Dynamic probability assessment of urban natural gas pipeline accidents considering integrated external activities

Li, Xinhong; Zhang, Yi; Abbassi, Rouzbeh; Yang, Ming; Zhang, Renren; Chen, Guoming

DOI
10.1016/j.jlp.2020.104388

Publication date
2021

Document Version
Final published version

Published in
Journal of Loss Prevention in the Process Industries

Journal of Loss Prevention in the Process Industries 69 (2021) 104388

Contents lists available at ScienceDirect

Journal of Loss Prevention in the Process Industries

journal homepage: http://www.elsevier.com/locate/jlp

Dynamic probability assessment of urban natural gas pipeline accidents considering integrated external activities

Xinhong Li [a,*], Yi Zhang [a], Rouzbeh Abbassi [b], Ming Yang [c], Renren Zhang [a], Guoming Chen [d]

[a] School of Resources Engineering, Xi'an University of Architecture and Technology, No.13 Yanta Road, Xi'an, 710055, China
[b] School of Engineering, Faculty of Science and Engineering, Macquarie University, Sydney, Australia
[c] Safety and Security Science Section, Faculty of Technology, Policy, and Management, Delft University of Technology, the Netherlands
[d] National Engineering Laboratory of Offshore Geophysical and Exploration Equipment, China University of Petroleum, Shandong, 266580, China

ARTICLE INFO

Keywords:
Urban gas pipeline
External activities
Integrated risk assessment
Bayesian network

ABSTRACT

Urban gas pipelines usually have high structural vulnerability due to long service time. The locations across urban areas with high population density make the gas pipelines easily exposed to external activities. Recently, urban pipelines may also have been the target of terrorist attacks. Nevertheless, the intentional damage, i.e. terrorist attack, was seldom considered in previous risk analysis of urban gas pipelines. This work presents a dynamic risk analysis of external activities to urban gas pipelines, which integrates unintentional and intentional damage to pipelines in a unified framework. A Bayesian network mapping from the Bow-tie model is used to represent the evolution process of pipeline accidents initiating from intentional and unintentional hazards. The probabilities of basic events and safety barriers are estimated by adopting the Fuzzy set theory and hierarchical Bayesian analysis (HBA). The developed model enables assessment of the dynamic probabilities of consequences and identifies the most credible contributing factors to the risk, given observed evidence. It also captures both data and model uncertainties. Eventually, an industrial case is presented to illustrate the applicability and effectiveness of the developed methodology. It is observed that the proposed methodology helps to more accurately conduct risk assessment and management of urban natural gas pipelines.

1. Introduction

Aging urban natural gas pipelines have high operational risk due to their exceptional location and long service life (Mao et al., 2014; Li et al., 2020). The 10th EGIG report indicates that 28.37% of accidents of European onshore gas pipelines are caused by external interference and, 14.9% of accidents are triggered by ground movement (EGIG, 2018), as shown in Fig. 1. Halim et al. (2020) investigated the causal factors of the pipeline incident data reported in databases of US PHMSA, Canada National Energy Board (NEB), and European Gas Pipeline Incident Data Group (EGIG). It can be found that external activities such as external interference and ground movement are the most significant factors resulting in gas pipeline failures. This paper uses the term of external activities to describe causations of natural gas pipeline accident from external interference and ground movement et al., defined in EGIG report.

Nowadays, natural gas pipelines have gradually become the target of terrorist attacks due to their economic value and the significant impacts of destruction. In the past few years, many accidents to oil and gas pipelines, due to intentional damage, have been observed. For example, a natural gas pipeline in the Republic of Dagestan, Russia, was exploded due to terrorist attacks, which interrupted gas supply to 100,000 people (Chen et al., 2015). Also, a natural gas pipeline leak in Egypt's Sinai Peninsula was caused by a terrorist attack. The leak incident escalated into a fire and explosion, which disrupted Egypt's natural gas transmission to Israel and Jordan (Chen et al., 2015). Thus, the external damage-causing pipeline failures are not only accidental but can also be intentional. The external activity that casing pipeline accident in this paper is further divided into intentional and unintentional parts. The unintentional part means the activities without deliberate intent or irresistible natural factors, whereas the intentional part means the external activities with purpose or intent. It is significantly important to integrate unintentional and intentional factors in quantitative risk assessment of urban natural gas pipeline accidents from external activities.

Currently, considerable efforts have been made on qualitative and

* Corresponding author.
E-mail addresses: safety_lxh@163.com, lixinhong@xauat.edu.cn (X. Li).

https://doi.org/10.1016/j.jlp.2020.104388
Received 20 June 2020; Received in revised form 16 December 2020; Accepted 28 December 2020
Available online 8 January 2021

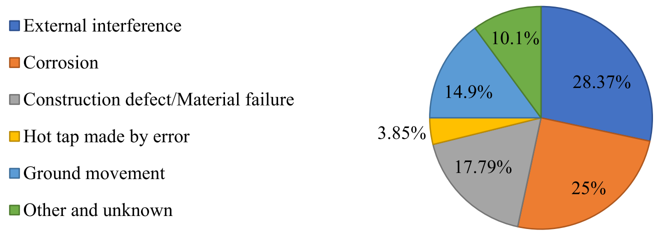

Fig. 1. Incident distribution per cause (EGIG, 2018).

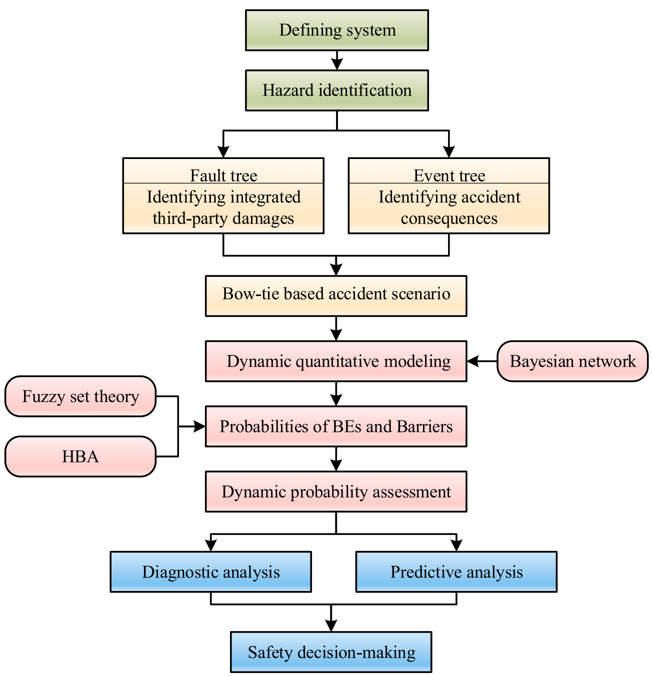

Fig. 2. Framework of the methodology.

quantitative risk studies of urban oil and gas pipelines. Li et al. (2019) analyzed the cause of accidents based on a combination of DEMATEL, ISM, and BN to reduce pipeline network risk and avoid leak accidents. Xing et al. (2020) studied urban pipeline accidents from a systematic perspective, and the direct and indirect causes of the accident were considered to deeply analyze the accident-causing factors and identify the risk associated with the leaks. Gong et al. (2018) studied long-distance oil pipelines to extend the cause-and-effect analysis from immediate failures to a systemic perspective and explained the reasons. Guo et al. (2016) used a cloud inference method for risk (third-party damage, corrosion damage, design flaws, etc.) assessment of natural gas pipelines. Wang et al. (2017) built an advanced two-step approach to assess the failure probabilities of urban buried gas pipeline. Badida et al. (2019) used a fuzzy fault tree to analyze the likelihood of natural gas pipeline failure due to natural hazards. Ma et at. (2013) conducted a quantitative risk analysis for urban natural gas pipeline networks using geographical information systems (GIS). Han and Weng (2011) established a risk index system by using a qualitative method and constructed a quantitative method consisting of probability assessment of potential consequences and risk assessment.

Meanwhile, external activities, as one of the leading causes of oil and gas pipeline failure, has also attracted the attention of many scholars. Guo et al. (2018) identified the risk factors after the oil and gas pipeline accident caused by a third-party based on BN. Cui et al. (2020) investigated pipeline risks caused by unintentional external activities by integrating Bayesian network and game theory; Liang et al. (2012) focused on the application of SOMs to assess third-party risk in the pipeline and classify risk patterns. Bajcar et al. (2015) quantified the impact of external activities risks on natural gas pipelines to accurately define the level of risk by studying population density; Li et al. (2016) evaluated the failure probability of urban natural gas pipelines on external activities by AHP and fuzzy mathematical theory.

The above-mentioned researches have discussed different qualitative and quantitative techniques for risk assessment of the oil and gas pipelines. However, there are two issues that remain to be addressed. First, we need to investigate how to model the integrated risk of aging urban natural gas pipelines, abnormal events that can be divided into accidental events and intentional events, which are respectively caused by unintentional risk and intentional risk (i.e., terrorism, vandalism, and mischief). Both unintentional and intentional hazards should be considered in risk assessment. However, it is inadequate that the previous studies on risk assessment of natural gas pipelines mainly focused on the accidental risk. Aging urban natural gas pipelines remain vulnerable due to the intentional risk. Hence, it is necessary to perform an integrated external activities risk assessment of aging urban natural gas pipelines. Second, the previous risk assessment of urban oil and gas pipelines mainly focused on addressing the limitations arising from the static structure of conventional methods. Moreover, the quantitative risk analysis is also challenged by limited or missing data, and this increases the uncertainty in assessment outcomes. Expect for considering the interdependencies among risk factors, this work also accounts for the data uncertainty of basic risk factors which is addressed by using integrated probability estimation techniques. Thus, the developed model could capture both data and model uncertainties.

