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A risk assessment model of a sewer pipeline in an underground utility tunnel based on a Bayesian network

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ABSTRACT

A utility tunnel typically houses various types of urban lifelines. As one of the assembled pipelines in a utility tunnel, the sewer pipeline is of great importance for city life. For example, leakage of toxic and combustible gases and a subsequent explosion can result in severe accidents. The potential hazards in the sewer pipeline compartment of a utility tunnel are greatly different from those in traditional directly buried sewer pipelines. In this study, a risk assessment method based on a Bayesian network (BN) and Dempster-Shafer (D-S) Evidence theory was developed to evaluate complicated sewer pipeline accidents in a utility tunnel. First, potential hazards and typical accident scenarios were identified based on case studies of sewer pipeline accidents and evaluated by experts. Then, a BN-based risk assessment framework for the sewer pipeline in a utility tunnel was established. Using the proposed model, BN inferences of sewer pipeline accident scenarios were conducted. Furthermore, sensitivity analysis (SA) was conducted to identify the critical threats of the sewer pipeline in a utility tunnel. The proposed risk assessment framework can help to prevent and mitigate sewer pipeline accidents in utility tunnels.

1. Introduction

With the rapid urbanization of China, underground utility tunnels have been extensively constructed, which are effective for arranging urban lifelines. Chinese utility tunnels normally house various types of pipelines in different compartments, such as gas, sewer, electricity, heat, water and telecommunication (Wang et al, 2018). According to the technical code for urban utility tunnel engineering (Wang, 2015), a feasible prototype of a utility tunnel is presented in Fig. 1. Underground utility tunnels save urban underground space and facilitate the installation, inspection, replacement, and maintenance of urban lifelines (Lee et al, 2018). The sewer pipeline is a significant component of the urban drainage system, which transports wastewater from people's daily life, industries, and rainfall. Like the directly buried sewer pipeline, a large quantity of toxic, hazardous, inflammable, or explosive gases (such as CH_4, H_2S, CO, and SO_2) are produced during the microbial decomposing process. These gases will leak out of the pipeline for various reasons such as corrosion, earthquakes, man-made damage, etc. If the gas leakage develops to a certain concentration limit, once being triggered by a fire source, it may cause combustion and explosion accidents, leading to severe consequences. For example, the sewer pipeline explosion in Guadalajara, Mexico, in 1992, caused 252 fatalities and made 15 thousand people homeless. More than that, except for general consequences such as casualties and economic loss, a prominent problem particularly related to sewer pipelines is the pollution of environment including air, soil and water, which are serious secondary hazards and to be taken into adequate account in this paper.

In the past few decades, many researchers have focused on performing risk assessments of directly buried sewer pipelines. Mark et al. (1998) proposed a method for urban sewer pipeline risk analysis based on numerical modeling and the GIS system, and they discussed the spread rules of underground sewer accidents and treatment techniques for the sewer system. Whitaker et al. (2014) developed a risk assessment model for the combined sewer system and introduced risk mitigation measures by estimating the failure of sewer pipelines. Other methods, such as the conventional Fault Tree and Event Tree, were also used to perform safety assessments of sewer pipeline accidents (He et al., 2011; Guo, 2014). However, these types of methods are static, and the states of the variables implemented in these methods are binary ("Yes" and "No") to model an accident scenario. Considering the limitations of these types of conventional methods, synthetic methods, such as the Artificial Neural Network, Fuzzy System and Analytic

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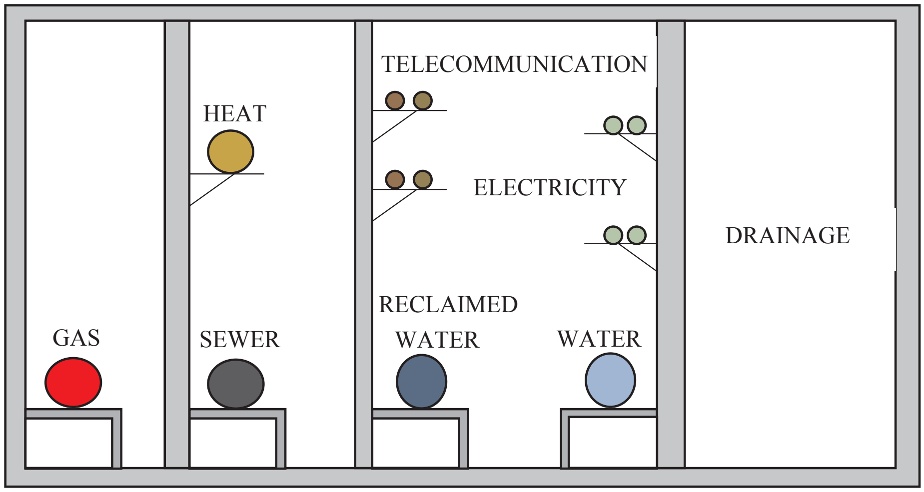

Fig. 1. Profile of a feasible design for a utility tunnel in China.

Hierarchy Process, have been employed (Legrand et al, 2004; Canto-Perello et al., 2013; Stanić et al., 2013; Jiang et al., 2016; Mohammad et al., 2017). These comprehensive methods can set up several levels of accident consequences and make a semi-quantitative decision. During the process of risk analysis, each variable has more than two states, and each state has a corresponding graded score given by experts. In the grading system, a smaller subdivision of grade indicates a more accurate result. However, this situation can make it more difficult for experts to provide a final opinion. One limitation of such types of methods for performing a dynamic risk assessment is the time-consuming recalculation since all relevant parameters must be recalculated when the model variables change.

For a dynamic risk assessment of complex systems, the Bayesian network (BN) has significant advantages (Trucco et al., 2008). First, the Bayesian network is appropriate for representing a large variety of uncertain scenarios because multi-state BN nodes can be established. Second, the Bayesian network takes advantage of conditional probabilities to represent causal relationships, which are subject to continuous distributions instead of discrete figures. Moreover, the Bayesian network is flexible in updating the probability with newly provided evidence. Based on case-specific data and updating mechanisms, it is permissible to update the probabilities of the BN nodes, which are initially obtained from generic data during the design phase of the target system. Thus, the Bayesian network can make a prediction and diagnosis and has proven to be effective in various areas (Khakzad et al., 2012; Sousa and Einstein, 2012 Kabir et al., 2016; Wang and Chen, 2017; Beaudequin et al., 2017; Gan et al., 2017, Wu et al., 2018). However, research on BN-based risk analysis of the sewer pipeline in utility tunnels is scarce. In addition, the potential hazards in the sewer pipeline compartment of a utility tunnel are different from those of a conventional directly buried sewer pipeline.

