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RISK ASSESSMENT OF SUBWAY STATION FIRE BY USING A BAYESIAN NETWORK-BASED SCENARIO EVOLUTION MODEL

Xuewei LI[1,2], Jingfeng YUAN[2]✉, Limao ZHANG[3], Dujuan YANG[4]

[1]Department of Engineering Management, School of Mechanics and Civil Engineering, China University of Mining and Technology, Xuzhou 221116, P. R. China
[2]Department of Construction and Real Estate, School of Civil Engineering, Southeast University, Nanjing 210096, P. R. China
[3]School of Civil and Hydraulic Engineering, National Center of Technology Innovation for Digital Construction, Huazhong University of Science and Technology, 1037 Luoyu Road, Hongshan District, Wuhan, Hubei 430074, China
[4]Information Systems in the Built Environment, Eindhoven University of Technology, Vertigo 9.09, 5600 MB, Eindhoven, the Netherlands

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Abstract. Subway station fires frequently result in massive casualties, economic losses and even social panic due to the massive passenger flow, semiconfined space and limited conditions for escape and smoke emissions. The combination of different states of fire hazard factors increases the uncertainty and complexity of the evolution path of subway station fires and causes difficulty in assessing fire risk. Traditional methods cannot describe the development process of subway station fires, and thus, cannot assess fire risk under different fire scenarios. To realise scenario-based fire risk assessment, the elements that correspond to each scenario state during fire development in subway stations are identified in this study to explore the intrinsic driving force of fire evolution. Accordingly, a fire scenario evolution model of subway stations is constructed. Then, a Bayesian network is adopted to construct a scenario evolution probability calculation model for calculating the occurrence probability of each scenario state during subway station fire development and identifying critical scenario elements that promote fire evolution. Xi'an subway station system is used as a case to illustrate the application of Bayesian network-based scenario evolution model, providing a practical management tool for fire safety managers. The method adopted in this study enables managers to predict fire risk in each scenario and understand the evolution path of subway station fire, supporting the establishment of fire response strategies based on "scenario–response" planning.

Keywords: subway station, fire safety, scenario analysis, Bayesian network, deduction analysis, sensitivity analysis.

✉Corresponding author. E-mail: *jingfeng-yuan@seu.edu.cn*

1. Introduction

Subway stations have many combustible materials (e.g. billboards and decoration materials), electrical and mechanical equipment (e.g., elevators, wires and cables) and unsafe practices by passengers or staff that may cause fire accidents (Zhang et al., 2019). Complete fire safety in subway stations is believed to be impossible. Considering the massive passenger flow, semiconfined space and limited conditions for escape and smoke emissions, subway station fires exhibit certain characteristics, such as rapid increment in ambient temperature, long duration and firefighting and emergency rescue difficulties, frequently resulting in massive casualties, economic losses and even social panic (Ji et al., 2011). For example, London's massive fire disaster in 2005 caused 56 deaths and left more than 700 people severely injured (Tsukahara et al., 2011). In accordance with global subway incident statistics, fire hazard is the most generic form of accidents and accounts for 30%–50% of incidents (Li et al., 2021). Therefore, assessing the fire risk of subway stations is essential for optimising their capacity to respond to fire hazards and minimise economic losses and adverse social effects.

Many prior studies have conducted research on the fire safety management of subway stations to assist in fire hazard assessment and response. Some scholars have adopted different numerical simulation models or software, such as computational fluid dynamics models (Weng et al., 2014; Roh et al., 2009), fire dynamics simulator (Kim et al., 2008; Li et al., 2012), agent-based models (Zou et al., 2021) and

Monte Carlo simulation models (Zhang et al., 2017), to assess the effectiveness of structural fire protection design and the evacuation efficiency of facilities and equipment (e.g., escalators and emergency exits) by simulating smoke flow and personnel evacuation behaviour during fires. However, existing fire simulation models require a massive amount of initial data and excessive computation time; moreover, they do not reflect the overall fire risk of subway stations. Therefore, system analysis and statistical analysis methods, such as analytic hierarchy process (Ju et al., 2022), failure mode and effect analysis (FMEA) (Nezhad et al., 2015) and optimised neural network (Yu & Zhang, 2016), have been widely adopted to realise the rapid assessment of overall fire risk in subway stations. For example, Nezhad et al. (2015) adopted the FMEA model to assess the fire risk of Zagros subway station and identified six critical fire risk factors. Yu and Zhang (2016) determined 23 fire risk factors of subway stations and then constructed a fire risk assessment model by using a neural network.

Various hazardous factors and emergency response activities occur during the development of subway station fire. The combination of different states of these factors can generate a vast number of fire scenarios, making the fire evolution path overly complex and uncertain (Wu et al., 2018). Brannigan and Kilpatrick (2000) emphasised that fire losses are determined by different fire scenarios. Traditional methods cannot describe subway station fire development, and thus, cannot assess fire risk under different fire scenarios. The "scenario–response" method that predicts the evolution path of a fire hazard on the basis of its current state can be an effective strategy for assessing fire risk under different scenarios and providing effective guidance to managers in developing effective fire prevention measures.

Scenario analysis can be defined as a description of the future evolution path of an event and its potential outcomes (Kahn & Wiener, 1967). Many prior studies have conducted research on the scenario analysis of subway station fires to assist in hazard assessment and response. The event tree, fault tree, and bow tie methods have been widely adopted in conducting scenario analyses of fire hazards (Lin et al., 2020; Roshan & Daneshvar, 2015; Xie et al., 2021). Moreover, they can qualitatively describe the evolution path of a hazard and quantitatively calculate the probability of the occurrence of disastrous consequences under different fire scenarios. For example, Roshan and Daneshvar (2015) constructed an event tree for the fire evolution path in a subway station and used it to estimate the probabilities of different scenarios and the corresponding economic losses of the Tehran subway station fire hazard. However, these methods cannot describe conditional dependencies between scenario elements, leading to scenario analysis uncertainties that cannot be resolved. In addition, these scenario analysis methods are static and cannot achieve probability updating during the analysis of actual fire scenarios.

A Bayesian network (BN) is one of the most effective tools for realising dynamic scenario analysis in complex environments (Chen & Pollino, 2012; Wu et al., 2016; Hu et al., 2022). Multistate nodes and conditional probability distribution between nodes allow BN to represent various uncertain scenarios. In addition, BN exhibits the flexibility required to update probability in accordance with newly provided evidence during scenario analysis, and thus, it can conduct predictive and diagnostic analyses and support the timely creation of "scenario–response" strategies (Cinar & Kayakutlu, 2010; Afenyo et al., 2017; Chang et al., 2019a). With regard to the scenario analysis of fire hazards, Liu et al. (2010) proposed a BN model for the scenario analysis of a ship engine room fire. The proposed method presented the fire evolution path from ignition to extinguishment and was used to predict fire losses and provide decision-making suggestions for firefighting. Matellini et al. (2018) quantitatively examined dwelling fire losses by using a three-part BN model. The model provided a scenario-specific analysis of common firefighting measures and conditional dependency in fire development. Khakzad (2018) applied BN to the modelling and hazard assessment of fire evolution in oil terminals and identified the best fire prevention and control measures under different fire scenarios. Existing studies have shown that BN is suitable for dynamic scenario analysis and efficiently supports hazard prediction, diagnosis and decision-making. However, only a few BN-based scenario analysis studies on subway station fires have been conducted.

To realise scenario-based fire risk assessment, scenario elements that correspond to each scenario state in the fire development of subway stations are identified in the current study to explore the intrinsic driving force of fire evolution, and thus, a fire scenario evolution model of subway stations is constructed. Then, BN is adopted to construct a scenario evolution probability calculation model for calculating the probability of occurrence of each scenario state during subway station fire development and identifying critical scenario elements that promote fire evolution. In this study, the scenario evolution model of subway station fire is constructed by identifying the elements of a subway station fire evolution scenario and their relationships. This model can facilitate the understanding of the evolution mechanism of subway station fire. Meanwhile, the BN-based scenario evolution probability calculation method can solve the uncertainty and dynamic problems in the fire risk assessment of subway stations and improve the accuracy and effectiveness of fire risk assessment. Furthermore, the method adopted in this study can help managers to predict fire risk in each scenario and understand the evolution path of subway station fire, providing support for the establishment of fire response strategies based on "scenario–response" planning.

2. Literature review

To construct a BN-based scenario deduction network of subway station fires, relevant scenario evolution processes and scenario elements should be determined (Xin & Huang, 2013). This section reviews literature on the two significant perspectives.

