Safety Assurance of Existing Pipelines in Tunneling Construction

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ABSTRACT
A novel decision support approach based on fuzzy Bayesian networks (FBN) is developed for safety risk analysis in this paper with detailed step-by-step procedures, including risk mechanism analysis, FBN model establishment, fuzzification and defuzzification, and fuzzy Bayesian inference. A conceptual causal framework is proposed to investigate the causal relationships between tunnel-induced pipeline damage and its influential variables on a basis of failure mechanism analysis. The probability inference model is then built by combining the conceptual causal framework with FBN to implement fuzzy Bayesian inference. The approach proposed in this paper is capable of calculating the probability distribution of potential safety risks and identifying the most likely potential causes of accidents under both prior knowledge and given evidence circumstances. A case concerning the safety analysis of the underground buried pipelines adjacent to the construction of Wuhan Yangtze River Tunnel is presented. The results demonstrate the feasibility of the proposed FBN approach and its application potential. The proposed approach can be used as a decision tool to provide support for safety assurance and management in tunnel construction, and thus increase the likelihood of a successful project in a complex project environment.

INTRODUCTION
Due to an increase in urbanization all over the world, tunneling has become a preferred construction method for subway transportation and underground utility systems. The exploitation of urban underground space presents several geotechnical engineering problems, one of which is the effect of tunnel construction on existing pipelines (Zhang & Huang, 2012). Urban underground areas are congested with underground municipal pipelines that support gas transmission, water supply, electric power, and telecommunications. Many pipelines are too brittle to sustain deformations in addition to those caused by aging and corrosion over the term of their service. The excavation of a new tunnel generates ground movement around nearby pipelines, which may deform or damage pipelines. Tunneling-induced pipeline deformation may disrupt the conveyance of important services and resources, and thus threaten the safety and security of urban inhabitants (Wang, Shi, & Ng, 2011). Therefore, it is necessary to investigate the complicated causal relationship and risk mechanism of tunnel-induced pipeline damage, providing support for safety assurance of pipelines at different risk levels.

A Bayesian network (BN) is a powerful tool for graphically representing the relationships among a set of variables. Unlike rule-based approaches for risk modeling,
e.g., approximate reasoning approaches, BN is capable of replicating the essential features of plausible reasoning in a consistent, efficient, and mathematically sound way (Pearl, 1988). BN can also describe the dependencies between variables both qualitatively and quantitatively, and is widely applied for risk and reliability analysis in complex environments (Lee, Kim, & Seong, 2008; Yet, et al., 2013). On the other hand, BN is criticized for the utilization of a probability measure to assess uncertainty. Too much precise information (e.g. prior probability and conditional probability of node variables) is required in conventional BN analysis (Lauria & Duchessi, 2006). However, in construction fields, it is difficult or nearly impossible to obtain precise information due to insufficient data and incomplete knowledge (Mentes & Helvacioglu, 2011). Hanss (1999) indicated that fuzzy set theory (FST) provides a successful tool to solve engineering problems under uncertainty. The uncertainty can then be taken into account in terms of intervals or fuzzy numbers (Horcik, 2008). However, the main limitation of fuzzy reasoning approaches is the lack of ability to conduct inference inversely. Feed-forward-like approximate reasoning approaches are strictly one way: that is, when a model is given a set of inputs, it can predict the output, but not vice versa (Ren, Jenkinson, Wang, Xu, & Yang, 2009). This may have limitations on the flexibility of a safety analysis and assessment method that focuses on exploring causal relationships among risk factors. Thus, it is certainly quite appropriate to investigate the amalgamation of FST and BN, which may well prove to provide an indispensable means to facilitate a probabilistic risk analysis under uncertainty (Eleye-Datubo, Wall, & Wang, 2008). This paper therefore investigates the possibility of merging BN and FST to provide an alternative way to conduct the causal analysis of pipeline safety in a tunneling environment. A novel decision support approach based on fuzzy Bayesian networks (FBN) is developed to provide guidelines for safety assurance of existing pipelines due to tunneling excavation. A case study is presented to analyze the safety performance of the underground buried pipelines adjacent to the construction of Wuhan Yangtze River Tunnel. The results demonstrate the feasibility of the proposed FBN approach and its application potential.