In this study, based on case studies of sewer pipeline accidents and expert experiences, a BN-based risk assessment framework for the sewer pipeline in a utility tunnel is proposed. The conditional probabilities of the Bayesian nodes are collected based on expert experience with treatment by the Dempster-Shafer (D-S) evidence theory. Using the proposed framework, the evolution process of a sewer pipeline accident from its causes to consequences can be explicitly presented, and the critical threats of a sewer pipeline accident in a utility tunnel can be identified based on sensitivity analysis (SA). The proposed risk assessment framework can help to prevent and mitigate sewer pipeline accidents in utility tunnels.

2. Methodology

2.1. Bayesian network

The Bayesian network (BN) is a Directed Acyclic Graph (DAG) that includes two types of nodes (parent nodes and child nodes), directed links (relationship) between parent and child nodes, and conditional probability tables (CPTs) of each node to represent dependencies (Li et al, 2017). The Bayesian network has been proven to be an effective quantitative tool for risk analysis and decision making. A basic sample of a Bayesian network is illustrated in Fig. 2, where X_1 and X_2 are defined as the root nodes or "parent" nodes, respectively, and X denotes an intermediate node or "child" node. The directed links between the nodes indicate the corresponding causalities, and the CPTs of each node are presented.

The Bayesian network works based on Bayesian theory, in which conditional probability plays a key role. Probability in a Bayesian network is updated using the following basic equation.

$$p(A|B) = \frac{p(B|A)p(A)}{p(B)} \tag{1}$$

Eq. (1) represents the basic principle of Bayesian theory, where $p(A)$ and $p(B)$ are the probabilities of events A and B, respectively; $p(B|A)$ is the probability of B when A occurs; and$p(A|B)$ is the probability of A when B occurs. The great advantage of the Bayesian network is its ability to update data. The posterior probability of an event can be calculated by updating the prior probability with new evidence:

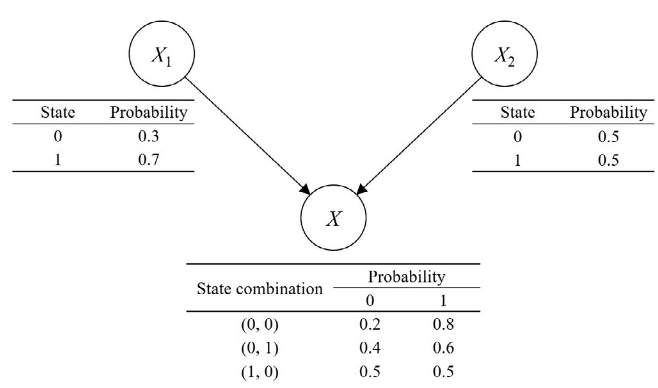

Fig. 2. Basic sample of a Bayesian network.

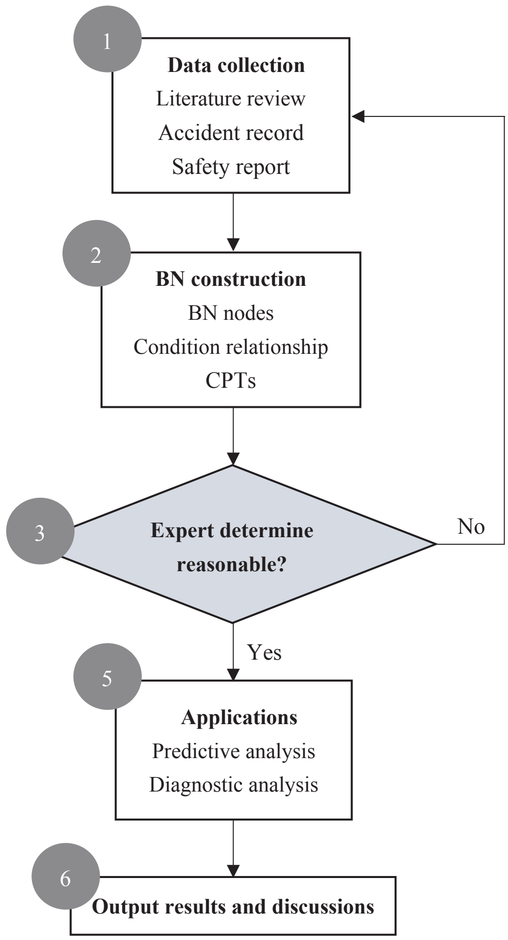

Fig. 3. Process of Bayesian analysis.

$$p(A|e) = \frac{p(e|A)p(A)}{p(e)} = \frac{p(e|A)p(A)}{\sum_{i=1}^{m} p(e|Ai)p(Ai)} \quad (2)$$

where $p(A)$ is the prior probability of event A, $p(A|e)$ is the posterior probability under given evidence E, $p(e|A)$ is defined as the likelihood of the evidence under event A, and $\sum_{i=1}^{m} p(e|Ai)p(Ai)$ is the joint probability distribution of the evidence E. The main process of Bayesian analysis is illustrated in Fig. 3.