2.1. Scenario evolution processes of subway station fire

Fire development is a chain reaction. Fire accidents in subway stations evolve constantly on the basis of scenarios. Fire scenario evolution in subway stations follows general building fire development and can be divided into four stages: fire ignition, fire growth, personnel evacuation and full development to extinguishment. Table 1 provides the characteristics of each scenario evolution of a subway station fire.

Table 1. Characteristics of each scenario of a subway station fire

Fire scenario	Characteristics
Fire ignition	Owing to equipment failure, unsafe behaviour of passengers and poor management of a subway station, ignition sources come in contact with combustible materials, causing combustion (Wu et al., 2018).
Fire growth	After fire ignition, the untimely response of the fire detection system and human firefighters in the subway station leads to further growth of the fire (Chen et al., 2018a).
Personnel evacuation	The rapid development of fire with high temperature and copious amounts of toxic smoke forces personnel evacuation (Chen et al., 2021).
Full development to extinguishment	As temperature increases accompanied by the release of copious amounts of toxic smoke, fire will break through fire compartments and develop in full scale in subway stations until it is extinguished (Matellini et al., 2018).

2.2. Scenario elements in a subway station fire

During subway station fire, scenario elements refer to factors that determine the evolution path of the incident (Postma & Liebl, 2005). Clearly defined scenario elements are the basis for establishing an incident's evolution model. In accordance with the triangular framework of public safety science and technology proposed by Fan et al. (2013), an academician from China Engineering Academy, the scenario elements of a subway station fire are divided into three types: (1) scenario state, which refers to the state of scenario evolution processes, as explained in Section 2.1; (2) hazardous factor, i.e., the external environmental factor that leads to the continuous development of the fire; and (3) emergency response activity, i.e., measures taken by rescuers based on the scenario state of the fire. The evolution path of a fire from one scenario state to the next is determined by the corresponding hazardous factors and emergency response activities (Bjelland & Borg, 2013). If emergency rescuers are effective in firefighting, then the fire will evolve in an optimistic direction, indicating that the fire can be extinguished; conversely, it will develop in a pessimistic direction that requires further rescue measures. A fire continuously evolves until it is extinguished. In this section, hazardous factors and emergency response activities that drive scenario evolution in each scenario of subway station fire are reviewed.

2.2.1. Scenario elements in the fire ignition stage

Various ignition sources exist within subway stations. Some scholars have proposed that passenger unsafe behaviour, equipment unsafe state and poor environmental condition are the major hazardous factors of fire ignition in subway stations (Wu et al., 2018). Passenger unsafe behaviour, which typically occurs suddenly, includes smoking, carrying flammable and explosive materials and intentional arson (Chen et al., 2019). Device failure includes the malfunction of electrical and mechanical equipment (due to inferior quality and improper maintenance), equipment overload and aging of lines (Lin et al., 2020). In addition, poor environmental condition refers to elevated temperature and humidity (Lin et al., 2020). With the deepening of research on fire causes in subway stations, poor fire prevention management measures, such as untimely equipment monitoring, inappropriate application of security screening system and ineffective human fire safety training, are considered the root causes of fires in subway stations (Yan et al., 2016).

To monitor fires in a timely manner, an equipped fire alarm system is required in a subway station. The fire alarm system can detect flame and smoke in the early stage of fire and generates alarms in a timely manner for people in a subway station (Matellini et al., 2018). Thereafter, personnel (subway staff and passengers) take timely and effective measures to extinguish the fire, such as using fire extinguishers to suppress fire development in its early stage (Li et al., 2016).

2.2.2. Scenario elements in the fire growth stage

Subway station fires enter the growth stage if they are not extinguished during the ignition stage. Fire development in the growth stage is related to combustible load (Zhang et al., 2019). Therefore, using decorative materials with flame retardant properties in subway stations and avoiding stacking combustible materials can reduce fire spread rate. In addition, effective emergency response measures, including operational sprinkler systems, trained subway staff and firefighters, should be adopted to prevent a fire from entering the full development stage (Wang et al., 2021a). Once a fire ignites in a subway station, it grows rapidly. Sprinkler systems and human firefighting are critical emergency response measures before professional firefighters arrive, reflecting fire resistance in a subway station (Wu et al., 2018). Timely firefighting actions can decrease fire severity and reduce the possibility of a fire evolving in a pessimistic direction. In general, the time from fire ignition to flashover and outward spreading is 15 min. Thus, after receiving a fire call, firefighters should arrive at the fire scene immediately to conduct professional firefighting and avoid the spread of fire (Chen et al., 2018b). Therefore, fire stations should be set up at reasonable locations near subway stations to minimise the fire brigade's arrival time and the likelihood of fire flashover and severity during the growth stage.

2.2.3. Scenario elements in the personnel evacuation stage

Personnel evacuation is related to the number of fire casualties. During the preliminary stages of fire development, ambient temperature and toxic gas concentration are low and do not threaten human lives (Cai et al., 2016). Thus, timely personnel evacuation can increase the likelihood of evacuating people to safe areas and decrease the number of casualties. The vertical structure of subway stations includes three types: single floor, double floor and complex. The complicated vertical structure of subway stations increases the difficulty for personnel to escape aboveground (Wu et al., 2018). The three major types of subway station platforms are the island, side and combined types. The subway station area and changes in passenger flow are different for the three platform types, significantly affecting personnel evacuation (Long et al., 2020). Furthermore, passenger escape skill is considered a crucial factor that affects evacuation (Wang et al., 2021a).

Evacuation systems should be activated immediately after fire ignition. They include evacuation passages, evacuation ports, direction indicators, emergency lighting and broadcasted audio cues. Effective evacuation systems allow personnel to choose evacuation passages accurately and rapidly, decreasing the number of casualties (Tsukahara et al., 2011). In addition, the state of the smoke extraction system determines whether toxic smoke generated by a fire can be discharged in time. The timely discharge of smoke during fire development has an important effect on increasing evacuation time (Ji et al., 2011).

2.2.4. Scenario elements in the full development to extinguishment stage

In the full development stage, fire will spread throughout the subway station. Fireproof endurance rating and zoning are considered the major hazardous factors during the full development stage. Fireproof endurance rating is a graded scale that measures the degree of fire resistance of a building (Matellini et al., 2018). A subway station with a high fireproof endurance rating can reduce the rate of fire spread. Fire zoning can prevent the fire from spreading to other areas, controlling fire development (Wu et al., 2018). During the full development stage, a subway station should activate active emergency response equipment, including fire shutters, fire doors and fans, to control the spread of fire and reduce property damage (Jeon & Hong, 2009). Moreover, firefighting decision-making capability, such as resource allocation and strategies, is significant for controlling fire spread (Tang et al., 2022). Firefighters with high emergency decision-making capability can reduce the combustion time of fire, and consequently, the damages caused by fire.

3. Research framework and methodology

This research adopts BN to construct a scenario evolution probability calculation model that can assess the risk of subway station fires during each development stage and predict the evolution path of subway station fires. The constructed BN can also rank hazardous factors and emergency response activities that influence fire evolution direction to provide decision-making support for the risk prevention, control and emergency management of subway station fires. A three-phase framework is proposed as shown in Figure 1. Phase I aims to construct a scenario evolution model of subway station fires, including the identification of scenario elements and their causalities. In Phase II, a survey questionnaire is designed to gather experts' opinions on the probability distribution of each scenario element (Step 3). Thereafter, Dempster–Shafer (D–S) evidence theory is used to combine all expert opinions and generate an aggregated probability distribution for each scenario element (Step 4). In Phase III, the constructed scenario evolution model and the aggregated probability distribution for each scenario element are inputted into GeNIe 3.0 software to build a BN-based scenario evolution model (Step 5). Finally, reasoning and sensitivity analysis are conducted to realise risk assessment, critical hazardous factors and emergency response activity identification (Step 6).

3.1. Phase I: Construction of the scenario evolution model of a subway station fire

Step 1: Identify scenario elements

Firstly, on the basis of the triangular framework of public safety science and technology, 25 scenario elements grouped into 3 types (i.e., scenario state, hazardous factor and emergency response activity) were identified to represent subway station fire evolution from the existing literature, as indicated in Table 2. Notably, several collective concepts are developed for integrating details of fire protection specifications, such as S_3H_8 (the complexity of a subway station), S_3E_7 (the reliability of evacuation facilities) and S_3E_8 (the reliability of a smoke extraction system).

