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An integrated EDIB model for probabilistic risk analysis of natural gas pipeline leakage accidents

Xing-lin Chen [a], Wei-dong Lin [b], Chun-xiang Liu [a], Fu-qiang Yang [a,*], Yong Guo [a], Xin Li [a], Shuai-qi Yuan [c,**], Genserik Reniers [c,d,e]

[a] College of Environment and Safety Engineering, Fuzhou University, Fuzhou, 350116, China
[b] Fujian Provincial Institute of Architectural Design and Research CO. LTD., Fuzhou, 350001, China
[c] Safety and Security Science Group, Faculty of Technology, Policy and Management, TU Delft, 2628 BX, Delft, the Netherlands
[d] Faculty of Applied Economics, Antwerp Research Group on Safety and Security (ARGoSS), Universiteit Antwerpen, 2000, Antwerp, Belgium
[e] CEDON, KULeuven, 1000, Brussels, Belgium

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A B S T R A C T

Natural gas pipeline construction is developing rapidly worldwide to meet the needs of international and domestic energy transportation. Meanwhile, leakage accidents occur to natural gas pipelines frequently due to mechanical failure, personal operation errors, etc., and induce huge economic property loss, environmental damages, and even casualties. However, few models have been developed to describe the evolution process of natural gas pipeline leakage accidents (NGPLA) and assess their corresponding consequences and influencing factors quantitatively. Therefore, this study aims to propose a comprehensive risk analysis model, named EDIB (ET-DEMATEL-ISM-BN) model, which can be employed to analyze the accident evolution process of NGPLA and conduct probabilistic risk assessments of NGPLA with the consideration of multiple influencing factors. In the proposed integrated model, event tree analysis (ET) is employed to analyze the evolution process of NGPLA before the influencing factors of accident evolution can be identified with the help of accident reports. Then, the combination of DEMATEL (Decision-making Trial and Evaluation Laboratory) and ISM (Interpretative Structural Modeling) is used to determine the relationship among accident evolution events of NGPLA and obtain a hierarchical network, which can be employed to support the construction of a Bayesian network (BN) model. The prior conditional probabilities of the BN model were determined based on the data analysis of 773 accident reports or expert judgment with the help of the Dempster-Shafer evidence theory. Finally, the developed BN model was used to conduct accident evolution scenario analysis and influencing factor sensitivity analysis with respect to secondary accidents (fire, vapor cloud explosion, and asphyxia or poisoning). The results show that ignition is the most critical influencing factor leading to secondary accidents. The occurrence time and occurrence location of NGPLA mainly affect the efficiency of emergency response and further influence the accident consequence. Meanwhile, the weight ranking of economic loss, environmental influence, and casualties on social influence is determined with respect to NGPLAs.

1. Introduction

Pipeline transportation is one of the most important transportation methods for natural gas worldwide. The rapid construction of natural gas pipelines promotes international and domestic energy transportation and also stimulates industrialization development. However, the safety issues associated with natural gas pipelines are still challenging and are receiving more and more public attention. (Kraidi et al., 2021). Although pipeline transportation is reported to have a lower rate of leakage accidents compared to road transportation, pipeline leakage accidents cause more casualties than road transport (Hou et al., 2021). This is because natural gas pipelines generally need to pass through the areas with high population density, such as the residential and commercial areas in cities. Inadequate inspection and maintenance

* Corresponding author. College of Environment and Safety Engineering, Fuzhou University, No. 2 Xueyuan Road, University Town, Fuzhou, Fujian Province, China.
** Corresponding author. Safety and Security Science Section, Faculty of Technology, Policy and Management, TU Delft, Delft, the Netherlands.
E-mail addresses: yangfuqiang@fzu.edu.cn (F.-q. Yang), S.Yuan-2@tudelft.nl (S.-q. Yuan).

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of transportation equipment, poor personnel management, and the influence of urban geological hazards lead to natural gas pipeline leakage, and also possibly trigger secondary accidents (e.g., poisoning, asphyxiation, fires, and explosions), thus inducing catastrophic consequences (Pan and Jiang, 2002; Biezma et al., 2020; Chen et al., 2021). Particularly, the construction of natural gas pipelines (NGP) and associated safety issues attracted massive attention in China. The construction of natural gas pipelines in China is showing a significant increasing trend compared with that of liquid fuel pipelines (Gao, 2022). The length of natural gas pipelines accounts for more than half of all oil and gas pipelines in China (China energy news, 2021). The dominant gas fuel consumption has shifted from LPG (Liquefied Petroleum Gas) to LNG (Liquefied Natural Gas). The safety of natural gas pipelines has ever been an important issue.

In the last decades, accident analysis models have been proposed and employed to investigate natural gas pipeline leakage accidents (NGPLA) widely (Yang et al., 2011; Shan et al., 2017). Generally, the ambiguity, randomness, and unknowability caused by the accident uncertainty must be well addressed to establish the NGPLA prediction/analysis models (Wu et al., 2017). In reality, accidents are more often in an intermediate state of happening or going to happen. Classical accident analysis methods (such as traditional fault trees and event trees) almost only set the event states as occurring or not occurring, with the intermediate state ignored, and generally only consider discrete variables, with fewer continuous variables considered. This makes it insufficient and difficult to describe the dependencies between variables, thus limiting the diagnostic and inference capabilities of the classical accident analysis methods (Martins et al., 2014). Hence, new approaches and techniques need to be developed to meet the above-mentioned requirements and describe the accident development and evolution process effectively. Bayesian network (BN) is a relatively new approach to describing the interdependence between events through directed graphs. It diagnoses and deduces the accident consequences based on the interdependency between events/nodes and the evidence of the influence from the nodes (Yuan et al., 2015; Li et al., 2023). BNs are able to infer from incomplete, imprecise, or uncertain knowledge and information, and also, BNs support setting multiple states for the events/nodes and updating the state probabilities during the operation process (Khanzad et al., 2011). As a result, BNs have been widely used for probabilistic risk analysis of various oil & gas pipeline accidents, such as urban oil & gas pipeline leakage accidents (Wu et al., 2017; Wang et al., 2017; Chang et al., 2018; Zhang et al., 2018; Qiu et al., 2018; Li et al., 2019), subsea oil & gas pipeline leakage accidents (Li et al., 2016, 2022), risk analysis on the operation of pipeline maintenance (Zhu et al., 2019), risk analysis of third-party damage to oil & gas pipelines (Cui et al., 2020; Ruiz-Tagle et al., 2022) and reliability analysis of pipeline networks/systems (Mokhtar et al., 2016; Chen et al., 2020; Fan et al., 2022).

During the development process of a BN model, the network structure is usually determined by experts with the help of other methods, such as fault tree (Sakar et al., 2021) and bow-tie (Khakzad et al., 2013). However, there are still gaps in properly employing expert knowledge and accident data to support the determination of the network structures for BNs. There are some methods available for the analysis of complex systems, such as SEM (Structural Equation Modeling), DEMATEL (Decision-making Trial and Evaluation Laboratory), and ISM (Interpretative Structural Modeling), which are able to determine the relationships between factors within a system (Huang et al., 2021; He et al, 2022; Khorasane et al., 2022; Wang et al., 2018a). Those methods are also with the potential to support the construction of hierarchical networks based on expert knowledge and judgment. Therefore, the combination of DEMATEL and ISM was considered in this study to help the construction of BN models.

Although BN is capable of reasoning and diagnosing under conditions of uncertainty, the element underlying its use for analysis, the conditional probability, still needs to be determined by other methods. Fuzzy set theory is one of the methods for providing data support with the combination of classic accident analysis methods (Badida et al., 2019; Dong and Yu., 2005; Shahriar et al., 2012). However, fuzzy set theory relies on expert knowledge and experience to determine the affiliation function, and the expert's expertise and their consensus usually play a crucial role in terms of model accuracy (Ferdous et al., 2012). This feature leads to conclusions that lack sufficient objectivity (Lavasani et al., 2015; Yan et al., 2017). Additionally, the Dempster-Shafer evidence theory was widely used to enhance the consistency and credibility in obtaining conditional probabilities of interdependent events based on expert knowledge (Wu et al., 2017; Zhou et al., 2020). Although the conditional probability obtained by this method is still subjective, it helps to obtain relatively reasonable and credible results. In summary, comparing the two methods, this study considers the Dempster-Shafer evidence theory to help obtain conditional probabilities.