2.2. Dempster-Shafer evidence theory

The Dempster-Shafer evidence theory was introduced by Dempster and later extended by Shafer (Dempster, 1967; Shafer, 1976); before long, it was brought into the field of artificial intelligence (Barnett, 1981). This method is concerned with the question of the belief in a proposition and systems of propositions (Basir and Yuan, 2007), being of great use for multi-source information fusion and applied to a very large class of situations of data collection, including expert systems (Basir and Yuan, 2007; Sun et al, 2008; Tian and Yang, 2014). Just like in this study, adopting the D-S evidence theory can help to determine conditional probabilities, which are required by the BN method and must be extracted from collecting different experts' knowledge. The basic principle of the D-S evidence theory is as follows:

(a) Θ is the frame of discernment, which is a finite set of mutually exclusive elements for a particular proposition. By defining the mass function m as the mapping from the power set 2^{Θ} to a number between 0 and 1, we obtain $m(\mathrm{A})$ as the mass function of object A and the Basic Probability Assignment (BPA) of the D-S evidence theory, which must satisfy the following conditions:

$$\begin{cases} m(\phi) = 0 \\ \sum_{\mathrm{A}\subseteq\Theta} m(\mathrm{A}) = 1 \end{cases} \quad (3)$$

(b) Dempster's combinational rule for multiple evidence is calculated with Equations (4) and (5):

$$m(\mathrm{A}) = \begin{cases} \frac{\sum_{\cap \mathrm{A}_i=\mathrm{A}} \prod_{1\leqslant i\leqslant N} m_i(\mathrm{A}_i)}{1-K}, & \mathrm{A}\neq\phi \\ 0, & \mathrm{A}=\phi \end{cases} \quad (4)$$

$$K = 1 - \sum_{\cap \mathrm{A}_i\neq\phi} \prod_{1\leqslant i\leqslant N} m_i(\mathrm{A}_i) \quad (5)$$

At the same frame Θ of discernment, A is any event to be estimated and $m_i(\mathrm{A}_i)$ is the BPA for a series of evidence to be combined. Thus, $\sum_{\cap \mathrm{A}_i\neq\phi} \prod_{1\leqslant i\leqslant N} m_i(\mathrm{A}_i)$ is the conflict degree of evidence and K is defined to be the normalization factor.

When using the D-S method, the collected data from experts should be firstly evaluated according to the Cronbach's coefficient alpha (α) (Cronbach, 1951), which refers to the statistical consistency and reliability. The value of alpha ranges from 0 to 1 and the higher, the more reliable (Santos, 1999). It has been indicated that 0.7 is a threshold value of acceptable reliability (Nunnaly, 1978). Also, it is generally thought to be acceptable while $\alpha > 0.8$ for fundamental researches and $\alpha > 0.6$ for practical researches. The Cronbach's coefficient Alpha can be calculated as follows:

$$\alpha = \frac{K}{K-1}\left(1 - \frac{\sum_{i=1}^{K} \sigma_Y^2}{\sigma_X^2}\right) \quad (6)$$

3. Bayesian network development

3.1. BN nodes and relationships

In this study, the BN was learned from typical sewer pipeline accidents and further evaluations made by professional experts. One of the accidents was happened at 2014 in Wuhan Province, China (Zhang et al., 2015); and one of the experts participated in the accident investigation. According to the investigation conclusion, this accident might have originated from the anticorrosion coating's spalling; and then the corrosion of the sewer pipeline, with the addition of the influences of external construction and geological condition, caused a puncture occurring on the pipe wall and gradually developing into a rupture, while the gas kept leaking out into the confined space of the compartment. After a period of time, the accumulation of gas reached the explosive limit and unfortunately it came in contact with an open flame; as a result, an explosion accident happened and caused two deaths and serious road damage. Through many case studies like this, the codes and causal relationships between them were obtained. The detailed description of each node is as follows.

(a) Coating spalling. Coating is an effective measure to protect the inner surface of sewer pipelines from corrosion. Different anticorrosion coatings are required for different sewer pipelines. Epoxy polyurethane and melting epoxy powder are commonly used anticorrosive materials in China (Yang et al, 2013). The serious state of coating spalling can cause serious internal corrosion of sewer pipes.
(b) Inhibitor failure. A corrosion inhibitor can help to protect the inner surface of sewer pipelines.
(c) External interference. External interferences such as overload and

industrial constructions may directly damage utility tunnels and sewer pipelines. In particular, an overload can be due to the constant pressure imposed by aboveground constructions or the instant pressure due to heavy traffic moving over the utility tunnel.

(d) Earthquake. Generally, utility tunnels should reach the seismic design of a category-II structure (levels 5 ~ 6). This node represents the probability of earthquakes over level 6 in urban areas.

(e) Unreasonable design. Design flaws in small underground spaces may eventually cause serious accidents.

(f) Incorrect manipulation. This node represents human errors, which consist of bad welding, bad installation by unprofessional operators, and mechanical damage during the process of transportation, installation and maintenance.

(g) Fire source. It is difficult to avoid fire during the welding process or in other situations, such as electric spark, electrostatic or external arson, in a utility tunnel.

(h) Accident area. Sewer pipelines are extensively installed under residential areas, commercial areas and office areas. A serious accident in these areas will cause serious casualties and economic loss and have a social impact.

(i) Occurrence time. The effect of the time of an accident can be significant. If an accident occurs at night (rest time), it will not directly cause large casualties around the sewer pipeline. In daytime (working time), the consequences of an accident will be more complex and serious.

(j) Internal corrosion. Coating spalling and inhibitor failure may cause internal corrosion, sewer pipe leakage and other secondary accidents.

(k) Defect of the sewer pipeline. This node describes the damaged condition of sewer pipelines. The “slight” state implies a punctured pipeline, and the “serious” state indicates a rupture.

(l) Geological hazard. Geological hazards such as subsides and landslides might damage the sewer pipeline in a utility tunnel. Actually, the probabilities of most geological hazards will increase with the occurrence of an earthquake.

(m) Puncture. This node indicates that the damage condition of a sewer pipeline is slight and that there is only a small amount of sewage and hazardous gas leak.

(n) Rupture. This node represents serious damage to the sewer pipeline, which causes a large amount of sewage and hazardous gas to leak into the utility tunnel. As a result, the entire sewer system and utility tunnel will break down.

