensation X_{513}	Xiangtian NIE et al. [12] Zhang X et al. [49]
	Risks of sudden public safety events X_{52}	Terrorist attack X_{521} Fire accident in engineering operation management unit X_{522} Cross-channel bridge traffic accident X_{523} Malicious poisoning X_{524} Malicious destruction of engineering equipment and facilities X_{525}	
Economic risks X_6	Decrease in operational revenue of the project X_{61}	Reduced water demand in the receiving area for project water diversion X_{611}	Xiangtian NIE [12]
	Increase in operational costs of the project X_{62}	Increase in loan interest rates X_{621} Rise in repair and maintenance costs X_{622}	

3.3. Risk Measurement Model for the Safe Operation of IBWTPs

3.3.1. Risk Probability Estimation

1. Dynamic Bayesian network;

A Bayesian network is established based on graph theory and probability theory. The network graph consists of nodes and directed edges. Nodes represent variables, while directed edges represent logical relationships between nodes. The schematic diagram of the Bayesian network is shown in Figure 1, and it can be denoted as $BN = (G, \theta)$, where G represents the network structure and θ represents the network parameters. Specifically, $G = (X, V)$ is the directed acyclic graph, where $X = \{X_1, X_2, \dots, X_n\}$ is the set of nodes, and V is the set of directed edges, representing the causal dependencies between nodes. The network parameter θ consists of the conditional probabilities that describe the causal relationships between nodes, denoted by $P(X_i | \pi(X_i))$.

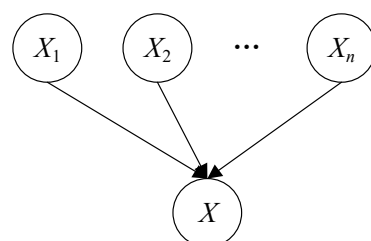


Figure 1. Schematic Representation of a Bayesian Network.

A dynamic Bayesian network is an extension of a static Bayesian network along the time dimension, consisting of multiple time points, each of which can be modeled as a static

Bayesian network. Let a set of random variables $X[0], X[1], \dots, X[T]$ be defined by incorporating the time factor, where $X[t]$ represents all the nodes in the static Bayesian network at time t , such that $X[t] = \{X_1[t], X_2[t], \dots, X_n[t]\}$. The construction of a dynamic Bayesian network model typically requires the satisfaction of the following two assumptions [44]:

- The process of conditional probability change remains consistently smooth for all t within a finite time frame;
- The dynamic probabilistic process follows a Markovian property, where the probability of a future state depends solely on the current state, and not on any previous states.

At this stage, the dynamic Bayesian network (DBN) is defined as $DBN = (G_0, G_{\rightarrow})$, where G_0 represents the initial network, $G_{\rightarrow}$ represents the transfer network, and the schematic diagram of the dynamic Bayesian network is provided in Figure 2.

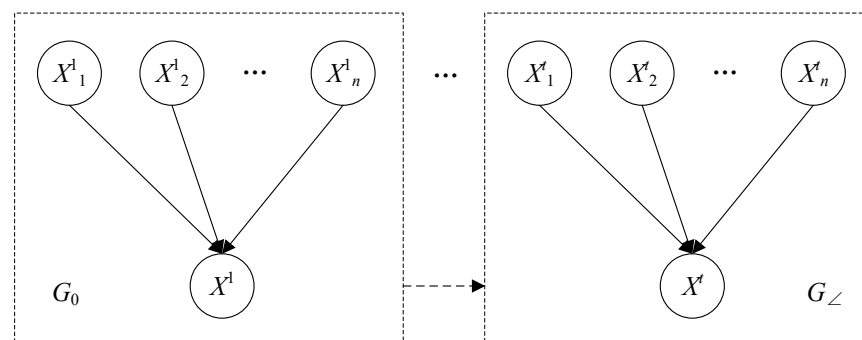


Figure 2. Schematic diagram of dynamic Bayesian network.

2. DS Evidence Theory;

DS evidence theory employs the belief function (Bel) to represent the degree of trust in events, and the plausibility function (Pl) to represent the degree of non-objection to events [50]. Both Pl and Bel define the upper and lower bounds of the support for an event's occurrence, as illustrated in Figure 3. Furthermore, DS evidence theory facilitates the fusion of evidence from multiple independent sources.

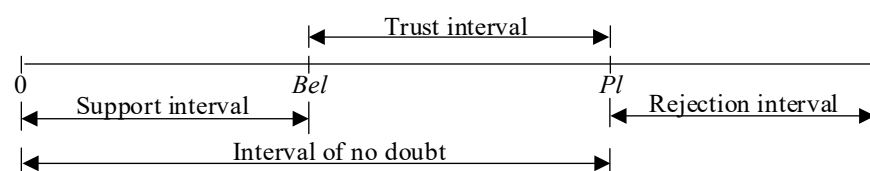


Figure 3. The confidence interval of the event occurrence.

3. Risk Occurrence Probability Estimation Model;

For analytical convenience, the following symbolic definitions for the risk factors are adopted: Let X denote the risk of safe operation for IBWTPs, representing the first-level risk factor. Let X_i represent the i -th type of risk factor within the safe operation risk of IBWTPs, corresponding to the second-level risk factor, where $i = 1, 2, \dots, 6$. Let X_{ij} indicate the j -th type of risk factor under the i -th category of risks, representing the third-level risk factor, where $j = 1, 2, \dots, 5$. Let X_{ijk} denote the k -th risk factor under the j -th type of risk within the i -th category of risks, representing the fourth-level risk factor, where $k = 1, 2, \dots, 7$. Let P represent the probability of risk occurrence, and $t = 1, 2, \dots, T$ denote different time moments.

In DS evidence theory, Bel and Pl represent the degree of belief and the degree of non-objection to an event, respectively. The interval $[Bel, Pl]$ represents the trust interval for the event. In this study, this trust interval is used to define the upper and lower bounds of the probability P for the occurrence of a risk event.

By describing the uncertainty of the risk state for the fourth-level risk factor X_{ijk} at time t and analyzing the data source, it is treated as evidence information. Using Equations (1)–(4), the belief function $Bel(X_{ijk}^{t,a})$ and the probability function $Pl(X_{ijk}^{t,a})$ for the risk factor X_{ijk} at time t in state a can be derived. Consequently, the probability range for the occurrence of risk X_{ijk} in state a at time t is $[Bel(X_{ijk}^{t,a}), Pl(X_{ijk}^{t,a})]$.

$$m(X_{ijk}^{t,a}) = \begin{cases} \frac{\sum_{A_i \cap B_j \cap \dots \cap Z_l = X_{ijk}^{t,a}} m_1(A_i)m_2(B_j) \dots m_n(Z_l)}{1-K}, & \forall X_{ijk}^{t,a} \in \Theta, X_{ijk}^{t,a} \neq \emptyset \\ 0, & X_{ijk}^{t,a} = \emptyset \end{cases} \quad (1)$$

$$Bel(X_{ijk}^{t,a}) = m(X_{ijk}^{t,a}) \quad (2)$$

$$Pl(X_{ijk}^{t,a}) = 1 - Bel(\overline{X_{ijk}^{t,a}}) \quad (3)$$

where $m_1, m_2, \dots, m_n$ denote the basic probability distribution functions of the n evidence sources, $A_i, B_j, \dots, Z_l$ denote the sets of events in the corresponding evidence sources, respectively, and K denotes the conflict coefficient between the fused evidence, which can be expressed as

$$K = \sum_{A_i \cap B_j \cap \dots \cap Z_l = \emptyset} m_1(A_i)m_2(B_j) \dots m_n(Z_l) < 1 \quad (4)$$

The occurrence probability range of tertiary risk X_{ij}^t , secondary risk X_i^t , and primary risk X^t at moment t can be determined through Bayesian network inference, as shown in the inference model in Figure 4.

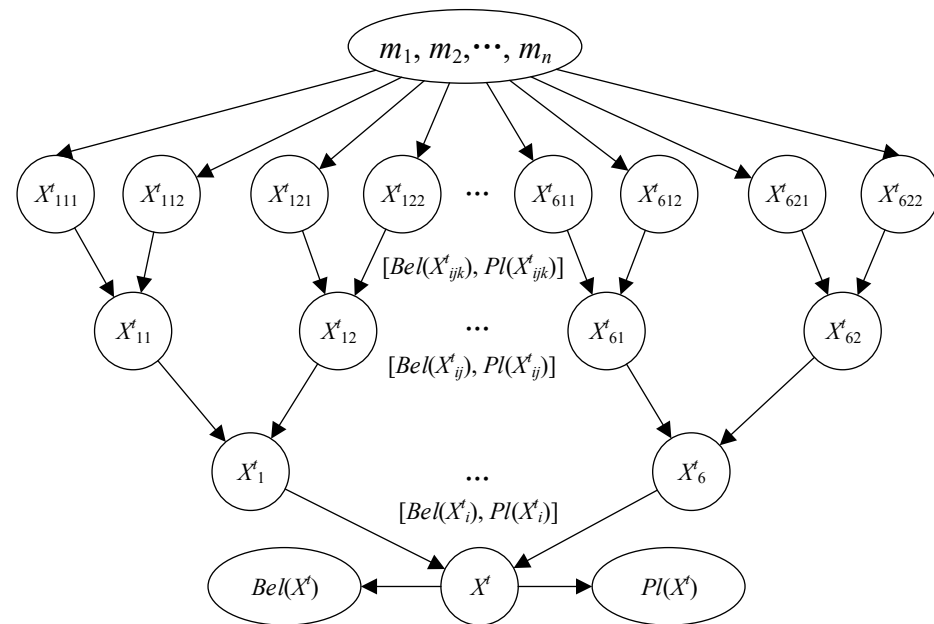


Figure 4. Bayesian inference model for risk node trust interval.