A FBN-BASED DECISION SUPPORT APPROACH

Aiming to improve the effectiveness and accuracy of safety assurance in complex project environments, a decision support analysis approach based on FBN is developed to investigate how the risks and risk factors interact with each other. In the proposed approach, the following five steps are adopted.

Step 1: FBN construction

The design of a BN model involves determining the network structure and its parameters. Structure learning involves figuring out a proper DAG, confirming the association relationship between variables (nodes) (Sierra, Lazkano, Jauregi, & Irigoien, 2009). The network structure can be developed by creating directed edges from one node (fault causes) to another node (its consequence). Indeed, fault trees (FTs) or event trees (ETs), one of the most commonly used techniques for risk and reliability studies, can provide a logic diagram that displays the inter-relationships between a potential critical event and the causes in a system. Bobbio et al. (Bobbio, Portinale, Minichino, & Ciancamerla, 2001) and Khakzad et al. (Khakzad, Khan, & Amyotte, 2011) conducted the detailed transforming rules from a fault tree or event tree (FT/ET) to a network structure. Therefore, the approved FTs/ETs in construction fields can be transferred into a BN model.
structure. Parameter learning aims to determine the conditional probability table (CPT) of each variable (node) under an established network structure (Wong & Guo, 2008).

**Step 2: Fuzzification**

Fuzzification plays a crucial role in fuzzy decision analysis, which attempts to define the basic event data as a fuzzy probability set and uses them in subsequent computation (Ferdous, Khan, Veitch, & Amyotte, 2009). In fuzzy-based probability analysis, the imprecise failure probabilities of basic events are defined by characterizing the basic event with a suitable membership function. It is difficult to have an exact estimation of the failure rate due to a lack of sufficient data. Generally, a group decision making method is therefore employed to define the linguistic terms to assess the fuzzy probability of occurrence of basic events. In this research, seven linguistic terms [Extremely Low (EL), Very Low (VL), Low (L), Medium (M), High (H), Very High (VH), and Extremely High (EH)] are used to assess the probability of occurrence.

To conduct the fuzzy failure probability of each root node of each state, various domain experts are invited to get the assessment results by means of the above seven linguistic terms. Subsequently, the arithmetic mean method is employed to obtain the fuzzy failure probability of the \( i \)th root node of the \( j \)th state, represented by \( P_{ij} \). \( P_{ij} \) can be calculated by Eq. (1). \( k=1,2,...,M \) stands for the judgment result of the fuzzy failure probability of \( P_{ij} \) by the \( k \)th expert. \( M \) stands for the number of the experts involved in the investigation. \( Q_{i} \) stands for the total number of the states of the root node \( X_{i} \).

\[
P_{ij} \cong \frac{P_{ij}^1 + P_{ij}^2 + \cdots + P_{ij}^M}{M} = (a_{ij}, b_{ij}, c_{ij}), \quad i = 1,2,...,n; j = 1,2,...,Q_{i} \tag{1}
\]

**Step 3: FBN inference**

Having obtained the above fuzzy probabilities, the established FBN model can now be used to conduct various types of analysis. Ren et al. (Ren, et al., 2009) indicated that the most important use of FBN is in revising probabilities in light of actual observations of events. It is therefore possible to calculate the probability distribution of potential safety risks and identify the most likely potential causes in the occurrence of accidents. In this paper, we mainly discuss fuzzy Bayesian inference and sensitivity analysis.