(o) Hazardous gas leakage. As mentioned, there are several types of hazardous gases in the sewer pipeline. The state of this node is classified according to the dangerous levels of CH_4, H_2S, and CO. As soon as one of the three gases reaches its dangerous concentration level, the corresponding state is recognized. CH_4 is most likely to cause a fire or an explosion due to the CH_4 concentration in the sewer pipeline. Therefore, this node only considers the explosive limit of CH_4, while the other two gases are only considered in terms of their poison limit. Hence, the slight state is $C(CH_4)$ less than 5%, $C(H_2S)$ less than 70 mg/m^3 or C(CO) less than 200 ppm; the moderate state is when $C(CH_4)$ is close to 5% and 15%, $C(H_2S)$ is 70–760 mg/m^3, or C(CO) is 200–1300 ppm; and the serious state is $C(CH_4)$ of 5–15% or $C(H_2S) > 760$ mg/m^3 or $C(CO) > 1300$ ppm (Fan and Ding, 2016; An et al., 2006; Wang, 2011).

(p) Damage of the utility tunnel. This node represents the damage caused by a sewer pipeline explosion and the pollution due to sewage leakage.

(q) Fire/Explosion. This node describes a secondary accident due to hazardous gas leakage. In specific scenarios of a fire/explosion, the released energy may cause large fatalities and economic loss. The slight state represents heat radiation in a fire scenario of less than 5.0 KW/min or overpressure in an explosion scenario of less than 3.5 psi according to the individual data from the Environmental Protection Agency (EPA) and National Oceanic and Atmospheric Administration (NOAA).

(r) Economic loss. This node measures the consequences of sewer pipeline accidents. The classifications are based on the Production Safety Accident Report, the Investigations and Handling Rules, China. The light state is less than 50 million, the moderate state is 50–100 million, and the serious state is > 100 million.

(s) Casualties. This node is another important measurement of the consequences of sewer pipeline accidents. According to the Production Safety Accident Report, Investigations and Handling Rules, China, casualties can be graded into three states. The light state represents fewer than 10 deaths or fewer than 50 injuries, the moderate state represents 11–30 deaths or 51–100 injuries, and the serious one represents > 30 deaths or > 100 injuries.

(t) Pollution. Sewage flow in a utility tunnel may result in high concentrations of toxic pollutants and bacteria in the compartment. Additionally, the decomposition of degradable organic components by microorganism may cause an oxygen deficit in the utility tunnel (Holeton et al., 2011; Madoux-Humery et al., 2013; Brzezińska et al., 2016).

After determining the variables and dependencies of the nodes, the basic structure of the Bayesian network for the sewer pipeline in a utility tunnel is established, as presented in Fig. 4, where the textboxes of parent nodes are filled with grey color to be distinguished from those transparent ones representing child nodes; and the classified states of every BN node are listed in Table 1.

3.2. Conditional probability tables

Conditional probability tables (CPTs) are essential to perform a quantitative risk assessment of a sewer pipeline accident. However, the records of such accidents in a utility tunnel are rare. In this situation, the Dempster-Shafer evidence theory can be used to determine the CPTs by combining expert experience and knowledge. The Dempster-Shafer evidence theory is effective for performing an accident analysis (Hegarat-Mascle et al., 1997; Tesfamariam et al., 2010; Nordgard and Sand, 2010; Zhao et al., 2012). In this study, the prior probabilities of the parent nodes were estimated referring to related accident records and incomplete statistics, as listed in Table 2. The probability distribution (0.40, 0.40, 0.20) of the node “External Interference” implies that external interferences can occur in an urban area with a probability of up to 80% in two ways: overloads and industrial constructions.

For the child nodes, their CPTs were determined by five experts using questionnaires with the treatment of the Dempster-Shafer evidence theory. Taking the determination of the CPTs of the child node “Internal Corrosion” for example, the probability distribution of “Internal Corrosion” depends on its parent nodes “Coating Spalling” and “Inhibitor Failure”; and from the expertise questionnaires, the five experts provided their judgement in Table 3. Symbols m_1 (1, 2) to m_5 (1, 2) are the probability distributions given by the five experts, where the pair of digits within parentheses (1, 2) indicate the states of (Yes, No) respectively, corresponding to the labeled states listed in Table 1. In the first line where the combined conditions are “Coating Spalling: Yes” and “Inhibitor Failure: Yes”, $m_1(1,2) = (0.71, 0.29)$ means that the first expert believed that the “Internal Corrosion” will happen with a probability of 71% (not happen with 29%) if both the “Coating Spalling” and “Inhibitor Failure” happen. The treatment of the collected data from the five experts by the D-S method based on Eqs. (4) and (5) yields the experts’ elicitation in the last column, “Calculated results”. Here Eq. (6) was adopted to calculate the Cronbach’s coefficient and we obtained $\alpha = 0.804$, satisfying the statistical consistency and reliability. Utilizing the conditional probabilities listed in Table 3 and the prior probabilities listed in Table 2, the probability distribution of the child code can be calculated by the Bayesian formula. The calculation of the probability of “Yes” for “Internal Corrosion” is demonstrated as