The available accident statistic reports are analyzed to find previously unrecognized intentional damage factors. BN is a graphical inference probability technique that describes the relationship between the cause and consequence of a system (Arzaghi et al., 2017; Baksh et al., 2018). This method can effectively solve the problem of interconnected and multi-state input abnormal events, and can appropriately update the probability of accidents and their consequences according to changes in risk. BN is used in this work to model urban natural gas pipeline failure from the integrated external activities. Besides, fuzzy set theory utilizes linguistic variables to represent boundaries between system states and state probabilities, and it is suitable for the situation where state boundaries cannot be defined in the form of probability data. HBA is widely used to handle source-to-source uncertainty. The related data collected from different sources can be used in the HBA framework to estimate the probability of an event. Thus, fuzzy set theory, HBA and BN can be used to handle both the data and model uncertainties in risk assessment of integrated external activities to urban natural gas pipelines.

The purpose of this paper is to establish a model for dynamic risk assessment of the integrated external activities to urban natural gas pipelines. The uniqueness of this work is an integration of intentional and unintentional external activities to an urban gas pipeline. The Bow-tie method is used to identify the integrated hazards and construct an accident scenario. It is then mapped into a BN to capture the dependency among interacting causations and find the accident evolution path of urban gas pipeline failure due to integrated external activities. The fuzzy set theory and hierarchical Bayesian analysis (HBA) are used to estimate the probabilities of basic events and safety barriers under uncertainty. The developed model has a dynamic feature. Firstly, it can update the state of integrated hazards given new evidence and secondly, it also can perform dynamic probability learning given the available precursor data.

The remainder of the paper is organized as follows. Section 2 presents the framework and methods of the risk assessment and discusses the steps of this model. A case study is presented in Section 3 to illustrate the effectiveness and applicability of the proposed model. Section 4 presents the conclusions of this work.

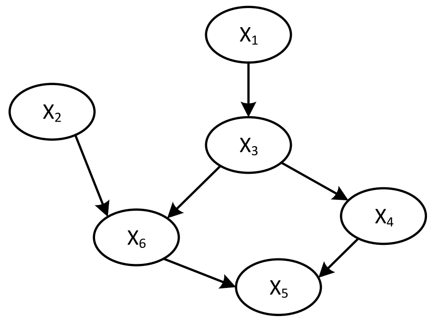

Fig. 3. A schematic of a BN model.

2. The methodology

Fig. 2 presents the framework of the methodology used for integrated external activities risk assessment of the aging urban natural gas pipeline. The main steps include: 1) Identifying integrated hazards for external activities on urban gas pipelines, including intentional and unintentional factors; 2) Identifying pipeline failure consequences; 3) Accident scenario modeling using Bow-tie model; 4) Dynamic quantitative accident modeling; 5) Probabilities estimation of BEs and Barriers; 6) Dynamic assessment of accident probabilities.

2.1. Step 1: Identifying integrated external activities

Hazard identification is a fundamental step in of quantitative risk assessment framework. This work uses a fault tree (FT) to determine the risk factors related to the impact of external activities on urban natural gas pipelines. FT is a directed logical tree describing the occurrence of an event from accident results to causations. The top event (TE) is the urban gas pipeline leak due to external activities. Basic events (BEs) are potential causations that lead to the occurrence of TE. In this paper, BEs are mainly identified from some available literature, e.g. EGIG, UKOPA and PHMSA et al., and the opinions of experts who work in this field for long years. By analyzing through FT, the underlying accident causations can be identified to decide on prevention of the accident. In this work, the hazards related to external damages on urban natural gas pipeline are identified from both the intentional and unintentional aspects.

2.2. Step 2: Identifying accident consequences

The urban natural gas pipeline leak may lead to some unexpected consequences, including the loss of assets, and a threat to human life, resulting from flammable gas dispersion, fire, and explosion. The event tree (ET) is a useful tool to deduce the unexpected consequences from an initial incident. ET analysis a process from causation to its impacts which can be used to analyze the consequence states of an accident. The safety barrier is designed to prevent the initial event escalating into severe consequences. It has two states, i.e. success and failure. The two branches of success and failure also have two states of success and failure, respectively in the next stage. This is repeated until the final consequences are identified to generate a horizontal tree. In this way, through analyzing the state change of safety barriers, different states of consequences are obtained. This work uses ET to find the potential consequences from external activities induced urban gas pipeline leak.

2.3. Step 3: accident scenario construction

A bow-tie (BT) model is comprised of an FT and an ET, which well describes the evolution process of an unexpected incident from its causations to its consequences (Delvosalle et al., 2005, 2006). Although BT as a popular tool, was adopted in previous studies for risk analysis, it is subject to some limitations. BT is a static model and cannot capture the dependent failure and dynamic change of hazard states. Therefore, this work uses BN to relax the inherent limitations of the BT model. BT is mapped into a BN based on the established mapping algorithm (Khakzad et al., 2012). In this paper, BT is mainly used to construct an urban natural gas pipeline accident due to integrated external activities. Then, the BT model is used as an informative base to establish a BN model.

2.4. Step 4: Dynamic quantitative accident modeling

BN is a network based on probabilistic graphics, and it is a directed acyclic graph. Fig. 3 presents a simple example of a BN. BN is mainly used to solve the model uncertainty problem (Afenyo et al., 2017; Cai et al., 2016). Compared with the conventional methods, e.g., FT, ET, and BT, BN considers conditional dependencies and describes the interrelationship among nodes. The significant advantage of BN is that the probability assigned to a node can be updated given the observed new evidence (He et al., 2018). Therefore, BN is utilized to construct the relationship among variables and solve the model uncertainty.

The joint probability distribution $P(U)$ of a set of variables $U = \{A_1, A_2, A_3 \ldots\}$ can be presented Eq. (1).

$$P(U) = \prod_{i=1}^{n} p(A_i | Pa(A_i)) \tag{1}$$

where $Pa(A_i)$ is parent set of variables $U = \{A_1, A_2, A_3 \ldots\}$.

Through Bayes' theorem presented in Eq. (2), the posterior probability of a variable is obtained when new evidence is observed.

$$P(U|E) = \frac{P(U,E)}{P(E)} = \frac{P(U,E)}{\sum_U P(U,E)} \tag{2}$$

2.5. Step 5: Probability estimation of BEs and barriers

Using the BN model, the probability of integrated external activities on urban natural gas pipeline accidents can be assessed dynamically. This step is designed to determine the probabilities of basic events and safety barriers which are the essential inputs of the BN model. The basic event and safety barrier are divided into three types according to their data source.

- The probability of basic event and safety barriers can be found directly from the literature and databases;
- There are no direct data for BEs and Barriers, but these probabilities are determined through consulting with experts in the field. This can be achieved by fuzzy set theory in which fuzzy judgment language from experts is converted into crisp probabilities;
- For some BEs and Barriers, there are partially available failure data, but they are not sufficient for determining the probabilities using available statistical methods. This paper collects the indirect but relevant data and uses them in a hierarchical Bayesian analysis (HBA) framework to evaluate the probabilities.

The following section briefly introduces the fuzzy set theory and HBA techniques used in this study.

2.5.1. Fuzzy set theory

Fuzzy set theory is widely applied to solve the challenge of data uncertainty, and it converts qualitative knowledge or judgments into quantified numerical reasoning. The expert language judgment is generally fuzzy and subjective, and fuzzy numbers are used to relax this limitation. Fuzzy numbers are divided into triangular fuzzy numbers (TFN) and trapezoidal fuzzy numbers (ZFN) (Ferdous et al., 2011). TFN is utilized in this paper to describe the uncertainty of expert language. TFN is a vector (P_l, P_m, P_u) representing the lower bound, the most likely value and the upper bound, respectively (Huang et al., 2001). The main steps of the fuzzy set theory are presented as follows.