(1) Fuzzy Bayesian inference. Fuzzy Bayesian inference aims to capture the probability distribution of the risk event (\( T \)) under a combination of root nodes (\( X_{1}, X_{2}... X_{n} \)) and intermediate nodes (\( Y_{1}, Y_{2},..., Y_{m} \)). The states of each root node and intermediate node can be treated as evidence input into the FBN model. Compared with traditional FTA/ETA, the Bayesian inference of FBN models does not need to get minimal cut sets, increasing greatly the computational efficiency. Probability distribution of \( T \), represented by \( P(T=t) \), can be calculated by Eq. (2). \( P(T=t) \) can serve as an indicator to evaluate the risk of \( T \), helping construction decision makers take proper prevention measures in advance.

\[
P(T=t)\cong \sum_{t_{1},t_{2}...t_{p}} \left\{ P(T=t | X_{1}=x_{1},...,X_{n}=x_{n},Y_{1}=y_{1},...,Y_{m}=y_{m}) \right\} \times \prod_{i=1}^{n} P(X_{i}=x_{i}) \times \prod_{j=1}^{m} P(Y_{j}=y_{j}),
\]

\( i = 1,2,...,n; j = 1,2,...,m \)
Herein, the construction decision makers refer to a group of people who control resources or have power to make important decisions in construction, such as the project owners and/or contractors depending on the delivery mode of a specific project.

(2) Sensitivity analysis. Sensitivity refers to how sensitive a model’s performance is to minor changes in the input parameters. Sensitivity analysis is particularly useful in investigating the performance of each risk factor’s contribution to the occurrence of an accident. The most natural way of performing sensitivity analysis is to change the values of the input parameters, and then monitor the effects of changes on the output probabilities. In this research, a performance-based indicator, Sensitivity Performance Measure (SPM) is proposed to measure the contribution of each risk factor \( X_i \) to risk event \( T \). Key risk factors can then be identified to help the decision makers determine the main checkpoints in the construction phase. Under the prior probabilities, the SPM of each root node \( X_i \), represented by \( SPM(X_i) \), can be calculated by Eq. (3). \( X_i \) is more likely to become the direct cause of an accident \( T \) when \( SPM(X_i) \) is close to 1. In light of actual observations of events, for instance, \( X_i \) is observed to stay in the state of \( q_i ( x_i^q ) \), and \( SPM(X_i) \) can also be calculated by Eq. (4) under given evidence.

\[
SPM(X_i) \approx \frac{1}{Q_i} \sum_{i=1}^{Q_i} \left| \frac{P(T = t \mid X_i = x_i) - P(T = t)}{P(T = t)} \right| \quad (3)
\]

\[
SPM(X_i) \approx \frac{1}{Q_i - 1} \sum_{i=1}^{Q_i} \left| \frac{P(T = t \mid X_i = x_i) - P(T = t \mid X_i = x_i^q)}{P(T = t \mid X_i = x_i^q)} \right| \quad (4)
\]

Step 4: Defuzzification

In the above fuzzy based risk analysis, the calculated results for each root or leaf node remain fuzzy triangular numbers, represented by \( P=(a_j, b_j, c_j) \). For the purpose of risk ranking in Bayesian inference, it is therefore necessary to transform fuzzy values into crisp values for the defuzzification stage. Specifically, the objective of defuzzification is to determine an exact value as the representative of the fuzzy number. Currently, several defuzzification methods have been developed, such as centre of gravity (COG) (Østergaard, 1976), mean of maxima (MOM) (Braae & Rutherford, 1978), centre of maxima (COM) (Mamdani, 1974), and the height method (HM) (Maeda & Murakami, 1987). According to Detyniecki and Yager (2000), some information was lost during the transforming process in the above defuzzification methods. Detyeniecki and Yager (2000) proposed an \( \alpha \)-weighted valuation method, and results indicated the proposed method was efficient in reducing the information loss. Therefore, the \( \alpha \)-weighted valuation method is adopted for defuzzification, and presented in a case study later in this research. Using the \( \alpha \)-weighted valuation method, a transformation formulation is derived by Eq. (5).