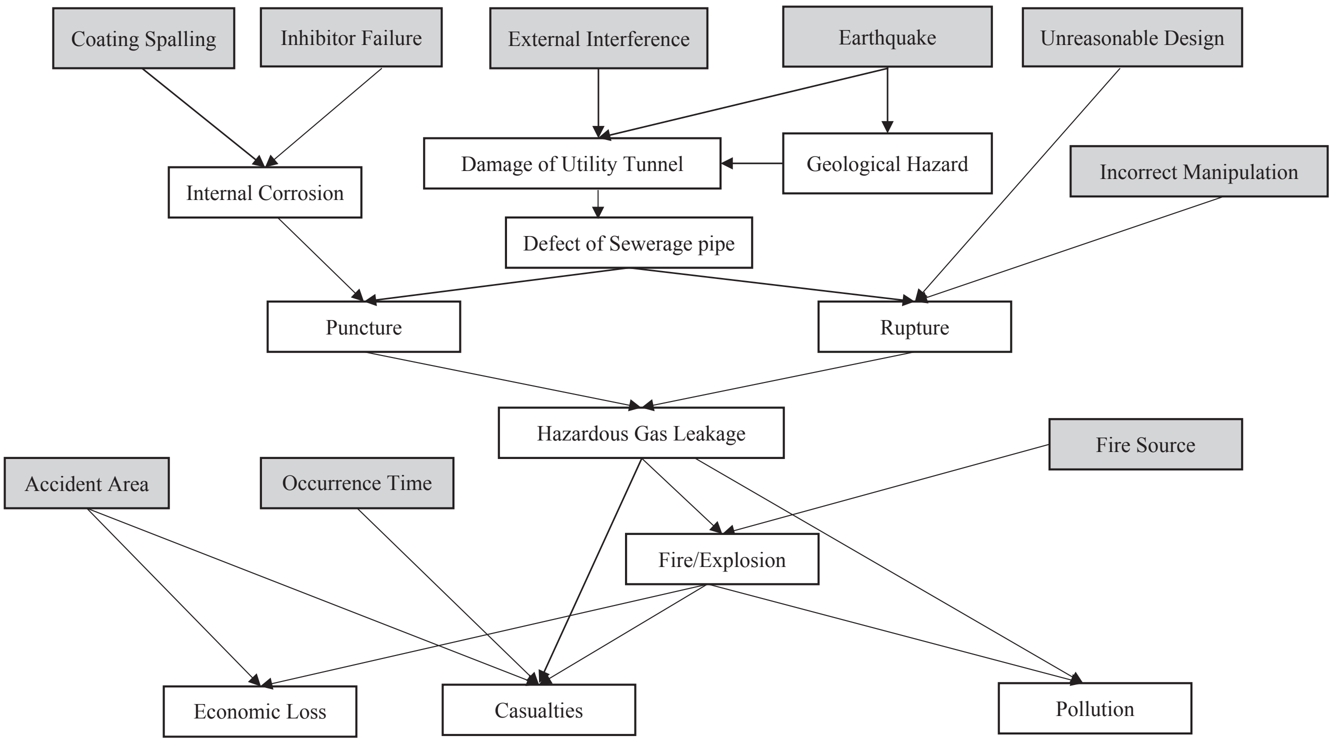

Fig. 4. Initial Bayesian network of a sewer pipeline accident.

Table 1
. Classified states of sewer pipe accident Bayesian network nodes.

Bayesian nodes	States of nodes
Coating Spalling	①Yes ②No
Inhibitor Failure	①Yes ②No
External Interference	①Overload ②Industrial Construction ③None
Earthquake	①Yes ②No
Unreasonable Design	①Yes ②No
Incorrect Manipulation	①Bad Weld ②Bad Installation ③Mechanical Damage ④None
Fire Source	①Yes ②No
Accident Area	①Business District ②Remote Area
Occurrence Time	①Working Time ②Rest Time
Internal Corrosion	①Yes ②No
Defect of Sewer Pipe	①Slight ②Serious
Geological Hazard	Subside ② Landslides ③None
Puncture	①Yes ②No
Rupture	①Yes ②No
Hazardous Gas Leakage	①Slight ②Moderate ③Serious
Damage of Utility Tunnels	①Slight ②Moderate ③Serious
Fire / Explosion	①Slight ②Serious
Economic Loss	①Slight ②Moderate ③Serious
Casualties	①Slight ②Moderate ③Serious
Pollution	①Slight ②Moderate ③Serious

Table 2
. Prior probabilities of the parent nodes.

Bayesian nodes	State of Bayesian nodes	Probability of node state
Coating Spalling	①Yes	0.50
	②No	0.50
Inhibitor Failure	①Yes	0.35
	②No	0.65
External Interference	①Overload	0.40
	②Industrial Construction	0.40
	③None	0.20
Earthquake	①Yes	0.01
	②No	0.99
Unreasonable Design	①Yes	0.30
	②No	0.70
Incorrect Manipulation	①Bad Weld	0.15
	②Bad Installation	0.15
	③Mechanical Damage	0.15
	④None	0.55
Fire source	①Yes	0.25
	②No	0.75
Accident Area	①Business District	0.50
	②Remote Area	0.50
Occurrence Time	①Working Time	0.50
	②Rest Time	0.50

below:

$$
\begin{aligned}
&P(\text{C:Yes}) \\
&= P(\text{C:Yes }|\text{A:Yes,B:Yes})P(\text{A:Yes})P(\text{B:Yes}) + P(\text{C:Yes }|\text{A:Yes,B:No})P(\text{A:Yes})P(\text{B:No}) \\
&+ P(\text{C:Yes }|\text{A:No,B:Yes})P(\text{A:No})P(\text{B:Yes}) + P(\text{C:Yes }|\text{A:No,B:No})P(\text{A:No})P(\text{B:No}) \\
&= 0.9\times 0.5\times 0.35 + 0.75\times 0.5\times 0.65 + 0.4\times 0.5\times 0.35 + 0.12\times 0.5\times 0.65 \\
&= 0.51025
\end{aligned}
\tag{7}
$$

where A and B indicate the parent nodes “Coating Spalling” and “Inhibitor Failure” respectively, C indicates the child node “Internal Corrosion”.

Based on the aforementioned procedure of expert elicitation with the D-S method, the CPTs of all the Bayesian nodes can be determined; thus, the complete Bayesian network of sewer pipeline accidents in a utility tunnel is established (see Fig. 5). In this study, BN probability inference and sensitivity analysis is conducted using Netica (Netica 4.16, Norsys Software Corp, Vancouver, BC, CANADA), which has been widely used in Bayesian network analysis.

4. Results and discussion

This section presents an accident scenario analysis and critical-

Table 3
. Conditional probability distribution calculation of the node "Internal Corrosion"

BN nodes		Experts' opinions					Calculated results
Coating Spalling	Inhibitor Failure	$m_1(1,2)$	$m_2(1,2)$	$m_3(1,2)$	$m_4(1,2)$	$m_5(1,2)$	$m(1,2)$
Yes	Yes	(0.71,0.29)	(0.69,0.31)	(0.60,0.40)	(0.55,0.45)	(0.48,0.52)	(0.90,0.10)
Yes	No	(0.54,0.46)	(0.56,0.44)	(0.59,0.41)	(0.57,0.43)	(0.51,0.49)	(0.75,0.25)
No	Yes	(0.43,0.57)	(0.39,0.61)	(0.59,0.41)	(0.48,0.52)	(0.51,0.49)	(0.40,0.60)
No	No	(0.33,0.67)	(0.37,0.63)	(0.33,0.67)	(0.48,0.52)	(0.51,0.49)	(0.12,0.88)

threat identification based on the established BN. The accident scenario analysis focuses on the effect of "Fire Source", "Earthquake", "Incorrect Manipulation" and "External Interference" by changing their states when the states of other nodes are set (Table 4). The critical threats of sewer pipeline accidents are identified by the sensitivity analysis method, and the sensitivity values of the parent nodes are calculated.