In this study, an integrated approach was developed to conduct probabilistic risk assessments of NGPLA based on BN. Accident report analysis, event tree analysis, DEMATEL, ISM, and expert judgment were combined to support the building of a BN model. An event tree (ET) was employed to illustrate the evolution process of the NGPLA scenarios. The combination of the DEMATEL and the ISM was adopted to support the development of the BN model in terms of network structure construction. Prior conditional probabilities of the nodes in the BN model were determined based on the data analysis of 773 accident reports or expert judgment with the help of the Dempster-Shafer evidence theory. The developed BN model is capable of risk analysis of a variety of NGPLA. Additionally, the developed BN model is able to assess the severity of the secondary accidents resulting from gas leakage with the consideration of the influence of emergency response. The rest of this paper is organized as follows. Section 2 illustrates the methodology of the proposed model. Section 3 identifies the accident evolution factors associated with NGPLA and determines their interrelationships through interviews with experts. And then, a BN model was developed and the conditional probability tables (CPTs) of the nodes were assigned based on accident statistical data or expert judgment with the help of the Dempster-Shafer evidence theory. The results obtained by the BN model are presented and discussed in Section 4. In Section 5, the proposed approach is compared with several typical accident analysis models developed by other studies to reveal its strengths and limitations. Finally, conclusions and an outlook on future research are given in Section 6.

2. Methodology

2.1. Event tree analysis

ET analysis is a common method of inductive reasoning and analysis. In the first step of ET, the NGPLA reports should be collected and analyzed. Then, the evolution process of the gas leakage accidents is obtained and illustrated by an ET based on the analysis of the accident reports. ET derives subsequent events that can be formed from initial events (comprising multiple key events) based on the temporal order of the accident evolution (Huang et al., 2013). The construction of the ET follows three steps: i) identifying the initial event and its subsequent events, ii) setting the occurrence states between the initial event and the subsequent events, and iii) determining the final consequence of each ET path.

In this study, ET does not describe all critical factors associated with gas leakage but only sorts out the accident process. To facilitate the construction of the BN model, it is necessary to identify the critical underlying events during the accident evolution, as well as the interrelationships between the events. Consequently, DEMATEL and ISM are introduced to refine the accident evolution paths derived from the ET.

2.2. Decision-making trial and evaluation laboratory

DEMATEL is a system analysis method that uses graphical and matrix tools for understanding complex problems in the actual world (Zhang et al., 2020). The main objective of this method is to determine the influencing relationships between the elements and the position of each element inside the investigated system. The specific steps of the DEMATEL method are given below.

Step 1. Identifying the critical factors of accident evolution.

In this step, the various critical factors associated with the accident evolution are identified by reviewing accident reports and research articles, and also with the help of expert opinions. Additionally, secondary accidents induced by gas leakage under different environmental conditions should be investigated. Therefore, considering the complexity of the accident evolution, some similar critical factors are combined in this study to simplify the analysis process. At the same time, the identified critical influencing factors are denoted by x_i ($i = 1, 2, \ldots \ldots, n$) and make up the factor set X.

Step 2. Determining the initial direct influence matrix *M*.

This step identifies the associated indicators of the identified critical factors in step 1 and quantifies the interrelationships between those critical factors. We used the scales 0,1, 2, 3, 4, and 5 to represent the range from "no influence" to "very high influence" (Liou., 2015). Experts were asked to evaluate whether there was a direct influence relationship between factor *i* and factor *j* in terms of direction and influence. The mean value of all experts' identical views was derived as an initial direct influence matrix $M = (a_{ij})_{n\times n}$.

Step 3. Determining the normalized direct influence matrix *N*.

Normalization is a normal operation for standardizing influence factors. The key operation is to take the maximum value as a reference value for normalization. Each row of matrix A is summed, and the max-value is obtained among these values. This step is represented by Eq. (1).

$$A_{imax} = max\left(\sum\nolimits_{j=1}^{n} a_{ij}\right) \tag{1}$$

After the maximum value is obtained by Eq. (1), the normalization direct influence matrix *N* can be calculated by Eq. (2).

$$N = \left(\frac{a_{ij}}{A_{imax}}\right)_{n\times n} \tag{2}$$

Step 4. Deriving the comprehensive influence matrix *T*.

The self-multiplication of the normalized direct influence matrix represents the indirect influence added between the elements. When all the indirect influences are added up, the comprehensive influence matrix *T* is obtained. This step is presented in Eq. (3).

$$T = N(I - N)^{-1} \tag{3}$$

where *I* is the identity matrix, $(I\text{–}N)^{-1}$ is the inverse matrix of *(I–N)*.

2.3. Interpretative structural modeling

ISM can illustrate all possible evolutionary paths of the initial event and also provide a simplified and hierarchical topology without losing the system features. The basic aim of the ISM is to discuss the prior and subsequent relationships with factor sets to facilitate the understanding of complex system states (Malone, 1975). After the comprehensive influence matrix is obtained by DEMATEL, the overall influence matrix *O* can be obtained by using the ISM method. The overall influence matrix *O* can be calculated by Eq. (4). After that, other steps of the ISM method need to be conducted and are illustrated as follows.

$$O = I + T \tag{4}$$

Step 1. Developing the accessibility matrix *R* based on matrix *O*.

Within the accessibility matrix, the interrelationship among all elements is represented by Boolean logic, where 1 indicates relevant and 0 shows irrelevant. In order to transform the overall influence matrix into an adjacency matrix *A*, a threshold α should be set. The transformation criterion based on the threshold α is illustrated in Eq. (5).

$$A_{ij} = \begin{cases} 1, if\ O_{ij} \geq \alpha \\ 0, if\ O_{ij} < \alpha \end{cases} (i,j = 1, 2, \ldots, n) \tag{5}$$

Once the adjacency matrix is obtained, the accessibility matrix *R* can be obtained by following Eq. (6). Meanwhile, the accessibility set *R(i)*, the antecedent set *Q(i)*, and the common set *T(i)* can be obtained based on matrix *R* according to Eq. (7) to Eq. (9).

$$(A + I)^{(k-1)} \neq (A + I)^{k} = (A + I)^{(k+1)} = R \tag{6}$$

$$R(i) = \{x_i | x_i \in R, A_{ij} = 1, i = 1, \ldots, n\}, j = 1, \ldots, n \tag{7}$$

$$Q(i) = \{x_j | x_j \in R, A_{ij} = 1, j = 1, \ldots, n\}, i = 1, \ldots, n \tag{8}$$

$$T(i) = R(i) \cap Q(i), i = 1, \ldots, n \tag{9}$$

Step 2. Developing a hierarchy diagram.

After obtaining set *R(i)*, set *Q(i)*, and set *T(i)*, the factors of each level of the ISM model can be determined according to Eq. (9), with the determination rule being that some factors are accessibility and others are not. After this step, it can determine which factor belongs to which level and then combine the accessibility sets of these factors to determine the links between the factors. Finally, a directed hierarchical topology diagram of those influencing factors can be obtained.

2.4. Bayesian network

A BN comprises a directed acyclic graph (DAG) and conditional probability tables (CPTs). The directed edges of the DAG represent the dependencies between preceding and following events (Wu et al., 2015; Tien and Der Kiureghian., 2016). The combination of ET, DEMATEL, and ISM provides a preliminary structure (a directed hierarchical topology diagram) for the BN model. However, some modifications should still be made in terms of the node types and node states to develop a BN model. The CPTs of the child nodes are derived from the prior probabilities of the parent nodes. The conditional probability calculation involves conditional independent and joint probabilities, as indicated in Eqs. (10) and (11).

$$P(x_1, x_2, \ldots, x_n) = \prod\nolimits_{i=1}^{n} P(x_i) \tag{10}$$

$$\mathrm{P}(\mathrm{x}_1, \mathrm{x}_2, \ldots, \mathrm{x}_n) = \prod\nolimits_{i=1}^{n} \mathrm{P}(\mathrm{x}_i | \mathrm{parent}(\mathrm{x}_i)) \tag{11}$$

where x_i is the node; $P(x_i)$ is the probability of x_i; *parent* (x_i) is the parent node of x_i; P (x_i| *parent* (x_i)) is the CPT of x_i; *i* and *n* present the number of nodes in BN. Sensitivity analysis is widely-used to validate the probabilistic parameters of Bayesian networks (Castillo et al., 1997). It is done by investigating the effect of small changes in the model prior probabilities and conditional probabilities on the posterior probabilities. The sensitivity can be calculated as follows:

$$SV_{ij} = \begin{cases} \dfrac{P(x_j = 1 | x_i = 1) - P(x_j = 1 | x_i = 0)}{P(x_j = 1 | x_i = 0)}, \Delta P_{ij} \geq 0 \\ 0, \Delta P_{ij} < 0 \end{cases}, 1 \leq j < i \leq n \tag{12}$$

where SV_{ij} is the sensitivity of the node; x_i *is the prior event*; x_j *is the posterior event*; $\Delta Pij = P(x_j = 1 | x_i = 1)\text{-}P(x_j = 1 | x_i = 0)$.