Step 2: Validate the identified scenario elements and construct the scenario evolution model

Subsequently, the identified scenario elements were further validated through interviews with experienced subway station fire management professionals to ensure that the listed scenario elements are real and practical. The experts personally confirmed the validity of the preliminarily identified scenario elements. Moreover, the experts

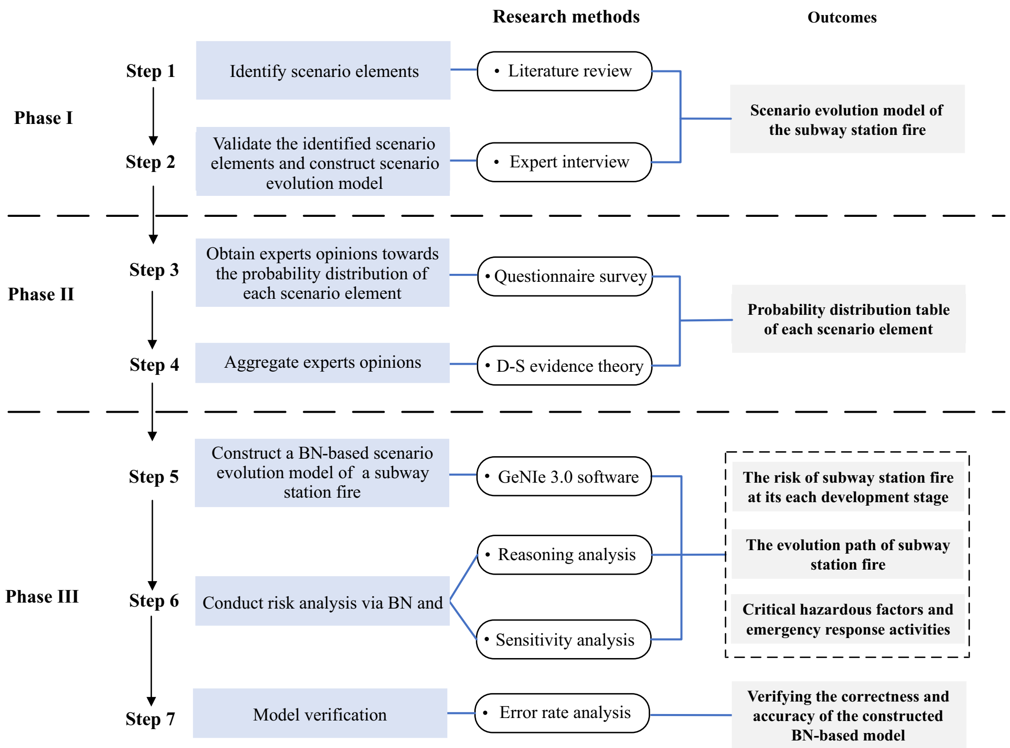

Figure 1. Research framework

Table 2. Summary of the scenario elements of subway station fire evolution

Scenario state, corresponding hazardous factors and emergency response activities. Coding and contents			References
Fire ignition stage (S_1)			
Hazardous factor (S_1H)	S_1H_1	Passenger behaviour	Chen et al. (2019)
	S_1H_2	Equipment and environment state	Lin et al. (2020)
	S_1H_3	Reliability of security screening system	Yan et al. (2016)
	S_1H_4	Regular equipment and environment inspection	Yan et al. (2016)
Emergency response activity (S_1E)	S_1E_1	Reliability of fire alarm system	Matellini et al. (2018)
	S_1E_2	Reliability of fire hydrants	Li et al. (2016)
	S_1E_3	Effective response of human firefighting	Li et al. (2016)
Fire growth stage (S_2)			
Hazardous factor (S_2H)	S_2H_5	Large amount of combustible materials	Zhang et al. (2019)
	S_2H_6	Firefighters will arrive at the fire scene within 15 min	Chen et al. (2018a)
	S_2H_7	Good firefighting skill	Chen et al. (2018a)
Emergency response activity (S_2E)	S_2E_4	Effective response of fire and rescue services	Wang et al. (2021b)
	S_2E_5	Reliability of sprinkler system	Wu et al. (2018)
	S_2E_6	Effective emergency response of subway station staff	Wu et al. (2018)
Personnel evacuation stage (S_3)			
Hazardous factor (S_3H)	S_3H_8	Complexity of subway station	Long et al. (2020)
	S_3H_9	Good passenger escape skill	Wang et al. (2021b)
Emergency response activity (S_3E)	S_3E_7	Reliability of evacuation facilities	Tsukahara et al. (2011)
	S_3E_8	Reliability of smoke extraction system	Ji et al. (2011)
Full development to extinguishment stage (S_4)			
Hazardous factor (S_4H)	S_4H_{10}	High fireproof endurance rating	Matellini et al. (2018)
	S_4H_{11}	Effective fire zoning	Wu et al. (2018)
Emergency response activity (S_4E)	S_4E_9	Reliability of active emergency response equipment	Jeon and Hong (2009)
	S_4E_{10}	Good firefighting decision-making capability	Tang et al. (2022)

proposed that the incident result should be considered to represent the end state of each stage of fire evolution and reflect fire severity. Economic loss and casualty are the most important indicators for measuring fire severity in subway stations. They were proposed to represent the incident results of a subway station fire. The supplemented two incident result elements were finally adopted upon the consensus of the four experts. Thereafter, the scenario evolution model was constructed in accordance with the scenario evolution processes of a subway station fire and the identified scenario elements of each scenario state, as illustrated in Figure 2.

3.2. Phase II: Obtaining a probability distribution table of each scenario element

BN-combined probability analysis and graphical theory are used as inferential models to represent uncertain knowledge and address the randomness and uncertainty of event development in scenario deduction analysis (Uusitalo, 2007; Leu & Chang, 2015; Hu et al., 2022). BN is a directed acyclic graph (DAG) that describes the causality between nodes through directed edges. Conditional probabilities are used to reflect the strength of causality between nodes (Zhou et al., 2020; Qiu et al., 2020). Figure 3 shows a simple BN model, where N1 and N2 are the root nodes or 'parent' nodes, and N is an intermediate node or a "child" node. The arcs between nodes represent the corresponding causality. The probability distribution table of each node is also presented, and those of the parent and child nodes are called prior probability and conditional probability, respectively.

Thus, the network structures and probability distributions of each node form a complete BN. In this study, the constructed model in Phase I can be used as the network structure of the BN-based scenario evolution model of subway station fires. In addition, data learning, expert knowledge leveraging and the combination of the two

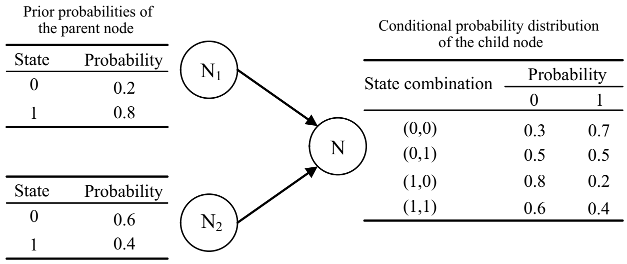

Figure 3. Simple BN model

methods are the three techniques used to obtain the probability distribution of each node (Chen & Wang, 2017; Huang et al., 2019). Previous studies have shown that expert knowledge is a necessary and reliable tool for developing node probabilities in the absence of sufficient historical data (Zhou et al., 2020; Zhao et al., 2012). Given the limited records of subway station fire incidents, questionnaire surveys were used in the current study to utilise expert experience for determining the probability distribution of each scenario element (i.e., BN node). Thereafter, D–S evidence theory was adopted to further process the data collected from the questionnaires, and thus, reduce the limitations and subjectivity of expert judgment (Tian & Yang, 2014).

Step 3: Conduct a questionnaire survey to obtain the probability distribution of each scenario element

After the identified scenario elements and their causalities are validated through expert interviews, the prior probabilities of parent nodes and conditional probability distributions of child nodes of the BN-based scenario evolution model were obtained from the questionnaire surveys. Notably, when the data source used for the probability distribution of each BN node is obtained through questionnaire surveys, the node state with binary parameters should be set (Musharraf et al., 2016; Zhang et al., 2018).