Assuming multiple states for each risk node, let l_{ak} , l_{bj} , l_{ci} , and l_d denote the failure state types for level 4 risk node X_{ijk} , level 3 risk node X_{ij} , level 2 risk node X_i , and level 1 risk node X , respectively. Here, $i = 1, 2, \dots, 6$, $j = 1, 2, \dots, 5$, $k = 1, 2, \dots, 7$, $l_{ak} = 1, 2, \dots, L_{ak}$, $l_{bj} = 1, 2, \dots, L_{bj}$, $l_{ci} = 1, 2, \dots, L_{ci}$, $l_d = 1, 2, \dots, L_d$, where L_{ak} , L_{bj} , L_{ci} and L_d denote the number of states for each level of risk nodes. The interval bounds I represent the trust interval, and the probability range for each node, expressed in terms of the number of intervals P , can be determined using evidence theory. This allows the probability intervals

for the occurrence of a specific state of the third-level risk node X_{ij} , second-level risk node X_i , and first-level risk node X at time t to be calculated.

$$P_I^t(X_{ij}^t = X_{ij}^{t,l_{bj}}) = [Bel(X_{ij}^t = X_{ij}^{t,l_{bj}}), Pl(X_{ij}^t = X_{ij}^{t,l_{bj}})] \quad (5)$$

$$P_I^t(X_i^t = X_i^{t,l_{ci}}) = [Bel(X_i^t = X_i^{t,l_{ci}}), Pl(X_i^t = X_i^{t,l_{ci}})] \quad (6)$$

$$P_I^t(X^t = X^{t,l_d}) = [Bel(X^t = X^{t,l_d}), Pl(X^t = X^{t,l_d})] \quad (7)$$

According to the full probability formula of the Bayesian network, the upper and lower bounds of the probability of occurrence for different states of the risk node at time t can be obtained. In this paper, the risk probability is estimated by taking the average of the upper and lower bounds of the occurrence probability for each risk state, thereby providing the prior probability for the risk states.

4. Inference of Dynamic Probability Changes;

As time progresses from a state at time t to a subsequent state at $t + 1$, the observation of new evidence leads to a dynamic update in the probability of risk occurrence. While static Bayesian network inference can be applied sequentially to compute the occurrence probabilities of nodes at $t + 1$, its application over numerous time steps leads to a substantial increase in computational complexity, primarily due to the fundamental limitation of its inability to model temporal correlations [44]. The Markov assumption, fundamental to Dynamic Bayesian Networks, posits that the state of all nodes at time $t + 1$ is conditionally dependent only on their state at time t , thereby being independent of the entire historical sequence prior to t . This assumption thereby resolves the computational bottleneck encountered when modeling multiple time steps with static networks. Furthermore, the stationary process assumption in Dynamic Bayesian Networks stipulates that the conditional transition probabilities between any two consecutive time steps remain constant. This not only aligns with realistic scenarios where risk mechanisms are stable over short periods but also significantly reduces model complexity by minimizing the number of parameters requiring estimation [44]. Consequently, Dynamic Bayesian Networks provide a suitable framework for conducting dynamic probability inference of risks. The specific steps are as follows.

Model construction

Since the probability of higher-level risks can be inferred from that of lower-level risks, the dynamic Bayesian network model focuses solely on the transition probabilities among the four defined risk levels. The probabilistic inference mechanism for assessing safe operation risks in IBWTPs using the dynamic Bayesian network is illustrated in Figure 5.

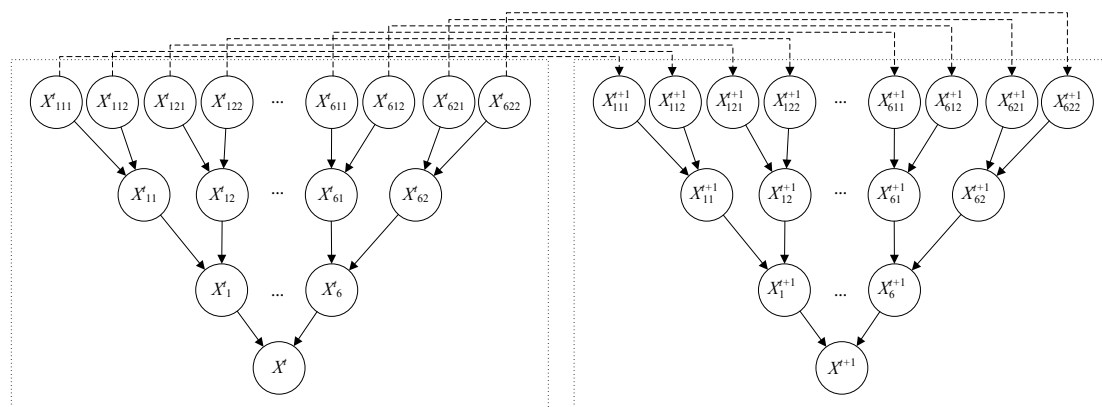


Figure 5. Probabilistic Inference Process of DBNs for Safety Operation Risks in IBWTPs.

Model Parameter Determination

Prior probabilities can be obtained through the DS evidence theory and Bayesian network inference discussed earlier.

The conditional probabilities are derived from the predefined likelihoods of Level 4 risks, and the occurrence probabilities of Level 3, Level 2, and Level 1 risks are subsequently computed using Formulas (8)–(10).

$$P(X_{ij}^{l_{bj}} | X_{ij1}^{l_{a1}}, X_{ij2}^{l_{a2}}, \dots, X_{ij7}^{l_{a7}}) = \frac{P(X_{ij}^{l_{bj}} \cap (X_{ij1}^{l_{a1}}, X_{ij2}^{l_{a2}}, \dots, X_{ij7}^{l_{a7}}))}{P(X_{ij1}^{l_{a1}}, X_{ij2}^{l_{a2}}, \dots, X_{ij7}^{l_{a7}})} \quad (8)$$

$$P(X_i^{l_{ci}} | X_{i1}^{l_{b1}}, X_{i2}^{l_{b2}}, \dots, X_{i5}^{l_{b5}}) = \frac{P(X_i^{l_{ci}} \cap (X_{i1}^{l_{b1}}, X_{i2}^{l_{b2}}, \dots, X_{i5}^{l_{b5}}))}{P(X_{i1}^{l_{b1}}, X_{i2}^{l_{b2}}, \dots, X_{i5}^{l_{b5}})} \quad (9)$$

$$P(X_1^{l_d} | X_1^{l_{c1}}, X_2^{l_{c2}}, \dots, X_6^{l_{c6}}) = \frac{P(X_1^{l_d} \cap (X_1^{l_{c1}}, X_2^{l_{c2}}, \dots, X_6^{l_{c6}}))}{P(X_1^{l_{c1}}, X_2^{l_{c2}}, \dots, X_6^{l_{c6}})} \quad (10)$$

The transition probabilities account solely for risk level transitions among the four defined categories and are calculated using Equation (11). Each risk level includes only two possible states, occurrence and non-occurrence, denoted as $l_a = 1$ and 2.

$$P(X_{ijk}^t | X_{ijk}^{t-1}, X_{ijk}^{t-2}, \dots, X_{ijk}^1) = P(X_{ijk}^t | X_{ijk}^{t-1}) = y \begin{matrix} y & n \\ \begin{bmatrix} \alpha & 1 - \alpha \\ \beta & 1 - \beta \end{bmatrix} \end{matrix} \quad (11)$$

In the formula, y represents the occurrence of a risk, and n represents its non-occurrence. The parameter α denotes the probability that risk X_{ijk} occurs at time t , given that it also occurred at time $t - 1$, whereas β denotes the probability that risk X_{ijk} occurs at time t despite its non-occurrence at time $t - 1$.

3.3.2. Loss Estimation

Currently, the quantitative estimation of risk consequences is primarily expressed in monetary terms. Some scholars have employed fuzzy loss rates [51] and risk consequence equivalents to provide a standardized measure of risk-related losses [52]. Given the large number of risk categories and the need for comparability, this paper utilizes the equivalent method to estimate the magnitude of risk losses.

In accordance with the relevant provisions of China's National Compensation Law, the Regulations on Work-Related Injury Insurance, the Interpretation of Certain Issues Concerning the Application of Law in the Trial of Personal Injury Claims, and the Provisions on the Procedures for Reporting and Investigating Major Accidents in Engineering and Construction, and by referencing studies on equivalent losses, this study calculates the compensation based on the actual benefits provided to victims across various aspects. For the equivalent indicators of environmental and social loss, they are determined based on studies of equivalent loss consequences and considering China's level of economic development. The details are as follows.

Taking the death of one person as one loss equivalent, the following risk losses are each considered equivalent to one loss: first, three individuals seriously injured or fifty individuals slightly injured; second, CNY 1 million in economic losses; third, minor environmental damage; and fourth, minor social impact. The values of loss equivalents and the criteria for assessing the degree of loss are shown in Table 2.

Table 2. Values of loss equivalents and criteria for loss degree.