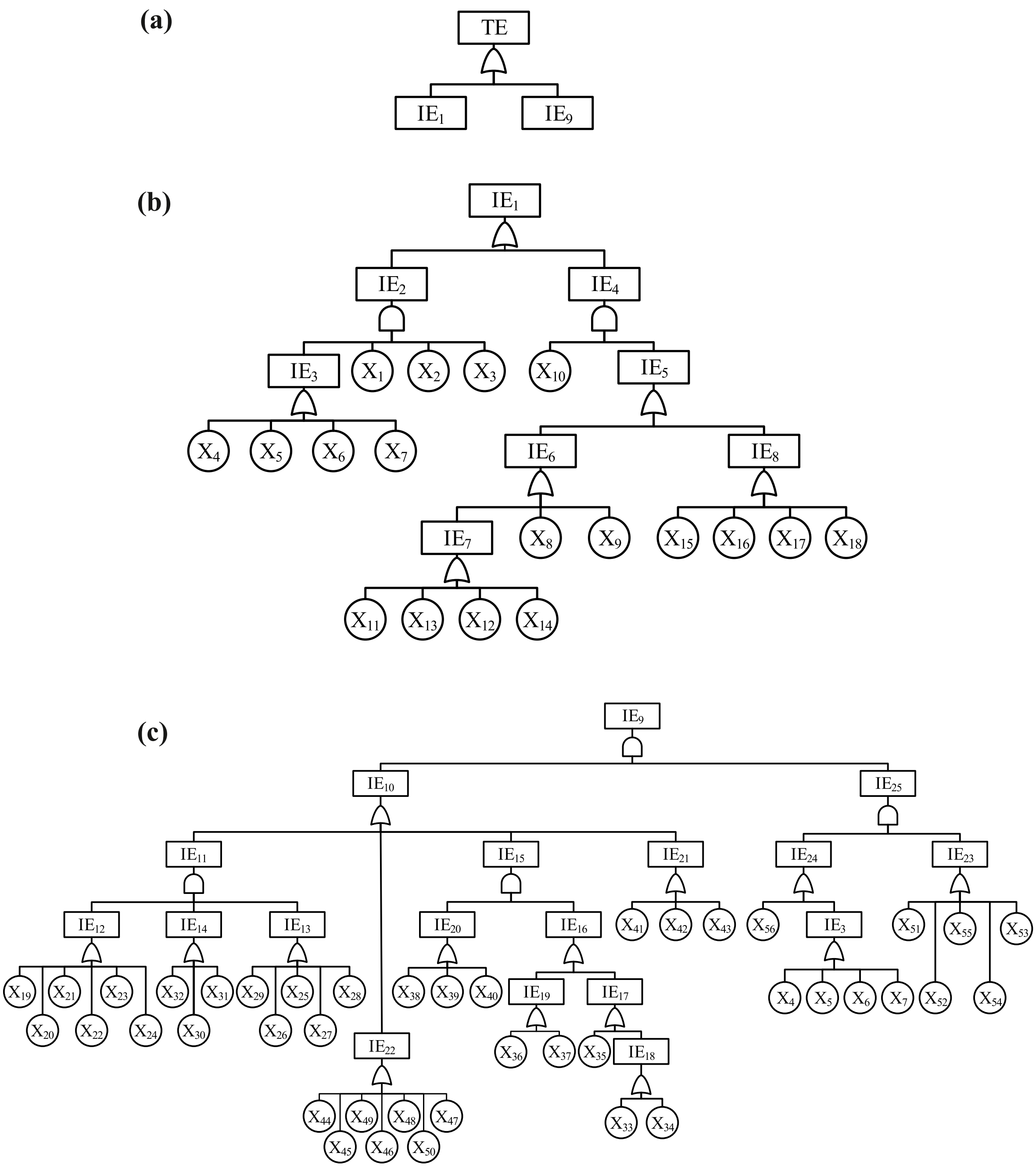

Fig. 4. (a) FT for urban natural gas pipelines failure due to external activities. (b) Sub-FT for pipeline failure due to intentional due to external activities. (c) Sub-FT for pipeline failure due to unintentional external activities.

Firstly, the opinions on basic events from multi-experts are expressed in language terms which are divided into seven levels of Very Low (VL), Low (L), Fairly Low (FL), Medium (M), Fairly High (FH), High (H), Very High (VH). The language term from an expert is converted into fuzzy numbers. Considering the difference among backgrounds of multiple experts (e.g. different education levels, different experiences in a particular field, etc.), the multi-experts' judgments are aggregated using the weight averaging method, as explained in Eq. (3) (Li et al., 2018).

$$P_i = \frac{\sum_{j=1}^{m} w_j P_{i,j}}{\sum_{j=1}^{m} w_j} \tag{3}$$

where, P_i represents the aggregated fuzzy number of input event i; $P_{i,\,j}$ represents the fuzzy number of input event i from expert j; w_j is the weight of expert j, and m represents the number of experts.

Secondly, the aggregated fuzzy numbers are converted into a fuzzy probability score (FPS). FPS represents an integrated assessment of probabilities of BEs by multiple experts. Several methods are available to convert the aggregated fuzzy number into FPS. This paper uses max-min aggregation method to defuzzify the aggregated fuzzy number. The maximum and minimum fuzzy set are shown in Eq. (4).

$$\begin{aligned} f_{max}(x) &= \begin{cases} x, & (0 \le x \le 1) \\ 0, & (otherwise) \end{cases} \\ f_{min}(x) &= \begin{cases} 1-x, & (0 \le x \le 1) \\ 0, & (otherwise) \end{cases} \end{aligned} \tag{4}$$

Subsequently, the right and the left score of fuzzy set can be computed as Eq. (4). Then, the FPS can be obtained by calculating the left and right fuzzy set scores, as shown in Eq. (5) (Yazdi and Kabir,

Table 1
Basic events considered in FT.

Symbol	Description	Probability determination approach
X_1	Interest-driven activity	Fuzzy set theory
X_2	Deficiency of safety education	Available data source (2.58E-03)
X_3	Deficiency of legal education	Available data source (1.54E-03)
X_4	No regular patrolling	Fuzzy set theory
X_5	Low patrolling frequency	HBA
X_6	Low responsibility of patrolmen	Fuzzy set theory
X_7	Low skill of patrolmen	Fuzzy set theory
X_8	Mental illness	HBA
X_9	Heresy-driven activity	HBA
X_{10}	Worse public security	Fuzzy set theory
X_{11}	Personal interest loss	HBA
X_{12}	Suffering unfair treatment	HBA
X_{13}	Abnormal social expectation	HBA
X_{14}	Reactionism-driven activities	Fuzzy set theory
X_{15}	War	Fuzzy set theory
X_{16}	Partisan bickering	Fuzzy set theory
X_{17}	Resource disputes	Fuzzy set theory
X_{18}	Sovereignty disputes	HBA
X_{19}	Illegal digging	Available data source (7.54E-03)
X_{20}	Illegal piling	Available data source (5.49E-03)
X_{21}	Illegal drilling	Available data source (4.31E-03)
X_{22}	Illegal blasting	Available data source (5.14E-03)
X_{23}	The contractor is without qualification	HBA
X_{24}	Unlicensed operations of the contractor	HBA
X_{25}	Informative missing of pipeline	Fuzzy set theory
X_{26}	Without update of pipeline route information	HBA
X_{27}	Insufficient communication between contractor and government	Fuzzy set theory
X_{28}	No warning signs above pipeline	HBA
X_{29}	Warning sign above pipeline is destroyed	HBA
X_{30}	Operational errors of constructors	Available data source (1.34E-03)
X_{31}	Insufficient experience of constructors	Available data source (4.89E-03)
X_{32}	Backward construction techniques	Fuzzy set theory
X_{33}	Poor town planning	HBA
X_{34}	Illegal land approval procedure	HBA
X_{35}	Temporary buildings above the pipeline	Available data source (2.65E-03)
X_{36}	Construction materials stacked	Fuzzy set theory
X_{37}	Heavy construction equipment stacked	Fuzzy set theory
X_{38}	Government regulation not in place	Fuzzy set theory
X_{39}	Management deficiency of construction organizations around the pipeline	Fuzzy set theory
X_{40}	Poor safety awareness of residents around the pipeline	Fuzzy set theory
X_{41}	High traffic density around the pipeline	Available data source (2.89E-03)
X_{42}	High-intensity personnel activities above the pipeline	Available data source (1.23E-03)
X_{43}	Agricultural activities around the pipeline	Available data source (2.26E-03)
X_{44}	Earthquake	Available data source (4.58E-04)
X_{45}	Debris flow	Available data source (3.49E-04)
X_{46}	Landslide	Available data source (7.24E-04)
X_{47}	Typhoon	Available data source (9.58E-04)
X_{48}	Lightning	Available data source (3.97E-04)
X_{49}	Stress on the pipeline from growing plants	Available data source (1.23E-04)
X_{50}	Damage by wildlife and livestock	Available data source (3.23E-04)
X_{51}	Design defect of pipeline	Available data source (1.34E-03)
X_{52}	Welding defect	Available data source (1.46E-03)
X_{53}	Structural degradation of pipeline	Fuzzy set theory
X_{54}	Depth of cover is too shallow	HBA
X_{55}	Deficiency of anticorrosive design	Fuzzy set theory
X_{56}	Imperfect failure alarming management	Fuzzy set theory

Table 2
TE and IEs considered in FT.

Symbol	Description	Symbol	Description
TE	Urban natural gas pipeline leak	IE_{13}	Unknown pipeline route
IE_1	Damage due to intentional external activities	IE_{14}	Construction defect
IE_2	Stealing natural gas	IE_{15}	Excessive pressure on pipeline
IE_3	Failure of the pipeline inspection system	IE_{16}	Overload
IE_4	Terrorist attacks	IE_{17}	Construction overload
IE_5	Terror action	IE_{18}	Unreasonable building planning
IE_6	Psychological problem	IE_{19}	Material stacking
IE_7	Dissatisfaction with society	IE_{20}	Difficult to manage
IE_8	Political dispute	IE_{21}	Frequent ground activity
IE_9	Damage due to unintentional external activities	IE_{22}	Natural factors
IE_{10}	Third-party external interference	IE_{23}	Pipeline conditional defects
IE_{11}	Construction damage	IE_{24}	Failure of pipeline defect inspection
IE_{12}	Illegal development and construction around pipelines	IE_{25}	High pipeline vulnerability

2017).

$$FPS(P_i) = \left[FPS_{Right}(P_i) + 1 - FPS_{Left}(P_i)\right]/2 \tag{5}$$

Eventually, FPS can be converted into failure probability for quantitative analysis by using Eqs. (6) and (7) (Onisawa, 1990).

$$PF_i = 1/10^k \tag{6}$$

$$k = 2.301 \times [(1 - FPS/FPS)]^{1/3} \tag{7}$$

2.5.2. Hierarchical Bayesian analysis

HBA is a technical method used in probabilistic risk analysis (PRA) to solve the uncertainty caused by lack of, or even no, data. This technique can deal with the source-to-source variability in indirect but relevant data. In general, a multi-stage prior distribution is solved in the HBA framework, which is a very complicated numerical process and requires high computational requirements. However, with the application of Markov Chain Monte Carlo (MCMC) sampling, the operation of HBA has been promoted (Kelly and Smith, 2009). The advantages of HBA over conventional Bayesian models are mainly two points: 1) HBA can solve the problem of the population variability of data from different sources; 2) It is able to borrow strength from indirect but relevant data (Yang et al., 2015).

