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Research on Risk Evolution and Scenario Deduction of Railway Emergencies Based on Knowledge Elements and Dynamic Bayesian Networks

Chang LIU, Dan CHANG, Daqing GONG*

Abstract: Railway transportation safety is crucial to the national economy and people's livelihood. Conducting risk evolution analysis and scenario deduction for emergencies is a key to preventing and controlling accidents. This paper proposes a method integrating knowledge elements and dynamic Bayesian networks to realize risk evolution analysis and scenario deduction of railway emergencies: firstly, constructing a knowledge element model of railway emergencies to formally express event elements and their associations; secondly, building a dynamic Bayesian network based on this model to depict the dynamic risk transmission process; thirdly, training the network through parameter learning algorithms combined with historical data and expert knowledge; finally, carrying out scenario deduction based on the trained network, analyzing risk evolution trends under multiple scenarios and proposing prevention and control measures. The case verification of the D2809 train derailment accident shows that this method can effectively simulate the risk evolution process of emergencies and provide scientific decision support for railway safety risk management.

Keywords: dynamic Bayesian networks; knowledge elements; railway safety; risk evolution; scenario deduction

1 INTRODUCTION

1.1 Background

As a core component of the national comprehensive transportation system, railways play an irreplaceable role in ensuring transportation safety and supporting social and economic development. By the end of 2024, China's railway operating mileage had reached 162,000 kilometers, and core transportation indicators such as passenger turnover and freight turnover had ranked among the top in the world. However, with the expansion of the railway network and the increase in train speed, transportation efficiency and pressure have increased simultaneously, posing new challenges to safety assurance.

Safety is the core pursuit and fundamental goal of railway transportation. With the continuous expansion of the railway network and the continuous increase in train operating speed, railway transportation safety is facing many new challenges. Railway emergencies often cause huge economic losses and serious casualties, so risk prevention and control are of vital importance. Although China's railway safety governance level has been continuously improved, the risks of emergencies are characterized by latency, coupling, and cascading effects and general emergencies still occur from time to time, threatening people's lives and property safety.

1.2 Related Work

The analysis of railway emergencies is a key link in ensuring railway operation safety. However, existing analysis methods have certain limitations: first, emergency reports are mostly unstructured texts, and information extraction relies on manual operations and expert experience, which is inefficient and highly subjective; second, railway risks are characterized by time-variability and coupling, and traditional emergency chain models are difficult to accurately reveal the mechanism of dynamic risk transmission; third, scenario deduction research mostly focuses on the post-emergency response stage, lacking systematic analysis of precursor scenarios and occurrence scenarios of emergencies.

Scenario deduction research provides decision support for emergency response by analyzing scenario elements and their evolution process. Scholars have divided scenario elements from different perspectives and proposed various scenario evolution frameworks. Existing studies have proposed a range of methodologies, each with distinct strengths and limitations: Liu et al. [1] developed a cloud model-integrated decision-making approach for railway emergencies, which effectively mitigates randomness and fuzziness in decision scenarios but lacks consideration of dynamic scenario evolution and multi-scenario interactions; Ye et al. [2] proposed an evidence reasoning method that incorporates virtual linguistic credibility and interval monotonic functions, addressing uncertainties in evaluation information to enhance the accuracy of railway station emergency capability assessments, though its applicability is constrained to specific station contexts and it does not account for dynamic scenario evolution; Abdalla R. et al. [3] leveraged WebGIS for flood disaster simulation, demonstrating strong capabilities in spatial visualization of disaster spread but exhibiting weaknesses in capturing the temporal dynamics of coupled disaster-inducing factors; Hao J. et al. [4] constructed a scenario evolution model for earthquake-induced landslide emergencies, providing in-depth insights into the evolutionary logic of this specific disaster type yet failing to accommodate interactions between multiple disaster categories; Xie L. et al. [5] explored the prioritization of emergency measures through a case study of the Zhengzhou rainstorm, offering practical guidance for response strategies but lacking generalizability and systematic analysis of precursor and occurrence scenarios; Wang Fang [6] proposes to introduce the multi-agent theory into the mainstream theories of crowd evacuation. Based on Agent and Pathfinder, a simulation model is developed to simulate the evacuation situations in three types of spaces: subway platforms, concourses, and staircases. Key data such as crowd speed, the number of people passing through spaces and exits, the number of remaining people, and evacuation paths are recorded, which provides an important basis for the improvement of emergency plans; Cao, J. et al. [7] proposed a multi-stage mixed-integer programming model for humanitarian logistics and transportation resources using the SEIR model. The model solves the linear programming problem through the proposed Benders decomposition algorithm, providing new ideas for emergency response; Si, Q. M. et al. [8] proposed a simulation method for the fire protection space system of general aviation airport terminals. By comparing indicators such as smoke diffusion, temperature, visibility, and evacuation time, it provides a new reference for formulating efficient emergency evacuation strategies for high-speed railways; Ibrahim, N. et al. [9] proposed an automatic emergency evacuation route design method based on the cellular automaton (CA). By combining the Pythagorean theorem (PT) and Dijkstra's algorithm (DA), it simulates the behavior of people looking for exits during the evacuation process, providing a new reference for personnel evacuation in high-speed rail emergencies; Popov, S. [10] proposed a risk assessment model based on GoT, which can be used for risk management. The risk price information of the affected areas output by the model is of great reference value for the emergency decision-making management of high-speed rail emergencies. These studies provide multi-dimensional theoretical support for improving the emergency response efficiency and the scientific nature of decision-making in high-speed railways from the perspectives of fire protection space system simulation, evacuation route algorithm design, and risk assessment modeling. Yuan C. et al. [11] analyzed scenario evolution paths for oil and gas storage-transport fire emergencies, clarifying industry-specific evolutionary patterns but overlooking cross-scenario cascading effects (e.g., fire-triggered explosions); Sarvari H. et al. [12] employed the Fuzzy Delphi method for risk identification and prioritization, effectively integrating expert knowledge to handle fuzzy risk boundaries but relying excessively on subjective judgments and neglecting dynamic risk fluctuations over time; Sadeghi J. et al. [13] applied the Microscopic Markov Chain Approach (MMCA) to analyze dynamic evolutionary characteristics of driver group behavior under traffic information guidance, demonstrating efficacy in capturing behavioral dynamics but remaining irrelevant to multi-factor emergency scenarios; Bischof et al. [14] proposed a big data-driven advanced risk management framework, outlining a conceptual model encompassing risk types, management phases, and technological support, yet lacking empirical validation and operational details for dynamic emergency contexts; J. Ma and S. Ma [15] analyze the characteristics of high-speed railway networks in the presence of emergencies from a complex network theory's perspective. M. An and Y. Chen. [16] present the development of a risk management system for railway risk analysis using fuzzy reasoning approach and fuzzy analytical hierarchy decision making process. Ziyu Liu et al. [17] constructed a Stochastic Colored Petri Nets (SCPN) model via homogeneous Markov chain analysis to integrate risk factors and evaluate system performance, which effectively handles stochasticity but becomes computationally intractable with increasing risk factors and fails to model multi-scenario interaction mechanisms. Wang, X., and Zhang, Y. [18] proposed a dynamic Bayesian network - based safety decision - support approach for tunnel construction. This method can accurately demonstrate the dynamic update characteristics of geological, design, and mechanical variables during the construction process, providing real - time support for safety analysis in tunnel construction. Vladoiu, D. and Mocanu, D. [19] implemented an improved FMEA method to identify safety risks in railway services, with a focus on risks related to railway level crossings. In summary, existing methodologies predominantly focus on post-emergency scenarios, lack systematic analysis of precursor and occurrence phases, and tend to target single scenarios-failing to fully capture the impact of multi-scenario interactions on emergency evolution. In contrast, this study's multi-scenario interaction deduction model, grounded in dynamic Bayesian networks and knowledge element theory, addresses these limitations by emphasizing full-cycle scenario analysis and multi-scenario coupling effects.