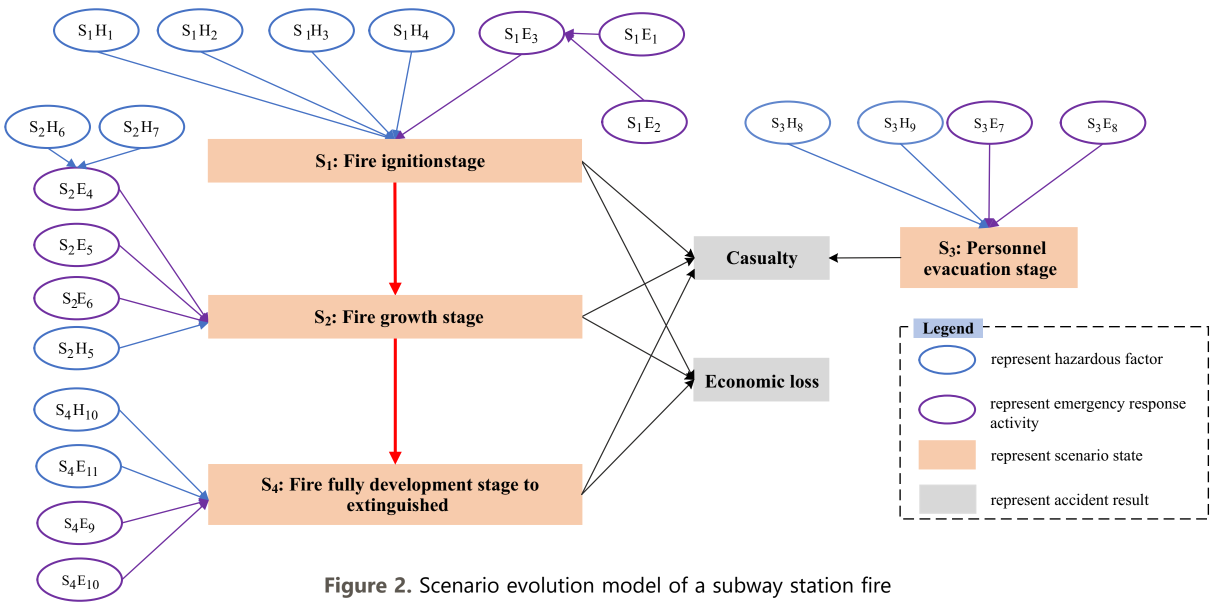

Figure 2. Scenario evolution model of a subway station fire

This state is in line with the characteristics of participants' understanding and memory of causalities of historical events, enabling experts to recall their related work experience correctly when filling questionnaires. Therefore, BN nodes that represented hazardous factors and emergency response activities were set with two state parameters: "Failure" and "Not Failure", in which the former indicates the current node failure, and vice versa. The states of BN nodes that represented the scenario state were set as "Yes" and "No", in which "Yes" indicates that the current node is occurring, and vice versa. In addition, two states, i.e., "Yes" and "No", of economic loss and casualty cannot represent the differences in the accident results caused by the distinct stages of fire development. In accordance with the Production Safety Accident Report of China and fire incident cases, economic loss was divided into four states: no economic loss, burning proportions of main fire body parts were ≤30%, burning proportions of main fire body parts were 30%–70% and burning proportions of main fire body parts were ≥70%. Casualty loss was also divided into four states: no casualty, ≤50 injuries or ≤10 deaths, 50–100 injuries or 10–30 deaths and ≥ 100 injuries or ≥ 30 deaths.

Xi'an subway has served about 2.59 million passengers daily since it started operations in 2011. Interviews with the safety managers of Xi'an subway's operating company indicated that Xi'an subway's station system has suffered from several fire incidents during its 10 years of operation caused by various factors, such as equipment system failure, wire deterioration, and electric welding work for interchange channel construction etc. These fire incidents have provided the operational staff of Xi'an subway's operating company with experience in dealing with fires and knowledge regarding conditional dependencies amongst different fire scenario elements. Thus, the Xi'an subway system was selected as a case study to explain the construction of a BN-based scenario evolution model and how this model can help operational staff and decision makers assess and respond to subway station fire risks at the city level. At the time of this study, all Xi'an subway stations are operating in accordance with the same fire protection specifications. Thus, inviting its operational staff to assess fire risks at the city level on the basis of the overall design scheme and operating conditions of the Xi'an subway station system is suitable. Moreover, considering that most cities in China started operating subways in the past 10 years, the city-level fire risk analyses of subway stations exhibit a slight difference because of the similar fire protection specifications of various subway stations within a city. Banuls et al. (2013) adopted the Delphi expert evaluation method and suggested obtaining the opinion of 3–5 experts if 10–20 elements are present. Accordingly, the current study sought the judgements of eight experts to evaluate the probability distributions of the 27 identified scenario elements in the constructed BN-based scenario evolution model of subway station fires. Table 3 provides the demographic information of the eight interviewees. The eight invited experts included frontline operational safety management staff, safety designers and company safety managers from Xi'an subway's operating company. All the experts had over 6 years of working experience in subway operations and considerable exposure to the fire safety management of subway stations. Therefore, the interviewed experts are considered valid data sources for our research.

In the questionnaire survey, interviewees were required to judge the probability distribution of two types of nodes (parent and child nodes) individually. For the parent node, the interviewee was asked to assign probabilities to the node in the "Yes/Failure" and "No/Not Failure" states, and the sum of the probabilities of the two states for a node should be 100%. For example, one of the interviewees assigned the probability distribution of "regular equipment and environment inspection" (S_1H_6) as 45% Failure and 55% Not Failure. The probability distribution of the child node depends on its parent node. Therefore, the interviewee should assign probabilities to the child node in the "Yes/Failure" and "No/Not Failure" states under the different state combinations of each of its parent node.

Table 3. Demographic information of the eight interviewees

No.	Section	Working experience	Professional experience
1	Equipment and environment inspection	6 years	3 years as an equipment and environment inspector and 3 years as an equipment and environment inspection consultant
2	Equipment and environment inspection	8 years	5 years as an equipment and environment inspector and 3 years as an equipment and environment inspection manager
3	Passenger service management	6 years	1 year as a safety screening officer and 5 years as a passenger safety training staff
4	Passenger service management	7 years	1 year as a safety screening officer, 3 years as a passenger safety training staff and 3 years as a passenger service management manager
5	Subway station design	7 years	2 years as an electromechanical designer and 5 years as a subway safety designer
6	Subway station design	8 years	8 years as a subway safety designer
7	Emergency response	6 years	4 years as an emergency response staff and 2 years as a firefighting equipment management team manager
8	Emergency response	9 years	2 years as an emergency response staff and 7 years as a personnel evacuation team manager

For example, the probability distribution of "effective response of fire and rescue service" (S_2E_4) relies on its parent nodes, i.e. "firefighters arrive at the fire scene within 15 min" (S_2H_6) and "good firefighting skill" (S_2H_7), as shown in Figure 2. Each interviewee made their estimations from the questionnaires, as indicated in Table 4. m_1 (1, 2) refers to the probability distribution of "effective response of fire and rescue service" provided by one interviewee, wherein the digits in parentheses (1, 2) refer to (Failure, Not Failure), respectively. On the first line where the combined conditions are "effective emergency response plan: Failure" and "good firefighting skill: Failure," m_1 (1, 2) = (0.9, 0.1) indicates that the first expert believes that "effective response of fire and rescue service" is in a Failure state with a probability of 90% ("Not Failure" with 10%) when "firefighters arrive at the fire scene within 15 min" and "good firefighting skill" are both in a Failure state.

Table 4. Probability distribution of "effective response of fire and rescue service" (S_2E_4)

BN nodes		Expert opinions
Firefighters arrive at the fire scene within 15 min	Good firefighting skill	m_1 (1, 2)
s_1 Failure	s_1 Failure	(0.9, 0.1)
s_1 Failure	s_2 Not Failure	(0.75, 0.25)
s_2 Not Failure	s_1 Failure	(0.45, 0.55)
s_2 Not Failure	s_2 Not Failure	(0.2, 0.8)

Step 4: Collecting all experts' opinions and generating an aggregated probability distribution for each scenario element

After the answered questionnaires were obtained from the eight interviewees, D–S evidence theory was adopted to further process the data collected from the questionnaires and reduce the limitations and subjectivity of expert judgement. D–S evidence theory, which was proposed by Dempster (1967) and Shafer (1976), can synthesise data from diverse sources and redistribute uncertain information to new evidence. It has been widely adopted in information fusion (Tian & Yang, 2014; Li & Wei, 2019). D–S evidence theory provides a frame of discernment Θ and a mass function *m*. *m* must be subject to the following rule (Tian & Yang, 2014):

$$\begin{cases} m(\phi)=0 \\ \sum\limits_{A\subseteq\Theta} m(A)=1. \end{cases} \quad (1)$$