In the HBA framework, an informative prior distribution of interest parameter γ from different sources is constructed. The uncertain parameter γ follows a general distribution with its parameters called hyperparameters, α and β, which are recorded as $h(\gamma|\alpha,\beta)$. This is the first-stage prior distribution. Also, the hyperparameters α and β are also unknown, which follow diffusive or non-informative distributions, such as uniform distributions or Jeffries priors (EI-Gheriani et al., 2017). This

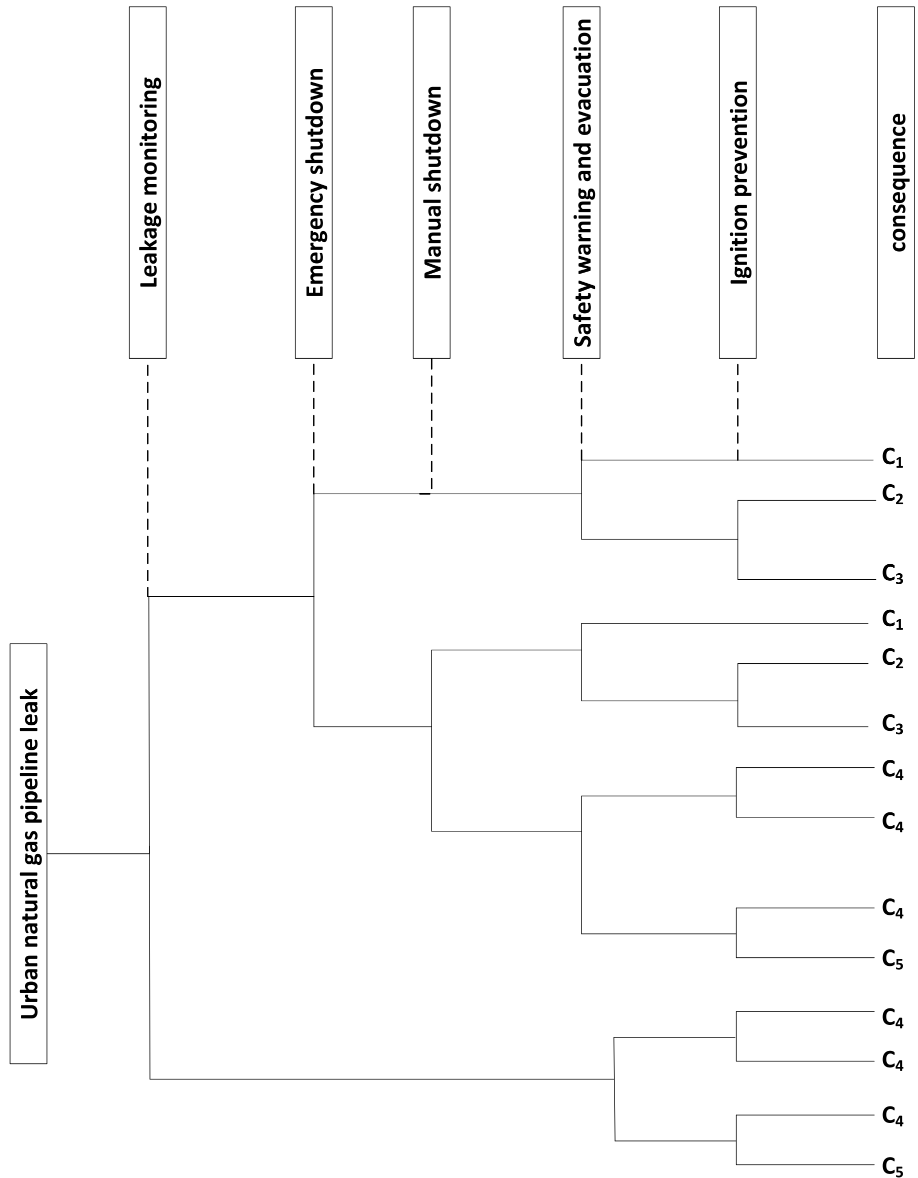

Fig. 5. ET for urban natural gas pipeline failure due to external activities.

is the second-stage distribution of uncertainty in α and β.

The generic data D collected from a different source can be utilized to update the second-stage distribution to obtain the posterior distribution of hyperparameters, which can be calculated by Eq. (7) (Yu et al., 2017).

$$h(\alpha,\beta|D)=\frac{h(\alpha,\beta)l(D|\alpha,\beta)}{\iint h(\alpha,\beta)l(D|\alpha,\beta)d\alpha d\beta} \tag{8}$$

where the $h(\alpha,\beta|D)$ is the posterior distribution of hyperparameters. The likelihood function of hyperparameters $l(D|\alpha,\beta)$ can be shown as Eq. (8) (EI-Gheriani et al., 2017).

$$l(D|\alpha,\beta)=\int l(D|\gamma)h(\gamma|\alpha,\beta)d\gamma \tag{9}$$

After obtaining the posterior distribution of α and β, the posterior distribution h_1 of γ can be updated by calculating the average value of α and β, as shown Eq. (9) (Khakzad et al., 2014).

$$h_1(\gamma|D)=\iint h(\gamma|\alpha,\beta)h(\alpha,\beta|D)d\alpha d\beta \tag{10}$$

As more case-specific information D^* is found, based on Bayes' theorem, $h_1(\gamma|D)$ can be further written as $h_1(\gamma|D, D^*)$.

$$h_1(\gamma|D,D^*)=\frac{h_1(\gamma|D)l(D^*|\gamma)}{\int h_1(\gamma|D)l(D^*|\gamma)d\gamma} \tag{11}$$

2.6. Step 6: Dynamic assessment of accident probability

By conducting step 5, the probabilities of basic events and safety barriers are obtained. They are then used as the inputs in BN framework for dynamic probability reasoning of the system. The probabilities of BEs and safety barriers are utilized in a forwarding inference to assess the probability of different consequences of accident scenarios in the BN model. As new evidence is observed, the probability of basic event nodes can be updated in BN based on backward inference to find the most probable hazards. Furthermore, BN can perform probability learning. When the available data is continuously observed, dynamic probabilities of urban natural gas pipeline accidents at different times can be obtained.

The above is a Bayesian network-based dynamic risk assessment

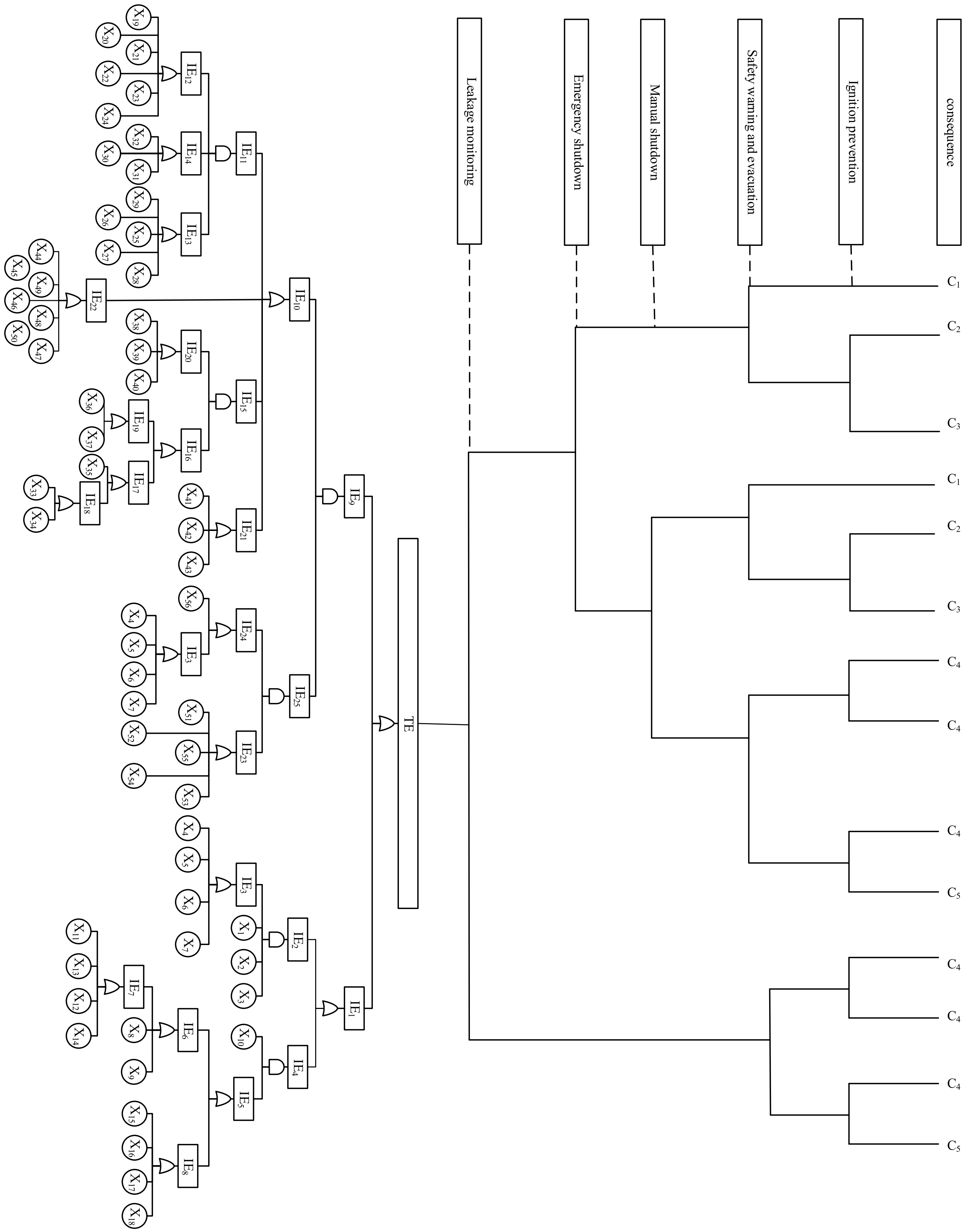

Fig. 6. BT for urban pipeline leak due to integrated external activities.