\[
Val(F_j) = \frac{\int_{a_j}^{b_j} \text{Average}(F_j) \times f(\alpha)d\alpha}{\int_{a_j}^{b_j} f(\alpha)d\alpha} = \frac{a_j + 2b_j + c_j}{4} \quad (5)
\]

Step 5: Decision making

Decision making provides a means for systematically dealing with complex problems to arrive at a decision. According to the FBN-based risk analysis results, the
critical risks and risk factors can be determined. Then relevant safety control measures could be proposed for risk response ahead of time. Safety monitoring and reviewing can be carried out to secure the rationality of the influential variables of a specific risk event. In the meantime, the implementation effect can be subsequently analyzed when corresponding control measures are adopted, which can also provide feedback and suggestions for adjustments or optimizations in previous steps.

CASE STUDY

Owing that existing pipelines play a basic role in urban infrastructure systems and are closely related to the quality of life of urban residents, the first priority should be placed on the safety assurance of underground buried pipelines when considering environmental safety prevention in tunneling construction. A case concerning the risk assessment and management of existing pipelines in the construction of the Wuhan Yangtze River Tunnel (WYRT) is presented in this paper.

Background

Wuhan Yangtze River Tunnel (WYRT) is the first tunnel under the Yangtze River. WYRT is an important route connecting two large cities of Wuhan, namely Wuchang and Hankou. WYRT is designed to go through five existing urban trunk roads, of which the Zhongshan Road is one of the main urban traffic roads in Hankou district. There are in total nine existing pipelines under the surface of the Zhongshan Road, including water supply pipes (JS), drain pipes (PS), communication pipes (DX) and others.

Figure 1 displays the neighboring spatial relation between the tunnel structure and the underground buried pipes in the cross section profile of the Zhongshang Road. In this case study, three pipes, denoted by 1#, 2# and 3# (see Figure 1), are taken as examples to present the detailed computation process. Between 2006 and 2013, researchers at Huazhong University of Science and Technology have developed safety control systems for metro construction and operation tasks for Shenyang, Zhengzhou, Shenzhen and Wuhan metro systems (Ding & Zhou, 2013). In accordance with the aforementioned Steps 1 in the proposed FBN approach, a tunnel-induced pipe damage network (TPDN) was established, as seen in Figure 2, with prior expert knowledge and approved FTs/ETs taken into account.
**Fuzzy Bayesian inference**

The calculation of the probability of the occurrence of some events or consequences can be implemented using a Bayesian inference mechanism given causes and evidence. In this case, fuzzy Bayesian inference aims to determine the probability distribution of tunnel-induced pipeline damage \( T \) under the fuzzy probabilities of root nodes in the pre-construction phase of tunnel construction. Owing that most of the important decisions are made in the pre-construction phase, this phase plays a significant role in guaranteeing the safety of the tunnel construction and surrounding environments.

To be specific, in the initial proposal stage, a deep understanding about the factual situation related to the safety status of potential risks was lacking, since no definite information about the tunnel construction was provided. However, in the situation that is represented by Scenario A, the prior fuzzy probability of root nodes \( X_1 \) defined by expert judgments can be entered into TPDN as input evidence. Using Eq. (2), the probability of \( T \) within each state can be obtained. For instance, the probability of "I (Very Safe)" of \( T \) was:

\[
P(T = 1) = \sum_{x_1, x_2, \cdots, x_4} P(x_1, x_2, \cdots, x_4) = (0.009, 0.018, 0.031)
\]