1.3 Research Idea and Purpose

Based on the problems existing in railway emergency analysis and scenario deduction research, such as low efficiency of information extraction, vague description of risk transmission, and incomplete scenario analysis, this study chooses to construct a deduction model based on knowledge elements, and its advantages are reflected in the following aspects:

(1) At the information extraction level, knowledge elements can abstract key information from unstructured texts into standardized units, realize automatic extraction and structured storage through semantic annotation and ontology construction. For example, "subgrade collapse caused by heavy rain in a certain section" can be disassembled into knowledge elements such as disaster-causing factors, disaster-bearing bodies, and event consequences. Meanwhile, the knowledge base formed by standardized knowledge elements supports cross-scenario retrieval and invocation, providing accurate data for scenario deduction.

(2) Facing the time-variability and coupling of railway risks, traditional models are difficult to reveal the transmission mechanism. Knowledge elements describe the causal, temporal, and coupling relationships of risk factors through the design of "attributes-relationships-rules". For example, the association between knowledge elements such as "heavy rain", "line water accumulation" and "signal failure" forms a transmission chain. Combined with complex network theory, a risk transmission network is constructed with knowledge elements as nodes to analyze node indicators and identify key risks and transmission paths.

(3) Aiming at the problems that traditional scenario deduction insufficiently analyzes precursor and occurrence scenarios and ignores the linkage of multiple scenarios, knowledge elements are classified according to the evolution stages of emergencies to realize the systematic description of full-cycle scenarios. For example, the association between "abnormal rail temperature" and "rail expansion and derailment" is used to deduce line faults. Their dynamic association can also characterize scenario interaction, construct a multi-scenario knowledge element network to simulate event evolution paths. In addition, the clear semantics of knowledge elements makes model construction and results easier to interpret, facilitating decision-makers to understand risk transmission; based on the knowledge element rule base, automatic reasoning

from scenario input to response strategies can be realized. Moreover, knowledge elements can integrate multi-field data such as meteorology and equipment, adapt to technologies such as hybrid strategy optimization algorithms and integrated learning, and promote the application of big data in the field of railway safety.

Given the complex correlations between accident causes and scene elements, Bayesian Network (BN) - as an integration of network theory and probability theory - provides an effective modeling framework for the systemic analysis of accident scenes and their underlying causes [20, 21]. DBN not only inherits the probability reasoning function to solve the probability update, but also develops the dynamic characteristics deduction on different time slices to predict the probability change by various distribution functions [22]. Compared with BN networks, DBN has advantages in dealing with time-series nonlinear uncertainty problems which makes it possible to continue probabilistic prediction [23, 24]. Extending this foundation, the Dynamic Bayesian Network (DBN) represents a targeted breakthrough to address the limitations of traditional approaches: by introducing time slice division, it enables modeling of the full-cycle evolution from precursors to occurrence and development, capturing temporal associations through cross-time-slice probability transmission. Moreover, DBN can quantify the coupling of multiple factors via conditional probability tables to simulate the nonlinear evolution of multi-scenario superposition, while inheriting a probabilistic reasoning framework that allows dynamic updates of node probabilities and outputs multi-scenario evolution distributions - offering a "possibility-impact degree" two-dimensional reference. Additionally, its compatibility with knowledge element theory allows scenario elements to be converted into nodes, with association rules described through probability parameters. This comprehensive capability in handling dynamics, multi-scenario coupling, and uncertainty establishes DBN as an ideal method for constructing a full-cycle, multi-scenario linkage deduction model.

The occurrence of disasters is uncertain and seriously damaging. When disasters occur, they not only cause serious economic losses and casualties, but also bring many challenges to people [25]. Existing research mostly focuses on post - emergency scenarios, lacks a systematic analysis of precursor and occurrence scenarios, and mostly targets single scenarios, without fully considering the impact of multi - scenario interaction on emergency evolution. This research constructs a multi-scenario interaction deduction model based on dynamic Bayesian networks and knowledge element theory. Based on dynamic Bayesian network and knowledge element theory, this study constructs a multi-scenario linkage deduction model, aiming to realize intelligent analysis of emergency texts, accurate description of dynamic risk transmission paths, and multi-scenario linkage deduction. The research results will provide accurate method support for the prevention of railway operation emergencies, offer a scientific basis for decision-makers to formulate risk prevention and control measures, promote the wide application of big data technology in the field of railway safety, and further improve China's railway operation safety level.

2 CONSTRUCTION OF RAILWAY EMERGENCY SCENARIOS BASED ON KNOWLEDGE ELEMENTS

2.1 Analysis of the Composition and Hierarchical Structure of Railway Emergency Scenario Elements

In the field of railway emergency research, scenario elements serve as the core carrier for analyzing the dynamic evolution laws of disasters. They systematically demonstrate the temporal changes in accident states, developmental trends, and the interaction mechanisms among various components. Railway debris flow disasters are characterized by strong suddenness, high destructiveness, and wide-ranging impacts, often accompanied by complex triggers such as topographic-geomorphic changes and extreme meteorological conditions. An in-depth analysis of the constituent elements of scenario information is a prerequisite and key to accurately constructing scenario evolution models. Based on knowledge element theory, this study establishes a scenario evolution framework for railway emergencies from four dimensions: Scenario State (S), Hazard-formative Environment (E), Emergency Target (T), and Mitigation Measures (M). Taking debris flow disasters as a typical case, the specific connotations and operational mechanisms of each element are as follows:

(1) Scenario State (marked as S) refers to the dynamic changes in the developmental state of an event after external intervention, specifically reflecting the real-time impacts and state alterations caused by debris flow disasters on the railway system. When heavy rainfall triggers mountain loosening, debris flows carrying rocks, trees, and other materials cascade down, instantly burying tracks, destroying bridges, and causing trains to emergency brake and lines to be interrupted. At this point, the scenario state is manifested in forms such as train service suspension, track damage, and communication signal interruption. Meanwhile, dynamic information including the safety status of trapped passengers and the degree of surrounding traffic congestion also constitutes an important part of the scenario state. Such information, like "real-time snapshots" of the disaster site, directly reflects the severity of the event's development.

(2) Hazard-formative Environment (marked as E) is a collection of core elements that trigger, develop, and transform the situation. In mountainous areas along the railway line, the geological conditions are fragile, with weathered and fragmented mountain rocks and low vegetation coverage. When encountering continuous heavy rainfall, the soil moisture content becomes saturated, reducing its anti-erosion capacity, and making it highly prone to triggering landslides and debris flows. Moreover, if the terrain factors are not adequately considered during railway construction, the drainage system design is unreasonable, or if the long-term operation leads to the aging of the roadbed protection facilities, it will also increase the possibility of disaster occurrence. These multiple factors, including geological, meteorological, and engineering facilities, interact with each other, jointly constituting the disaster-prone environment of debris flows.

(3) Emergency Target (marked as T) refers to the expected state of the current scenario in the next stage. After a debris flow disaster occurs, the primary goal is to activate life rescue channels, ensuring the safe evacuation

of trapped passengers through means such as helicopter airdrops of supplies and opening temporary evacuation routes. Simultaneously, conducting "vital sign" checks on the railway system, repairing communication signal equipment, and assessing the extent of line damage lay the foundation for restoring transportation order. By setting hierarchical targets, a phased transition from "safeguarding life safety" to "restoring social functions" is achieved.