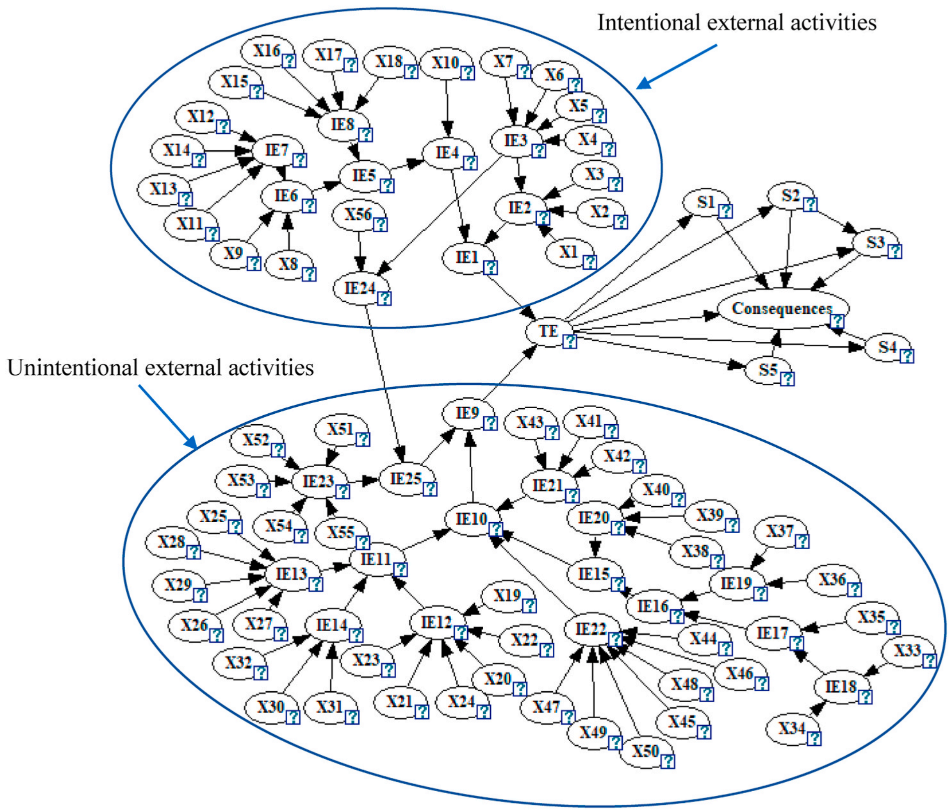

Fig. 7. BN model for urban natural gas pipeline accident due to external activities.

Table 3
BEs' probabilities from fuzzy set theory.

Symbol	Experts knowledge (E1, E2, E3)	Prior probabilities
X_1	(L, M, VL)	5.61E-04
X_4	(M, FH, VL)	2.90E-03
X_6	(FH, H, FL)	8.80E-03
X_7	(H, M, M)	8.80E-03
X_{10}	(M, H, L)	4.80E-03
X_{14}	(FL, FL, FH)	2.80E-03
X_{15}	(VL, VL, VL)	2.14E-05
X_{16}	(L, VL, FL)	2.99E-04
X_{17}	(L, L, FH)	1.10E-03
X_{25}	(FH, M, M)	6.10E-03
X_{27}	(H, M, FL)	7.10E-03
X_{32}	(FH, FH, M)	8.10E-03
X_{36}	(H, M, FH)	1.16E-02
X_{37}	(VH, H, FH)	2.81E-02
X_{38}	(L, H, FL)	2.50E-03
X_{39}	(L, H, FH)	4.60E-03
X_{40}	(FL, H, FH)	6.90E-03
X_{53}	(FH, FH, VH)	1.68E-02
X_{55}	(H, FH, VH)	2.52E-02
X_{56}	(H, FL, M)	7.00E-03

Table 4
Precursor data for BEs and consequences.

Year	1	2	3	4	5	6	7	8	9	10
X_5	1	0	1	1	2	3	2	1	2	1
X_8	0	0	1	0	1	0	1	0	0	3
X_9	1	0	2	0	1	0	1	1	2	0
X_{11}	0	1	2	0	0	1	1	0	1	2
X_{12}	1	0	0	1	0	1	2	2	3	0
X_{13}	3	0	1	0	1	1	0	0	2	0
X_{18}	0	1	0	0	2	0	3	0	1	0
X_{23}	1	2	1	2	3	1	2	3	0	3
X_{24}	2	2	1	2	2	0	1	2	3	2
X_{26}	0	3	1	1	0	2	1	2	0	1
X_{28}	3	2	3	0	2	1	2	3	2	0
X_{29}	1	1	2	1	3	0	1	3	3	3
X_{33}	0	1	0	2	3	3	1	2	3	0
X_{34}	1	0	1	2	3	1	3	2	2	1
X_{54}	1	3	1	3	1	2	3	0	2	2
C1	5	3	4	4	3	5	3	2	4	3
C2	3	4	3	5	3	3	2	4	5	3
C3	3	3	5	2	3	5	3	3	2	3
C4	4	3	3	2	3	2	3	3	2	4
C5	3	2	2	3	3	3	4	3	2	2

framework for integrated external activities to an urban natural gas pipeline. The methodology is designed to dynamically assess the integrated risk of external activities to an urban gas pipeline. It can be used to predict accident probability and find the most probable hazards to formulate management and control strategy further.

3. Case study

3.1. Identification of integrated hazards

This section takes an urban natural gas pipeline in China as an example to illustrate the applicability of the methodology. Using urban natural gas pipeline leak due to external activities as top event, the involved hazards are identified from intentional and unintentional aspects, shown in Fig. 4. These risk factors are found from literature and expert knowledge (You et al., 2014; EGIG, 2018; Xing et al., 2020; Li et al., 2019; Halim et al., 2020). The BEs, IEs and TE in the FT model are explained in Table 1 and Table 2. The unintentional external activities account for a significant percentage in all pipeline failures due to external activities. Both the unintentional activities and high pipeline vulnerability contribute to the pipeline failure from unintentional external activities. Unintentional activities include four parts, i.e.

Table 5
BEs' probabilities estimated using HBA.

Symbol	Prior probability	97.5% Confidence interval
X_5	6.22E-03	(2.27E-03,1.14E-02)
X_8	3.42E-03	(3.33E-06,9.35E-03)
X_9	3.74E-03	(5.32E-04,8.31E-03)
X_{11}	3.74E-03	(6.13E-04,8.10E-03)
X_{12}	4.65E-03	(4.78E-04,1.07E-02)
X_{13}	3.99E-03	(9.04E-05,1.02E-02)
X_{18}	4.02E-03	(1.48E-06,1.14E-02)
X_{23}	7.91E-03	(3.25E-03,1.37E-02)
X_{24}	7.52E-03	(3.06E-03,1.32E-02)
X_{26}	5.03E-03	(9.54E-04,1.05E-02)
X_{28}	8.00E-03	(2.76E-03,1.47E-02)
X_{29}	7.86E-03	(3.03E-03,1.41E-02)
X_{33}	6.72E-03	(1.38E-03,1.39E-02)
X_{34}	7.11E-03	(2.77E-03,1.26E-02)
X_{54}	7.95E-03	(3.03E-03,1.44E-02)

construction damage, excessive pressure on pipeline, frequent activities around the pipeline, and natural factors. This pipeline crosses an urban area with a high population density, which makes it easily exposed to unintentional external interference. The construction damage due to the operation errors and frequent activities of ground personnel and vehicles could lead to the failure of the pipeline. This pipeline was built before the development of the city, which means that the buildings were built above the pipeline. The pipeline may crack and break due to overload over a long time. Besides, natural factors are also another type of unintentional external interference, including earthquake, debris flows, landslides, typhoons, lightning and wild animal and plant growth on pipes. The high vulnerability of pipelines is an essential reason that the failure of pipelines, in the case of unintentional external interferences, would occur. The causations leading to high vulnerability of pipeline include defects and flaws, as well as inspection shortfalls and maintenance planning.

However, as discussed in the introduction, natural gas pipelines gradually become the targets of intentional attack due to their economic value and the serious impacts following the destruction. The intentional external interferences on pipelines are comprised of stealing natural gas and terrorist attacks.

3.2. Identification of consequences

ET is used to identify different consequence states caused by urban natural gas pipeline failure. As shown in Fig. 5, when a leak occurs, five safety barriers, i.e. (S_1) leak monitoring, (S_2) emergency shutdown, (S_3) manual shutdown, (S_4) safety warning and evacuation and (S_5) ignition prevention are considered to prevent further escalation of the leak accident with catastrophic consequences. Due to the sequential failure of safety barriers, there are five different types of consequences related to the level of economic losses and casualties caused by accident, and they are (C_1) near miss; (C_2) general economic losses; (C_3) general economic losses and casualties; (C_4) major economic losses; (C_5) major economic losses and casualties. The established ET model is subjected to the following assumptions: 1) When (S_1) leakage monitoring fails, (S_2) emergency shutdown and (S_3) manual shutdown fail; 2) Only when (S_2) emergency shutdown fails, (S_3) manual shutdown will be judged, that is, if (S_2) emergency shutdown has already taken action, (S_3) manual shutdown will be skipped.

3.3. Accident scenarios construction

A BT model is developed by integrating above-mentioned FT and ET, which describes the entire process, from the hazards related to external activities, to pipeline failure and final catastrophic consequences. Fig. 6 presents the developed BT model for urban natural gas pipelines due to integrated external activities.

However, as discussed in 2.1, the BT model is static, assuming that system variables are independent with each other and does not take into account the complex dependencies among hazards and the change of risk factor states over time. To relax these limitations, the BT model is mapped into a BN, as illustrated in Fig. 7. Basic events, intermediate events and top events in BT are mapped into root nodes and leaf nodes in BN. The nodes are connected by arcs, indicating the interaction between the events. The CPT in BN is used to depict the conditional dependency relationship between child nodes and parent nodes. CPT is determined by modifying the relationship presented in the logical gate of FT. The logical gate of FT presents a deterministic relationship between BEs and the corresponding IE. For example, if X_4, X_5, and X_6 and X_7 occur simultaneously, the pipeline inspection system will fail inevitably. This is presented by deterministic value, i.e., 0 and 1. However, the pipeline inspection system may not fail actually. There are some uncertainties in the mentioned logical inference between BEs and IE. This can be considered by modifying the value CPT, and uncertain values, such as 0.99 and 0.01, are used in CPT. The modification can be based on the expert's experience or data-driven method.