Equation (2) shows the information fusion rule of D–S evidence theory, in which: m_1; m_2; ... m_n refer to mass functions generated on the basis of information in the frame of discernment Θ (Tian & Yang, 2014). A represents the event state, and K reflects the inconsistency level amongst m_1; m_2; ... m_n. The calculation principle of K is shown in Eqn (3) (Tian & Yang, 2014). For example, the eight experts made their estimation of the probability distribution of 'Reliability of security screening system' (S_1H_4) in the questionnaires, as indicated in Table 5. m_1 (1, 2) to m_8 (1, 2) are the probability distributions of 'Reliability of security screening system' (S_1H_4) provided by the eight experts. From Eqns (2) and (3), the D–S evidence theory method was adopted to integrate the obtained data from the eight experts, as indicated in the last column of Table 6. Through the aforementioned method, the probability distributions of all the nodes in the BN-based scenario evolution model of subway station fire can be determined.

$$m(A)=\begin{cases} \dfrac{1}{1-K}\sum\limits_{A_1\cap A_2\ldots\cap A_n} m_1(A_1)m_2(A_2)\ldots m_n(A_n),\ A\neq\Phi \\ 0,\ A=\Phi \end{cases}; \quad (2)$$

$$K=\sum_{A_1\cap A_2\ldots\cap A_n\neq\phi} m_1(A_1)m_2(A_2)\ldots m_n(A_n)= 1-\sum_{A_1\cap A_2\ldots\cap A_n} m_1(A_1)m_2(A_2)\ldots m_n(A_n). \quad (3)$$

3.3. Phase III: Constructing BN and conducting risk analysis

Bayesian theory provides the mathematical foundations for BN to conduct scenario deduction analysis, in which conditional probability equation $P(x_i|y)$ and joint probability equation $P(x_1, x_2, x_3, ..., x_n)$ play critical roles (Uusitalo, 2007). As shown in Eqns (4) and (5), *x* and *y* represent the sets of parent and child nodes in BN, respectively (Wu et al., 2016). *n* denotes the number of nodes in the set of parent nodes, and *P* is the probability value. From Eqns (4) and (5), the probability distribution of all the nodes in the network can be calculated on the basis of the nodes' prior probabilities, causalities and their conditional probabilities, enabling BN to perform scenario deduction analysis.

$$P(x_i\mid y)=\frac{P(x_i\cap y)}{P(y)}=\frac{P(x_i)P(y\mid x_i)}{\sum\limits_{j=1}^{n}P(x_i)P(y\mid x_j)}; \quad (4)$$

$$P(x_1,x_2,\cdots,x_n)=\prod_{i=1}^{n}P(x_i\mid x_1,x_2,\cdots,x_{i-1}). \quad (5)$$

In addition, sensitivity analysis is a critical part of the BN model for quantifying the influence of each parent node on target nodes (Christopher Frey & Patil, 2002).

Table 5. Aggregating all expert opinions based on D–S evidence theory

BN nodes	Expert opinions on the probability distribution of S_1H_4								Result m (1, 2)
Reliability of security screening system	m_1 (1, 2)	m_2 (1, 2)	m_3 (1, 2)	m_4 (1, 2)	m_5 (1, 2)	m_6 (1, 2)	m_7 (1, 2)	m_8 (1, 2)	(0.07, 0.93)
	(0.4, 0.6)	(0.45,0.55)	(0.35, 0.65)	(0.45, 0.55)	(0.4, 0.6)	(0.45, 0.55)	(0.4, 0.6)	(0.45, 0.55)	

Identifying which parent nodes exert the most influence on the target nodes can assist in optimising management strategies. Sensitivity analysis can provide assurance that the model is built correctly and performs as expected (Matellini et al., 2018).

GeNIe 3.0 software contains various BN reasoning algorithms and can represent changes in each node's probability distributions through a straightforward visual interface. Thus, GeNIe 3.0 software was adopted in this study to construct the BN-based scenario evolution model of subway station fires based on the identified network structures and node probability distributions. The risk analysis results of the Xi'an subway station fire through BN are discussed in Section 4.

4. Case study results and discussion

4.1. Forward deduction analysis

From Eqns (4) and (5), the developed BN-based fire scenario evolution model of Xi'an subway station can perform deduction analysis. Forward deduction analysis is a cause-to-effect analysis, in which the probability of the target node is predicted on the basis of the probability of the cause nodes and the causal relationship amongst them; it is an appropriate method for assessing fire risk in different scenario states (Zhang et al., 2013). From the forward deduction analysis results presented in Figure 4, the occurrence probabilities of the fire ignition, growth and full development to extinguishment stages of the Xi'an subway station system are 70%, 72% and 23%, respectively. In addition, the successful probability of personnel evacuation once fire ignites is 65%.

From Figure 4, S_2E_6 (effective emergency response of subway station staff), S_2E_4 (effective response of fire and rescue services), S_2H_5 (large amount of combustible materials), S_1H_1 (passenger behaviour) and S_3H_9 (good passenger escape skill) have frequent failure probabilities of 72%, 71%, 65%, 62% and 61%, respectively, ranking as the top five amongst all influential factors. Specific to each stage of fire evolution, S_1H_1 (passenger behaviour) is the most critical hazardous factor that causes fire ignition in the Xi'an subway station system. Moreover, the failure probability of S_1E_3 (effective response of human firefighting) is up to 58%. For the fire growth stage, S_2H_5 (large amount of combustible materials) is a significant factor that leads to fire spread. In addition, untimely fire rescue, including S_2E_4 (effective response of fire and rescue services) and S_2E_6 (effective emergency response of subway station staff) further contributes to fire spread. Given the more active fire resistance capability of the Xi'an subway station system, including S_4H_{10} (high fireproof endurance rating), S_4H_{11} (effective fire zone) and S_4H_9 (reliability of active emergency response equipment), the probability of a fire entering the fully developed stage is lower. For the personnel evacuation stage, S_3H_9 (passenger escape skill) has the highest failure probability.

From the perspective of resilience capacity, the Xi'an subway station system evidently has low capacity to prevent fire ignition and resist fire growth. In addition, the aforementioned failure probability results show that the Xi'an subway station system has not been operating for a long time, and thus, the influential factors of preventing fire evolution in physical equipment dimensions, such as S_1H_2 (equipment and environment state), S_2E_5 (reliability of sprinkler system) and S_3E_7 (reliability of evacuation facilities), are highly robust. However, organisational and management factors, such as S_1H_3 (reliability of security screening system), S_1E_3 (effective response of human firefighting), S_2H_4 (effective response of fire and rescue services) and S_3H_9 (passenger escape skill), are insufficient. Therefore, the operational staff's fire safety skills and emergency response capabilities should be improved through professional training and fire emergency drills. To improve the effectiveness of fire and rescue services, fire stations and dedicated fire escapes should be set up near subway stations to ensure that firefighters can reach the fire scene within 15 min. Furthermore, strengthening passengers' fire safety awareness and knowledge through regular broadcasts in subway stations is significant for decreasing passengers' unsafe behaviour and improving their escape skill.

4.2. Backward deduction analysis

Backward deduction can be used to observe specific nodes by using effect-to-cause analysis (Zhang et al., 2013). The marginal probabilities of unobserved nodes are obtained by deducing the effect of the observed specific nodes through the BN model in a backward manner. In the currents study, all the specific nodes (i.e. economic loss and casualty) are set to the most severe states, i.e., P (economic loss = burning proportions of main fire body parts ≥70%) = 1, P (casualty = ≥100 injuries or ≥30 deaths) = 1, to diagnose the fire evolution paths with severe incident results and the corresponding most influential scenario elements. In accordance with the backward deduction analysis results presented in Figure 5, when the fire results of Xi'an subway station are in the most severe states, the occurrence probabilities of the fire ignition, growth and full development to extinguishment stages are 98%, 99% and 83%, respectively, indicating serious incident results once a fire enters the fully developed stage. In addition, the failure probability of personnel evacuation is 61%, where S_3H_9 (good passenger escape skill) is the most critical influence factor. Thus, the fire prevention, emergency rescue capability and personnel evacuation capability of the Xi'an subway station system in the fire ignition and growth stages should be improved. As shown in Figure 5, S_1E_3 (effective response of human firefighting), S_2E_4 (effective response of fire and rescue services) and S_4E_{10} (good firefighting decision-making capability) exhibit the greatest failure probability that results in "fire ignition → growth → full development" and causes serious fire losses. Therefore, fire emergency response activities, including fire rescue by operational staff and professional firefighting teams, are the most important guarantee for preventing fire evolution in the Xi'an subway system. Moreover, S_3H_9 (good passenger escape skill) is significant for increasing the possibility of the successful evacuation of passengers.