Degree of Risk Loss	Tiny	Mild	Moderate	Seriousness	Extremely Serious
Equivalent value	0~1	1~10	10~50	50~100	100 and above

3.3.3. Risk Measurement Model

Through the aforementioned steps, the probability of occurrence for each risk node, the equivalent risk loss value, and the expected loss value of the risk can be derived as key dimensions for risk measurement. Consequently, the overall risk, denoted as R , can be expressed as follows:

$$R = (P, S, P \times S) \quad (12)$$

where P represents the probability of risk occurrence, S denotes the corresponding risk loss equivalent value, and $P \times S$ reflects the expected value of risk loss.

Based on the Guidelines for the Identification of Hazard Sources and Risk Evaluation of Water Conservancy and Hydropower Projects (including Reservoirs and Sluice Gates), Guidelines for the Identification of Hazard Sources and Risk Evaluation of Water Conservancy and Hydropower Projects (including Hydropower Stations and Pumping Stations), Guidelines for the Identification of Hazard Sources and Risk Evaluation of Water Conservancy and Hydropower Projects (including Embankments and Silt Dams), Guidelines for the Identification of Hazard Sources and Risk Evaluation of the Construction of Water Conservancy and Hydropower Projects, and the related literature [52–54], we classify the probability of occurrence and the degree of loss associated with the safe operation risks of the IBWTP into five categories, providing the corresponding value ranges for each category. Specifically, refer to Tables 3–6.

Table 3. Risk probability level and corresponding risk probability range.

Risk Probability Level	Almost Impossible (Extremely Low) (Level I)	Unlikely to Occur (Low) (Level II)	Occasional Occurrence (Moderate) (Level III)	Likely to Occur (High) (Level IV)	Frequently Occurs (Very High) (Level V)
Range	$<10^{-4}$	$10^{-4} \sim 10^{-2}$	$10^{-2} \sim 0.1$	$10^{-1} \sim 0.5$	$0.5 \sim 1$

Table 4. Risk loss level and corresponding risk equivalent value range.

Loss Level	Slight (Level I)	Lower (Level II)	Normal (Level III)	Seriousness (Level IV)	Catastrophic (Level V)
Loss equivalent range	0~1	1~10	10~50	50~100	≥ 100

Table 5. Risk level division.

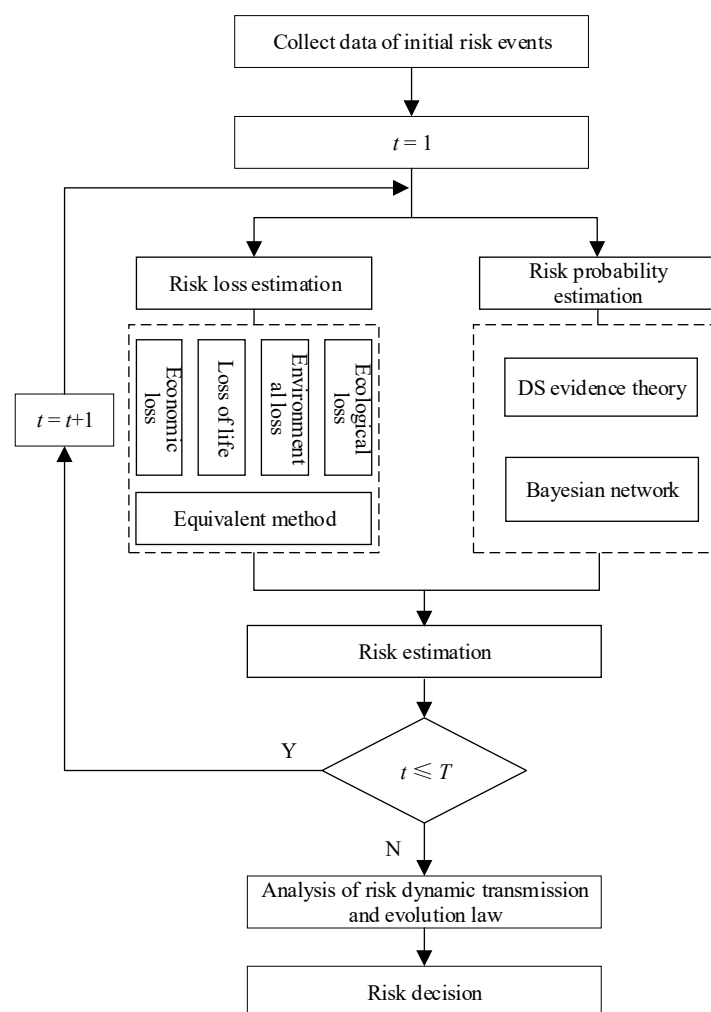
Loss Level	1 Slight	2 Lower	3 Lower	4 Seriousness	5 Catastrophic
Probability Level Risk Level					
1 Next to impossible	I	I	I	II	III
2 Hard to happen	I	I	II	III	III
3 Happen by chance	I	II	III	III	IV
4 May happen	II	III	III	IV	IV
5 Frequent occurrence	III	III	IV	IV	V

Table 6. Description of risk levels and acceptance criteria explanation.

Risk Level	Risk Level Description	Risk Acceptability	Instructions
I	Very low risk	Negligible	Can be neglected
II	Low risk	Acceptable	Measures are not necessary, but attention should be paid
III	Medium risk	Tolerable	Measures can be taken to reduce the risk
IV	High risk	Unacceptable	Measures must be taken to significantly reduce the risk
V	Extremely high risk	Totally unacceptable	Measures must be taken to eliminate the risk

3.4. Evolutionary Modeling of Dynamic Risk Transfer for the Safe Operation of IBWTPs

The process of analyzing the evolution of dynamic risk transfer for the safe operation of IBWTPs is depicted in Figure 6, which includes the collection of initial risk data, estimation of risk probability, estimation of risk loss, analysis of risk estimation, dynamic transfer evolution, examination of the evolution law of risk dynamic transfer, and risk decision-making.

**Figure 6.** Evolutionary analysis process of risk transfer for safe operation of IBWTPs.

3.4.1. Evolutionary Model of Dynamic Risk Transfer

The development of a dynamic risk transfer evolution model is essential for conducting risk evolution analysis. By integrating Bayesian network theory, the model represents risks as nodes and the relationships of risk transfer as edges, allowing for the construction of a Bayesian network model for the evolution of risk transfer in the safe operation of IBWTPs. Considering the dynamic changes over time, the evolution of risks primarily depends on the progression of the underlying (level 4) risk events, focusing only on the influence

between two consecutive time points. Based on this approach, a dynamic risk transfer evolution model can be established using the Bayesian network framework. The model for the dynamic transfer evolution of IBWTP safety operation risks is shown in Figure 7.

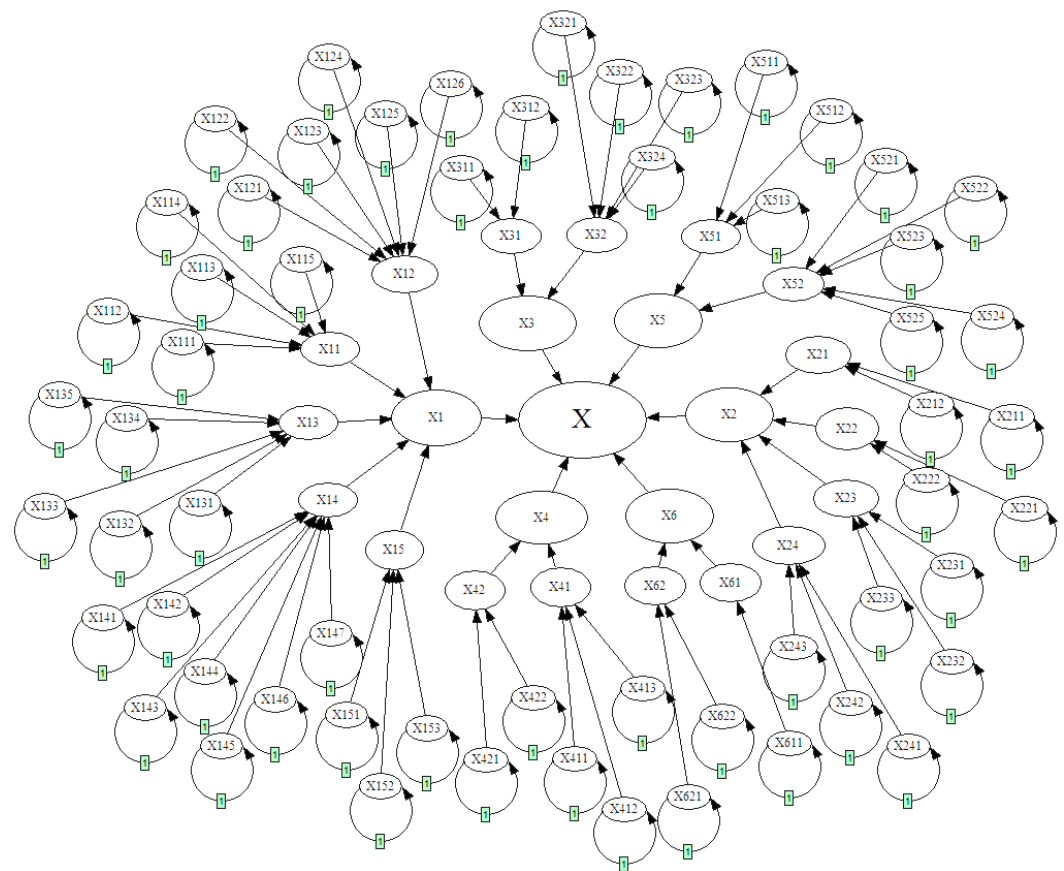


Figure 7. Evolutionary Bayesian network model for the dynamic transfer of risks of safe operation of IBWTPs.