3.4. Probability estimation of BEs and safety barriers

The sources of the BEs probabilities in the FT are divided into three types, e.g. 1) the probability are available from the literature; 2) the probability which is subjective and imprecise needs to be determined by fuzzy set theory based on expert opinions, 3) the probability needs to be determined by HBA method due to the data of event probability being limited and insufficient, as shown in Table 1.

For the second type of BEs, the probabilities are estimated by expert judgments. Based on the educational background and work experience, a particular weight is assigned to each individual expert. The method described in section 2.2.1 is adopted to aggregate and calculate expert opinions to obtain the probabilities of BEs. The experts' knowledge and the crisp probability of BEs are presented in Table 3.

HBA framework is utilized to estimate the probability of BEs and safety barriers in which the data is insufficient according to different available sources. For the sake of illustration, the hypothetical precursor data of BEs and consequences are shown in Table 4, which are the occurrence numbers of these factors in each year. It assumes that these precursor data are observed for 10 years from 235 pipelines. The assumption of the form of precursors is based on the actual engineering basis. The oil and gas company usually performed an annual inspection to ensure the integrity of aging gas pipeline. The form of precursors used in this paper can be derived from the inspection report. As shown in Table 5, the BEs' probabilities are inferred based on the indirect but related precursor data through HBA. It should be noted that the last column means the confidence interval is on the estimation, not on their accuracy. As discussed in section 2.2.2, the binomial distribution of the interest parameter p is assigned to each BE to model the number of failures per time interval, where p follows a beta distribution with hyperparameters a and b, which follows the independent diffusion distributions (Li et al., 2018). Fig. 8 shows the expected value of the failure probability of the BEs at the 97.5% confidence interval. Similarly, the failure probabilities assigned to the safety barriers can also be obtained.

3.5. Diagnostic analysis for critical hazards identification

The probabilities of external activities-induced pipeline failure and five consequence states can be obtained through forwarding reasoning after using the probabilities of BEs and safety barriers as inputs. The probability of urban gas pipeline leak is estimated to be 1.68E-01. The probabilities of consequence states are presented in Table 6. The probabilities of the five consequences states from high to low are C_1, C_2, C_4, C_3, and C_5. However, the severity of the five accident consequences from high to low is C_5, C_4, C_3, C_2, and C_1. The most important advantage of BN is that it can perform the probability update. In this work, C_4 is used as

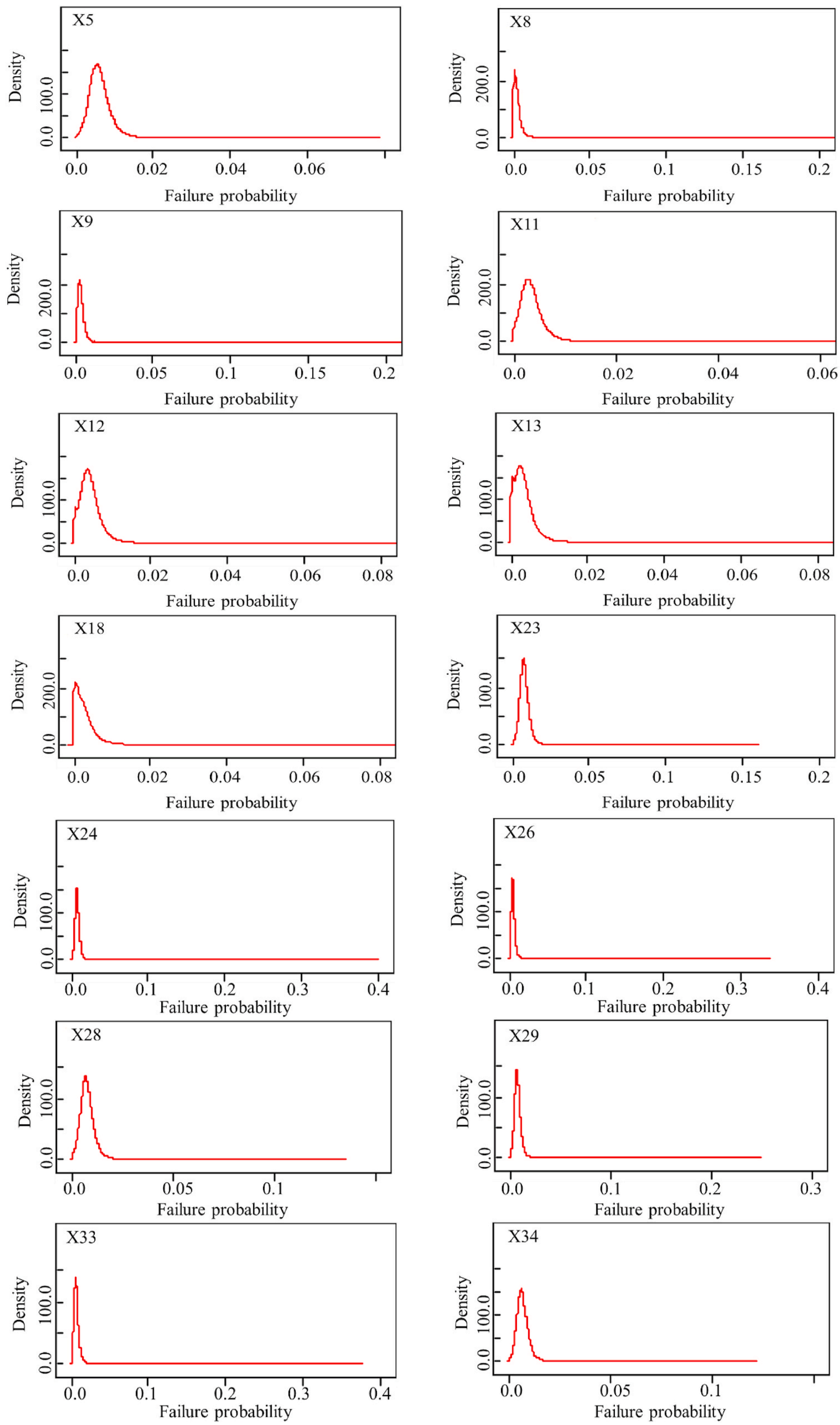

Fig. 8. Predictive distributions for failure probabilities of BEs.

 Journal of Loss Prevention in the Process Industries 69 (2021) 104388

Table 6
The probability of consequence states by BN.

Consequence state	Probability
C_1	1.58E-01
C_2	7.20E-03
C_3	2.17E-04
C_4	2.30E-03
C_5	3.01E-06

the new evidence observed due to its high severity and probability. The probabilities of BEs and safety barriers are updated through back reasoning. The most probable BEs and safety barriers are identified to formulate targeted preventive measures, and it makes BN superior in comparison with BT.

A comparison of the prior and posterior probabilities of BEs is shown in Fig. 9. As illustrated in this figure, BEs with obvious probability increase are X_1 (Interest-driven activity), X_2 (Deficiency of safety education), X_3 (Deficiency of legal education), X_4 (No patrolling regularly), X_6 (Low responsibility of patrolmen), X_8 (mental illness), X_9 (Heresy-driven activity), X_{11} (Personal interest loss), X_{13} (Abnormal social expectation), X_{15} (War), X_{17} (Resource disputes), X_{18} (Sovereignty disputes), X_{23} (Contractor is without qualification), X_{24} (Unlicensed operations of the contractor), X_{41} (High traffic density around pipeline), X_{43} (Agricultural activities around pipeline), X_{53} (Structural ageing of the pipeline) and X_{55} (Deficiency of anticorrosive design). It means that these events are most sensitive to consequence state C4. Among them, X_1, X_2, X_3, X_4, X_6, X_8, X_9, X_{11}, X_{13}, X_{15}, X_{17}, X_{18} are the BEs involved in intentional damage, accounting for two-thirds of the total key events. This is due to the fact that intentional damage is often planned in advance, and it is not easy to detect or manage, which is the reason that leakage accidents often evolve into catastrophic consequences. Therefore, these most probable events should be paid more attention.

Similarly, the comparison of the prior and posterior probabilities of safety barriers is shown in Fig. 10. It is observed that the increase of S_1 is the most obvious. Except for S_1, S_2 has the most substantial increase among the remaining four safety barriers. The reason is that S_1 is the first