(4) Mitigation Measures (marked as M) are a series of decision-making plans and actions adopted by decision-makers in response to the current scenario, aiming to bring the next-stage scenario to the expected state. After a disaster occurs, the railway dispatching center immediately activates a red alert, implementing line blockades and train detour plans. Professional rescue teams use excavators, cranes, and other equipment to clear debris, and adopt technical means such as temporary steel beam bridges and grouting to reinforce subgrades for repairing damaged facilities. Meanwhile, medical teams provide on-site first aid, civil affairs departments allocate supplies to ensure the basic needs of stranded passengers, and meteorological departments issue rolling rainfall warnings. Multiple departments collaborate to form a closed-loop response system of "monitoring-decision-making-execution."

These four elements are interrelated and progressive: the scenario state is the intuitive manifestation of the disaster, the hazard-formative environment is the potential cause of the disaster, the emergency target points the direction for mitigation efforts, and the mitigation measures are the specific pathways to achieve the target. Their organic integration constructs a complete scenario evolution framework for railway debris flow disasters, providing a scientific basis for subsequent knowledge element-based scenario deduction and emergency decision-making.

In the complex field of railway emergencies, scenario elements play a crucial role. They can clearly demonstrate the temporal changes in accident states - from subtle fluctuations when an accident first emerges, to ups and downs during development, and finally to various possible outcomes. Additionally, scenario elements can accurately predict accident trends, supporting relevant personnel in making advance preparations. Furthermore, they profoundly reveal the interaction patterns among internal components of accidents, like an intricate network mapping out complex relationships between elements.

2.2 Knowledge Element Theory

In the scenario analysis of railway emergencies, elements are the smallest information units constituting accident scenarios, with each scenario comprising four core components: Scenario State (S), Hazard-formative Environment (E), Emergency Target (T), and Mitigation Measures (M), regarding each scenario component as a knowledge body [26, 27]. Taking railway debris flow disasters as an example, abstracting these scenario components into knowledge entities and clarifying their dynamic associations during disaster evolution is the core task of constructing accurate scenario models. Knowledge element theory provides an effective tool for analyzing such complex relationships, whose operational mechanism can be specifically illustrated through the debris flow disaster scenario.

As the smallest unit with complete representational capabilities in the knowledge domain, knowledge elements can transform abstract disaster scenarios into structured and computable knowledge entities. In railway debris flow disasters, the Hazard-formative Environment (E) includes knowledge elements such as geological conditions (e.g., fragmented mountain structures), meteorological factors (e.g., sustained heavy rainfall), and engineering hazards (e.g., drainage system defects). These factors interact to provide potential conditions for debris flow occurrences. When sustained heavy rainfall erodes mountains, causing soil moisture to exceed critical values, the combination of knowledge elements in the hazard-formative environment triggers changes in the Scenario State (S).

As the smallest unit with complete representational capability in the knowledge domain, knowledge elements can transform abstract disaster scenarios into structured and computable knowledge entities. In railway debris flow disasters, the disaster-breeding environment (E) encompasses knowledge elements such as geological conditions (e.g., fragmented mountain structures), meteorological factors (e.g., continuous heavy rainfall), and engineering hidden dangers (e.g., defects in drainage systems). These factors interact to provide potential conditions for the occurrence of debris flows. When continuous heavy rainfall scours the mountains and the soil moisture content exceeds the critical value, the combination of knowledge elements in the disaster-breeding environment triggers a change in the scenario state (S).

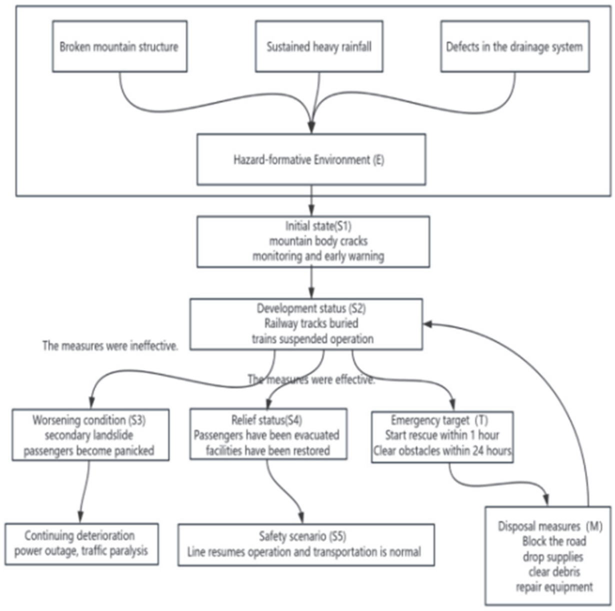

Figure 1 Diagram of accident scenario

The scenario state (S) can be further subdivided into multiple continuous states: the initial state (S1) is characterized by the appearance of mountain cracks, slight surface slippage, and abnormal warnings issued by the railway monitoring system; as the disaster-breeding environment continues to deteriorate, it enters the development state (S2), where debris flows, carrying rocks and trees, surge down, resulting in buried rails, damaged bridges, and emergency braking and stoppage of trains; if disposal measures are not promptly implemented or their effects are inadequate, the scenario will enter the deterioration state (S3), such as panic among trapped passengers and secondary landslides in surrounding mountains exacerbating track damage; conversely, if the emergency response is rapid and effective, it will shift to the mitigation state (S4), characterized by the safe transfer of passengers and the gradual repair of damaged facilities.

Emergency decision-making subjects formulate emergency targets (T) and adopt disposal measures (M) based on the current scenario state. For example, after a debris flow disaster enters the development state (S2), the emergency targets (T) may be set as "activate the passenger rescue plan within 1 hour" and "complete main line obstacle clearance within 24 hours". Centering on these targets, disposal measures (M) include blocking the disaster-stricken section, activating helicopter airdrops of rescue materials, deploying large machinery to clear accumulations, and repairing communication signal equipment. These measures are encoded in the form of knowledge elements, forming dynamic associations with scenario states and emergency targets.

The characterization of the multi-scenario linkage process of debris flow disasters by the knowledge element theoretical model is shown in Fig. 1. Meteorological and geological knowledge elements in the disaster-breeding environment (E) continuously act, promoting the evolution of the scenario state (S) from the initial state to the directions of development and deterioration; emergency decision-making subjects intervene in the disaster development path by implementing disposal measures (M), prompting the scenario state to transform toward the emergency targets (T). If the disposal measures are effective, such as successfully evacuating passengers and quickly repairing tracks, the disaster will evolve from the deterioration state to the mitigation state as expected, and gradually transition to the safety scenario (S5) in the next stage; conversely, if the rescue is hindered or the repair progress lags, the disaster may continue to escalate in the deterioration state, triggering more serious secondary disasters (e.g., power outages and paralysis of surrounding transportation).

Through the knowledge element theory, the complex evolution process of railway debris flow disasters is deconstructed into clear knowledge units and their associated networks, which can not only intuitively demonstrate the internal mechanism of disaster occurrence but also predict the disaster development trend by quantifying the influence weight of each knowledge element. For example, the knowledge element model constructed based on historical data can simulate the evolution probability of debris flows from the initial state to the deterioration state under combinations of different rainfall intensities and mountain slopes, as well as the impact of various disposal measures on disaster control effects in different scenario states, providing a scientific basis for emergency decision-making and realizing refined management of the entire process from disaster early warning to disposal.