3.4.2. Analysis of the Evolutionary Process of Risk Transfer in IBWTPs

The process of analyzing the evolution of risk transmission in the safe operation of the IBWTP includes information collection, estimation of node risk probabilities, risk evolution analysis, and estimation of node risk losses.

1. Information Collection;

After establishing the risk transfer evolution model, it is essential to collect data on the fundamental risk events, including the occurrence of these events within a specific time period (usually based on a water transfer year); the probability of their occurrence, which can be obtained from risk databases or risk management manuals; and an analysis of the losses resulting from these risk events.

Basic risk event data can be obtained through literature reviews, operational detection and monitoring data, web-based data mining, and expert knowledge. In cases where data directly related to risk events is insufficient, indirect but relevant data from other regions or related industries can be used to supplement the analysis.

2. Nodal Risk Probability Estimation and Transfer Evolution;

For basic risk events with sufficient data, the occurrence probability can be calculated using statistical methods. For events lacking sufficient data, the probability of occurrence can be estimated by utilizing the collected evidence, with Equations (1)–(4) used to determine the upper and lower bounds of the probability.

Once the range of occurrence probabilities for basic risk events is determined, the probability of occurrence for each risk node can be inferred using the probability estimation model in Section 3.3.1. Considering the dynamic nature of time, the probability dynamics can be inferred using the dynamic Bayesian network. Two key elements in dynamic Bayesian probabilistic inference are the initial probability and the state transition probability. The initial probability can be calculated based on the model in Section 3.3.1. For the state transition probability, it can be derived using maximum likelihood estimation, Bayesian estimation, or other methods when sufficient data is available. Alternatively, it can be defined using a Markov process or C-K equation if the mechanism of risk probability change is well understood. When data or knowledge about risk mechanisms is lacking, expert experience can be utilized to estimate the state transition probability [54–57].

Finally, based on the results of probability estimation for risk nodes and dynamic inference, the overall risk level is determined, and the impact of each risk indicator on the overall risk size, as well as the temporal evolution of the risk, is analyzed.

3. Nodal Risk Loss Estimation;

To harmonize measurement standards and facilitate the quantitative analysis of risk transfer, the equivalent method is employed to convert risk losses into equivalent values. This method estimates the equivalent loss for each risk based on the results of evaluating risk losses through research on risk events and analysis of risk-related data.

4. Risk Estimation and Transmission Evolution;

Through the above steps, the probability of occurrence for each risk node and the equivalent value of risk loss for the event can be determined, and the risk measurement value can be derived using Equation (12). Given the difficulty in directly quantifying the multidimensional risk measure, the expected loss value is used as a medium for analysis. Let the probability of occurrence of risk X_i be P_i , and the corresponding risk loss be S_i ; then, the expected risk loss value is

$$R_i^* = P_i \times S_i \quad (13)$$

The risk transfer parameters are

$$\lambda_i = \frac{R_i^*}{\sum R_i^*} \quad (14)$$

The risk of a child node, after risk transfer, is the sum of the expected risk loss values from its corresponding parent nodes.

$$R^* = \sum R_i^* \quad (15)$$

Based on the risk measurement level classification, the risk level of each risk can be determined. If the risk level is V, measures must be implemented to eliminate the risk and prevent the occurrence of the risk event. If the risk level is IV, measures should be taken to reduce the risk. For level III risks, the size of the risk value (R^*) should be compared with the input of normal risk control measures. If the input of normal risk control measures exceeds the risk loss, the current risk response measures can remain unchanged. If the input of normal risk control measures is less than or equal to the risk loss, additional risk management efforts should be made to either reduce the probability of risk occurrence or mitigate the consequences to reduce the overall risk value. For level II risks, no immediate measures need to be taken, but monitoring should be increased, and timely intervention should be implemented to prevent escalation. Level I risks are considered negligible. Additionally, for risks with a low overall risk value but a high probability of occurrence or

significant potential loss, targeted measures should be taken to either reduce the likelihood of the risk or minimize the severity of the risk loss.

As time progresses and new evidence is incorporated, the probability of risk occurrence can be updated using DS evidence theory. Subsequently, the risk value of each intermediate node and the overall system can be inferred through a Bayesian network. Based on whether the obtained risk value exceeds the acceptable threshold, appropriate risk decision-making, along with the establishment of effective risk control strategies and countermeasures, can be implemented. By leveraging the dynamic Bayesian network, the temporal changes in risk values can be identified, allowing for the analysis of the risk evolution process. From the perspective of risk evolution, targeted measures can be formulated to either prevent or slow the malignant progression of risk, encourage its benign evolution, and minimize risk losses.

4. Case Study

4.1. Project Overview

The CLPSNWD draws water from the Taoqiao Drainage Head of the Danjiangkou Reservoir in the upper reaches of the Han River. The water transmission channel extends over 1432 km, passing through four provinces and municipalities: Henan, Hebei, Beijing, and Tianjin. It crosses the four major river basins of the Yangtze River, the Huaihe River, the Yellow River, and the Haihe River. The channel includes drainage sections, such as those in coal mine hollow areas and deep excavation areas. In addition to channels and pipeline projects, there are various cross-buildings and post-construction crossings over the channel.

4.2. Risk Estimation

1. Data Collection;

The primary methods of data collection include reviewing historical information, such as literature and reports, and conducting expert interviews. The historical information collected includes the China SNWDP Construction Yearbook, the SNWDP Flying Inspection Report, the CLPSNWD Safety Risk Assessment Report, and the SNWDP Operational Safety Inspection Technology Research and Demonstration Project Report [58]. In addition, five experts involved in the construction and operation of the SNWDP were interviewed to obtain information on risk events that occurred during the project's operation. The dataset consists of two components: quantitative estimates for the probability of risk factor occurrence and descriptive information on risk events, with 2020 serving as the baseline year for the fundamental risk data.

After data collection, five experts with specialized knowledge in the operation and management of the first phase of the CLPSNWD were invited to evaluate the consistency between the risk data and actual project conditions. All five experts are senior engineers, including three from China South-to-North Water Diversion Group Central Route Co., Ltd., one from its Henan Branch, and one from its Hebei Branch. Each expert possesses more than eight years of professional experience in the operation and management of the CLPSNWD.

The evaluation adopted a five-point Likert scale: 1 = Completely inconsistent with reality (indicating extreme deviation between assessed values and actual conditions); 2 = Fairly inconsistent with reality (significant deviation); 3 = Generally consistent with reality (minor deviation); 4 = Fairly consistent with reality (values largely consistent with actual conditions); 5 = Completely consistent with reality (values highly consistent with actual conditions). Based on the evaluation results, the accuracy of the risk indicator data was assessed using mean scores and weighted Kappa coefficients. The mean scores of the

58 risk indicators ranged from 3.6 to 4.2, with 24 indicators scoring between 3.6 and 4.0 and 34 indicators scoring between 4.0 and 4.2, indicating that the former were largely consistent with actual conditions, while the latter exhibited relatively high consistency. The weighted Kappa coefficients for the 58 risk indicators, as evaluated by the five experts, ranged from 0.5 to 0.8. Among them, 19 indicators fell within the 0.5–0.6 range, signifying substantial agreement among experts on these metrics. For the remaining 39 indicators, the weighted Kappa coefficients ranged from 0.6 to 0.8, indicating a high level of inter-expert agreement. Overall, the risk data demonstrate good consistency with the actual engineering conditions and can therefore be regarded as reliable.

2. Probability Estimation;

In the Bayesian network model of risk dynamic transfer evolution, the occurrence of a parent node risk triggers the occurrence of its child node risk. Additionally, a child node may have multiple parent nodes, leading to various combinations of occurrence states. To simplify subsequent risk transfer calculations, all intermediate risk node states in this study are categorized into two types: “occur” and “do not occur.”

Based on the values of the trust function and likelihood function for the probability of occurrence of the basic risk event, the probabilities of occurrence for other intermediate risk nodes can be inferred. The probability of occurrence for the secondary risk is presented in Table 7.

Table 7. Probability of second-level risk occurrence.

Index	Risk	Probability of Risk Occurrence		Mean Probability of Risk Occurrence
		<i>Bel</i>	<i>Pl</i>	
1	X_1	0.2347	0.6805	0.4576
2	X_2	7.08×10^{-2}	0.3063	0.1886
3	X_3	4.44×10^{-4}	2.3×10^{-2}	1.17×10^{-2}
4	X_4	2.11×10^{-2}	0.3024	0.1618
5	X_5	2.27×10^{-2}	0.1867	0.1047
6	X_6	1.52×10^{-2}	0.1517	8.35×10^{-2}

According to Tables 3 and 7, among the risks affecting the safe operation of the CLPSNWD, engineering risk (X_1), natural risk (X_2), Operational risk (X_4), and social risk (X_5) are classified as level 4, indicating a high probability of occurrence, and are in a probable state. Among them, engineering risk has the highest probability of occurrence, water quality pollution risk (X_3) and economic risk (X_6) are classified as level 3, representing a medium probability of occurrence, and are in an occasional occurrence state.

The CLPSNWD’s safety operation risk is a complex, comprehensive risk involving a variety of risk combinations. If the risk state is simply divided into occurrence and non-occurrence, it will not provide enough precision. Therefore, based on the combinations of different types of risk, the overall risk is categorized into five states. State 1 represents the smallest risk consequences, while state 5 represents the largest. The specific classification and probability of occurrence for each risk state are shown in Table 8.