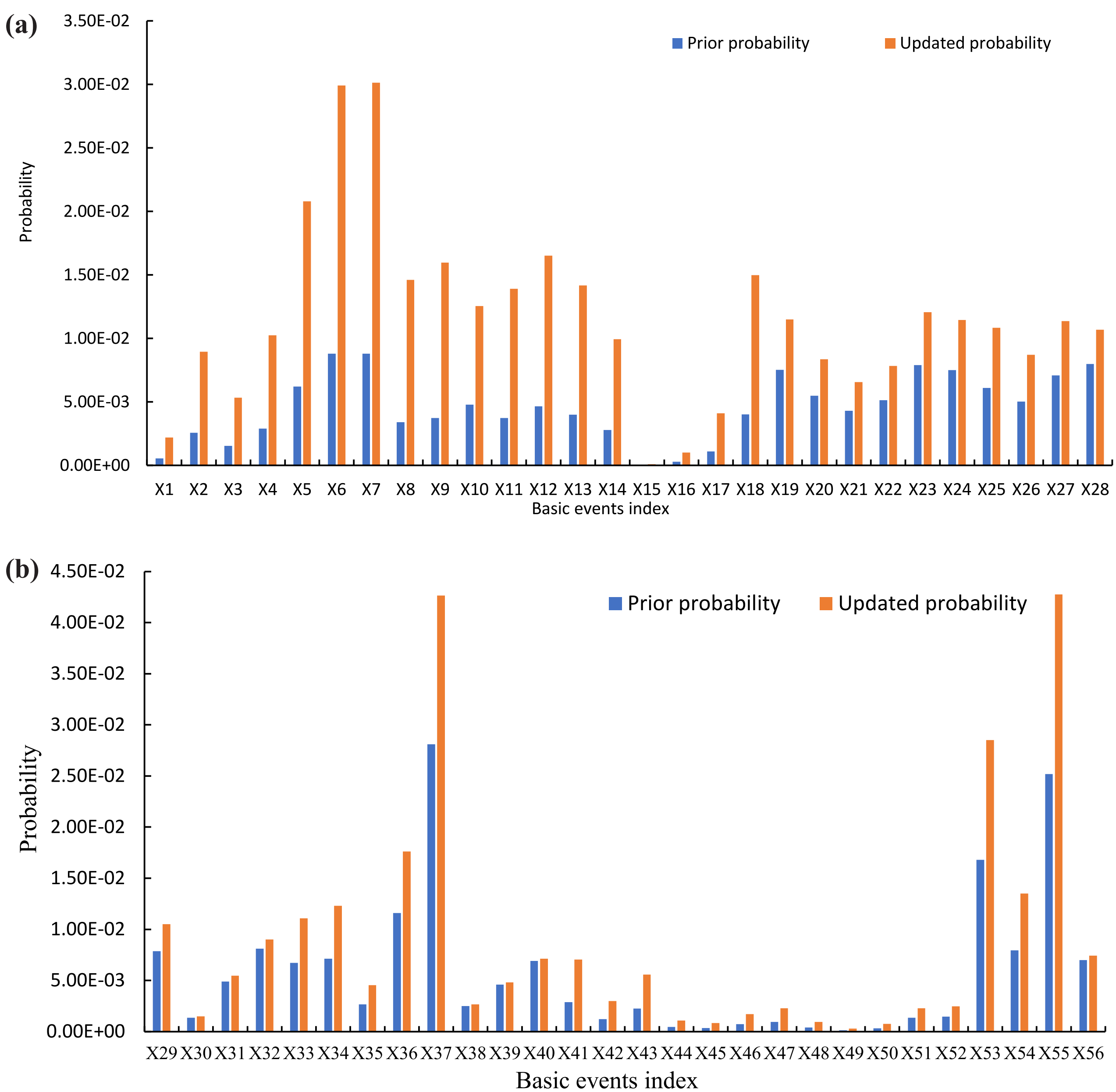

Fig. 9. (a) Comparison of prior and updated probabilities of BEs (X_1-X_{28}). (b) Comparison of prior and updated probabilities of BEs (X_{29}-X_{56}).

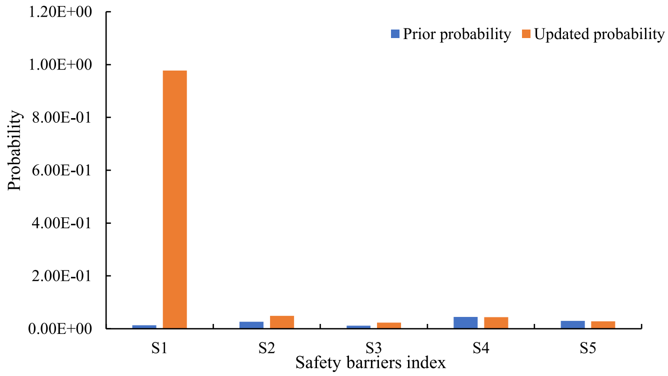

Fig. 10. Comparison of prior and updated probabilities of safety barriers.

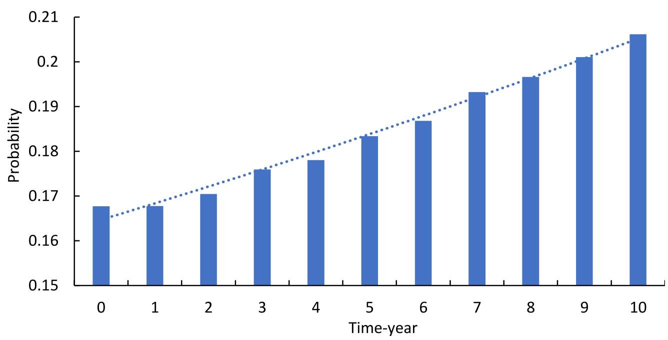

Fig. 11. The dynamic occurrence probability of aging urban natural gas pipelines leak.

barrier after the accident, and it is also a barrier to alert people. Once the S_1 fails, people will not notice the occurrence of a pipeline leak, so emergency and manual shutdown systems will not start, and the leak incident will continue until a catastrophic consequence occurs. S_1 is the most important barrier, and if it fails, the consequences will be severe. In addition, an emergency shutdown is the first action after the leak is detected. If the emergency shutdown responds quickly, the source of the leak will be shut down in time to prevent the continuing leakage, and the accident consequences will not be serious. However, if the emergency shutdown measures do not respond, there is the possibility of causing a major accident, because manual shutdown may also fail. Therefore, S_1 and S_2 are the critical safety barriers that cause the consequence of the C_4 accident. These barriers need to be regularly checked and repaired to ensure that they would work properly in case of accidents.

3.6. Dynamic probability analysis

In addition to probability updating, probability learning is another critical feature of the established BN model. Probability learning is a process that revises the probability of BE nodes through real-time observation to dynamically update the probability of accident and consequence states. In this study, Table 3 presents the precursor data obtained from the industrial sector for the BEs and safety barriers of interest. With these data propagated in BN, the probability over time of accident and consequence states can be dynamically updated. Fig. 11 demonstrates the real-time dynamic probability update of the leakage accident caused by the external activities of aging urban gas pipeline over 10 years. Year 0 is the accident probability calculated in section 3.4. It can be found that the probability of pipeline leak increases over 10 years. In the third, seventh, and tenth years, the probability increases are larger. This is related to the fact that the critical events have occurred more frequently in these three years. The present variation trend of pipeline leak probabilities is the results that prior probabilities are updated continuously with precursor data. When the probability of occurrence exceeds an acceptable level, the targeted prevention decisions need to be made.

Figs. 12 and 13 present the time-dependent probabilities of safety barriers and consequence states over 10 years, respectively. The failure probabilities of safety barriers gradually increase, given the observed new data. S4 and S5 increase rapidly. For the consequences due to external activities induced pipeline leak, the probability of C_1 gradually decreases over time. Near miss can be regarded as a safe state, which will decrease as the accident probabilities increase. On the contrast, the probabilities of C_3, C_4, and C_5 are increasing over 10 years. The main reasons for this are that the probabilities of consequences are updated subject to the assumption that no improvement measures are adopted. C_2 gradually increases in the first three years and gradually stabilizes in the fourth year. C_3, C_4, and C_5 are accident states, and they are the opposite state of C_1. Thus, the probability of C_3, C_4, and C_5 will increase as the probability of C_1 decreases over 10 years.

The important BEs and weak safety barriers obtained through probability updating and learning should be the focus of pipeline manager's attention. In the risk assessment, targeted measures would be taken to avoid the failure of these nodes to improve the reliability of the system and to reduce the impact caused by accident.

4. Conclusions

This paper presents a model for dynamic risk assessment of

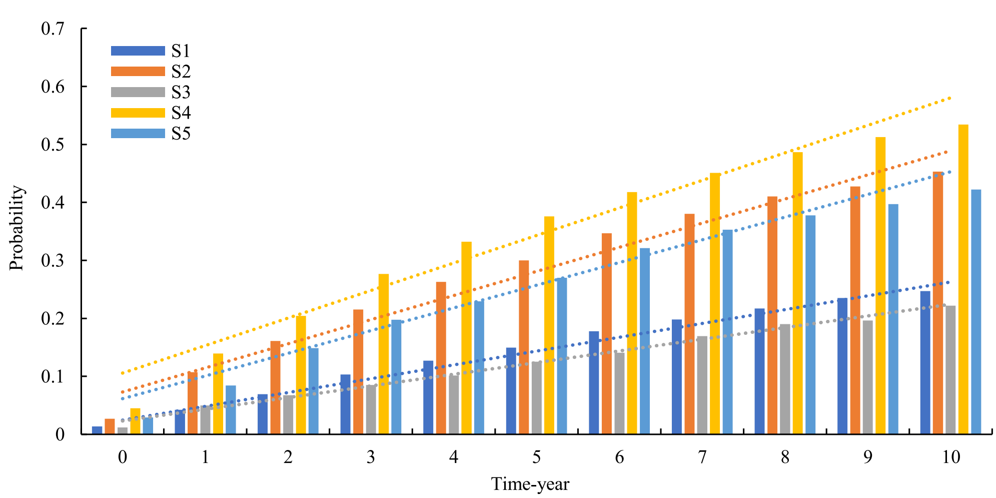

Fig. 12. Dynamic failure probability of safety barriers.

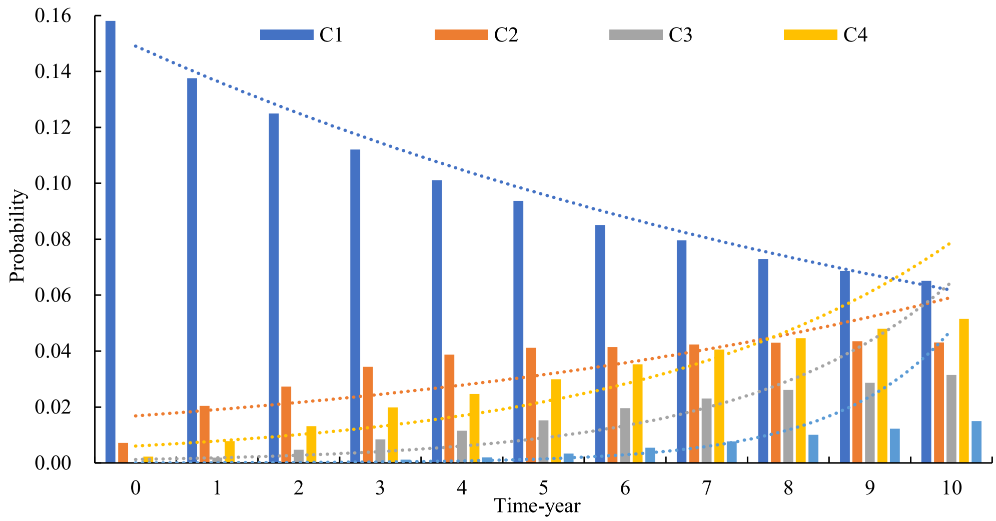

Fig. 13. Dynamic occurrence probabilities of consequence states.

integrated external activities on urban natural gas pipelines. It includes not only the unintentional external activities but also the intentional external activities, i.e. terrorist attack. Probabilistic risk assessment is performed in a BN-based assessment framework. FT and ET are utilized to identify BEs and consequences, respectively. BT is utilized to develop the accident scenarios and then mapped into BN to conduct quantitative reasoning. The probabilities of BEs and safety barriers are handled by fuzzy set theory and HBA. BN is used to capture complex dependencies among hazards and the change of hazard state. The developed methodology enables us to perform a robust probabilistic assessment considering uncertain information.