Similarly, \( P(T=2) = (0.056, 0.102, 0.108) \); \( P(T=3) = (0.238, 0.443, 0.796) \); \( P(T=4) = (0.157, 0.284, 0.497) \); \( P(T=5) = (0.076, 0.153, 0.293) \). To produce a quantifiable result in fuzzy logics, Eq. (5) was used to transform a fuzzy number into a crisp number as follows: \( P(T=1) = 0.109 \); \( P(T=2) = 0.092 \); \( P(T=3) = 0.480 \); \( P(T=4) = 0.306 \); \( P(T=5) = 0.169 \). Meanwhile, to satisfy the normalization condition, the normalized formula as seen in Eq. (6) can be used to obtain the final results as follows: \( P'(T=1) = 0.018 \); \( P'(T=2) = 0.086 \); \( P'(T=3) = 0.451 \); \( P'(T=4) = 0.287 \); \( P'(T=5) = 0.158 \). The results indicated that the potential safety status of tunnel-induced pipeline damage corresponded to Level III (Dangerous) under prior probabilities, since \( P'(T=3) > P'(T=4) > P'(T=5) > P'(T=2) > P'(T=1) \). Besides that, the potential safety risk of the existing pipelines showed a considerable tendency to move towards Level IV (Very Dangerous). In this way, the impact of the tunnel excavation on the pre-existing pipelines can be assessed without much given information. An initial
A protection scheme for existing pipelines can be developed in the proposal stage accordingly, which can also provide support to the investment estimation of the pipeline protection scheme.

\[
P(T = t) = \frac{P(T = t)}{\sum_{i=1}^{5} P(T = t)}, \quad t = 1, 2, ..., 5
\]

With the development of the construction survey and design process, the values of all influential variables for a specific existing pipe can be obtained. The state of each root node \(x_1-x_{11}\) can then be determined, and can be subsequently used as given evidence in the Bayesian inference. With regard to Pipe 1#, 2# and 3#, the vertical distances, types, diameters, service-life ratios and materials of these three pipes differed from each other (see Figure 1). For simplification, the situation with Pipe 1#, 2# and 3# can be represented by Scenarios B, C and D, respectively. Thus, we listed the variable values of each scenario, entered their current variable states (I, II,...,V) into TPDN as given evidence, and then calculated the probability distribution of the risk event \(T\). The results as seen in Table 1 indicated that the safety status of Pipe 2# was basically Level IV (Very Dangerous), while Pipe 1# and 3# both lay within Level III (Dangerous). In other words, those three pipes were very likely to produce settlement deformation within an interval of 30-50 mm, which are beyond the safe range of the allowed safety control standard. Thus, to reduce the risk limit, the construction decision makers made some further adjustments and optimizations on the previous scheme according to the calculated results. Based on the same Bayesian inference process, the results were also calculated and presented in Table 1. The safety risk of these three pipes then tended to decrease to Level II (Safe), so the construction scheme can be optimized continuously until the high potential safety risk was under control.

<table>
<thead>
<tr>
<th>Stages</th>
<th>Scenarios</th>
<th>(P(T=1))</th>
<th>(P(T=2))</th>
<th>(P(T=3))</th>
<th>(P(T=4))</th>
<th>(P(T=5))</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Proposal A: Prior probabilities</td>
<td>0.018</td>
<td>0.086</td>
<td>0.451</td>
<td>0.287</td>
<td>0.158</td>
<td></td>
</tr>
<tr>
<td>B: Pipe 1#</td>
<td>0.117</td>
<td>0.191</td>
<td>0.297</td>
<td>0.260</td>
<td>0.137</td>
<td></td>
</tr>
<tr>
<td>C: Pipe 2#</td>
<td>0.071</td>
<td>0.172</td>
<td>0.252</td>
<td>0.367</td>
<td>0.138</td>
<td></td>
</tr>
<tr>
<td>D: Pipe 3#</td>
<td>0.119</td>
<td>0.186</td>
<td>0.285</td>
<td>0.239</td>
<td>0.171</td>
<td></td>
</tr>
<tr>
<td>Site Selection Scheme 1</td>
<td>B: Pipe 1#</td>
<td>0.159</td>
<td>0.261</td>
<td>0.225</td>
<td>0.188</td>
<td>0.167</td>
</tr>
<tr>
<td>C: Pipe 2#</td>
<td>0.200</td>
<td>0.228</td>
<td>0.214</td>
<td>0.200</td>
<td>0.159</td>
<td></td>
</tr>
<tr>
<td>D: Pipe 3#</td>
<td>0.218</td>
<td>0.272</td>
<td>0.204</td>
<td>0.163</td>
<td>0.143</td>
<td></td>
</tr>
<tr>
<td>Site Selection Scheme 2</td>
<td>B: Pipe 1#</td>
<td>0.159</td>
<td>0.261</td>
<td>0.225</td>
<td>0.188</td>
<td>0.167</td>
</tr>
<tr>
<td>C: Pipe 2#</td>
<td>0.200</td>
<td>0.228</td>
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<td>0.143</td>
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</tr>
</tbody>
</table>