According to Tables 4 and 8, the risk of safe operation in the CLPSNWD has a probability rating of 4 for states 1 and 2, indicating a high probability of occurrence and a possible occurrence state. States 3 and 4 have a probability rating of 3, indicating a medium probability of occurrence and an accidental occurrence state. State 5 has a probability rating of 2, reflecting a low probability of occurrence and a difficult occurrence state. Overall, as the risk progresses from state 1 to state 5, the consequences of risk gradually increase while the probability of risk occurrence gradually decreases.

Table 8. Risk state classification and occurrence probability.

Risk State	Risk Classification Description	Probability of Risk Occurrence		Mean Probability of Risk Occurrence
		<i>Bel</i>	<i>Pl</i>	
1	Single risk occurrence $X(1)$	0.2971	0.3582	0.3276
2	Simultaneous occurrence of 2 types of risks $X(2)$	3.2×10^{-2}	0.3547	0.1934
3	Simultaneous occurrence of 3 types of risks $X(3)$	1.27×10^{-3}	0.151	7.61×10^{-2}
4	Simultaneous occurrence of 4 types of risks $X(4)$	2.12×10^{-5}	2.95×10^{-2}	1.48×10^{-2}
5	Simultaneous occurrence of 5 or more types of risks $X(5)$	1.3×10^{-7}	2.4×10^{-3}	1.2×10^{-3}

3. Loss Estimation;

Based on the research on operational risk events and the quantitative assessment of risks in the CLPSNWD Safety Risk Assessment Report, an equivalent estimate of the losses for the basic risk events has been derived, as shown in Table 9.

Table 9. Loss equivalent estimated values for basic risk events in the safe operation of the CLPSNWD.

Index	Basic Risk Event	Risk Loss Equivalent Value	Index	Basic Risk Event	Risk Loss Equivalent Value	Index	Basic Risk Event	Risk Loss Equivalent Value
1	X_{111}	90	21	X_{145}	10	41	X_{323}	30
2	X_{112}	73	22	X_{146}	15	42	X_{324}	8
3	X_{113}	32	23	X_{147}	45	43	X_{411}	15
4	X_{114}	6	24	X_{151}	40	44	X_{412}	5
5	X_{115}	129	25	X_{152}	68	45	X_{413}	1
6	X_{121}	60	26	X_{153}	57	46	X_{421}	15
7	X_{122}	32	27	X_{211}	100	47	X_{422}	30
8	X_{123}	52	28	X_{212}	88	48	X_{511}	20
9	X_{124}	62	29	X_{221}	66	49	X_{512}	22
10	X_{125}	48	30	X_{222}	42	50	X_{513}	25
11	X_{126}	33	31	X_{231}	8	51	X_{521}	200
12	X_{131}	5	32	X_{232}	8	52	X_{522}	5
13	X_{132}	80	33	X_{233}	7	53	X_{523}	8
14	X_{133}	85	34	X_{241}	150	54	X_{524}	1
15	X_{134}	48	35	X_{242}	80	55	X_{525}	5
16	X_{135}	45	36	X_{243}	100	56	X_{611}	20
17	X_{141}	8	37	X_{311}	30	57	X_{621}	10
18	X_{142}	69	38	X_{312}	15	58	X_{622}	8
19	X_{143}	51	39	X_{321}	10			
20	X_{144}	38	40	X_{322}	15			

There are various states in which primary, secondary, and tertiary risks can occur, with different risk losses associated with each state. However, due to the logical “or” relationship in the risk transfer process, the risk probability of a child node is the sum of the probabilities of all parent node states. Therefore, primary, secondary, and tertiary risk losses cannot be calculated through simple summation. Instead, the risk value can be obtained using Equations (13) and (15), and the primary, secondary, and tertiary risk losses can be determined by dividing the risk value by the risk probability.

4. Risk Estimation;

By utilizing the probability of each basic risk event and its corresponding loss estimation equivalent value, the measurement value for each risk can be derived, and the results can be obtained as follows by comparing Tables 3–6:

Among the risks associated with channel engineering (X_{11}), pipeline engineering (X_{12}), cross-buildings for water conveyance (drainage) (X_{13}), and flood disasters (X_{21}), channel slope instability and failure (X_{115}) are classified as class IV risks, while damage to channel slope protection measures (X_{114}) and surface erosion of concrete and corrosion of reinforcement in buildings (X_{131}) are classified as class II risks. All other risks are classified as class III. The risk value for X_{115} is 12.390, while the risk values for X_{111} , X_{112} , X_{113} , X_{121} , X_{124} , X_{125} , X_{132} , X_{133} , X_{211} , and X_{212} fall within the range of 1 to 5. All other risk values are less than 1. Overall, X_{115} represents the primary risk and is classified as high-risk; therefore, countermeasures must be implemented to achieve a substantial reduction in this risk. X_{111} , X_{112} , X_{113} , X_{121} , X_{124} , X_{125} , X_{132} , X_{133} , X_{211} , and X_{212} are classified as medium-risk and should be prioritized, with appropriate countermeasures implemented to mitigate the risk. Additionally, the risk values for severe water shortages in receiving areas due to drought (X_{222}) and foundation collapse (X_{243}) are high, at 2.999 and 1.415, respectively. These risks require increased attention, with proactive measures implemented to reduce both the likelihood of occurrence and the potential impact.

Contingency plans should be developed for risks such as terrorist attacks (X_{521}) and earthquake damage (X_{241}), which pose significant potential losses but have a low probability of occurrence, to minimize the impact. Conversely, risks such as human operational errors (X_{413}), external power and communication system failures (X_{421}), and remote control system malfunctions (X_{411}), which have a smaller potential loss but a higher probability of occurrence, should receive sustained attention and be subject to focused inspections to reduce their likelihood.

Among the engineering risks (X_1) and natural risks (X_2), the risks associated with channel engineering (X_{11}), pipeline engineering (X_{12}), and cross-buildings for water conveyance (drainage) (X_{13}) are classified as Class IV, indicating high risk. The risks associated with cross-buildings for water conveyance (culverts) (X_{14}), control buildings (X_{15}), flooding disasters (X_{21}), and drought disasters (X_{22}) are classified as Class III, representing medium risk. Freezing disasters (X_{23}) are classified as Class I, indicating a very low risk. Specifically, X_{11} has the highest risk value of 22.549, followed by X_{12} with a risk value of 6.536, X_{13} with 7.176, X_{21} with 9.742, X_{22} with 3.289, X_{14} with 2.613, and X_{15} with 1.105. Overall, the primary focus should be on X_{11} , X_{12} , X_{13} , and X_{21} due to their higher risk values.

Among the secondary risks, engineering risk (X_1) and natural risk (X_2) are classified as Class IV, indicating high risk, while operational risk (X_4), social risk (X_5), and economic risk (X_6) are classified as Class III, representing medium risk. Water quality pollution risk (X_3) is classified as Class II, denoting low risk. The risk value of X_1 is 39.979, significantly higher than that of X_2 , which is 15.636, as well as the values for X_4 , X_5 , and X_6 . Therefore, the primary focus should be on mitigating the risks associated with X_1 and X_2 .

The sum of the probabilities across the five states of the safe operation risk of the CLPSNWD is 61.31%, with an overall risk value of 59.484. The estimated risk loss equivalent is 97, and the associated risk level is classified as Level IV. According to Table 6, Level IV corresponds to a high-risk category, indicating that mitigation measures must be implemented to reduce the risk.

4.3. Risk Evolution

The time interval for the state transfer of basic risk events is measured in years. This process considers that the operation and management unit will implement countermeasures in response to the occurrence of a risk event. Accordingly, the probabilities for risk state

transitions were derived by synthesizing the pre-established occurrence probabilities with structured expert judgment from the SNWDP Expert Committee.

The probabilistic evolution analysis was initiated with 2020 as the reference point. Specific occurrences of basic risk events from 2020 to 2024 (the first five time points) were used as evidence inputs for the model prior to the analysis. The dynamic evolution of risk was performed using GeNIe4.0. The mean probability values of the basic risk events and the inferred probabilities of the other risk nodes from the previous section were considered as the initial risk probabilities (i.e., $t = 0$). The risk evolution period was set to 6. The results of the dynamic evolution of the risk probabilities for the first phase of the SNWDP are shown in Figure 8. By integrating the risk loss equivalent values, the dynamic evolution of the risk expectation values is shown in Figure 9.