The final BN model is obtained by using the complete so-called ET-DEMATEL-ISM-BN (EDIB) method. In previous studies, sensitivity analysis and diagnostic inference (i.e., posterior probabilistic inference) were conducted to identify the critical factors (Quan et al., 2017; Wang et al., 2019; Chi et al., 2021). Apart from that, accident evolution analysis can also be performed by using the BN model.

2.5. The overall framework of the EDIB model

The operational framework of the EDIB model is shown in Fig. 1. The development procedure of the proposed model is divided into three sections, with the help of ET, DEMATEL-ISM, and BN, respectively. The results of each section are given in the following sub-sections.

3. The EDIB model for NGPLA

3.1. Event tree analysis

In this section, the possible accident evolution paths of NGPLs are illustrated by an ET (see Fig. 2). The initiating event of the ET is natural gas leakage. Then, considering the influence of ignition and confined space on the accident evolution, several possible accident evolution paths with their corresponding outcomes were determined.

3.2. Identification of influencing factors associated with accident evolution

ET describes the basic accident evolution process of NGPLAs. However, it cannot give the environmental conditions and the emergency response objects influencing the accident evolution (Zhang et al., 2018). As a result, it is necessary to identify influencing factors associated with accident evolution with the help of accident report analysis and consultation with experienced experts. It should be noted that this study mainly investigates the NGPs deployed in the cities rather than the long-distance gas transmission pipelines across cities or even countries. Thus, the data on 773 nature gas pipeline leakage accidents that happened in Chinese cities from April 2013 to April 2022 were collected and analyzed. All of the accident data was derived from provincial and municipal emergency management departments or the news reported from official provincial and municipal media. The offshore pipeline accidents and long-distance gas transmission pipeline accidents were not collected and considered in this study. After the influencing factors were identified based on the accident report analysis, the results were verified and revised by four experts (two experts from universities and two industry experts from local natural gas companies), who have over ten years of working experience related to natural gas pipelines and energy transportation. According to the results, there is no obvious difference/deviation between the judgments/answers from the four experts. Thus, we believe that the survey was considered feasible to some extent and can be used to support the model construction. Finally, 12 influencing factors (including emergency response) that may influence the evolution process of NGPLAs were identified. The details of the identified influencing factors, secondary accidents, and final consequences are shown in Table 1.

3.3. Determining the hierarchical network based on the DEMATEL-ISM method

In this part, the hierarchical structure of the accident evolution process was determined by using the DEMATEL-ISM method. The identified influencing factors and events in Table 1 were compiled into a questionnaire and the four experts were responsible for rating the interrelationships among those influencing factors and events by filling the direct influence matrix (as shown in Table 2). Generally, the selection of experts plays an essential role in ensuring the quality and rationality of the results derived from expert elicitation (Krueger et al., 2012). In this study, the respondents who have at least ten years of working experience related to natural gas pipelines and energy transportation were regarded as qualified. Two experts from universities and two professionals from local natural gas companies who with over ten years of working experience were invited to attend this semi-structured questionnaire and determine the initial scores. Then, the individual opinions of the four experts were combined to eliminate the expert bias to some extent. Finally, the normalized direct influence matrix N and the comprehensive influence matrix T (as shown in Table 3) can be obtained according to Eq. (2) and Eq. (3), respectively.

To obtain the accessibility matrix, a threshold value α should be assigned. Based on the matrix T, we determined a series of candidate thresholds ($\alpha = 0.15$, $\alpha = 0.16$, and $\alpha = 0.20$) to generate matrix R by using Eq. (5) and Eq. (6). After that, the ISM diagram corresponding to each threshold value was obtained from the matrix R. By comparing the obtained ISM diagrams and checking the rationality of the ISM structure, we finally determined that $\alpha = 0.16$ was the most suitable threshold value due to the inconsistent and irrational ISM diagram structures by using $\alpha = 0.15$ and $\alpha = 0.20$. Therefore, the accessibility matrix with the threshold $\alpha = 0.16$ is used, as shown in Table 4.

Then, a hierarchical network diagram was derived based on the accessibility matrix to describe the causal relationship and accident evolution process of natural gas pipeline leakage accidents. The hierarchical network diagram comprises nodes and directing arcs, which represent the dependency between nodes. To get the final hierarchy diagram, two principles were adopted to modify the initial diagram (Nadkarni and Shenoy, 2004). One principle is to delete the redundant links between factors and reduce the unnecessary complexity of the hierarchy diagram. The scoring results and the accessibility matrix therefore were re-checked and the redundant links were eliminated. Another principle is to ensure that there is no circular path in the hierarchical network diagram. The initial diagram was modified according to the above two principles. In this way, the final hierarchical network diagram may be obtained and is presented in Fig. 3.

It should be noticed that the emergency response node in Fig. 3

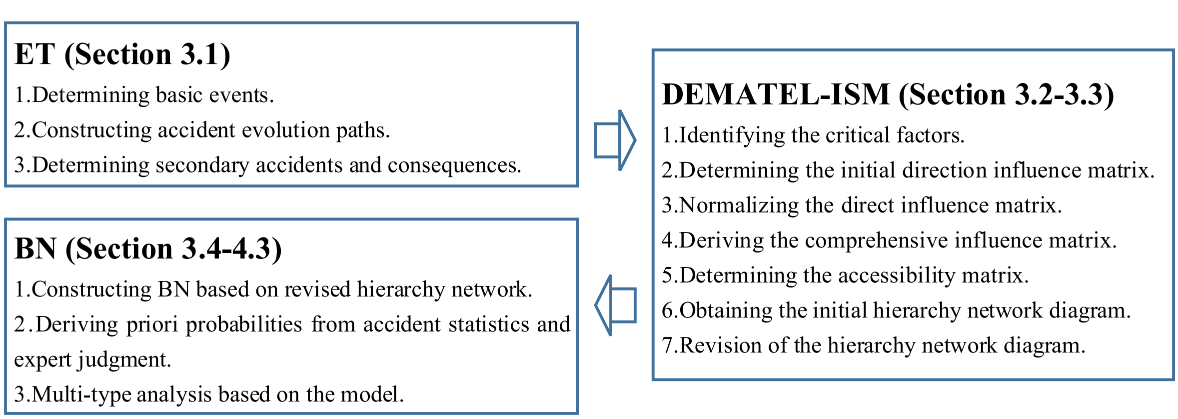

Fig. 1. The framework of the EDIB model.

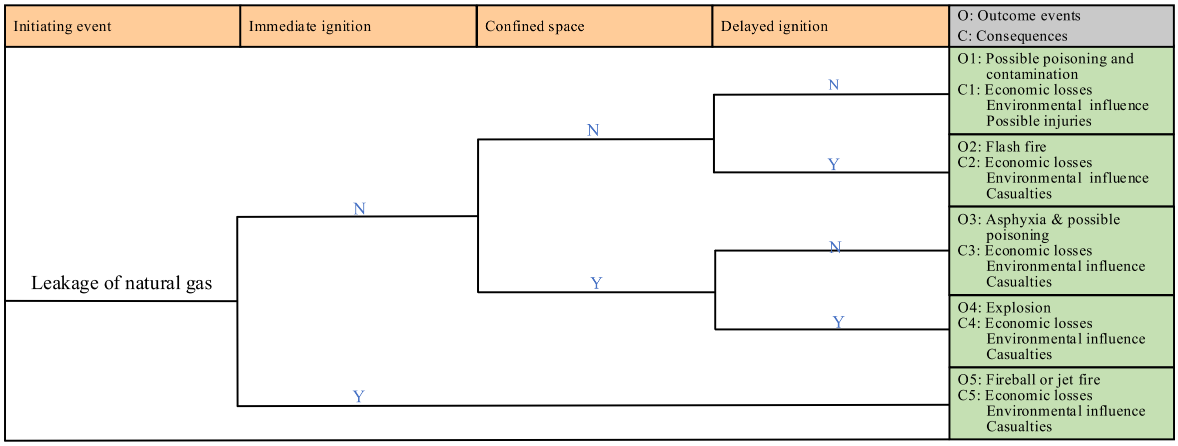

Fig. 2. The ET of natural gas leakage accidents.