4.1. Accident scenario analysis

4.1.1. Scenario 1: Effect of the fire source

Based on the proposed framework, the inference results of a typical accident scenario without a fire source or with a fire occurring in a business area during work hours are illustrated in Table 5. The results show that the fire source greatly affects all the consequence codes, including "Casualties", "Economic Loss" and "Pollution". For example, for the code "Casualties", as shown in Fig. 6, the probability of the serious state is 17.30% without a fire source and increases to 27.70% when a fire occurs. Accordingly, the probabilities of both the moderate and slight states decrease, implying an obvious tendency of accident severity. Note that the largest relative growth of severity appears at the node "Pollution", more than doubled probability of "Serious" (14.8% to 6.38%), particularly due to the sewer pipeline's functional characteristics. Such a phenomenon occurs because the fire sources are the direct event triggers for fire and explosion disasters, which can easily cause serious damage, even when all the concerned parent nodes, which are the majority of the cause of hazardous gas leakage, are set to "No" or "None" to minimize the probability of gas leakage. Therefore, it is important to avoid fire sources in the sewer pipeline compartment of a utility tunnel in any case, and if possible, more fire-proof measures should be arranged.

Table 4
. Typical sewer pipeline accident scenarios.

	Scenario 1	Scenario 2	Scenario 3	Scenario 4
Coating Spalling	No	No	No	No
Inhibitor Failure	No	No	No	No
External Interference	No	No	No	①Overload ②Industrial Construction ③None
Earthquake	No	①Yes ②No	No	No
Unreasonable Design	No	No	No	No
Incorrect Manipulation	No	None	①Bad Weld ②Bad Installation ③Mechanical Damage ④None	No
Accident Area	Business Districts	Business Districts	Business Districts	Business Districts
Occurrence Time	Working Time	Working Time	Working Time	Working Time
Fire Source	①Yes ②No	Yes	Yes	Yes

4.1.2. Scenario 2: Effect of an earthquake

This accident scenario focuses on the effect of an "Earthquake". Cities are mostly built in areas where the crustal movement is less

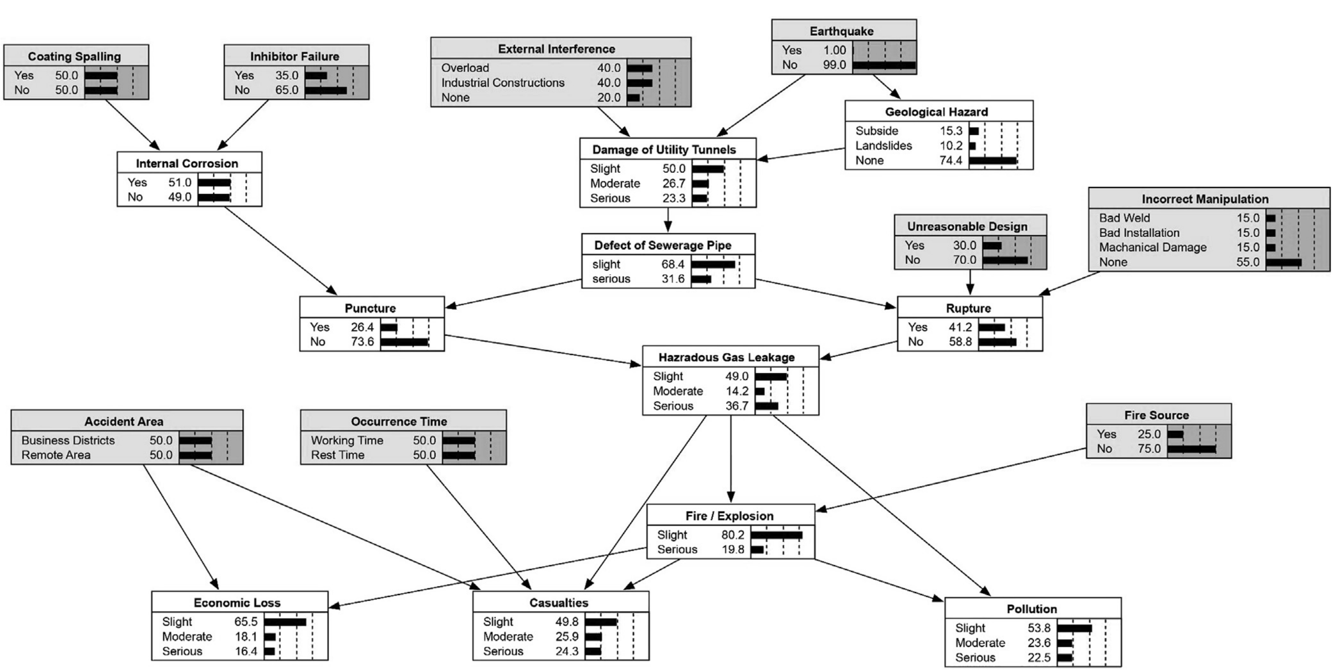

Fig. 5. Bayesian network of a sewer pipeline accident in a utility tunnel.

Table 5
. Probability distribution of Scenario 1.

BN nodes	Probability distribution					
	Slight		Moderate		Serious	
	Yes	No	Yes	No	Yes	No
Economic Loss	41.6%	47.8%	25.2%	28.7%	33.2%	23.5%
Casualties	44.8%	50.6%	27.6%	32.1%	27.7%	17.3%
Pollution	70.0%	76.8%	15.3%	16.9%	14.8%	6.38%

Fig. 6. Accident consequences with and without a fire source.

Table 6
. Probability distribution of Scenario 2.