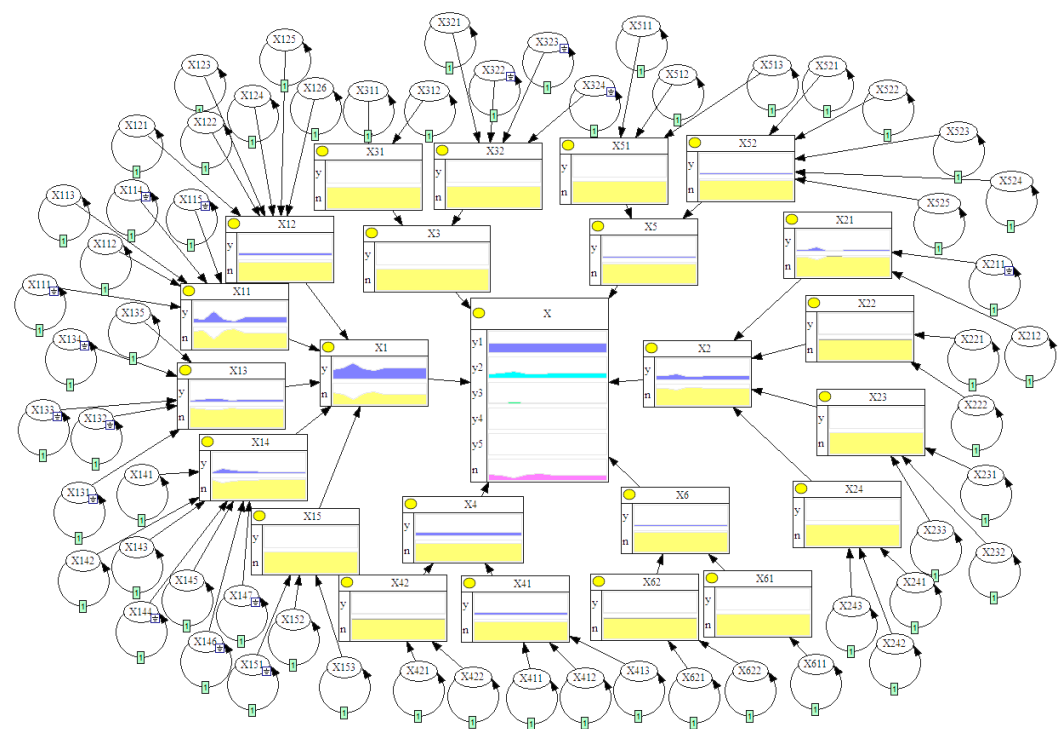


Figure 8. Dynamic evolution results of the risk probability of safe operation of the CLPSNWD.

According to Figure 9, it can be observed that the risks associated with X_{11} and X_{21} exhibit a sharp increase during the second moment, while the risk values of other factors show a gradual upward trend over time. Conversely, the risk values for X_{13} , X_{14} , and X_{32} fluctuate consistently between 0 and 5 moments. Additionally, the risk values for X_{41} , X_{42} , X_{52} , and X_{62} show a slow upward trend during the same period, while the remaining risks remain relatively stable.

The risk values for X_1 and X_2 experience a sharp increase during the second moment, with fluctuations observed at other times. This sharp increase is primarily attributed to the significant rise in the risk values of X_{11} and X_{21} during the second moment. In contrast, the risk values for X_3 , X_4 , X_5 , and X_6 remain relatively stable throughout the period.

The overall risk increases during the period from 0 to 2, followed by a continuous decrease from 2 to 5. A sudden and significant rise in risk occurs at moment 2, primarily due to the changing circumstances of X_1 and X_2 .

From the perspective of risk evolution, for risks X_{11} and X_{21} , which exhibit sudden changes in risk values, contingency plans should be developed and enhanced, with an emphasis on surveillance and early warning systems to minimize losses after risk events occur. For risks X_{13} , X_{14} , and X_{32} , which show unstable risk values, early warning and forecasting efforts should be strengthened, and targeted measures should be implemented

to stabilize and mitigate these risks. For risks X_{41} , X_{42} , X_{52} , and X_{62} , which demonstrate a gradual increase in risk values, regular inspections should be reinforced to identify potential issues and address them promptly, thereby reducing the likelihood of risk occurrence.

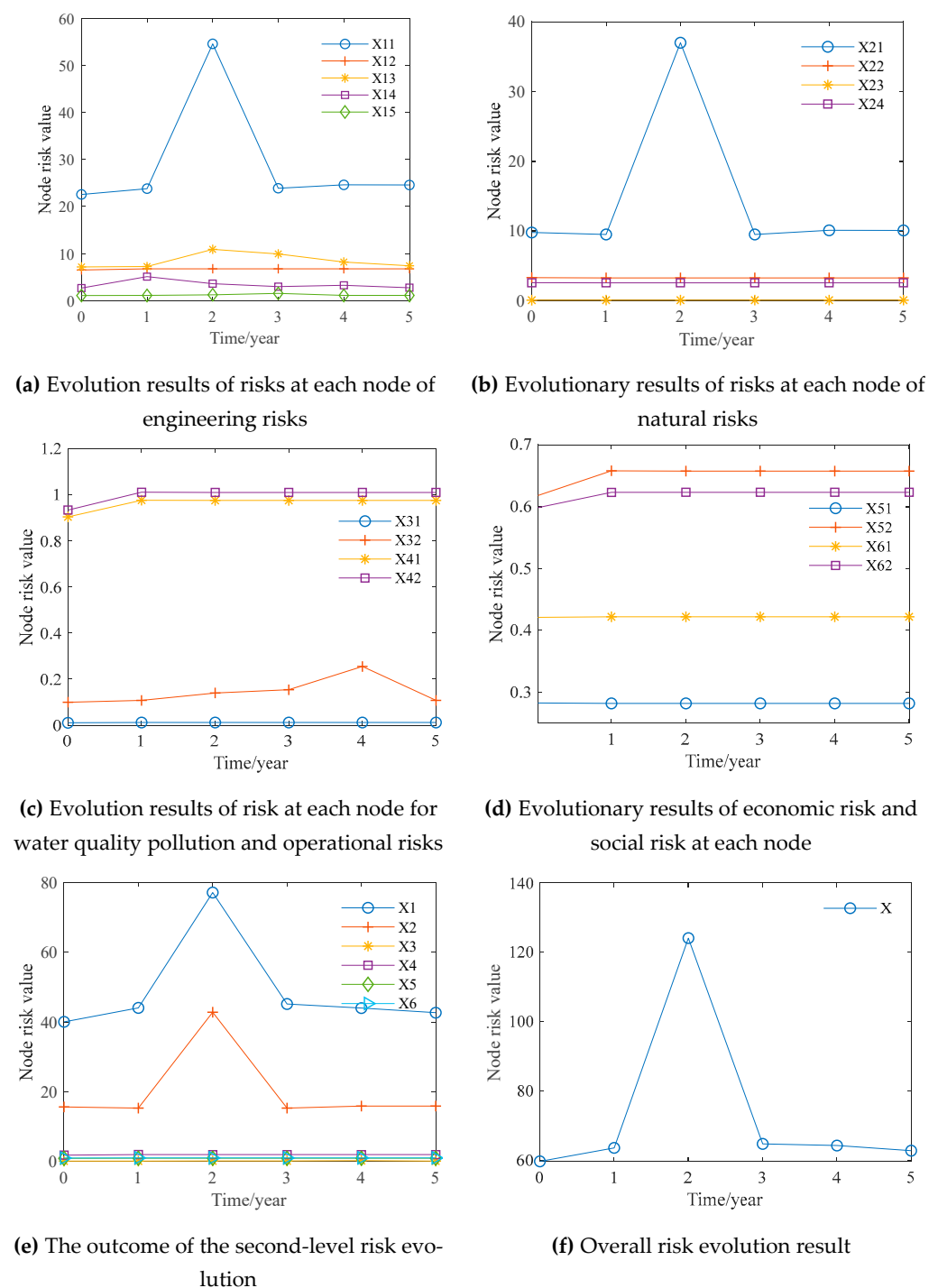


Figure 9. Dynamic evolution result.

5. Results and Discussion

5.1. Model Validation

Sensitivity analysis is widely adopted to evaluate model validity and reliability by examining the degree to which relevant variables influence the target variable [59]. In this study, sensitivity analysis is conducted to verify the reliability of the proposed model.

Based on the constructed Bayesian network inference model, sensitivity analyses were performed on the primary and secondary risk nodes associated with the safe operation of IBWTPs. Secondary risks are characterized by two possible states—occurrence and non-occurrence—whereas the variable X comprises six distinct states, five of which correspond to different levels of occurrence. Accordingly, the states $X_1 = y$, $X_2 = y$, $X_3 = y$, $X_4 = y$, $X_5 = y$, $X_6 = y$, and $X = n$ were selected as the target variables for the sensitivity analysis. A fluctuation parameter of 50% was applied to evaluate the sensitivity differences in fourth-level risk indicators, particularly regarding the non-occurrence of operational risks in inter-basin water transfer projects. The sensitivity analyses for X_1 , X_2 , X_3 , X_4 , X_5 , and X_6 are presented in Figure 10. For X , sensitivity is determined by the magnitude of the absolute negative fluctuation value, and the results are illustrated in Figure 11.

Figure 10 presents the four most sensitive Level 4 risk nodes corresponding to each Level 2 risk node. For X_1 , the most influential node is X_{115} , followed by X_{113} and X_{112} ; for X_2 , the most influential node is X_{222} , followed by X_{212} and X_{211} . Similarly, the most influential nodes are X_{324} , X_{413} , X_{523} , and X_{622} , for X_3 , X_4 , X_5 , and X_6 , respectively, with their subsequent influential nodes ranked as shown in Figure 10. Figure 11 presents the top 20 Level 4 risk nodes ranked by their influence on the Level 1 risk node before adjustment. Among these, fluctuations in X_{115} have the greatest impact on the overall risk level, followed by X_{222} , X_{113} , X_{212} , and X_{112} .