Table 1
Accident evolution influencing factors or events of NGPLA.

Symbols	Accident evolution influencing factors or events	Symbols	Accident evolution influencing factors or events
I_1	Occurrence time	I_{11}	Gas accumulation
I_2	Occurrence location	R	Emergency response
I_3	Pipeline pressure	S_1	Fireball or jet fire
I_4	Causes of leakage	S_2	Flash fire
I_5	Immediate ignition	S_3	Vapor cloud explosion
I_6	Delayed ignition	S_4	Asphyxia or poisoning
I_7	Nearby building density	C_1	Economic losses
I_8	Nearby population density	C_2	Environmental influence
I_9	Leakage strength	C_3	Casualties
I_{10}	Confined space	C_4	Social influence

includes many emergency actions (e.g., detecting and reporting the accident, emergency closing the valve, emergency ventilation, emergency repairs, evacuating nearby crowd, power outage and eliminating ignition sources, and isolating the site). Therefore, the emergency response node may affect multiple influencing factors/nodes in the hierarchical network. Because immediate ignition usually makes it difficult to intervene instantly, the influence of emergency response on immediate ignition is not considered. By contrast, delayed ignition occurs after a period of time of gas leakage and hence, emergency response may influence the probability of delayed ignitions. Additionally, emergency closing pipeline valves, emergency ventilation, and emergency repairs can affect leakage strength and gas accumulation. Isolating the site and evacuating nearby crowds helps to reduce the number of people getting affected by the accident. Therefore, the effects of emergency response on such nodes (e.g., delayed ignition, nearby population density, leakage strength, and gas accumulation) were considered.

3.4. *The BN model for NGPLA*

In this section, the hierarchical network graph presented in Fig. 3 was mapped to a BN model by using GeNIe 3.0 (www.bayesfusion.com). In order to simplify the structure of the developed BN model, some of the nodes in Fig. 3 were integrated into one node by using different states of the node. For instance, the fireball or jet fire node, and flash fire node in Fig. 3 were integrated into a node named “fire”, with None (N), Fireball or jet fire (FBoJF), and Flash fire (FF) states. Similarly, the immediate ignition node and delayed ignition node in Fig. 3 were integrated into one ignition node (with three states: None (N), Immediate ignition (II), and Delayed ignition (DI)) in the BN model. The BN nodes and their state settings and definitions are detailed in Table 5. The abbreviations in

Table 2
The direct influence matrix assigned by expert 1.

M^1	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9	I_{10}	I_{11}	R	S_1	S_2	S_3	S_4	C_1	C_2	C_3	C_4
I_1	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0
I_2	0	0	0	0	0	0	4	4	0	4	0	4	0	0	0	0	0	0	0	0
I_3	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0
I_4	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	0	0	0	0
I_5	0	0	0	0	0	0	0	0	0	0	0	0	5	2	3	0	0	0	0	0
I_6	0	0	0	0	0	0	0	0	0	0	0	0	3	3	3	0	0	0	0	0
I_7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0
I_8	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	5	0
I_9	0	0	0	0	0	0	0	0	0	0	4	0	4	4	0	0	0	0	0	0
I_{10}	0	0	0	0	0	0	0	0	0	0	3	0	0	0	0	0	0	0	0	0
I_{11}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	3	0	0	0	0
R	0	0	0	0	1	4	0	4	4	0	4	0	0	0	0	0	0	0	0	0
S_1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	4	4	0
S_2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	4	4	0
S_3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	3	4	4	0
S_4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	4	4	0
C_1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
C_2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
C_3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4
C_4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

Table 3
The comprehensive influence matrix T.

T	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9	I_{10}	I_{11}	R	S_1	S_2	S_3	S_4	C_1	C_2	C_3	C_4
I_1	0.00	0.00	0.00	0.00	0.02	0.05	0.00	0.05	0.05	0.00	0.06	0.22	0.02	0.02	0.03	0.01	0.02	0.02	0.03	0.02
I_2	0.00	0.00	0.00	0.00	0.02	0.05	0.22	0.27	0.05	0.22	0.10	0.22	0.02	0.02	0.04	0.02	0.08	0.02	0.09	0.04
I_3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.22	0.00	0.05	0.00	0.05	0.05	0.01	0.01	0.02	0.03	0.03	0.02
I_4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.22	0.00	0.05	0.00	0.05	0.05	0.01	0.01	0.02	0.03	0.03	0.02
I_5	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.23	0.14	0.20	0.00	0.12	0.14	0.13	0.09
I_6	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.16	0.20	0.20	0.00	0.12	0.14	0.13	0.09
I_7	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.26	0.00	0.00	0.06
I_8	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.24	0.05
I_9	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.22	0.00	0.22	0.22	0.05	0.05	0.11	0.13	0.12	0.08
I_{10}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.00	0.00	0.00	0.04	0.04	0.02	0.02	0.02	0.01
I_{11}	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.22	0.19	0.08	0.10	0.09	0.06
R	0.00	0.00	0.00	0.00	0.09	0.22	0.00	0.24	0.23	0.00	0.27	0.00	0.11	0.11	0.12	0.05	0.08	0.09	0.15	0.07
S_1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.22	0.24	0.23	0.16
S_2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.24	0.23	0.15
S_3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.24	0.23	0.15
S_4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.22	0.24	0.23	0.16
C_1	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.22
C_2	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.24
C_3	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.22
C_4	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Table 4
The accessibility matrix R ($\boldsymbol{\alpha} = 0.16$).

R	I_1	I_2	I_3	I_4	I_5	I_6	I_7	I_8	I_9	I_{10}	I_{11}	R	S_1	S_2	S_3	S_4	C_1	C_2	C_3	C_4
I_1	1	0	0	0	0	1	0	1	1	0	1	1	1	1	1	1	1	1	1	1
I_2	0	1	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
I_3	0	0	1	0	0	0	0	0	1	0	1	0	1	1	1	1	1	1	1	1
I_4	0	0	0	1	0	0	0	0	1	0	1	0	1	1	1	1	1	1	1	1
I_5	0	0	0	0	1	0	0	0	0	0	0	0	1	0	1	0	1	1	1	1
I_6	0	0	0	0	0	1	0	0	0	0	0	0	0	1	1	0	1	1	1	1
I_7	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	1	0	0	1
I_8	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	1	1
I_9	0	0	0	0	0	0	0	0	1	0	1	0	1	1	1	1	1	1	1	1
I_{10}	0	0	0	0	0	0	0	0	0	1	1	0	0	0	1	1	1	1	1	1
I_{11}	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	1	1	1	1
R	0	0	0	0	0	1	0	1	1	0	1	1	1	1	1	1	1	1	1	1
S_1	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	1	1	1	1
S_2	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1	1	1	1
S_3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1	1	1	1
S_4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1
C_1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	1
C_2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	1
C_3	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
C_4	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1

Table 5 were also used in the developed BN model.

The prior probabilities of some nodes (e.g., occurrence time, occurrence location, pipeline pressure, causes of leakage, confined space, and ignition) were derived from accident statistics, while for some nodes that lack statistical data, the prior probabilities were determined by expert judgment. To improve the reliability of expert judgment, the Dempster-Shafer evidence theory was used to process expert judgment in this study. Although Dempster-Shafer evidence theory has its shortcomings (possible huge computation and unreasonable results that cannot be ignored), the implementation of the Dempster-Shafer evidence theory helps to improve the reliability of expert judgment by fusing different evaluations of experts to obtain comprehensive evaluation distribution intervals. The workflow of implementing Dempster-Shafer theory is presented as follows: i) Establish the identification framework. The state probability P_i under each combination of conditions in the node is denoted as P_i ($i = 1, 2, \ldots, n$), and the uncertainty state probability is denoted as Θ, which constitutes the state probability identification framework $U = \{P_1, \ldots, P_n, \Theta\}$ for each combination of conditions. ii) Each expert's judgment is a mass function, denoted as $M_n(P_i)$ ($n = 1,2,3,4$). iii) Calculate the normalization coefficient K, and then calculate the combined mass function of P_i with the synthesis rule. iiii) Calculate the confidence function and likelihood function according to the specific formula, and thus compose the trust space of P_i, and the final confidence function is the finalized state probability. Finally, the developed BN model is depicted in Fig. 4.