The proposed model is applied to an urban natural gas pipelines. A total of 56 hazard factors related to external activities for urban natural gas pipelines are identified, including 18 intentional factors and 38 unintentional factors. The results of integrated risk assessment provide support for pipeline safety management. The probability updating using the observed evidence finds that a total of 18 BEs are the most probable factors, of which 2/3 BEs are intentional factors. Through comparison of the prior and posterior probabilities, it is found that interest-driven activity, deficiency of safety education, low responsibility of patrolmen and resource disputes are significant factors causing pipeline failure by intentional damage. Besides, leak monitoring is the most critical barrier to preventing pipeline leak. Probability learning reflects an increasing trend of operational risk of urban gas pipelines due to the integrated external activities. It indicates that the necessary mitigation measures should be applied to reduce the operational risk of the pipeline.

The uniqueness of the framework is that it integrates intentional and unintentional external activities on urban aging oil and gas pipeline. The proposed framework can help find the most probable external activities factors causing an accident and predict the dynamic risk evolution trend. It can be used to conduct efficient risk management of external activities on an urban natural gas pipeline. Overall, the present work is preliminary and can be extended further. Future work is planned to investigate the interactions and inter-dependency between safety- and security-related activities. Besides, future work will also consider the relationship among risk factors during their probability estimations.

Acknowledgment

The authors gratefully acknowledge the financial support provided by the Projects funded by National Natural Science Foundation of China (52004195), China Postdoctoral Science Foundation (2020M673355), Special Scientific Research Project of Education Department of Shaanxi Province, China (20JK0729), Major theoretical and practical research project of Social Science in Shaanxi Province, China (2020Z188), Fundamental Research Funds for the Central Universities (20CX02315A), Opening Fund of National Engineering Laboratory of Offshore Geophysical and Exploration Equipment.

References

Arzaghi, E., Abaei, M.M., Abbassi, R., Garaniya, V., Chin, C., Khan, F., 2017. Risk-based maintenance planning of subsea pipelines through fatigue crack growth monitoring. Eng. Fail. Anal. 79, 928–939.
Afenyo, M., Khan, F., Veitch, B., Yang, M., 2017. Arctic shipping accident scenario analysis using Bayesian Network approach. Ocean. Eng. 133, 224–230.
Baksh, A., Abbassi, R., Garaniya, V., Khan, F., 2018. Marine transportation risk assessment using Bayesian Network: application to Arctic waters. Ocean. Eng. 159, 422–436.
Badida, P., Balasubramaniam, Y., Jayaprakash, J., 2019. Risk evaluation of oil and natural gas pipelines due to natural hazards using fuzzy fault tree analysis. J. Nat. Gas Sci. Eng. 66, 284–292.
Bajcar, T., Cimerman, F., Širok, B., 2015. Towards more detailed determination of third-party impact on risk on natural gas pipelines: influence of population density. Process Saf. Environ. Protect. 94, 509–516.
Cui, Y., Quddus, N., Mashuga, C.V., 2020. Bayesian network and game theory risk assessment model for external activities to oil and gas pipelines. Process Saf. Environ. Protect. 134, 178–188.
Cai, B., Liu, H., Xie, M., 2016. A real-time fault diagnosis methodology of complex systems using object-oriented Bayesian networks. Mech. Syst. Signal Process. 80 (1), 31–44.
Chen, Z., Peng, Z., Wu, R., 2015. On anti-terror efforts in gas industry. Municipal Eng. Technol. 33 (2), 208–211.
Delvosalle, C., Fievez, C., Pipart, A., Debray, B., 2006. ARAMIS project: a comprehensive methodology for the identification of reference accident scenarios in process industries. J. Hazard Mater. 130 (3), 200–219.
Delvosalle, C., Fiévez, C., Pipart, A., Fabrega, J.C., Planas, E., Christou, M., Mushtaq, F., 2005. Identification of reference accident scenarios in SEVESO establishments. Reliab. Eng. Syst. Saf. 90 (2–3), 238–246.
EGIG, 2018. 10th report of the European gas pipeline incident data Group (period 1970 – 2016). https://www.egig.eu/.
El-Gheriani, M., Khan, F., Chen, D., Abbassi, R., 2017. Major accident modelling using spare data. Process Saf. Environ. Protect. 106, 52–59.
Ferdous, R., Khan, F., Sadiq, R., Amyotte, P., Veitch, B., 2011. Fault and event tree analyses for process systems risk analysis: uncertainty handling formulations. Risk Anal.: Int. J. 31 (1), 86–107.
Gong, Y., Li, Y., 2018. STAMP-based causal analysis of China-Donghuang oil transportation pipeline leakage and explosion accident. J. Loss Prev. Process. Ind. 56, 402–413.
Guo, X., Zhang, L., Liang, W., Haugen, S., 2018. Risk identification of external activities on oil and gas pipelines through the Bayesian network. J. Loss Prev. Process. Ind. 54, 163–178.
Guo, Y., Meng, X., Meng, T., Wang, D., Liu, S., 2016. A novel method of risk assessment based on cloud inference for natural gas pipelines. J. Nat. Gas Sci. Eng. 30, 421–429.
Halim, S.Z., Yu, M., Escobar, H., Quddus, N., 2020. Towards a causal model from pipeline incident data analysis. Process Saf. Environ. Protect. 143, 348–360.
Han, Z.Y., Weng, W.G., 2011. Comparison study on qualitative and quantitative risk assessment methods for urban natural gas pipeline network. J. Hazard Mater. 189 (1–2), 509–518.

He, R., Li, X., Chen, G., Wang, Y., Jiang, S., Zhi, C., 2018. A quantitative risk analysis model considering uncertain information. Process Saf. Environ. Protect. 118, 361–370.

Huang, D., Chen, T., Wang, M.J.J., 2001. A fuzzy set approach for event tree analysis. Fuzzy Set Syst. 118 (1), 153–165.

Kelly, D.L., Smith, C.L., 2009. Bayesian inference in probabilistic risk assessment—the current state of the art. Reliab. Eng. Syst. Saf. 94 (2), 628–643.

Khakzad, N., Khan, F., Amyotte, P., 2012. Dynamic risk analysis using bow-tie approach. Reliab. Eng. Syst. Saf. 104, 36–44.

Khakzad, N., Khan, F., Paltrinieri, N., 2014. On the application of near accident data to risk analysis of major accidents. Reliab. Eng. Syst. Saf. 126, 116–125.

Li, F., Wang, W., Dubljevic, S., Khan, F., Xu, J., Yi, J., 2019. Analysis on accident-causing factors of urban buried gas pipeline network by combining DEMATEL, ISM and BN methods. J. Loss Prev. Process. Ind. 61, 49–57.

Li, J., Zhang, H., Han, Y., Wang, B., 2016. Study on failure of external activities for urban gas pipeline based on fuzzy comprehensive evaluation. PloS One 11 (11).

Li, X., Han, Z., Zhang, R., Chang, D., 2020. An integrated methodology to manage risk factors of aging urban oil and gas pipelines. J. Loss Prev. Process. Ind. 66, 104154.

Li, X., Chen, G., Jiang, S., He, R., Xu, C., Zhu, H., 2018. Developing a dynamic model for risk analysis under uncertainty: case of external activities on subsea pipelines. J. Loss Prev. Process. Ind. 54, 289–302.

Liang, W., Hu, J., Zhang, L., Guo, C., Lin, W., 2012. Assessing and classifying risk of pipeline third-party interference based on fault tree and SOM. Eng. Appl. Artif. Intell. 25 (3), 594–608.

Mao, X., Hao, Y., Xing, Z., Yan, X., 2014. Simulation of dynamic leakage and diffusion characteristics of urban gas pipelines, 0 Oil Gas Storage Transp. 33 (4), 374–379.

Ma, L., Cheng, L., Li, M., 2013. Quantitative risk analysis of urban natural gas pipeline networks using geographical information systems. J. Loss Prev. Process. Ind. 26 (6), 1183–1192.

Onisawa, T., 1990. An application of fuzzy concepts to modelling of reliability analysis. Fuzzy Set Syst. 37 (3), 267–286.

Wang, W., Shen, K., Wang, B., Dong, C., Khan, F., Wang, Q., 2017. Failure probability analysis of the urban buried gas pipelines using Bayesian networks. Process Saf. Environ. Protect. 111, 678–686.

Xing, J., Meng, H., Meng, X., 2020. An urban pipeline accident model based on system engineering and game theory. J. Loss Prev. Process. Ind., 104062

You, Q., Zhu, W., Zhao, K., 2014. Vulnerability analysis of external threats for urban gas pipeline network system, 0 Oil Gas Storage Transp. 33 (9), 950–955.

Yang, M., Khan, F., Lye, L., Amyotte, P., 2015. Risk assessment of rare events. Process Saf. Environ. Protect. 98, 102–108.

Yazdi, M., Kabir, S., 2017. A fuzzy Bayesian network approach for risk analysis in process industries. Process Saf. Environ. Protect. 111, 507–519.

Yu, H., Khan, F., Veitch, B., 2017. A flexible hierarchical Bayesian modeling technique for risk analysis of major accidents. Risk Anal. 37 (9), 1668–1682.