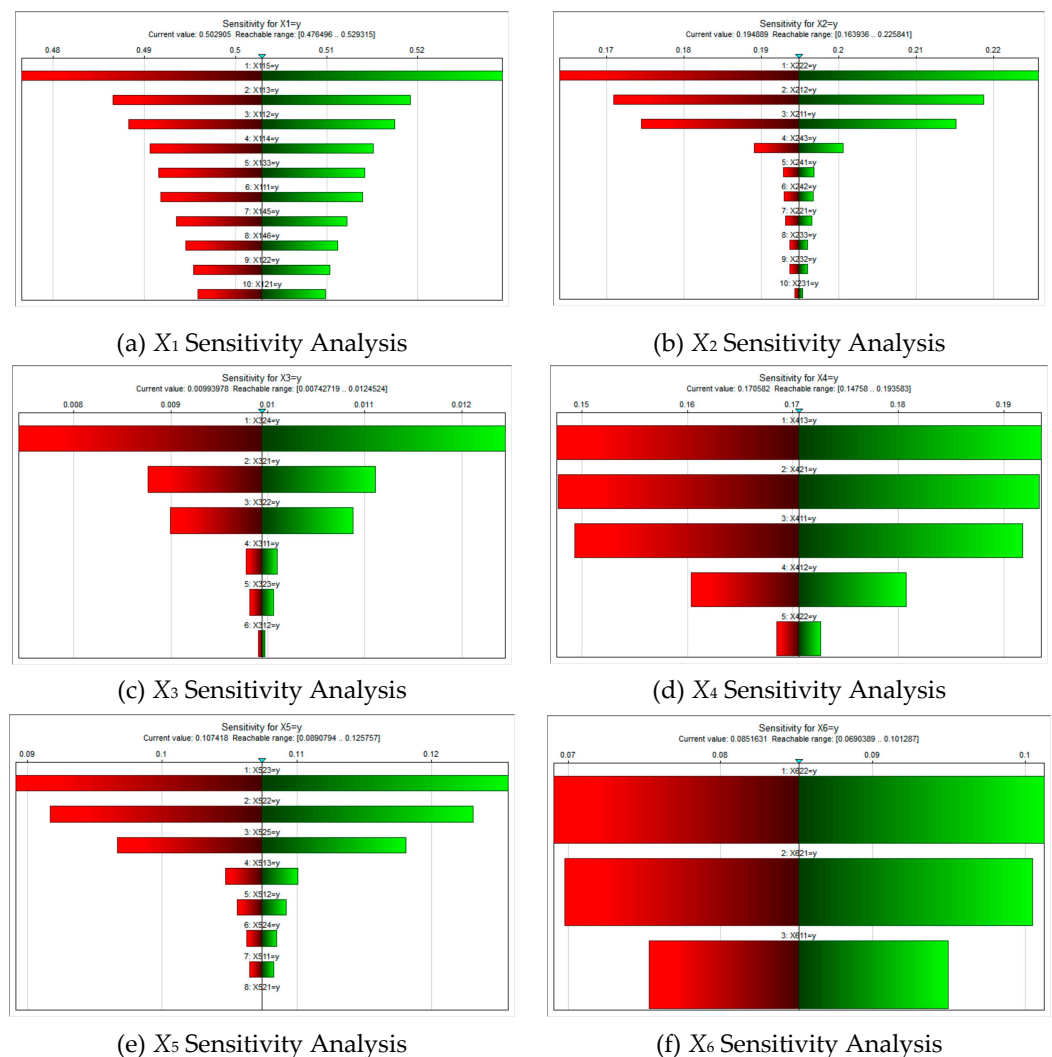


Figure 10. Secondary Risk Sensitivity Analysis Tornado Chart at 50% Fluctuation Parameter.

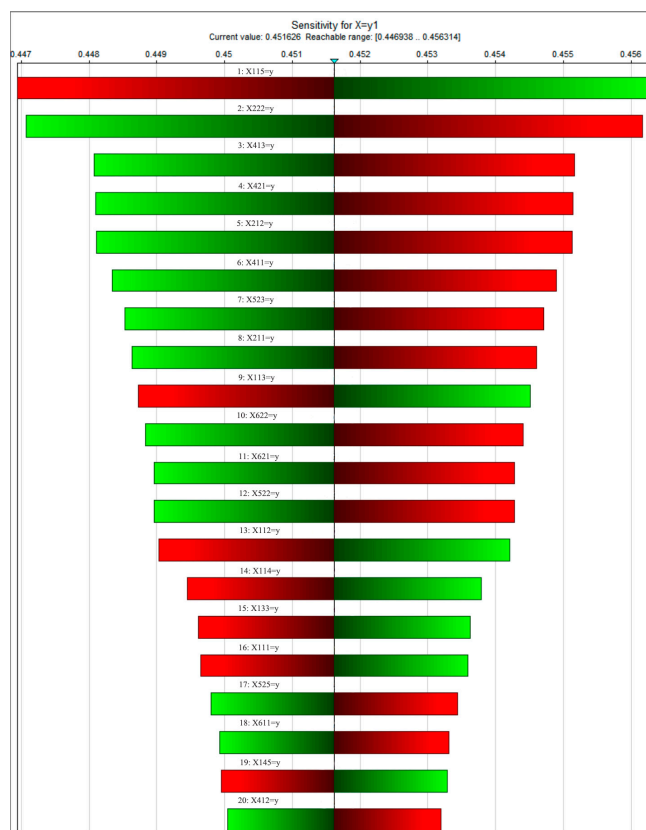


Figure 11. 50% Fluctuation Parameter Risk Sensitivity Analysis Tornado Chart for the first-level.

The results of the sensitivity analysis offer critical insights into the model by identifying key factors that influence the target variable. These findings support risk management decision-making by prioritizing strategies aimed at reducing the likelihood of critical risks. Moreover, the analysis constitutes an essential component in validating the model's reliability and accuracy, thereby enhancing the robustness of the research outcomes.

5.2. Results

The key risk factors influencing the safe operation of the project are identified through the measurement and dynamic transfer evolution analysis of the risk to safe operation in the CLPSNWD, as outlined below.

According to the results of the analysis of the probability dimension, the greatest impact on the system risk is the engineering risk, with a mean value of 36.1% for the degree of impact on different risk states, followed by natural risk, operational risk, social risk, and economic risk, with mean values of 19.2%, 17.5%, 13.3%, and 11.5% for the degree of impact on different risk states, and the smallest impact on the risk of water quality pollution which is only 2.3%. Therefore, in terms of risk categories, the focus should be on engineering risk, natural risk and operation scheduling risk. Among the four levels of risk, severe water shortage in the receiving areas due to drought, the external power and communication system failures, building instability and damage by flood erosion, human operational errors and channel slope instability and failure are ranked in the top five, which are the key risk factors.

According to the results of the loss dimension analysis, the loss equivalents for terrorist attacks, earthquake damage, channel slope instability and failure, flood overflow, and foundation collapse are all greater than or equal to 100, classifying their consequences as level 5, which denotes catastrophic impact. With the exception of the channel slope instability and failure risk, which has a relatively high probability of occurrence, the

likelihood of occurrence for all other risks is low. Notably, the risk of a terrorist attack, though highly improbable, could lead to extremely severe consequences.

The analysis of both probability and loss dimensions reveals that the risk values are substantial for several factors, including channel slope instability and failure, building instability and damage by flood erosion, flood overflow, uneven settlement of channel foundations, channel water overflow, uneven settlement of building substructure, and severe water shortage in receiving areas due to drought. Among these, the risk level for channel slope instability and failure is classified as level IV, while the risk levels for the other factors are classified as level III.

Through the evolution analysis of risk, it is observed that the system is in an unstable state, with a sudden change in risk values. This sudden change is primarily caused by shifts in the channel engineering risk, specifically the channel engineering risk and flood disasters. The main influencing factors include the damage to channel slope protection measures, channel slope instability and failure, and flood overflow. Additionally, the risks associated with cross-buildings for water conveyance (drainage), cross-buildings for water conveyance (culverts), and water quality pollution in the conveyance process exhibit relatively low amplitude fluctuations, while other risk factors remain largely stable.

Based on the risk analysis from various dimensions and the results of the risk dynamic transfer evolution analysis, the key risk factors affecting the safe operation of the CLPSNWD include channel slope instability and failure, severe water shortage in receiving areas due to drought, flood overflow, building instability and damage by flood erosion, channel water overflow, uneven settlement of channel foundations, uneven settlement of building substructure, damage to channel slope protection measures, foundation collapse, external power and communication system failure, human operational error, terrorist attacks, and earthquake damage.

5.3. Comparative Analysis with Existing Methods

To validate the accuracy of the proposed method, a fuzzy comprehensive evaluation approach was employed to assess the operational safety risks of the Phase I of the CLPSNWD using the data presented in this study. The evaluation procedure included: (1) defining the attribute set (Table 3), (2) establishing the risk indicator system based on risk-loss equivalent values, (3) constructing the evaluation matrix using the collected data, and (4) performing the comprehensive evaluation. The evaluation results show that the overall risk occurrence probability has the highest membership degree (0.58) at Level 4, indicating a high-risk condition. The probability obtained using the proposed method is 0.61, which is also classified as a high-risk level. This consistency verifies the validity and reliability of the proposed method.

In terms of risk state assessment accuracy, the method proposed in this study demonstrates results consistent with those of traditional fuzzy comprehensive evaluation approaches. However, by integrating the real-time posterior update mechanism of Bayesian networks with the temporal fusion capability of DS evidence theory, the proposed method enables dynamic risk evolution analysis and exhibits distinct methodological advantages.

5.4. Discussion

This paper presents a novel approach to studying the safe operation risks of IBWTPs by developing a risk measurement and dynamic evolution model. Through case analysis, key risk factors impacting the safe operation of the project are identified, providing valuable insights for the in-depth understanding and management of risks in IBWTPs.