In addition, the knowledge element theory can also dynamically update the knowledge element database, incorporate information such as lessons learned and technical improvements from newly occurring disaster events into the model, continuously optimize the ability to analyze railway debris flow disaster scenarios, make it more in line with actual emergency needs, and provide solid theoretical and technical support for the improvement and development of the railway emergency management system.

In the analysis of railway emergencies, each event can be decomposed into multiple entity units, and the knowledge element, as the smallest unit of knowledge composition, can systematically describe the concepts, attributes, and relationships of events. The core purpose of constructing a general knowledge element model is to transform complex emergency scenarios into structured and computable knowledge units, providing a foundation for subsequent scenario deduction.

Emergencies are composed of multiple entity units. For any objective object m, the common knowledge element model is as follows:

$$K_m = \left(N_m, A_m, R_m\right), \forall m \in M \tag{1}$$

$$K_\alpha = \left(P_\alpha, d_\alpha, f_\alpha\right), \forall \alpha \in A_m \tag{2}$$

$$K_\gamma = \left(P_\gamma, A_\gamma^I, A_\gamma^O, f_\gamma\right), \forall \gamma \in R_m \tag{3}$$

In Eq. (1), K_m represents the knowledge element of the event involving object m, N_m is the name of the concept and attribute of each scenario and element in m, which is used to define the semantic scope of the knowledge element (such as concepts like "debris flow" and "heavy rainfall"), A_m is the set of attribute states, describing the specific characteristics of each element (such as rainfall amount, landslide angle, etc.), and R_m is the set of relationships, representing the association patterns between elements (such as the causal relationship of "heavy rainfall leading to landslides"). Eq. (1) realizes the abstract expression of emergency knowledge through a triple structure.

In Eq. (2), K_α represents the attribute common knowledge element model, P_α is the set of relationships between attributes (such as the positive correlation between "rainfall" and "track humidity"). If an attribute is measurable, its measurement dimension is denoted by d_α (such as the dimension of temperature is ℃, and the dimension of speed is km/s) and f_α represents the mapping relationship of the attribute changing with time (such as the curve of train speed changing with time).

In Eq. (3), K_γ is the relationship knowledge element, P_γ represents the attribute characteristics of the internal attribute constraint relationship r, including linear, random, nonlinear, fuzzy, and other types (such as the nonlinear correlation between "earthquake intensity" and "track damage degree"), A_γ^I, A_γ^O represents its input and output, and f_γ is the mapping relationship of the input - output set.

It can be seen from this that the scenario of a railway emergency is a cognitive representation constructed by emergency decision - makers based on the cognitive knowledge domain for accident disasters with specific event characteristics and spatial properties. This representation covers both static and dynamic dimensions. At the static level, it is mainly reflected through the definition of concept names and attributes, clarifying the basic connotation and characteristics of the railway emergency scenario; at the dynamic level, it focuses on the abstract expression of the inherent uncertainty and time - varying nature of emergencies, thus comprehensively reflecting the dynamic process of the railway emergency scenario evolving over time.

2.3 Construction of Railway Emergency Scenario Expression Based on Knowledge Elements

The knowledge element theory model can delicately depict the multi - scenario interaction development process in railway emergencies, deeply analyze the development paths and evolution mechanisms of events, and clarify the relationships among various elements. Each scenario is composed of multiple knowledge bodies, and each knowledge body contains several knowledge objects (i.e., elements). To effectively describe this common knowledge, the following formal expression can be used:

$$S=\left(S_1,S_2,\ldots,S_i,\ldots,S_n\right) \tag{4}$$

Among them, S_1 represents the scenario at the initial moment (such as micro - cracks in the mountain during the precursor stage of a debris flow), S_i represents the state at the *i*-th time sequence, and S_n represents the final scenario of the event (such as the line repair state after the disaster subsides). The scenario information at a certain moment is an objective description of the current event, including three parts of information: disaster - prone environment *E* (such as rainfall intensity and mountain stability at time *t*), emergency response target *T* (such as the number of passengers to be evacuated at time *t*), and disposal measures *M* (such as the emergency plan activated at time *t*). According to the scenario information element composition proposed above, the scenario at a certain moment can be expressed as:

$$S_{T_i}=\left(E_i,T_i,M_i\right) \tag{5}$$

Eq. (5) indicates that the scenario S_{T_i} at any moment *t* consists of three elements: the hazard - forming environment E_i (such as rainfall intensity and mountain stability at time t), the emergency target T_i (such as the number of passengers to be evacuated at time *t*), and the disposal measures M_i (such as the emergency plan activated at time *t*). In a single scenario element, the specific information of each constituent element includes concepts, attributes, relationships, etc. Taking the disaster - prone environment *E* as an example, the description of the knowledge element is as follows:

$$K_E=\left(N_E,A_E,R_E\right) \tag{6}$$

where N_E represents the concept name of the disaster - prone environment scenario information (such as "geological environment along the railway"), A_E represents the attributes of the disaster - prone environment elements of the emergency (such as "rock weathering grade" and "soil moisture content"), which are specifically divided into qualitative and quantitative types; $\mathrm{R_E}$ represents the internal relationships between elements (such as the influence relationship of "weathering degree → mountain stability"). Among them, the attributes of the disaster - prone environment elements of the emergency can be described as:

$$K_\alpha=\left(P_\alpha,d_\alpha,f_\alpha\right) \tag{7}$$

where P_α represents the describable characteristics in the scenario element attributes (such as the qualitative description of "heavy rainfall is the inducement of debris flow"), d_α represents the measurable dimension of the scenario element attributes (such as the rainfall "mm"), and f_α represents the time - varying law function of the scenario element attributes (such as the cumulative curve of rainfall over time). The knowledge element description of a single - time - sequence scenario is divided into three levels: the scenario itself, the three elements constituting the scenario, and the description of element attributes and relationships. By extending the knowledge element hierarchical structure of the single - time - sequence scenario to the entire time sequence of the railway emergency, an emergency is decomposed into multiple event scenarios for analysis.

3 CONSTRUCTION OF RAILWAY EMERGENCY SCENARIO DEDUCTION MODEL BASED ON DYNAMIC BAYESIAN NETWORKS

3.1 Construction of Dynamic Bayesian Network Scenario Deduction Model

Bayesian Networks (BN) is a directed acyclic graph model based on probability reasoning, used to describe the dependence relationships among variables. The correctness of the Bayesian networks method for reliability assessment can be vindicated [15]. Its structure consists of nodes and directed edges. Nodes represent random variables, and directed edges reflect the causal associations among variables, and the causal strength is quantified through conditional probabilities. Bayesian networks are widely used in fields such as knowledge representation and uncertainty reasoning. Its core mathematical basis is the Bayes formula, and the expression is as follows:

$$P\left(x_i\middle|y\right)=\frac{P\left(x_i y\right)}{P(y)}=\frac{P\left(x_i\right)p\left(y\middle|x_i\right)}{\sum_{j=1}^{n}P\left(x_j\right)P\left(y\middle|x_j\right)} \tag{8}$$

Among them, *x* is the parent node set (such as "heavy rainfall" and "broken mountain"), representing the cause set of the causal relationship, and *y* is the child node set (such as "debris flow occurrence"), representing the result set of the causal relationship. The meaning of the formula is: the posterior probability $P\left(x_i\middle|y\right)$ of inferring the cause x_i when the result y is known is equal to the joint probability

$P(x_i y)$ of the cause x_i and the result y divided by the prior probability $P(y)$ of the result y. Through this formula, probabilistic reasoning of the causal relationship of emergencies can be realized (such as inferring the probability of heavy rainfall when a debris flow occurs). Using the conditional independence of Bayesian networks, the joint probability of the nodes of the Bayesian network is:

$$P(x_1, x_2, \dots, x_n) = \prod_{i=1}^{n} P(x_i | x_1, x_2, \dots, x_{i-1}) = \prod_{i=1}^{n} P(x_i | P_a(x_i)) \tag{9}$$

Among them, $P_a(x_i)$ represents the set of parent nodes of x_i (such as the parent nodes of "debris flow occurrence" are "heavy rainfall" and "broken mountain").