4. Results

4.1. Influencing factor analysis

4.1.1. Sensitivity analysis of influencing factors on secondary accidents

BN allows a sensitivity analysis of the causal factors to understand the degree of influence of each factor on the evolution of the accident. The sensitivity analysis was carried out by using the GeNIe 3.0 software in this study. An algorithm proposed by Khorasane et al. (2022)Kjaerulff and van der Gaag (2000) is implemented by GeNIe 3.0 to perform the sensitivity analysis. The sensitivities of 9 influencing factors to the secondary accidents are shown in Table 6.

It can be seen from Table 6 that the ignition influences the happening of fire and vapor cloud explosion significantly, with sensitivity values of 8.44e-2 and 0.28 respectively. The reason may be that ignition is one of the necessary conditions leading to fire and vapor cloud explosion. Gas accumulation has the greatest effect on asphyxiation or poisoning, with a sensitivity value of 0.117. The occurrence location (1.29e-2) and

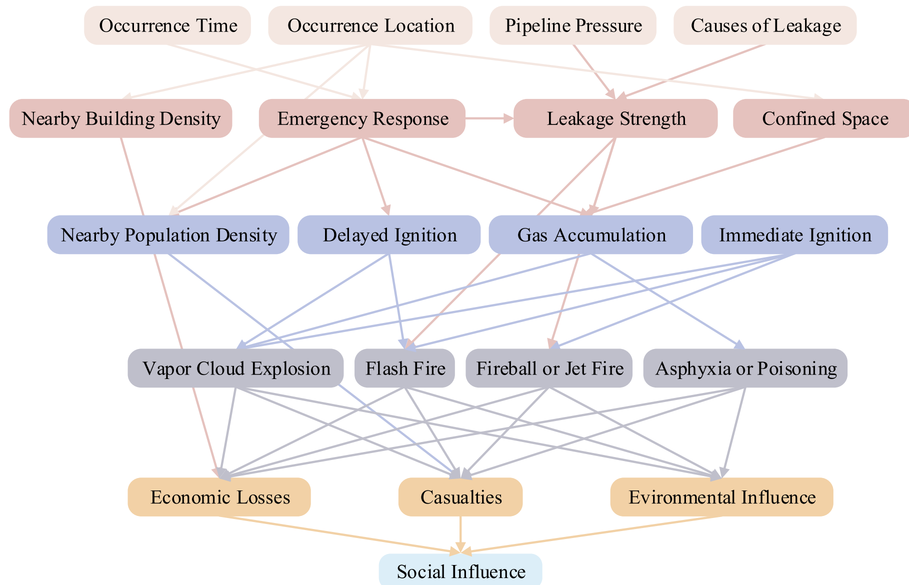

Fig. 3. A hierarchical network diagram of NGPLA.

confined space (1.1e-2) also have high sensitivity. Gas accumulation after natural gas pipeline leakage may induce asphyxia or poisoning. Pure methane is non-toxic to humans, and only becomes a simple asphyxiant at extremely high concentrations (Zheng et al., 2013). Toxic gas, such as tetrahydrothiophene, is usually mixed with methane in natural gas pipelines and may induce light poisoning. Asphyxiation or poisoning is based on a relatively confined space, and gas accumulation is the key event leading to these accidents. The cause of leakages, pipeline pressure, and leakage strength have low sensitivities to secondary accidents, and their sensitivity values are all less than 0.01. The reason may be that multiple emergency response actions (detecting and reporting the accident, emergency closing the valve, emergency on-site repair, emergency ventilation, and eliminating ignition sources, etc.) were considered in the proposed model. The intervention of emergency response reduces their sensitivities to the secondary accidents. It reflects that emergency response may control the adverse effects caused by those three influencing factors (cause of leakage, pipeline pressure, and leakage strength). It also explains why the emergency response has relatively high sensitivities to those three secondary accidents (Fire, VCE, and Asphyxiation or Poisoning), with sensitivity values of 8.73e-3, 2.4e-2, and 3.67e-2 respectively.

4.1.2. The effects of emergency response

In this study, the direct dependency between emergency response and leakage strength, ignition, gas accumulation, and nearby population density was considered, and further, it affects secondary accidents and final consequences. The predicted conditional probabilities of each affected factor given different states of emergency response (high, medium, and low) are shown in Table 7. It should be noted that the emergency response levels mentioned here are determined according to the actual response time of the emergency response actions. The three states (high, medium, and low) describe the efficiency of the emergency response actions after an accident occurs. The relevant descriptions are given in the footnotes of Table 5, and the following analysis is performed according to this definition.

As shown in Table 7, the effects of emergency response are obvious. A sudden change occurred to the status of each affected factor/event when the emergency response shifted from high to medium. The density of the nearby population is the most sensitive factor with respect to the status of emergency response. When the emergency response state changes, the probability of the nearby population density node changes with the maximum variations. Particularly, when the emergency response state changes from “low” to “medium”, the extremely densely populated area (EDP) state decreases sharply from 74.6 to 24.6. It reflects that on-site emergency response plays an important role in evacuating people nearby the leakage location and further reduce/avoid casualties caused by the natural gas pipeline leakage.

4.1.3. The influence of occurrence time and occurrence location

It can be seen from Table 6 that the occurrence time and occurrence location of NGPLAs have some influence on the happening of secondary accidents. One reason is that the efficiency (response time) of emergency intervention is associated with the occurrence time and occurrence location of the leakage accident according to the developed BN model. The time and place of occurrence may shorten the time for an emergency response to intervene the natural gas pipeline leakage accidents. This relationship/interdependence can be reflected by the simulation results of the BN model. As depicted in Fig. 5, the efficiency of emergency response is higher during the day (72.9% for ‘high’) than at night (67.3% for ‘high’). Similarly, the occurrence location also has an influence on the efficiency of emergency response. According to the accident report statistics, which were used to obtain the prior probabilities of occurrence time and occurrence location in Fig. 4, business zones and residential districts have an approximate proportion, and the number of accidents in these two areas has reached over 85% of the total number of accidents. Business zones and residential districts are densely populated and built-up areas in the city. Suburban districts are defined as areas in the city or on the urban fringe, with lower population density and building density than the first two. Because human activities are more frequent in business zones and residential districts, more technical facilities and emergency respondents are allocated in business zones and residential districts compared to suburban districts. Thus, the NGPLAs are easier to be detected and intervened in business zones and residential districts. As shown in Fig. 6, the proportion of emergency responses with high efficiency reaches 74.5% and 70.2% in business zones and residential districts respectively. By contrast, the emergency response with high efficiency is 67.9% in suburban areas, which is lower than that in commercial and residential areas.

4.2. Accident scenario analysis-case study

In this section, a case study is simulated by using the developed BN model. The scenario is set based on the case “7·4” gas pipeline leakage and explosion accident in Songyuan, Jilin in 2017. The configurations of

Table 5
The BN nodes definition of NGPLA.