1. Risk Factor Complexity and Dynamic Evolution Characteristics;

The risk factors affecting the safe operation of IBWTPs encompass multiple levels, including natural, engineering, and social factors, resulting in a highly complex risk system with significant interdependencies [15,16]. Engineering risks, such as channel slope instability and foundation settlement [15], are closely linked to natural risks like flooding and drought [7]. Flood overflow not only directly threatens the safety of channel structures but can also exacerbate foundation settlement due to prolonged immersion, triggering a chain reaction that undermines the overall stability of the project. Drought-induced water shortages in the receiving area may prompt the management unit to increase water flow [24], indirectly heightening the risk of canal overflow, further illustrating the non-linear correlation between natural and human factors in the system. This complexity necessitates a departure from traditional risk management approaches, requiring the establishment of a comprehensive risk management network that integrates real-time monitoring of multiple risk dynamics, promptly identifies critical nodes of interaction, and proactively implements joint response strategies.

Evolutionary analysis of the dynamic transfer of risk highlights the complexity and variability inherent in the system. Sudden changes in system risk, triggered by shifts in channel and flood-related risks, underscore the necessity for flexible, adaptive risk management. Earthquake damage, as a sudden and intense impact factor, can instantly alter the mechanical structure of the project, escalating risks such as slope instability and foundation failure. While terrorist attacks have a low probability, their occurrence can provoke social panic and operational disruptions, which, in turn, may delay the deployment of repair resources, amplifying the operational crisis and leading to a series of secondary risks. However, traditional risk management plans often focus on steady-state risks and are ill-equipped to address such sudden fluctuations. To overcome this, an intelligent decision-making system should be implemented. This system, powered by real-time monitoring data and machine learning algorithms, can predict risk trends and dynamically generate response strategies. For instance, as flood risk increases, the system could automatically trigger canal section closures and pre-deploy emergency resources. For minor risk fluctuations, regular assessments and routine maintenance should be performed, optimizing resource allocation and enhancing overall prevention and control efficiency.

2. Key Risk Factor Profiling and Risk Management Insights;

Dominant position of engineering risk

From the perspective of risk probability, engineering risk exerts the most substantial influence on system risk, with a mean value of 36.1%. This highlights that the structural stability of engineering components is central to the safe operation of the entire water transfer project. Risks related to destabilization of channel slopes and settlement of building foundations consistently emerge as key concerns [15]. This underscores the importance of strengthening engineering geological investigations throughout the project's lifecycle—during planning, construction, and operation and maintenance phases. It is essential to optimize structural designs, incorporate advanced reinforcement technologies, and implement regular inspection and maintenance programs. Special attention should be paid to high-risk sections and buildings, including the establishment of dedicated monitoring files and real-time tracking of structural status changes.

The impact of natural risk

Natural risks are predominantly associated with droughts and floods [27]. Droughts lead to water shortages in the receiving areas, which is crucial for fulfilling the water supply objectives, while floods result in catastrophic events such as overtopping and erosion of structures, posing significant threats. To address these challenges, it is essential to establish an integrated monitoring system that combines terrestrial and atmospheric data

to enable early disaster forecasting. Additionally, adaptive control mechanisms should be implemented, including optimized water distribution during the dry season [7] and dynamic adjustment of water levels and flows during the flood season. Furthermore, the design standards for flood protection and the impact resistance of engineering works must be reinforced to improve resilience against extreme natural events.

The hidden and critical nature of human and social risks

Although the probability of human operational errors and external power and communication system failure is relatively low, the potential consequences should not be overlooked. These risks highlight gaps in personnel training, equipment maintenance, and emergency management systems. To mitigate these risks, it is essential to develop detailed operation manuals and conduct simulations under complex working conditions. Additionally, redundant power and communication backups should be upgraded to ensure system resilience. Given the very low probability of terrorist attacks but their potentially high consequences, it is crucial to collaborate with public security and law enforcement agencies to establish an intelligence and early-warning network, as well as enhance security measures along the project route.

3. Risk Change Analysis;

Conventional risk assessment methodologies often adhere to the principle of indicator independence to ensure the accuracy of evaluation results. However, real-world risk systems are inherently dynamic. This dynamism is manifested not only through the temporal evolution of individual risks but also through the coupling and superposition of initially independent risk events, compounded by the persistent influence of long-term environmental factors. These interactions undermine the assumption of linear risk propagation, resulting in non-linear jumps in risk levels or long-term cumulative effects that deviate from conventional assessment models.

The interaction of initially isolated risk factors can lead to an amplified cumulative impact through a cascade of direct damage, secondary triggers, and delayed emergency response, thereby generating novel, composite risks. For example, the direct risk of a standalone terrorist attack typically involves structural damage to the channel, which is often categorized as a “localized high risk.” However, when coupled with other independent threats, the risk profile undergoes multidimensional diffusion, escalating into a systemic crisis. Should an attack coincide with a drought, the resulting channel damage and water supply disruption would directly exacerbate water scarcity in recipient areas, thereby escalating the risk from a “localized structural risk” to a “regional livelihood risk.” Conversely, if channel damage occurs during a flood, unrepaired breaches can trigger backflow, creating a triple-coupled risk scenario of “attack-infrastructure failure-flooding.” The combined losses in such a scenario can exceed those of a single attack by orders of magnitude.

Traditional risk assessments frequently rely on the assumption of “climate stability.” From a long-term risk management perspective, however, the “Hurst phenomenon”—which describes the persistence of climate elements such as wet or dry clusters over extended periods—has a fundamental impact on the risks associated with inter-basin water transfer projects [60]. This long-term environmental disturbance extends beyond short-term risk fluctuations. Rather, it alters both the “baseline probability” and the “impact intensity” of risk occurrence, leading to enduring biases in risk assessment outcomes. Dimitriadis et al. demonstrated through their global-scale research that the long-term clustering of hydrological processes (e.g., precipitation, runoff) significantly reshapes the natural risk landscape confronted by infrastructure [61]. For example, assessing flood risk based on short-term data from wet clustering periods may lead to an overestimation of a project’s flood protection capacity, whereas evaluating water supply risk using data from

dry clustering periods may underestimate the cumulative impact of prolonged droughts. These biases in risk assessment directly contribute to the failure of risk management strategies. Therefore, risk variability analysis must integrate both “independent threat coupling” and “long-term climate persistence” to more accurately characterize the dynamic evolution of risks, thereby offering more effective decision-making support for engineering risk management.

4. Universality and Limitation of Research Results;

The research findings presented in this paper, based on the CLPSNWD, provide valuable references for global IBWTPs. The risk categories, key factors, and evolution patterns exhibit common characteristics, such as engineering structure challenges, natural stresses, and human management issues, which are typical of large-scale water transfer projects. However, the geographic, climatic, and social conditions of different projects vary significantly, requiring the model to be tailored to local circumstances. For example, in alpine regions, the impact of freeze–thaw cycles on the project should be considered, while in mountainous areas, the focus should be on the dynamics of geological hazards. Future research should broaden the comparison of multiple case studies and refine the regional characteristic modules, aiming to enhance the model’s universality and applicability, thereby establishing a robust theoretical and practical foundation for the long-term and stable operation of cross-basin water transfer projects.

6. Conclusions

This paper develops a novel risk measurement model and risk evolution model based on Bayesian networks and DS evidence theory. It applies these models to analyze the quantitative measurement and dynamic transfer evolution of the safety operation risks in the CLPSNWD.

The influence of each risk factor on the system risk was analyzed from a probabilistic perspective. The analysis revealed that engineering risk, natural risk, and operational risks had the greatest impact. Among these, the top five factors were severe water shortage in receiving areas due to drought, external power and communication system failures, building instability and damage by flood erosion, human operational errors, and channel slope instability and failure.

The loss equivalent values of each risk factor were analyzed from the perspective of potential losses. It was found that the loss equivalents for terrorist attacks, earthquake damage, channel slope instability and failure, flood overflow, and foundation collapse were all greater than or equal to 100. Consequently, the loss consequences for these risks were classified as Level 5, indicating catastrophic severity.

The results, ranked based on the combined assessment of probability and loss, indicate that the risk values for channel slope instability and failure, building instability and damage by flood erosion, flood overflow, uneven settlement of channel foundations, channel water overflow, uneven settlement of building substructure, and severe water shortage in receiving areas due to drought in the receiving area are relatively high.

The evolutionary analysis of the risks indicates that the system risks are in an unstable state, with key influencing factors being channel engineering risks, flood disaster risks, pipeline engineering risks, and risks in cross-buildings for water conveyance (drainage).

The key risks affecting the safe operation of the CLPSNWD are identified by synthesizing the results of risk measurement and risk evolution analysis, with corresponding control measures proposed for these risks. In contrast to previous studies on the safe operation of IBWTPs, which primarily focused on comprehensive risk evaluation, this paper measures risk from three dimensions: probability, loss, and risk value. By analyzing risk evolution, this study identifies the key risk factors affecting the safe operation of the first phase of

the SNWDP, offering more targeted results that can aid in the risk management efforts of operation and management units.

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Abbreviations

The following abbreviations are used in this manuscript:

DS	Dempster–Shafer
IBWTP	Inter-basin water transfer project
CLPSNWD	Central Line Project of South-to-North Water Diversion
SNWDP	South-to-North Water Diversion Project
PCCP	Prestressed Concrete Cylinder Pipe

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