4.3. Sensitivity analysis

The results of the sensitivity analysis provide guidance for optimising the fire resistance of Xi'an subway station. The factors with higher sensitivity have a higher optimisation level (Christopher Frey & Patil, 2002; Chang et al., 2019b). In this section, sensitivity analysis was implemented to test the sensitivity of the focus nodes S_1 (fire ignition stage), S_2 (fire growth stage), S_3 (personnel evacuation stage) and S_4 (full development to extinguishment stage) to changes in their parent nodes. The sensitivity analysis function within GeNIe 3.0 was adopted to obtain a sensitivity value for each parent node. Figure 6 presents the sensitivity analysis results of S_1, S_2, S_3 and S_4.

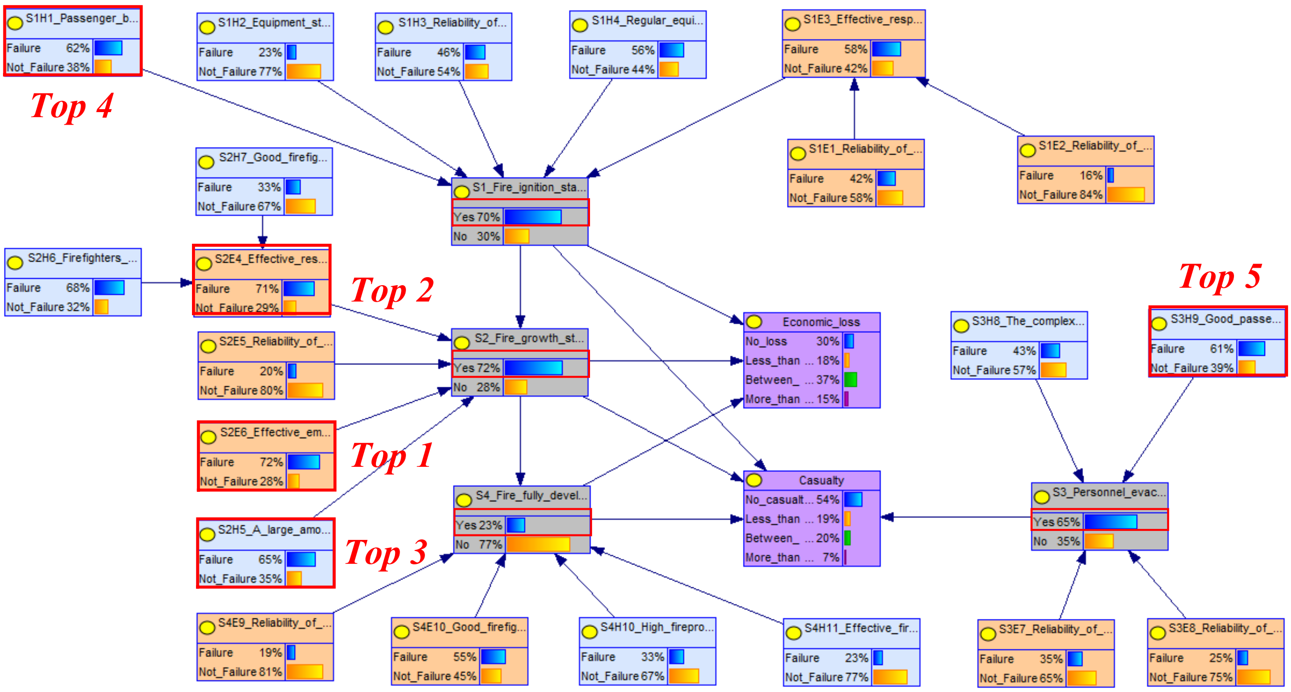

Figure 4. Forward deduction analysis for assessing the fire risk of subway station fires

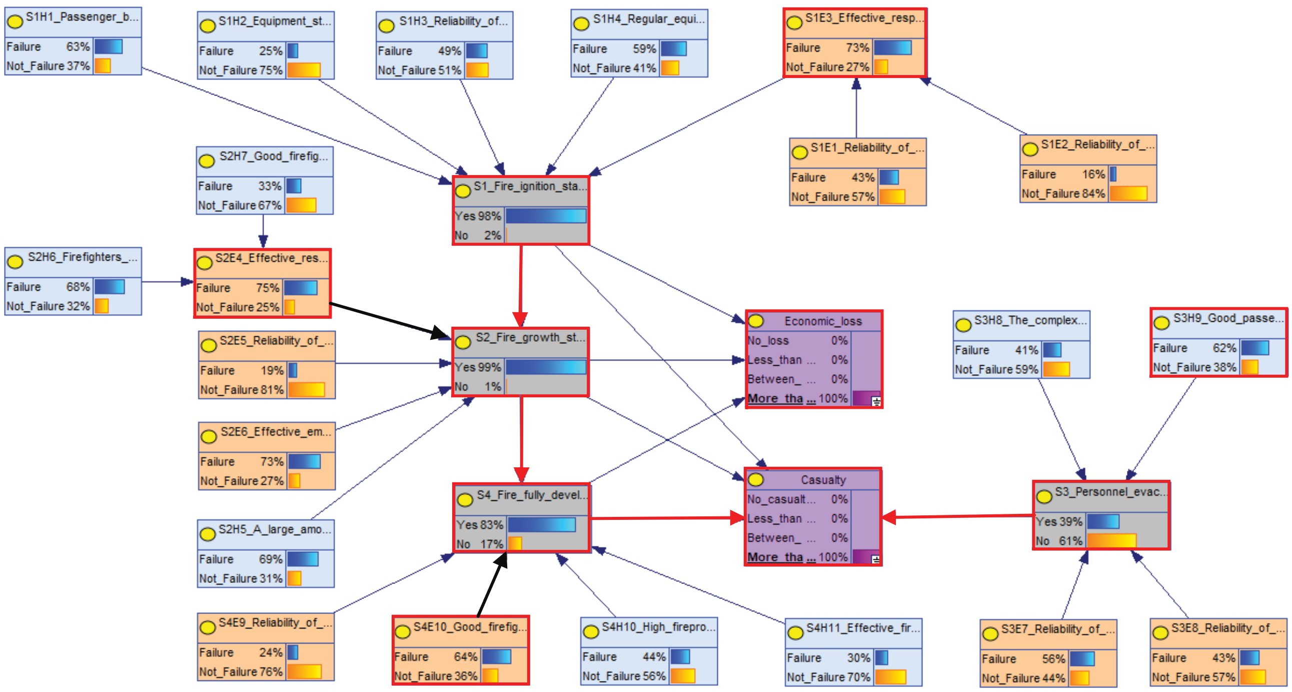

Figure 5. Backward deduction analysis for determining the critical fire evolution path

From Figure 6a, the most influential factor on S_1 (fire ignition stage) is S_1E_1 (reliability of fire alarm system) and S_1E_2 (reliability of hydrants). If S_1E_1 (reliability of fire alarm system) increases by 10%, then S_1 (fire ignition stage) will increase by 4.0%. If S1E2 (reliability of hydrants) increases by 10%, then S_1 (fire ignition stage) will increase by 2.4%. Notably, S_1E_1 (reliability of fire alarm system) and S_1E_2 (reliability of hydrants) are the root nodes that directly influence S_1E_3 (effective response of human firefighting). Thus, increasing fire alarm installation and hydrant allocation to improve the effectiveness of human firefighting is critical for decreasing the probability of fire ignition to the maximum.

Figure 6b shows that S_2 (fire growth stage) is most sensitive to S_2H_6 (firefighters arriving at the fire scene within 15 min). If S_2H_6 (firefighters arriving at the fire scene within 15 min) increases by 10%, then S_2 (fire growth stage) will increase by 4.5%. Thus, the prompt arrival of firefighters can maximise the effectiveness of fire growth control more than any other potential firefighting actions in the fire growth stage. Moreover, S_2 (fire growth stage) exhibits high sensitivity to S_2H_5 (large amount of combustible materials). Therefore, decorative materials with flame retardant properties should be adopted to control fire growth.

In accordance with Figure 6c, S_3 (personnel evacuation stage) is the most sensitive to S_3E_7 (reliability of evacuation facilities), indicating that adjusting and updating the number and installation locations of evacuation facilities on the basis of the latest fire evacuation specifications can maximise the efficiency of personnel evacuation. In addition, the sensitivity of S_3 (personnel evacuation stage) to S_3H_9 (good passenger escape skill) ranks second. Therefore, strengthening the publicity of fire evacuation knowledge is significant for improving the efficiency of personnel evacuation.