Names of nodes	Definition of states	Definition
Occurrence time[a]	1. Daytime (DT): 8.00 a.m.–8.00 p.m., 2. Night (N): 8.00 p.m.–8.00 a.m. the next day.	The time when the pipeline leakage accident happened.
Occurrence location	1. Business zone (BZ), 2. Residential district (RD), 3. Suburban district (SD).	The location when the pipeline leakage accident happened.
Pipeline pressure[b]	1.1.6< P ≤ 4.0 (H), 2.0.4< P ≤ 1.6 (SH), 3.0.01< P ≤ 0.4 (M), 4. P < 0.01(L).	Pressure inside the gas pipeline.
Causes of leakage	1. External damage (ED), 2. Aging and corrosion (AC), 3. Insufficient intrinsic safety (IIS), 4. Installation and maintenance issues (IMI).	The direct causes of the pipeline leakage accidents. The classification of causes refers to (European gas pipeline Incident data Group, 2020) .
Ignition	1. None (N), 2. Immediate ignition (II), 3. Delayed ignition (DI).	Ignition is one of the necessary causes for flames and explosions. Immediate ignition occurs within 30s after the gas release and delayed ignition occurs after 30s (IGEM, 2008).
Nearby building density[c]	1. Level 1 area (L1), 2. Level 2 area (L2), 3. Level 3 area (L3), 4. Level 4 areas (L4).	The building density where the pipeline is located (North China Municipal Engineering Design & Research Institute, 2020).
Nearby population density (NPD, Persons/km^2)[d]	1.4000< NPD (EDP), 2.2000 < NPD≤4000 (DP), 3.1000 < NPD≤2000 (MP), 4. NPD≤1000 (SP).	Average number of active people per km^2 where the pipeline is located.
Leakage strength	1. Massive leakage (ML), 2. Non-massive leakage (NML).	The strength of gas released from the pipeline when the pipeline leakage happened.
Confined space	1. False (F), 2. True (T).	Confined or poorly ventilated infrastructures near the leaking pipelines, which can be tunnels, residential buildings, etc.
Gas accumulation	1. False (F), 2. True (T).	Gas accumulation phenomenon caused by confined space and/or weak ventilations after gas leakage happened.
Emergency response[e]	1. High (H), 2. Medium (M), 3. Low (L).	Various emergency actions (e.g., detecting and reporting the accident, closing the valve, and eliminating ignition sources) implemented to mitigate accident consequences (Zhang et al., 2018).
Fire	1. None (N), 2. Fireball or jet fire (FBoJF), 3. Flash fire (FF).	Fires caused by gas pipeline leakage, including jet fire and flash fire.
Vapor cloud explosion	1. False (F), 2. True (T).	Vapor cloud explosion caused by delayed ignition and gas accumulation after the gas pipeline leakage.
Asphyxia or poisoning	1. None (N), 2. Light asphyxia or poisoning (LAoP), 3. Severe asphyxia or poisoning (SAoP).	Gas accumulation after natural gas pipeline leakage may induce asphyxia or poisoning. Toxic gas, such as tetrahydrothiophene, is usually mixed with methane and may induce poisoning.
Economic losses (CNY)[f]	1. EL ≥ 100 million, 2.50 million ≤ EL < 100 million, 3.10 million ≤ EL < 50 million, 4. EL < 10 million.	Direct economic loss caused by the accidents, including the costs of dealing with the aftermath, the value of the destroyed property, etc. (Ministry of Emergency Management of the People's Republic of China, 1986).
Environmental influence[g]	1.100 < FID, 2.100 = FID<200, 3. FID≥200. (Farthest influence distance, FID, Meters)	Environmental influence is measured by the farthest distance affected by gas pipeline leakage or its secondary accidents (Dai, 2020).
Casualties (Persons)	1.30≤deaths or 100≤serious injuries, 2.10≤deaths<30 or 50≤serious injuries<100, 3.3≤deaths<10 or 10≤serious injuries<50, 4. Deaths<3 or serious injuries<10.	The number of casualties caused by the accident within 30 days (within 7 days for fire accidents) (State Council of the People's Republic of China, 2019).
Social influence	1. Particularly serious (PS), 2. Major (M), 3. Serious (S), 4. Ordinary (O).	Social influence is used to express the influence of the accident on the social order and is evaluated by measuring the three direct consequences (casualties, environmental influence, and economic losses) (Zhang et al., 2018).

[a] The states of occurrence time is referred to from (China Meteorological Administration, 2015).
[b] The grades of pipeline pressure are set according to the 'code for design of urban gas pipeline (2020 Revision)' (GB 50028–2006) (North China Municipal Engineering Design & Research Institute, 2020). H = High, SH = Sub-High, M = Medium, L = Low.
[c] The grades of building density are set according to the 'code for design of urban gas pipeline (2020 Revision)' (GB 50028–2006) (North China Municipal Engineering Design & Research Institute, 2020). Level 1 area: An area with 12 or fewer individual buildings for human habitation. Level 2 area: An area with more than 12 and less than 80 individual buildings for human habitation. Level 3 area: An area with 80 or more individual buildings for human habitation. Level 4 area: Urban centers where buildings of 4 or more stories are common and predominant.
[d] The node states of the nearby population density are determined according to (Mao et al., 2015). The names and abbreviations of the node states are "extremely densely populated area (EDP), medium populated area (DP), sparsely populated area (MP), and sparsely populated area (SP)". Data refer to the "statistical yearbook of urban construction" (Ministry of Housing and Urban-Rural Development of the People's Republic of China., 2022).
[e] In this study, the grades of the emergency response are determined based on the response times. By investigating the data from the accident reports, we classified the emergency response performance as "high" for the emergency response actions (for instance, pipeline rehabilitation) completed within 3 h after an accident, as "medium" for completing response actions within 3–6 h, and as "low" for completing response actions after more than 6 h.
[f] The states of economic losses and casualties are determined based on the classification of accident levels in the 'Report on production safety accident and regulations of investigation and treatment' (State Council of the People's Republic of China, 2019). This is also the basis for determining the social influence levels (Wang et al., 2018b).
[g] The environmental influence of the NGPLA was expressed and graded in terms of the farthest influence range. The grade setting is determined according to (Dai, 2020).

the node states are shown in Table 8, and the simulation result is presented in Table 9.[1]

According to the results in Table 9, the node states of economic

[1] The total probability of part of nodes is not equal to 1 in Table 9, which is a display error caused by the rounding of node probability by the software and does not affect the result analysis. The accident report does not contain information about poisoning and asphyxiation, so the calculation results about poisoning and asphyxiation do not need to compare with the actual accident outcomes and are not given here.

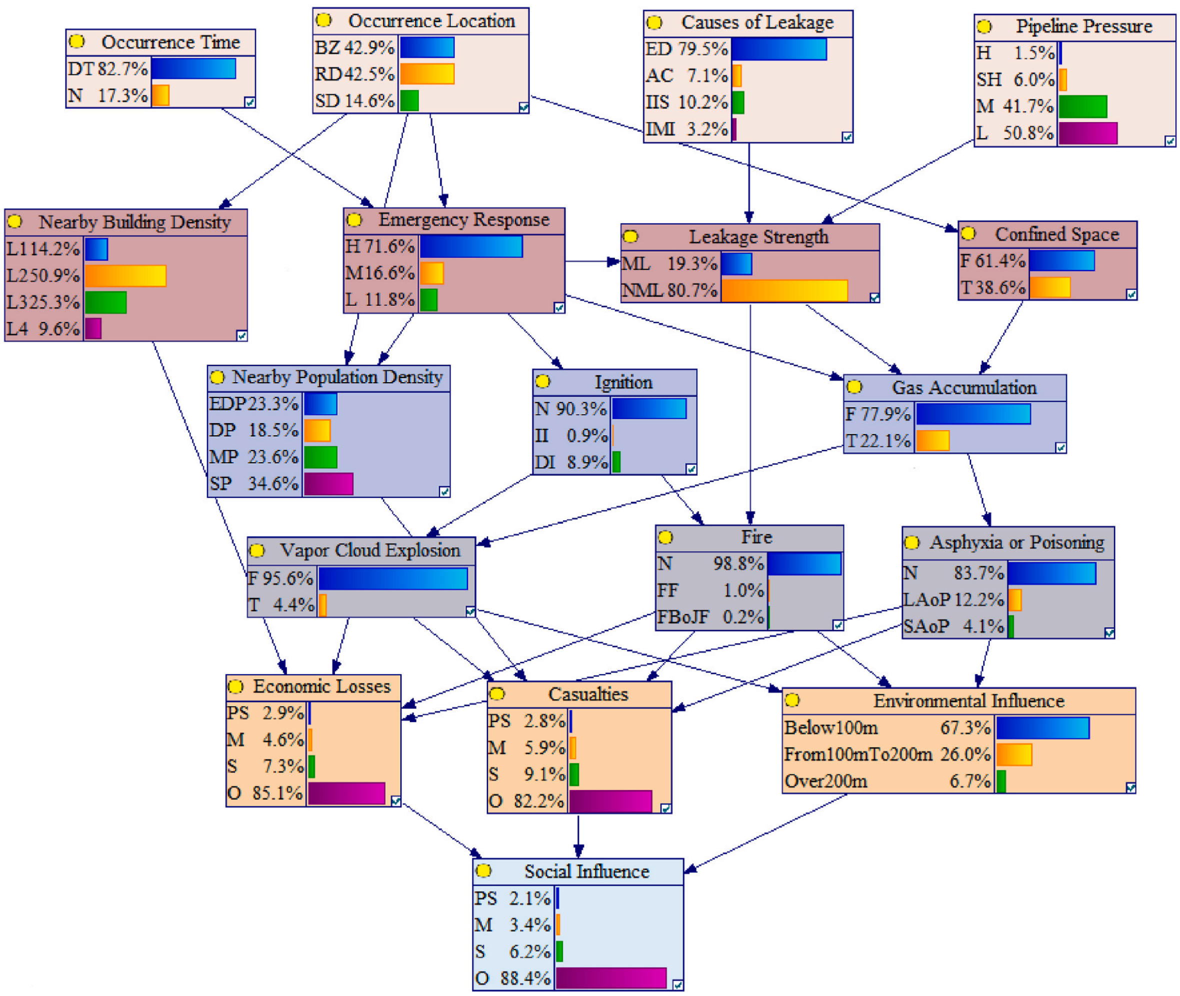

Fig. 4. The BN for NGPLA.