BN nodes	Probability distribution					
	Slight		Moderate		Serious	
	Yes	No	Yes	No	Yes	No
Economic Loss	37.7%	41.6%	23.0%	25.2%	39.3%	33.2%
Casualties	38.2%	44.8%	23.8%	27.6%	37.9%	27.7%
Pollution	59.6%	70.0%	14.1%	15.2%	26.2%	14.8%

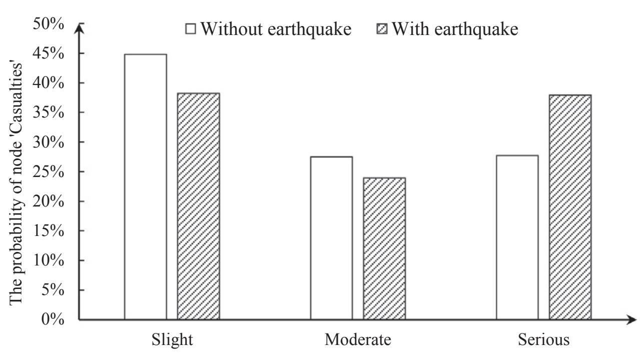

Fig. 7. Accident consequences with and without an earthquake.

active. However, the risk of earthquakes should not be neglected because the impact of an earthquake can be catastrophic, especially to underground facilities such as utility tunnels. In Table 6, we evaluate an accident scenario in which an earthquake occurs in a business area during work hours. The earthquake can cause a sharp increase in the probabilities of subside and landslide. Meanwhile, earthquake-induced fires often occur, so the state of the code “Fire Source” is set to “Yes”. Under the earthquake condition, the consequences are going to be more severe, such as the code “Casualties” illustrated in Fig. 7. And again, the largest relative growth of severity appears at the node “Pollution”, nearly twice as “Serious” (26.2–14.8%). The highly destructive consequences are probably due to the direct seismic damage to the entire structure of utility tunnels and, if unfortunately, secondary fires and

Table 7
. Probability distribution of Scenario 3.

BN nodes	Probability distribution											
	Slight				Moderate				Serious			
	None	Bad Weld	Bad Installation	MechanicalDamage	None	Bad Weld	Bad Installation	MechanicalDamage	None	Bad Weld	Bad Installation	MechanicalDamage
Economic Loss	40.3%	29.7%	32.1%	28.3%	24.5%	18.4%	19.8%	17.6%	35.2%	51.9%	48.1%	54.1%
Casualties	42.6%	24.9%	29.0%	22.5%	26.3%	16.0%	18.4%	14.7%	31.1%	59.1%	52.6%	62.8%
Pollution	66.5%	38.4%	45.0%	34.8%	14.9%	11.2%	12.0%	10.7%	18.6%	50.4%	43.0%	54.5%

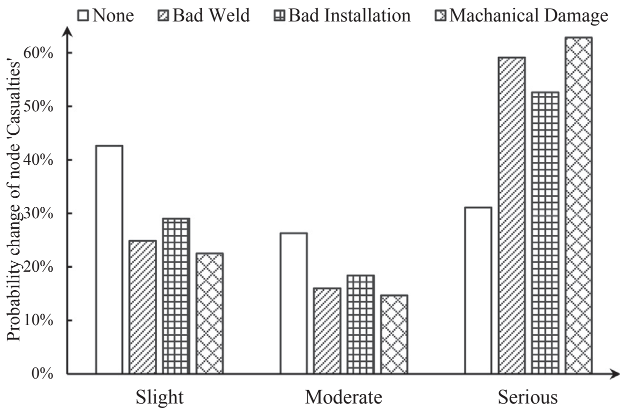

Fig. 8. Results of casualties induced by different types of incorrect manipulations.

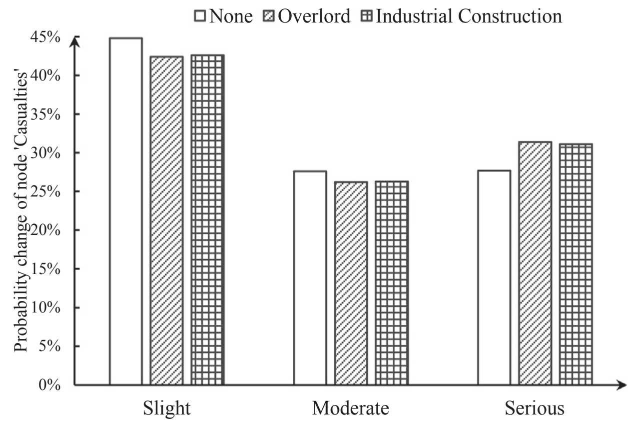

Fig. 9. Accident consequences of none, overload, and industrial constructions.

explosions occurring at the increasing level of "Hazardous Gas Leakage" caused by the seismic damage. Therefore, the optimization of the structure design of utility tunnels should receive more consideration to enhance their resistance and resilience to earthquakes. More effective preventive measures and emergency response plans are also essential to mitigate the damage from earthquakes.

4.1.3. Scenario 3: Effect of an incorrect manipulation

This accident scenario is presented to estimate the effect of human factors, such as "Bad Weld", "Bad Installation" or "Mechanical Damage", on the consequences of sewer pipeline accidents. The inference results are illustrated in Table 7. The probability of the serious state under incorrect manipulations dramatically increases compared to the result of "None" for an incorrect manipulation, just like the code "Casualties" illustrated in Fig. 8, implying the significant impact of incorrect manipulations on the sewer pipeline in a utility tunnel. "Mechanical Damage" is the most influential factor among the concerned types. The probability of serious casualties (the state "Serious" for the node "Casualties") under "Mechanical Damage" appears as high as twice the result of "None" (62.8–31.1%), and even three times (54.5–18.6%) for serious pollution (the state "Serious" for the node "Pollution"). According to this scenario analysis, safety training of workers is essential for the operation of the sewer pipeline in a utility tunnel.