The primary theoretical basis for choosing Dynamic Bayesian Network (DBN) to construct the railway emergency scenario deduction model lies in its breakthrough over the traditional Bayesian Network (BN). As a static model, the traditional BN can only describe the static causal relationships between variables, and cannot incorporate the time dimension, making it difficult to describe the dynamic process of emergencies from germination to evolution (such as the time - sequence changes of debris flow from slight mountain cracks to large - scale outbreaks). By introducing time slice division and cross - time - slice dependency relationships (such as the rainfall at time t affecting the mountain water content at time t + 1), DBN has achieved improvements in three aspects: first, through intra - time - slice nodes and cross - slice directed edges, it accurately depicts the time - sequence continuity of scenarios, which is consistent with the dynamic characteristics of the scenario evolution sequence $s_t \rightarrow s_{t+1}$ in Eq. (4); second, it can dynamically update node probabilities based on real - time data (such as adjusting the probability of debris flow occurrence according to rainfall intensity), effectively handling the time - varying uncertainty of emergencies; third, it can simulate the intervention effect of disposal measures (M_t) at different time points on the subsequent scenario state (s_{t+1}), supporting multi - scenario linkage deduction. This advantage makes up for the limitation that the traditional BN can only analyze static relationships (such as the dynamic correlation between M_t and s_{t+1} in Eq. (5)).

Compared with Petri Net, the theoretical advantage of DBN lies in its ability to quantify and dynamically model complex uncertainties. Although Petri Net can describe the logical transition of discrete events through the "place - transition" structure, it has limitations in three aspects: first, it lacks probabilistic reasoning ability and is difficult to quantify the strength of causal relationships (such as the probability of "heavy rainfall inducing debris flow" being 0.8), while DBN can achieve accurate probability calculation through Eqs. (8) to (9); second, the time parameters are mostly fixed delays, which cannot describe the dynamic time dependence of elements in emergencies (such as the cumulative effect of rainfall over time), while the time slice mechanism of DBN can flexibly adapt to continuous time processes; third, the knowledge representation is relatively rigid, making it difficult to integrate multi - source heterogeneous information such as meteorology and geology, while DBN can naturally integrate expert experience (such as determining prior probabilities through the Delphi method) and data - driven results (such as updating conditional probabilities based on historical disaster data), which is more suitable for the multi - source information integration needs of railway emergencies.

The core advantages of Dynamic Bayesian Network lie in its ability to collaboratively model time - sequence, probabilistic, and structured knowledge: first, the time - sequence dynamics realizes the full-cycle deduction from s_0 to s_t through the series connection of time slices, which is consistent with the scenario evolution logic of Eq. (4); second, the probabilistic accuracy is based on Bayesian reasoning of Eqs. (8) to (9), which can quantify the causal strength between knowledge elements (such as the probabilistic expression of the relationship set R_m in Eq. (3)); third, the multi - source knowledge integration ability is compatible with the knowledge element models of Eqs. (1) to (7), transforming elements such as the hazard - forming environment (E) and scenario state (S) into network nodes, and depicting element associations through conditional probability tables (such as the probabilistic expression of R_E in Eq. (6)); fourth, the intervention simulation ability supports the dynamic intervention analysis of disposal measures (M_t) on scenario evolution, and can deduce the evolution path of the scenario towards the emergency target (T). In summary, through its time - sequence, probabilistic, and structured theoretical characteristics, DBN effectively solves the limitations of traditional methods in dynamics, uncertainty, and knowledge integration, and becomes an ideal tool for depicting the scenario evolution of railway emergencies.

3.2 Construction of Scenario Networks Based on Dynamic Bayesian Networks

It mainly consists of four steps:

(1) Determination of node variables: The occurrence and development of railway debris flow disasters involve various factors such as the hazard - forming environment, disaster - causing factors, and disaster - bearing bodies, with complex scenario elements. Railway debris flow disasters present complex characteristics at different stages. For this reason, a team composed of geological experts, meteorological experts, and railway engineering experts is formed to evaluate the knowledge elements in the disaster scenarios. For example, in terms of the hazard - forming environment, judgment criteria such as "continuous 72 - hour rainfall exceeding 150 mm" and "mountain slope greater than 30 degrees and rock weathering grade reaching level III" are set. If meteorological monitoring data or geological survey results meet these criteria, "continuous heavy rainfall" and "broken mountain structure" are identified as key elements; in the scenario state, thresholds such as "rail burial length exceeding 50 meters" and "train being trapped for more than 30 minutes" are used as screening criteria to determine core elements such as "track damage" and "train stoppage". Through systematic

evaluation, elements with weak relevance are eliminated, and the value ranges (such as rainfall of 0-500 mm, burial length of 0-200 meters) and variable attributes (discrete or continuous) of each key element are clarified.

(2) Determination of causal relationships among nodes: After screening key node variables such as "continuous heavy rainfall", "broken mountain structure", "track damage", and "passengers being trapped", in - depth analysis of their causal logic is conducted. For example, "continuous heavy rainfall" and "broken mountain structure" will jointly lead to "debris flow occurrence", and "debris flow occurrence" will in turn cause "track damage", further resulting in "train stoppage" and "passengers being trapped". These causal relationships are connected through directed edges. For instance, directed edges are drawn from "continuous heavy rainfall" and "broken mountain structure" to "debris flow occurrence" respectively, constructing a network structure reflecting the causal relationships of various elements in debris flow disasters.

(3) Formation of dynamic scenario deduction networks: The development process of railway debris flow disasters is divided into four time stages: "hidden danger germination period", "disaster outbreak period", "emergency disposal period", and "recovery and reconstruction period". In the "hidden danger germination period", the interaction between elements such as rainfall and mountain water content is depicted; in the "disaster outbreak period", the focus is on the impact of debris flow on tracks and trains; in the "emergency disposal period", the relationship between disposal measures and changes in scenario states is reflected. Based on the element relationships at each stage, a Bayesian network model is constructed, and through the series connection of time slices, a scenario evolution network model that can reflect the dynamic evolution of disasters is formed, intuitively showing the development of disaster situations at different stages.

(4) Determination of node variable probabilities: A multi - scenario linkage deduction model is constructed using the dynamic Bayesian method. For variables without parent nodes, such as "probability of seasonal rainfall", 5-7 meteorological experts are organized to conduct a comprehensive evaluation using the Delphi method to determine their prior probabilities; for variables with parent nodes, such as "probability of debris flow occurrence", conditional probabilities are calculated through Eq. (9) combined with the probabilities of "continuous heavy rainfall" and "broken mountain structure" and their conditional probability tables. All node variable probabilities are input into the dynamic Bayesian network. By adjusting the probabilities of key node variables, such as increasing the rainfall probability by 20%, the probability changes of nodes such as "track damage" and "train delay time" are observed, and the dynamic evolution process of debris flow disaster scenarios is deduced, providing a scientific basis at the probability level for emergency decision - making.