Table 6
Sensitivity analysis of influencing factors with respect to secondary accidents.

Factor	Fire	VCE	Asphyxiation or Poisoning
Occurrence Time	1.5e-3	4.16e-3	5.89e-3
Occurrence Location	1.45e-3	5.04e-3	1.29e-2
Pipeline Pressure	8.12e-3	1.99e-4	1.07e-3
Causes of Leakages	3.5e-4	1.07e-5	5.99e-6
Confined Space	–	1.52e-3	1.1e-2
Ignition	8.44e-2	0.28	–
Leakage Strength	5.84e-3	1.23e-4	5.77e-4
Gas Accumulation	–	7.87e-3	0.117
Emergency Response	8.73e-3	2.4e-2	3.67e-2

Table 7
The conditional probabilities of affected factors given different states of emergency response (%).

Factors	Status of emergency response		
	High	Medium	Low
Leakage strength	[12.2, 87.8]	[36.2, 63.8]	[38.7, 61.3]
Ignition	[93.8, 0.6, 5.6]	[81.8, 1.6, 16.6]	[80.4, 1.8, 17.8]
Gas accumulation	[86.6, 13.4]	[57.9, 42.1]	[52.5, 47.5]
Nearby population density	[14.6, 16.8, 24.3, 44.3]	[24.6, 26.8, 34.3, 14.3]	[74.6, 16.8, 4.3, 4.3]

Note: Leakage strength, [ML, NML]; Ignition, [N, II, DI]; Gas accumulation, [F, T]; Nearby population density, [EDP, DP, MP, SP].

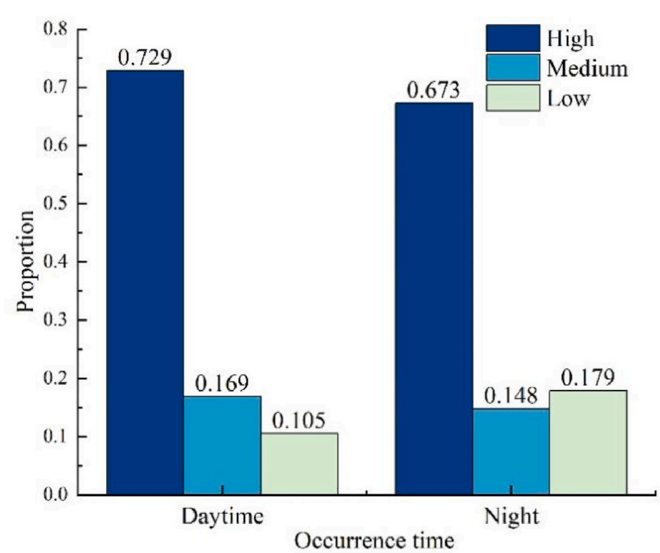

Fig. 5. Correlation between occurrence time and emergency response (The high, medium, and low in Fig. 5 are the states of emergency response).

losses, casualties, and social influence have the largest probability increase in the "Serious" state. The largest likelihood is the happening of a vapor cloud explosion, followed by flash fires. Based on the obtained

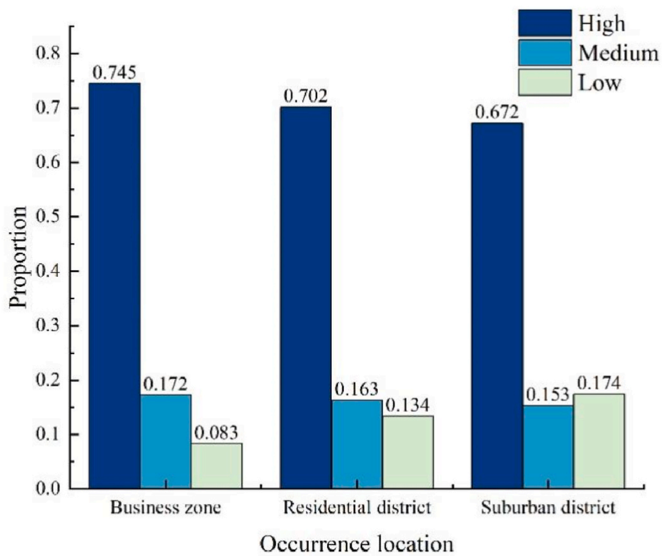

Fig. 6. Correlation between occurrence location and emergency response (The high, medium, and low in Fig. 6 are the states of emergency response).

Table 8
Configurations of the node states in BN.

Node name	Node status
Occurrence time	Daytime
Occurrence location	Residential district
Pipeline pressure	Medium
Causes of leakage	External damage
Confined space	True
Ignition	Delayed ignition
Nearby building density	Level 4 area
Nearby population density	4000< NPD (EDP)
Leakage strength	Massive leakage
Gas accumulation	True
Emergency response	Medium

Table 9
Simulation result based on EDIB model.

Secondary accident and consequence nodes	Node status	Estimated probabilities [Degree of increase or decrease]
Fire	1. None (N)	65.8% [-33%]
	2. Flash fire (FF)	34.2% [+33.2%]
	3. Fireball or jet fire (FBoJF)	0.0% [-0.2%]
Vapor cloud explosion	1. False (F)	32.4% [-63.3%]
	2. True (T)	67.6% [+63.3%]
Economic losses	1. Particularly serious (PS)	9.2% [+6.3%]
	2. Major (M)	13.5% [+8.9%]
	3. Serious (S)	20% [+12.7%]
	4. Ordinary (O)	57.4% [-24.8%]
Environmental influence	1. Below 100 m	51.3% [-16%]
	2. From 100 m to 200 m	33.6% [+7.4%]
	3. Over 200 m	15.1% [+8.6%]
Casualties	1. Particularly serious	4.7% [+1.9%]
	2. Major	7.7% [+1.8%]
	3. Serious	11.6% [+2.5%]
	4. Ordinary	76% [-4.2%]
Social influence	1. Particularly serious	5.1% [+3.0%]
	2. Major	8.1% [+4.7%]
	3. Serious	13.3% [+7.2%]
	4. Ordinary	73.5% [-14.9%]

results, it can be seen that the severity of the accident is most likely to be serious. In the investigation report of this accident, the investigators rated the accident as a serious accident according to relevant standards. Thus, it is validated that the EDIB model can predict the severity of NGPLAs effectively.

4.3. Social influence analysis

The influence of accidents on society is complex, and the consequences and causes of accidents will influence social order. Social influence is a comprehensive evaluation of the consequences of the accident. The diagnostic function of BNs is used to infer the posterior probabilities of economic losses, environmental influence, and casualties by giving different levels of social influence. This analysis aims to determine the weights relationship of the three kinds of consequences affecting social influence. The results are presented in Table 10.

Table 10 shows the posterior probabilities of the different states of economic losses, environmental influence, and casualties, under the conditions of giving different levels/states of social influence. The posterior probabilities were obtained by using inversion calculation of the BN model. By comparing the posterior probabilities with their initial probabilities, the sensitivities of economic losses, environmental influence, and casualties to social influence can be discussed. According to Table 10, economic losses and casualties are more sensitive to the states of social influence. For example, when the social influence is set as "Major", the "Major" probability of economic loss increases from 4.6% (initial value) to 28%. The "Major" probability of casualties increased from 5.9% (initial value) to 27.1%. According to the results, economic losses are more sensitive to the changes in social influence states compared to casualties. By contrast, the environmental influence was evaluated by the FID of the secondary accidents and has a lower sensitivity with respect to the changes in social influence states. The reason may be that the FID of poisoning and asphyxiation will not exceed 100 m generally. Only fires and VCEs have the possibility to cause serious environmental influence. Therefore, the weight ranking of the three kinds of consequences with respect to social influence is C1 (economic losses) > C3 (casualties) > C2 (environmental influence).