Finally, Figure 6d shows that the most influential factor on S_4 (full development to extinguishment stage) is S_4H_{11} (effective fire zone) and S_4E_9 (reliability of active emergency response equipment), indicating that improving the ability of a subway station to resist fire spread actively, including designing reasonable fire zoning and adjusting and updating the types and effectiveness of active emergency response equipment, is more important in controlling fire spread in the full development stage than human firefighting.

4.4. Model verification

To verify the correctness and accuracy of the constructed BN-based scenario evolution model of subway station fire, 30 cases of subway station fire accidents are used as the verification set. Appendix (Table A1) shows the node state of each accident case. The error rate of predicting subway station fire evolution through BN can be calculated using GeNIe software, as shown in Eqn (6), where $\sum Case_f$ refers to the number of cases the results of which predicted by the BN model are inconsistent with the actual situation. Meanwhile, $\sum Case_t$ refers to the number of cases the results of which predicted by the BN model are consistent with the actual situation.

$$Error = \frac{\sum Case_f}{\sum Case_f + \sum Case_t} * 100\%. \quad (6)$$

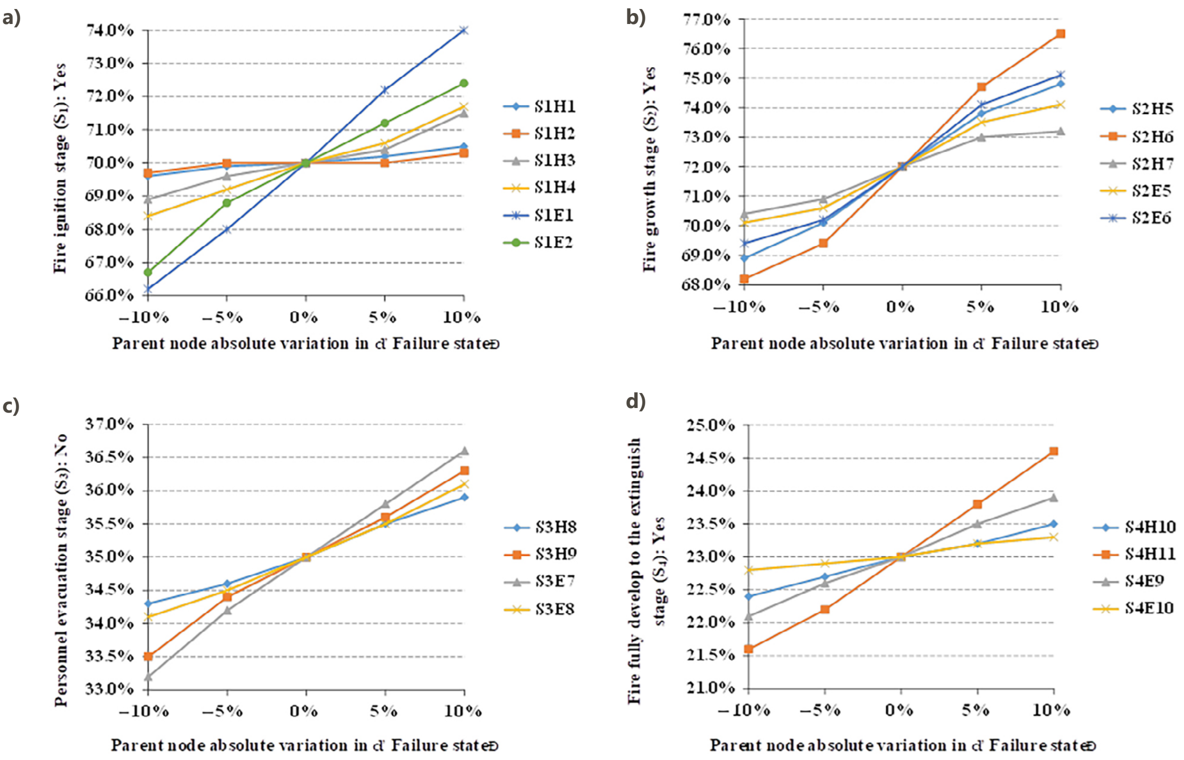

Figure 6. Sensitivity analysis results of S_1, S_2, S_3 and S_4

The node of S4 (full development to extinguishment stage) is selected as a target node to present the correctness and accuracy of the constructed BN-based model in evaluating the fire state of the selected 30 cases. Table 6 provides the verification results for the node of S_4 (full development to extinguishment stage). Using GeNIe software and Eqn (6), the error rate of the BN of the selected verification set is 10%. Shangguan et al. (2021) proposed that a BN model exhibits good correctness and accuracy if the error rate is lower than 15%. Thus, the constructed BN-based model can accurately predict the scenario evolution of a subway station fire.

Table 6. Verification results for the node S_4 (full development to extinguishment stage)

Predicted value		Actual value	Error rate
Yes	No		
16	2	Yes	$\frac{(2+1)}{30} = 10\%$
1	11	No	

4.5. Result discussions with comparative analysis

BN has been applied to scenario analysis research in recent years. It functions as predictive and diagnostic analyses and supports the timely creation of "scenario–response" strategies. For example, Matellini et al. (2018) employed a three-part BN model to analyse dwelling fire evolution. Their model can quantify fire losses and provide decision-making suggestions for firefighting. Therefore, risks are typically dependent and not additive. Compared with system analysis and statistical analysis models, BN models can exhibit this characteristic. The scenario elements that affect the risk of subway station fires are generally not independent. Thus, BN was used to assess subway station fire risk in the current study.

Analysing the fire evolution path and assessing its losses are difficult because dependency relationships amongst scenario elements related to subway station fires are frequently obtained in qualitative terms. To solve this problem, some scholars have proposed applying D–S evidence theory or fuzzy set theory to reduce the limitations and subjectivity of expert judgement. For example, Wu et al. (2016) applied D–S evidence theory to calculate judgement data obtained from experts, and thus, determined the causal relationship between each scenario element of mine water inrush hazard. Zhang et al. (2013) adopted a fuzzy BN for risk assessment during tunnel construction. To reduce the uncertainty of the constructed BN in dealing with expert judgement, the current study obtained data from eight experts, all of whom had over 6 years of working experience in subway operations and good exposure to the fire safety management of subway stations. Thereafter, D–S evidence theory was adopted to further process the data collected from the questionnaires, and thus, reduce the limitations and subjectivity of expert judgement. Therefore, the BN-based model adopted in the current study provides a more accurate approach for analysing fire evolution path and assessing fire risk as described in the case study section.

The BN-based method also assists managers in assessing the influences of different hazardous factors on subway station fire. Managers can identify which emergency response activities are the most effective. For example, the improvement of the reliability of evacuation equipment significantly increased the success probability of personnel evacuation in previous sensitivity analyses. This finding also complies with Matellini et al. (2018) who indicated that evacuation equipment is one of the most critical emergency response factors that influences personnel evacuation. In addition, improving the effectiveness of human firefighting, shortening the arrival time of firefighters and designing reasonable fire zones can reduce the probability of fire ignition, growth and full development, respectively. BNs can also enable managers to evaluate fire risk under different scenarios. These results can help managers make appropriate emergency response activities to decrease subway station fire risk. Therefore, utilising the BN-based method will increase safety during subway station fire.

5. Conclusions and future work

5.1. Theoretical contributions

Subway station fire risk assessment is associated with various evolution scenario uncertainties. This study constructs a scenario evolution network of subway station fires that can clearly present the possible scenario evolution path of subway station fires under the action of various scenario elements and provide the probability of occurrence of different scenarios through BN. This BN-based scenario evolution probability calculation method can be extended to fire risk assessment of other infrastructure:

1. For scenario-based fire risk modelling methods: On the basis of the triangular framework of public safety science and technology, literature review and expert interviews are combined to identify scenario elements and their causalities in each evolution stage of subway station fire, facilitating the understanding of the evolution mechanism of subway station fire.
2. For the BN-based scenario evolution probability calculation method: Firstly, the constructed scenario evolution model of subway station fire is simulated using the BN model, which maximises expert experience and knowledge to realise a comprehensive fire risk assessment. Compared with previous fire risk assessment methods (e.g. numerical simulation, system analysis and statistical analysis methods) that rarely consider the evolution of subway station fires, the BN-based scenario evolution model flexibly integrates information from hazardous factors and emergency response activity dimensions into each fire development stage of a subway station and cap-

tures the complex causalities amongst them. Secondly, compared with the event tree and fault tree analysis methods, the developed BN-based model generates various fire scenarios through forward and backward deduction analyses. Forward deduction analysis intuitively presents the roles of various scenario elements in the fire life cycle to enable managers to predict fire scenario states and assess fire risk. In addition, backward deduction analysis is an effective and efficient technique for diagnosing the most influential scenario elements that lead to a current fire scenario, assisting in making emergency response decisions.