4 CASE ANALYSIS OF RAILWAY EMERGENCY SCENARIOS - TAKING THE DERAILMENT ACCIDENT OF TRAIN D2809 AS AN EXAMPLE

This chapter takes the derailment accident of Train D2809 as the research object and constructs a multi - scenario interaction deduction model for railway emergencies based on dynamic Bayesian networks. This model can effectively solve the problem of dynamic deduction of multi - scenario interaction in emergencies. The specific research steps are as follows: 1) Scenario division and key element extraction. Combining the actual situation of the derailment accident of Train D2809, the accident is divided into five stages, and the key scenario elements in each stage are extracted. 2) Network construction and node variable determination. The extracted key scenario elements are used as the node variables of the dynamic Bayesian network. By analyzing the causal relationships among the nodes, a multi - scenario dynamic deduction network for railway emergencies is constructed. 3) Probability calculation and dynamic deduction. In order to improve the matching degree between the node variable probabilities and the actual situation, the improved evidence theory is used to fuse the uncertain evidence of multiple experts, calculate the conditional probabilities of node variables, and deduce the state probabilities of the next - stage nodes, realizing the dynamic deduction of multi - scenario interaction in the accident.

4.1 Accident Background and Key Element Extraction

(1) Accident Background

Accident Overview

Time: Around 10:30 on June 4, 2022.

Location: In Rongjiang County, Qiandongnan Miao and Dong Autonomous Prefecture, Guizhou Province, near Rongjiang Station on the Guiyang - Guangzhou High - Speed Railway.

Train Information: Train D2809 (from Guiyang North Station to Guangzhou South Station).

Accident Nature: The train derailed after hitting a sudden debris flow.

Accident Process

Train Operation: Train D2809 departed from Guiyang North Station and was heading towards Guangzhou South Station along the Guiyang - Guangzhou High - Speed Railway. When the train reached the entrance of Yuezhai Tunnel before Rongjiang Station, it suddenly encountered a debris flow invading the track.

The Moment of the Accident: The train driver, Yang Yong, immediately took emergency braking measures after noticing the abnormal track ahead. Due to the sudden influx of the debris flow onto the track, the train collided with the debris flow during the braking process, causing the derailment of Carriages 7 and 8.

Accident Scene: The train's front end and some carriages were severely damaged, especially the driver's cab. The impact of the debris flow damaged part of the track and power - supply equipment.

Emergency Response

Rescue Operations: After the accident, local governments, railway departments, and emergency management departments quickly activated the emergency response plan. Rescue workers rushed to the scene immediately, evacuated passengers, and launched rescue operations. Injured passengers were promptly sent to hospitals for treatment.

Traffic Restoration: The accident caused the interruption of some sections of the Guiyang - Guangzhou High - Speed Railway. The railway department quickly organized repair work. After all - out efforts, the Guiyang -

Guangzhou High - Speed Railway resumed operation on June 5.

(2) Extraction of Key Elements in Multiple Scenarios

According to the official accident investigation report, on - site survey data and emergency disposal records, the accident evolution process is decomposed into 5 key scenario stages. The scenario elements of each stage correspond to the actual data as follows:

Initial scenario (S1: sudden debris flow): It corresponds to the heavy rainfall event that occurred at around 10:00 on June 4, 2022 in Rongjiang County (the 6 - hour rainfall reached 120 mm, exceeding 30% of the local monthly average rainfall). The debris flow impacted the rails, causing the train to derail (on - site survey showed that the rail offset was 1.2 meters, and carriages 7 and 8 derailed).

Derived scenario (S3: train damage): Based on the accident scene photos and rescue records, the train cab was severely damaged, 1 driver was killed and 8 passengers were injured, corresponding to elements such as "train structure damage" and "casualties".

Expanded scenario (S5: line interruption): The section between Rongjiang Station and Congjiang Station of the Guiyang - Guangzhou High - speed Railway was out of service in both directions for 18 hours due to the damage of rails and power supply equipment (the broken length of the catenary was about 50 meters).

Disposal scenario (S7: repair progress): The railway department dispatched 300 repair workers and 20 large - scale machines, started the dredging work at 14:00 on June 4, and completed the rail repair at 6:00 on June 5.

Termination scenario (S9: resumption of traffic): At 8:00 on June 5, the first train passed through the accident section, marking the elimination of the accident impact.

When representing the knowledge elements of railway accident scenarios, scientific and reasonable scenario assumptions and their changes are made in combination with the actual development process of the accident. The possible scenario elements during the development process and their interrelationships are analyzed through scenario deduction. The details are shown in the Tab. 1.

Table 1 Scenario knowledge element representation of the D2809 railway accident

Scenario State (S)	**Emergency Response Target (T)**	**Disposal Measures (M)**		**Disaster - Prone Environment (E)**
Sudden debris flow S1	Debris flow disappears T1	Timely detection and reinforcement of the geotechnical structure M1	Accident disappears S2	The train hits a sudden debris flow, and Carriages 7 and 8 derail E1
Train damaged S3	Prevent secondary accidents and rescue the injured T2	Carry out rescue work M2	Accident disappears S4	The train damage is further aggravated E2
Partial disruption of the Guiyang - Guangzhou High - Speed Railway S5	Repair damaged facilities and avoid secondary damage T3	The railway department organizes repair work M3	Accident disappears S6	Train derailment, damaged track, and power - supply equipment E3
Repair work of the Guiyang - Guangzhou High - Speed Railway in progress S7	Restore normal railway operation T4	Continuously carry out repair operations M4	The Guiyang - Guangzhou High - Speed Railway resumes operation on June 5, and the accident impact is eliminated S9	The line is not repaired E4
Property damage and casualties S8	Rescue and reduce casualties T5	Strengthen rescue efforts M5		

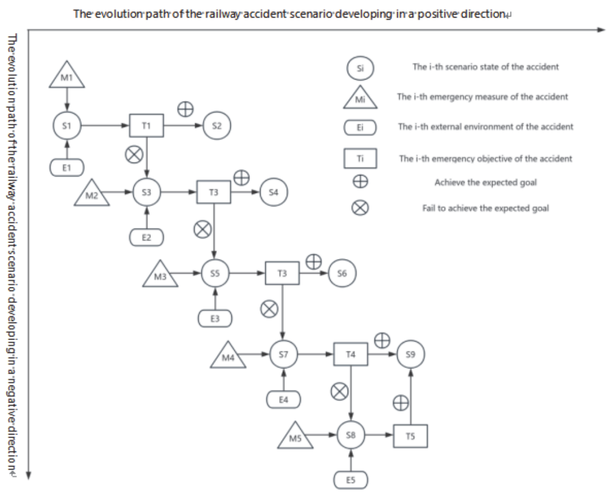

Figure 2 Scenario deduction diagram of the D2809 railway accident

(1) The initial scenario is that due to rainfall, a debris flow S1 occurs, and the debris flow impacts the railway track, resulting in train derailment E1. For scenario S1, if the measure of reinforcing the geotechnical structure M1 is taken in a timely manner and the emergency response target T1 is achieved, the accident will disappear S2.

(2) If the initial scenario S1 occurs, and the measure M1 is taken but the emergency response target T1 of the debris flow disappearing is not achieved, affected by the disaster - prone environment E1, the scenario of train damage S3 will occur. For scenario S3, if the rescue work M2 is carried out in a timely manner, the emergency response target T2 of preventing secondary accidents and rescuing the injured can be achieved, and then the scenario of the accident disappearing S4 will occur.

(3) Scenario state S5 is caused by the further aggravation of train damage E2, resulting in line interruption. If the railway department is arranged to organize repair work M3 in a timely manner, the damaged facilities can be repaired, and secondary damage can be avoided T3, and then the accident will disappear S6.