4.1.4. Scenario 4: Effect of external interference

Ground transportation and over/under-ground constructions may directly affect the utility tunnel structure. The BN inference results for this type of accident scenarios are illustrated in Table 8. Generally, the estimated probabilities of all the consequences caused by "Overload" are basically equal to those caused by "Industrial Constructions". The result is believable because these two types of external interferences have similar disaster-causing mechanisms, in which the concrete walls of the utility tunnel are damaged and then make the sewer pipeline break down. Perhaps for the reason that "Overload" and "Industrial Constructions" don't have a direct impact on the pipelines under the protection of the utility tunnel structure, only slightly increase the probabilities of serious consequences compared with "None" for external interference, as visually displayed in Fig. 9. It implies that "External Interference" appears to not have as significant an impact as those in the previous three scenarios, where the fire source, earthquake or incorrect manipulation are internal or overall factors and thus have destructive effect directly on the pipelines. Nonetheless, more attention should be paid to the location of utility tunnels, so that they are not too close to existing or planned urban roads and buildings.

4.2. Critical threats identification

According to the above scenario analysis, there are different causes of sewer pipeline accidents in utility tunnels with different effects. The impacts of fire source, earthquake and incorrect manipulation appear significant, whereas that of external interference is not. Thus, there may be critical threats, which should be identified and be given priority for treatment.

Sensitivity analysis (SA) is an effective method for identifying the critical threats of an accident based on the BN model (Matellini et al, 2013). Furthermore, the rank of the sensitivity values can verify the reasonability of the relationships among the BN nodes. The sensitivity value can be calculated using the following equation:

$$D\,(SA) = \frac{P\text{result change}}{\text{Pchange}} \tag{8}$$

where $D\,(SA)$ is the sensitivity value of an input node and Presult change and Pchange are the probability changes of the serious state in the target consequence node. We used the node "Casualties" as the target node.

The variance of the probability of the parent nodes is displayed in Fig. 10, and the sensitivity values are listed in Table 9. According to the quantitative results, "Fire Source", "Accident Area", "Incorrect Manipulation" and "Unreasonable Design" are identified as highly influential factors or critical threats, even not less than "Earthquake" that is generally regarded as a very big threat. Correspondingly, fire prohibition

Table 8
. Probability distribution of Scenario 4.

BN nodes	Probability distribution								
	Slight			Moderate			Serious		
	None	Overload	Industrial Constructions	None	Overload	Industrial Constructions	None	Overload	Industrial Constructions
Economic Loss	41.6%	40.1%	40.3%	25.2%	24.4%	24.5%	33.2%	35.5%	35.2%
Casualties	44.8%	42.4%	42.6%	27.6%	26.2%	26.3%	27.6%	31.4%	31.1%
Pollution	70.0%	66.1%	66.5%	15.3%	14.9%	31.1%	14.7%	19.0%	18.6%

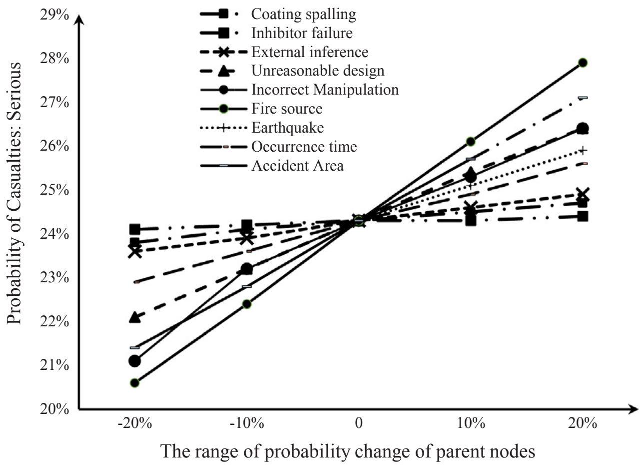

Fig. 10. Sensitivity analysis of "Casualties"

Table 9
. Sensitivity value of "Casualties"

Input node	Sensitivity value
Fire Source	0.1825
Accident Area	0.1425
Incorrect Manipulation	0.1325
Unreasonable Design	0.1075
Earthquake	0.0800
Occurrence Time	0.0675
External Interference	0.0325
Coating Spalling	0.0225
Inhibitor Failure	0.0075

and protection, appropriate site selection, normative operation and training, reasonable design and, especially, inherent safety design should be critical concerns in utility tunnel construction and operation.

5. Conclusion

In this study, a flexible risk assessment method was proposed for sewer pipelines, taking advantage of a Bayesian Network combined with the D-S evidence theory. The Bayesian Network was established to display the complex disaster-causing mechanism of sewer pipeline accidents in utility tunnels; and the D-S evidence theory was adopted to process different experts' knowledge. Bayesian inferences were carried out to estimate the probability distribution of consequences with different severity levels, under four typical accident scenarios; and the major findings were presented as follows:

"Fire source" is one of the most common causes of triggering combustion and explosion, which usually leads to serious consequences. Then taking "Earthquake" as a representative of natural hazards and "Incorrect manipulation" as a representative of human-made hazards, both of them can significantly increase the severity of the consequences. By contrast, the effect of "External interference" doesn't appear to be so serious, implying that the utility tunnel structure is able to protect the pipelines from direct destruction by some external interference. It is worth noting that "Pollution" shows up as a particular and prominent consequence of sewer pipeline accidents, in which the node "Hazardous Gas Leakage" plays a big part. Finally, by the means of sensitivity analysis, "Fire Source", "Accident Area", "Incorrect Manipulation" and "Unreasonable Design" are identified as critical threats and need to be paid high attention for proper treatment.

From the view of methodology, we've found that the BN-based framework is really an effective method of dynamic scenario inference for complex hazards and disasters. The significant benefits of expansibility, flexibility and the capability of fast calculation make it applicable to dynamic risk assessment, emergency planning and rapid decision making. In this paper, we focused on establishing and demonstrating this analytical approach though the results were influenced to some extent by subjectivity from experts' opinions, which can be improved in future with accumulation of practical data being produced during the actual operation of utility tunnels.

CRediT authorship contribution statement

Rui Zhou: Conceptualization, Methodology, Validation, Formal analysis, Writing - review & editing, Supervision, Project administration, Funding acquisition. **Weipeng Fang:** Formal analysis, Investigation, Writing - original draft, Visualization. **Jiansong Wu:** Conceptualization, Methodology, Resources, Data curation, Writing - review & 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.

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Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tust.2020.103473.

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