3. For the optimisation method based on sensitivity analysis: The BN model can provide optimisation strategies by ranking the optimisation priorities of various scenario elements, enabling managers to select optimisation strategies flexibly at different operating life stages to reduce the fire risk level.

5.2. Practical implications

The constructed BN-based scenario evolution model of subway station fires is a practical management tool for subway station system managers. It can also be flexibly applied to other subway stations in different cities by collecting questionnaire data on the probability distribution of each scenario element. On the basis of the results of the case study on the Xi'an subway system, the major findings are explained as follows:

1. For the scenario elements in subway station fire development: This study innovatively identifies 27 fire risk assessment indicators from the scenario state, hazardous factor, emergency response activity and incident result on the basis of the development of subway station fire hazards.
2. For the BN-based assessment results: The occurrence probability of the fire ignition, growth and full development to extinguishment stages of the Xi'an subway station system are 70%, 72% and 23%, respectively. Moreover, the failure probability of personnel evacuation once the fire ignites is 35%. The high fire risk of the Xi'an subway station system resulted from low fire resistance capacity in the fire ignition and growth scenarios, where "passenger behaviour", "effective response of human firefighting", "large amount of combustible materials", "effective response of fire and rescue services", and "effective emergency response of subway station staff" had high failure probabilities. The findings of the forward deduction analysis indicate that for a subway station system with a short running time, such as the Xi'an subway station system, most pieces of physical equipment that are related to fire risk are highly robust, but fire prevention and response experiences are insufficient. Thus, increasing investment in strengthening operational staff's fire safety skills and popularising fire safety knowledge to passengers is required. In addition, the results of the backward deduction analysis show that a fire will lead to serious economic losses and casualties once it enters the fully developed stage, where "effective response of human firefighting", "effective response of fire and rescue services", "good firefighting decision-making capability", and "good passenger escape skill" are the most influential factors that lead to "fire ignition → growth → full development" and cause serious accident losses. The aforementioned deduction analysis results not only reflect the fire risk level of Xi'an subway station system in each scenario state but also assist managers in determining scenario elements with the highest failure probabilities in fire prevention and response.
3. For the optimisation results based on sensitivity analysis: Assigning optimisation priorities to the scenario elements with the greatest critical importance to fire risk in each fire scenario state can maximise optimisation performance. In particular, improving the effectiveness of human firefighting, shortening the arrival time of firefighters and designing reasonable fire zones can reduce the probability of fire ignition, growth and full development, respectively. In addition, improving the reliability of evacuation equipment can increase the success probability of personnel evacuation.

5.3. Limitations and future work

The BN-based scenario evolution model in this study can contribute to assessing the fire risk of subway stations at each development stage and provide decision-making support for risk prevention and control. Nevertheless, the constructed model has limitations.

The constructed BN model includes collective concepts of scenario elements, with each element set having two states, to comply with the interviewees' memory characteristics of historical fire accidents. In addition, the probability distribution of each node in the BN model is obtained through questionnaire data, increasing the subjectivity of the results. Our future study will refine the scenario elements of the constructed BN model and set multiple states to support a more precise fire risk assessment. Moreover, one study will be implemented by setting distinct types of sensors in the subway station to collect operation information of equipment and behaviour information of humans. The accumulated quantitative information can be utilised as prior knowledge to facilitate the data-driven combination between BN and machine learning to realise the automated generation of conditional dependency relationships between scenario elements.

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Author contributions

Xuewei Li and Jingfeng Yuan proposed the study and undertook the design and development of the model. Xuewei Li and Limao Zhang undertook data collection and analysis. Dujuan Yang was responsible for modeling. Limao Zhang and Dujuan Yang were responsible for data interpretation. Xuewei Li wrote the first manuscript of the article.

Disclosure statement

The authors confirm that all of the content, figures, and tables in the submitted manuscript work are original works created by the authors. There are no competing financial, professional, or personal interests from other parties.

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APPENDIX

Table A1. Nodes state of each accident case

No.	S1H1	S1H2	S1H3	S1H4	S1E1	S1E2	S1E3	S1	S2H5	S2H6	S2H7	S2E4	S2E5	S2E6	S2	S3H8	S3H9	S3E7	S3E8	S3	S4H10	S4E9	S4E10	S4E11	S4
Case1	0	1	0	0	0	0	1	1	1	0	0	1	0	0	1	1	0	1	0	1	1	1	0	0	1
Case1	0	1	0	0	1	1	1	1	–	–	–	–	–	–	0	–	–	–	–	0	–	–	–	–	0
Case1	1	0	1	0	0	0	1	1	0	1	0	1	0	1	1	0	1	0	1	1	0	1	1	0	1
Case1	0	1	0	1	0	0	0	1	1	0	1	0	1	0	1	1	0	0	0	1	0	1	0	1	1
Case1	0	1	0	0	1	1	0	1	1	0	0	1	0	0	1	–	–	–	–	0	–	–	–	–	0
Case1	0	1	1	0	1	0	1	1	0	1	1	0	0	0	1	0	1	1	0	1	1	0	1	0	1
Case1	1	0	1	0	0	1	0	1	0	1	0	0	0	1	1	1	1	0	1	1	1	1	0	1	1
Case1	1	1	0	0	1	0	0	1	1	1	0	0	1	0	1	1	0	1	1	0	–	–	–	–	0
Case1	1	1	0	0	1	1	1	1	–	–	–	–	–	–	0	–	–	–	–	0	–	–	–	–	0
Case1	1	1	0	0	0	1	0	1	1	0	1	1	1	0	1	1	1	0	0	1	1	1	0	0	1
Case1	0	1	0	1	1	1	0	1	0	1	1	1	0	1	1	0	1	1	0	1	1	0	0	0	1
Case1	1	0	1	0	1	1	0	1	1	0	1	1	0	0	1	1	1	1	1	0	–	–	–	–	0
Case1	1	0	1	1	1	0	0	1	1	1	0	1	0	0	1	1	0	0	1	1	1	1	0	1	1
Case1	1	0	1	0	1	0	0	1	1	0	1	0	1	0	1	1	1	0	1	1	1	0	1	1	0
Case1	0	1	1	0	1	0	0	1	1	0	1	1	0	0	1	0	1	0	0	1	0	0	1	1	1
Case1	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	1	0	1	1	0	–	–	–	–	0
Case1	1	0	0	1	0	0	1	1	1	1	0	0	1	0	1	1	1	1	0	1	0	0	1	1	1
Case1	1	1	1	0	1	1	0	1	1	1	1	1	1	0	1	1	0	1	1	1	0	0	1	1	0
Case1	0	0	1	1	1	0	1	1	1	0	0	1	1	0	1	1	1	0	0	1	1	0	1	1	1
Case1	1	1	0	0	1	0	0	1	1	1	0	1	0	1	1	0	1	1	0	1	1	0	1	0	1
Case1	0	0	1	1	1	1	0	1	1	0	1	1	0	0	1	1	0	1	0	1	1	0	1	0	1
Case1	0	1	1	0	0	0	1	1	1	0	0	0	1	0	1	1	1	0	0	1	1	1	1	1	1
Case1	0	1	1	0	1	1	1	1	–	–	–	–	–	–	0	–	–	–	–	0	–	–	–	–	0
Case1	1	1	0	1	1	1	0	1	0	1	1	0	1	0	1	1	0	1	1	0	–	–	–	–	0
Case1	0	1	1	0	1	0	1	1	1	1	0	1	1	0	1	1	0	0	0	1	1	1	1	1	1
Case1	1	0	1	0	1	0	0	1	1	0	0	1	1	1	1	0	1	0	0	1	1	1	1	0	1
Case1	1	0	1	0	0	1	0	1	1	1	0	1	0	0	1	1	1	0	1	1	1	0	1	1	0
Case1	1	0	1	1	0	0	1	1	0	1	0	1	0	0	1	0	1	1	0	1	0	1	1	1	1
Case1	0	1	0	0	1	1	0	1	1	0	0	1	1	1	1	1	0	1	0	1	1	0	1	0	1
Case1	1	1	0	1	1	1	1	1	–	–	–	–	–	–	0	–	–	–	–	0	–	–	–	–	0

Note: "1" represents the state of "Yes", and "0" represents the state of "No".