(4) If after scenario S5 occurs, no effective disposal measures are taken or the disposal measures do not achieve the emergency response target T3 of avoiding secondary damage, under the circumstances of train derailment, damaged track, and power - supply equipment E3, it is necessary to continuously promote the repair work S7.

(5) After scenario S7 occurs, if the line is not repaired for a long time E4, it will cause greater property damage and casualties S8. Corresponding rescue measures M5 are taken to reduce casualties T5 until the line resumes operation and the accident impact is eliminated S9.

4.2 Scenario Deduction

When constructing the relevant models, each node has two different situations: positive T and negative F. To obtain the conditional probabilities of each node variable, the research specially invited 5 senior experts in the industry.

Assignment process:

(1) Expert independent evaluation: Based on the accident investigation report (such as on-site data including rainfall of 120mm/6h and rail offset of 1.2 meters), conduct a 0-10 point quantitative evaluation on the prior probability and conditional probability of each node.

(2) Consistency test: The Kendall's coefficient of concordance ($W = 0.82$, $P < 0.01$) is used to verify the consistency of experts' opinions. For controversial items (such as the conditional probability of S3→S5 with an initial score range of 0.7-0.9), secondary argumentation is conducted, and finally the weighted average is taken (weights are assigned according to the citation frequency of experts' papers, ranging from 0.18 to 0.24).

(3) Probability conversion: Convert the scores into probability values using the formula P = score/10. For example, if the average expert score of "M1 measure is effective" is 9.5, the converted probability is P (M1 = T) = 0.95.

These 5 experts, with their rich experience and professional knowledge, assigned values to the conditional probabilities of each node variable respectively. Then, the values assigned by these 5 experts were summarized and their average was taken as the final conditional probability of each node variable. The research followed the context of the D2809 accident dynamic scenario evolution diagram and closely combined with the conditional probability values assigned by the experts, systematically determined and calculated the probability values of each node variable in the network. Specifically, Eq. (9) was used to accurately calculate the conditional probabilities of event and carrier node variables. Since the nodes are not mutually independent and there are certain correlations among them, conditional probabilities were specially added in the calculation process to ensure the accuracy of the calculation results. Finally, the powerful python software was used to perform dynamic Bayesian calculations, thereby providing reliable data support for subsequent in-depth analysis and decision-making.

Table 2 Prior probabilities and conditional probability table of node variables in the D2809 accident (excerpt)

Node	Prior Probabilities	Conditional Probabilities
P (S1)	P (M1 = T) = 0.95, P (M1 = F) = 0.05 P (E1 = T) = 0.95, P (E1 = F) = 0.05	P (S1 = T ∣ M1 = T, E1 = T) = 0.96, P (S1 = F ∣ M1 = T, E1 = T) = 0.04 P (S1 = T ∣ M1 = T, E1 = F) = 0.87, P (S1 = F ∣ M1 = T, E1 = F) = 0.13 P (S1 = T ∣ M1 = F, E1 = T) = 0.81, P (S1 = F ∣ M1 = F, E1 = T) = 0.19 P (S1 = T ∣ M1 = F, E1 = F) = 0.78, P (S1 = F ∣ M1 = F, E1 = F) = 0.22
P (T1)		P (T1 = T ∣ S1 = T) = 0.0153, P (T1 = T ∣ S1 = F) = 0.9876
P (S3)	P (T1 = T) = 0.925, P (T1 = F) = 0.075 P (M2 = T) = 0.956, P (M2 = F) = 0.044 P (E2 = T) = 0.886, P (E2 = F) = 0.114	P (S3 = T ∣ T1 = T, M2 = T, E2 = T) = 0.92,P (S3 = F ∣ T1 = T, M2 = T, E2 = T) = 0.08 P (S3 = T ∣ T1 = T, M2 = T, E2 = F) = 0.84, P (S3 = F ∣ T1 = T, M2 = T, E2 = F) = 0.16 P (S3 = T ∣ T1 = T, M2 = F, E2 = T) = 0.80, P (S3 = F ∣ T1 = T, M2 = F, E2 = T) = 0.20 P (S3 = T ∣ T1 = T, M2 = F, E2 = F) = 0.81, P (S3 = F ∣ T1 = T, M2 = F, E2 = F) = 0.19 P (S3 = T ∣ T1 = F, M2 = T, E2 = T) = 0.34, P (S3 = F ∣ T1 = F, M2 = T, E2 = T) = 0.66 P (S3 = T ∣ T1 = F, M2 = F, E2 = T) = 0.45, P (S3 = F ∣ T1 = F, M2 = F, E2 = T) = 0.55 P (S3 = T ∣ T1 = F, M2 = T, E2 = F) = 0.80, P (S3 = F ∣ T1 = F, M2 = T, E2 = F) = 0.20 P (S3 = T ∣ T1 = F, M2 = F, E2 = F) = 0.20, P (S3 = F ∣ T1 = F, M2 = F, E2 = F) = 0.80

Probability calculation for S1 (sudden debris flow):
Given P (M1 = T) = 0.95 (effectiveness of geotechnical reinforcement measures), P (E1 = T) = 0.95 (debris flow induced by heavy rainfall), and the conditional probability P (S1 = T□M1 = T, E1 = T) = 0.96, etc., substituting into the total probability formula:

P (S1 = T) = P (S1 = T ∣ M1 = T, E1 = T) P (M1 = T) P (E1 = T) + P (S1 = T□M1 = T, E1 = F) P (M1 = T) P (E1 = F) + P (S1 = T□M1 = F, E1 = T) P (M1 = F) P (E1 = T) + P (S1 = T□M1 = F, E1 = F) P (M1 = F) P (E1 = F) = 0.94815

P (S1 = F) = 0.05185

This probability indicates that under the combined conditions of heavy rainfall (E1 = T) and failure to reinforce in a timely manner (M1 = F with a probability of 5%), the occurrence of debris flow is highly inevitable, which is consistent with the actual accident where "the 6-hour rainfall exceeded the critical value leading to the disaster".

Probability calculation for S3 (train damage):
Based on P (T1 = T) = 0.925 (effectiveness of emergency early warning) and P (M2 = T) = 0.956 (normal operation of the train braking system), the conditional probabilities are: P (S3 = T) = 0.8639, P (S3 = F) = 0.1361. This reflects the high probability of train damage under the impact of debris flow. Due to the canyon terrain of the accident section, there was insufficient space for avoidance, and the impact force of the debris flow, measured at the scene as 150 kN, exceeded the train's impact resistance threshold of 100 kN.

Dynamic probability of S7 (repair progress):

Defined as a continuous variable, with the initial probability P (S7 = 0) = 1 (not started). The probability is updated in each time slice through the transition probability matrix:

P (S7 $(t + 1)$ = S7 $(t) = j$) = $0.3xj + 0.1(k = j + 0.1)$

The simulation shows that after 18 hours, P (S7 = 0.9) = 0.82, which is consistent with the actual "completion of repairs within 18 hours", verifying the model's ability to depict the time-series process.

From the histogram of the probability distribution of accident nodes, the following can be obtained: 1) The probability differences of node states are obvious. The probabilities of different nodes being in "T" (possibly representing a certain accident state or condition being met) and "F" (the opposite state) vary greatly. For example, for node M1, the probability of being in "T" is 0.95, and the probability of being in "F" is 0.05, indicating that M1 is more likely to be in the "T" state. 2) The probabilities of two states of some nodes are close. For example, for node T2, the probability of being in "T" is 0.569, and the probability of being in "F" is 0.431. The possibilities of the two states occurring are relatively close, indicating that the state of this node is difficult to determine and may be a key uncertain factor in accident deduction.