5. Discussions

5.1. Model comparison

In this section, we briefly compare the proposed model with similar models from other studies and then specify the similarities and differences. Finally, the strengths and weaknesses of the present model are summarized. We compare the methods and research contents of four studies (see Table 11). For the sake of illustration, the three models developed by other studies are referred to as the FTB model, DSB model, and EEB model, respectively.

Table 10
Posterior probabilities of economic losses, environmental influence, and casualties by giving different levels of social influence (%).

Then:	If the states of social influence is:			
	Particularly serious (PS)	Major(M)	Serious(S)	Ordinary (O)
Economic Losses (%).	[22.3, 20.2, 21.3, 36.2]	[15.8, 28, 10.2, 36]	[11.5,15.2, 32.1, 41.2]	[1.4, 2.6, 4.7, 91.3]
Environmental Influence (%).	[53.3, 33.4, 13.3]	[55.1, 32.4, 12.5]	[60.8, 29.2, 10]	[68.5, 25.4, 6.1]
Casualties (%).	[17.5, 18.6, 16.5, 47.4]	[11.7, 27.1, 17, 44.1]	[9.6, 17.3, 34, 39.1]	[1.6, 4, 6.9, 87.5]

Note: Economic losses, [PS, M, S, O]; Environmental influence, [Below 100 m, From 100 m to 200 m, Over 200 m]; Casualties, [PS, M, S, O].

Table 11
Model comparison results.

Models	Methods	Research contents
FTB (Wang et al., 2017)	Fault tree analysis (FTA) and BNs	System failure probability analysis and incident factor sensitivity analysis yielded 34 key factors leading to the failure of buried urban gas pipelines.
DSB (Wu et al., 2017)	BNs and Dempster-Shafer evidence theory	Classical natural gas pipeline network incidents were analyzed and the influence of secondary hazards and emergency response on the final consequences was investigated.
EEB (Zhang et al., 2018)	ET, incident evolution diagram (IED), and BNs	Risk analysis of oil pipeline leakage accidents was conducted based on a BN model. ET and IED were used to facilitate the development of the BN model. Decision-making was considered in the developed model and influencing factor analysis was investigated. EEB used the number of people affected by an accident as a measure of social influence.
EDIB (This paper)	ET, DEMATEL-ISM, BNs, and Dempster-Shafer evidence theory	ET and DEMATEL-ISM were combined to facilitate the development of a BN model. Accident report statistics and Dempster-Shafer evidence theory were used to support the determination of the CPTs in the BN model. A sensitivity analysis of influencing factors was conducted and an accident scenario analysis was implemented to validate the feasibility of the proposed model. Economic loss, environmental influence, and casualties were all evaluated to determine the final social influence.

Among the four models in Table 11, emergency response was investigated as an important influencing factor to gas leakage accidents, except in the FTB model. Efficient emergency response plays a key role in accident mitigation and is widely regarded as a procedural safety barrier (Yuan et al., 2022). DSB model investigated the direct influence of emergency response on secondary accidents. For instance, the results show that effective emergency response reduces the probability of urban large-scale fire from 0.481 to 0.095 (Wu et al., 2017). EEB model investigated the influence of the emergency response on final accident consequences. The results show that the probabilities of economic loss "<10 million RMB" are 0.869 and 0.606 respectively, under effective and poor emergency response situations (Zhang et al., 2018). In this study, the dependency between emergency response efficiency and accident evolution events (e. g., gas accumulation, ignition, leakage strength, and nearby population density) were considered, instead of correlating the emergency response to the secondary accidents/accident consequences directly. For instance, when emergency response efficiency state changes from "high" to "low", the probability of gas accumulation increases from 0.134 to 0.475. Then, the gas accumulation probability will effect on the probabilities of the secondary accidents and further the final consequences. Due to the difference above mentioned, the prior estimated probabilities of economic loss and casualties in the proposed model are different to those in the EEB model (DSB model does not provide the initial estimations of economic loss probabilities and casualty probabilities, therefore is not compared here). For instance, the prior probabilities of the "Ordinary" state of economic losses and casualties in the proposed model are 0.851 and 0.822 respectively. By contrast, those values are 0.713 and 0.662 in the EEB model.

The proposed model sets fire, VCE, and asphyxiation or poisoning as secondary accidents, while in the DSB model they are large-area fires, pollution spread, and epidemics. In this model, the occurrence probability of secondary accidents (without differentiating the node states, the probability of the two scenarios is expressed as $Ps_1\%/Ps_2\%$) is 6.2%/19.6% (Fire), 2.4%/9.7% (VCE) and 13.3%/23.1% (asphyxiation or poisoning) when setting up two accident scenarios similar to the DSB model. By contrast, the probabilities of secondary accidents in the DSB model are 21.1%/37.7% (Pollution spread), 9.48%/48.1% (Large-area fire), and 17.8%/10.6% (Epidemics). It's clear that when the emergency response status changes, the changes in secondary accident probability in this model are isotropic and generally lower than that of the DSB model. However, the DSB model has anisotropic changes in the secondary accident probabilities. The proposed model divides the secondary accidents into three independent nodes, and their probabilities are determined by different combinations of events. While the DSB model combines the three accidents into one node, which is limited by the overall probability of the node, so the above situation occurs.

5.2. Advantages, limitations and future works

The proposed EDIB model established an accident evolution analysis and risk analysis tool for NGPLAs. This model fully considered the influence of emergency response on accident evolution and the final consequences. The combination of ET and DEMATEL-ISM was used to facilitate the determination of the BN model structure. The prior probabilities of some nodes in the BN model were determined by accident statistics from 773 accident reports. Additionally, the final social influence caused by NGPLAs can be predicted based on the assessment of economic loss, environmental influence, and human casualties. The sensitivity analysis of influencing factors was conducted to identify critical factors with respect to NGPLAs. A real accident scenario is simulated by using the developed BN model to validate the effectiveness of the proposed model. In future research, the EDIB model can be applied in other fields to provide support for risk analysis and accident evolution analysis of industrial accidents.

This study combines historical accident data and expert knowledge to develop an accident analysis model based on BN. Although a database with 773 accident cases was used to help the development of the BN model, the amount of data was still limited. As a result, the historical accident data was mainly used for influencing factor identification and BN node determination. For the dependency analysis of the nodes and the determination of the prior probabilities, expert judgment still plays a key role. When more and more data become available, future work may investigate the combination of historical accident data and expert judgment for the determination of the prior probabilities and conditional probabilities in the BN model.

6. Conclusion

In this study, a model was developed to conduct accident evolution analysis and risk analysis of natural gas pipeline leakage accidents. The proposed model integrates ET, DEMATEL, ISM, and BN to investigate the accident evolution process of natural gas pipeline leakage accidents with the consideration of key influencing factors. A sensitivity analysis was performed by using the developed BN to identify the key factors associated with secondary accidents. The results show that ignition and emergency response have a significant impact on the happening of secondary accidents caused by natural gas pipeline leakage. The cause of leakage has the least influence on the severity of the secondary accidents. In addition, the occurrence time and occurrence location would affect the emergency response efficiency. Based on the accident evolution analysis, the developed model was applied to simulate a real gas pipeline leakage accident that occurred in Songyuan, China. The obtained results are consistent with the real outcomes of the accident. By using the diagnostic function of BNs, the weight ranking of economic loss, environmental influence, and human casualties on social influence caused by natural gas pipeline leakage accidents was determined. The results show that economic losses and casualties have more weight with respect to adverse social influence caused by NGPLAs.

Although the developed model implements probabilistic analysis of NGPLA based on historical accident data and expert knowledge, expert judgment still plays a more critical role. As more data become available, future work will investigate the combination historical data and expert judgment to determine prior probabilities and conditional probabilities.

Author statement

Xing-lin Chen: Conceptualization, Methodology, Writing- Original draft preparation, Resources, Visualization. **Wei-dong Lin:** Funding acquisition. **Chun-xiang Liu:** Writing- Reviewing and Editing. **Fu-qiang Yang:** Supervision, Writing- Reviewing and Editing, Funding acquisition. **Yong Guo:** Investigation Writing- Reviewing and Editing. **Xin Li:** Methodology, Writing- Reviewing and Editing. **Shuai-qi Yuan:** Conceptualization, Writing- Reviewing and Editing. **Genserik Reniers:** Writing- Reviewing and Editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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