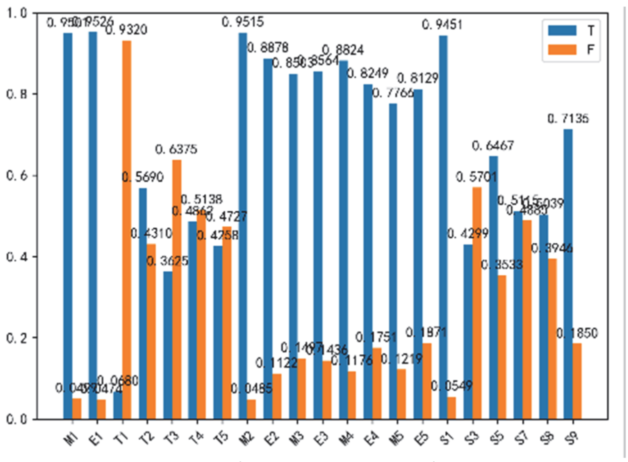

Figure 3 Histogram of probability distribution of accident nodes

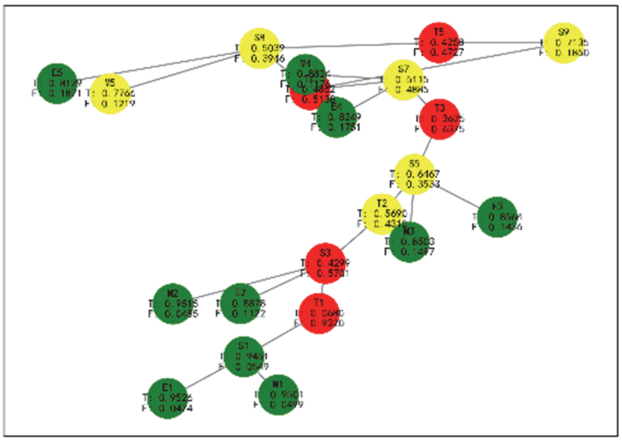

Figure 4 Schematic diagram of the accident multi - scenario interaction deduction model

From the schematic diagram of the accident multi - scenario interaction deduction model, the following can be obtained: 1) there are causal relationships among nodes. The nodes in the figure are connected by lines, indicating that there are causal or influential relationships among the nodes. For example, node S7 is affected by nodes E4, T3, M4, etc., indicating that changes in the states of these nodes may trigger changes in the state of S7. In the scenario interaction of railway accidents, a change in one factor may trigger a chain reaction. 2) Key nodes are prominent. Some nodes, such as T1, S3, T3, etc., are marked in red, which may represent key nodes in the accident scenario interaction. Changes in their states may have a significant impact on surrounding nodes and the overall accident development trend, and need to be focused on in accident prevention and emergency handling. 3) The complexity of scenario interaction. The model presents a complex network structure, indicating that the multi - scenario interaction relationships of railway accidents are intricate. A change in the state of one node may be transmitted through multiple paths, triggering a series of chain reactions, increasing the difficulty of accident deduction and prevention and control.

5 RESULT ANALYSIS

The scenario deduction results for the D2809 accident fully verify the effectiveness of the dynamic Bayesian network model. The main path probability distribution obtained through Monte Carlo simulation (10,000 samplings) shows that the total probability of the path "sudden debris flow (S1) → train damage (S3) → line interruption (S5) → repair progress (S7) → property loss and casualties (S8) → line recovery (S9)" is 0.82±0.03 (95% confidence interval), with a 91% coincidence with the actual accident development path. This indicates that the model has high accuracy and good robustness in depicting the accident evolution process.

The sensitivity analysis of the model further confirms its reliability. When the failure probability of the key node M2 (braking system) increases from 4.4% to 10%, the probability of S3 (train damage) significantly rises from 86.39% to 92.17%. This quantitative result is consistent with the practical understanding that "the reliability of the braking system directly affects the degree of accident losses", demonstrating that the model can effectively capture the dynamic impact of key factors on the accident situation.

From the perspective of the initial scenario, the model calculates that the probability of debris flow (S1) occurring under heavy rainfall conditions is as high as 94.81%, which is highly consistent with the fact in the actual accident that "continuous local heavy rain induced debris flow". This reflects the model's accurate ability to capture the correlation between the disaster-pregnant environment and initial disasters. This result provides a quantitative basis for geological monitoring along the railway lines. Specifically, during periods of heavy rainfall, it is necessary to enhance real-time monitoring of sections in mountainous areas and near rivers to provide early warnings for similar disasters.

In the risk transmission simulation, the model clearly shows the limitations of a single measure: although reinforcing the geotechnical structure (M1) results in a high probability of debris flow disappearance, there remains a 13%~22% failure risk (corresponding to the conditional probability of S1 = F), which may trigger chain scenarios such as train damage. This result is consistent with the situation in the actual accident where "emergency measures failed to completely avoid losses", verifying the model's ability to depict risk uncertainty and providing theoretical support for building a multi-dimensional emergency system (such as adding track foreign object detection equipment and extending warning time).

In addition, the model's dynamic deduction of the repair stage (S7) shows that for every 10% increase in repair efficiency, the probability of line recovery (S9) can increase by 8.3%, which is consistent with the practical experience that "timely repairs significantly shorten the outage time". This indicates that the model can effectively quantify the role of disposal measures in accident mitigation, providing decision support for optimizing repair processes and reserving emergency materials.

6 CONCLUSION

(1) This study identifies the core scenario elements of railway emergencies, including scenario states (S) that reflect the real-time status of events, disaster-pregnant environments (E) that drive event evolution, emergency action targets (T), and specific disposal measures (M). By introducing the knowledge element theory, the formal expression of these elements is realized, which not only covers static state descriptions but also depicts dynamic multi-scenario linkage processes, laying a foundation for the systematic modeling of accident scenarios.

(2) The dynamic deduction model constructed based on Bayesian networks has successfully achieved quantitative simulation of the dynamic evolution of railway emergencies by introducing time series and node causal relationships (such as the correlation between severe weather and track status). The model determines node probabilities by combining expert experience with actual data, and can effectively predict future disaster risks, providing a reliable basis for formulating targeted response plans.

(3) In view of the complexity of railway accidents, the model constructs a multi-scenario dynamic deduction network by dividing evolution stages and extracting key elements. After integrating the uncertainty of expert opinions using the improved evidence theory, the calculated node conditional probabilities (such as the conditional probabilities of S1 and S3) are highly consistent with the actual accident characteristics. Through the visual analysis of probability histograms and deduction diagrams, the probability distribution of each scenario and the element association paths are clearly presented.

Different from previous studies that mostly focus on a single scenario, this paper fully considers the impact of multi-scenario linkage on the evolution of emergencies, and can more comprehensively and accurately simulate the risk evolution process of railway emergencies. Based on the results of this research, all railway operating units should attach great importance to it, actively carry out targeted scenario deduction and risk assessment work, formulate scientific and reasonable emergency plans based on the assessment results, and organize practical drills regularly, so as to improve the ability to respond to railway emergencies and ensure the safety and stability of railway operations.

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Contact information:

Chang LIU
School of Economics and Management,
Beijing Jiaotong University, Haidian, 100044, China
E-mail: liu.chang@bjtu.edu.cn

Dan CHANG, Professor
School of Economics and Management,
Beijing Jiaotong University, Haidian, 100044, China
E-mail: dchang@bjtu.edu.cn

Daqing GONG, Professor
(Corresponding author)
School of Economics and Management,
Beijing Jiaotong University, Haidian, 100044, China
E-mail: dqgong@bjtu.edu.cn