**Sensitivity analysis**

In current construction practice, the decision makers are likely to invite domain experts to join the expert group meeting when an accident first occurs. Then the experts discuss the direct causes of the accident, and propose prompt control measures. This is likely to miss the critical time of handling problems, causing more serious losses.
Sensitivity analysis attempts to calculate the occurrence likelihood of some causes resulting in a certain consequence, and can be used to identify the suspected causes for real-time fault diagnosis once an accident occurs. In Scenario A (prior probability) of this case, the values of all influential variables were unknown, and Eq. (3) can be used to calculate the performance sensitivity of all the root nodes PSM(Xi) (i=1,2,...,11), as seen in Figure 3 (a). The results indicated that x4, x1 and x2 became the top three suspected factors when pipeline settlement was observed to fall to a level of V (Extremely Dangerous, 50-70 mm), since x4 > x1 > x2 > x3 > x5 > x11 > x9 > x7 > x8 > x6 > x10 in the sensitivity ranking when P(T=5) =1 occurred. At the same time, x1, x3 and x4 were likely to become the direct causes when the pipeline settlement was observed to fall to a level of IV (Very Dangerous, 40-50 mm), since x1 > x3 > x4 > x5 > x9 > x2 > x6 > x10 > x7 > x8 > x11 in the sensitivity ranking when P(T=4) =1 occurred. In short, under prior probability environments, x1, x2, x3 and x4 should be the focus of a practical check for real-time fault diagnosis until the high potential safety risk was under control. In this way, the route for fault diagnosis in tunnel-induce pipeline damage could be extracted. In the meantime, when the safety status of the tunnel-induced pipeline damage (T) dropped to a low risk level, such as P(T=3) =1, x6, x7 and x9 turned out to be the three most unfavorable factors (see Figure 3 (a)), and should be the focus for actual fault diagnosis cross this time.

Figure 3. Sensitivity analysis results of all root nodes in different scenarios: (a) Scenario A (Prior probabilities); (b) Scenario B; (c) Scenario C; (d) Scenario D

In Scenarios B, C and D of this case, the values of all influential variables were determined, and Eq. (4) can be used to calculate the performance sensitivity of all the root nodes PSM(Xi) (i=1,2,...,11), as seen in Figure 3 (b)-(d). The results indicated that there were some changes in the sensitivity of root nodes when the states of influential variables had been observed, and the contribution of each root node (Xi) to the leaf node (T) varied greatly in different scenarios. With respect to the average sensitivity measure, x4, x3 and x5 can be considered as the nodes most sensitive to the occurrence of a high safety risk level in Scenario B, as seen in Figure 3 (b). In Scenario C, x3, x1 and x4 were very likely to become the direct causes in the occurrence of a high safety risk level, as seen in Figure 3
(c). In addition, in Scenario D, $x_4$, $x_3$ and $x_2$ turned out to be the most sensitive nodes, as seen in Figure 3 (d). As a consequence, key checking points (root nodes) can be changed given the observed states of influential variables were different among different pipes. Accordingly, the major focus of concern for safety control and management can be shifted among different scenarios (pipes) during the construction process.

CONCLUSION

In the past ten years, tunneling construction has presented a powerful momentum for rapid economic development worldwide, especially in China. Tunneling excavation is bound to produce significant disturbance to surrounding environments, and safety violations occur frequently because of the complicated risk mechanism of tunnel-soil-environment interaction. The tunnel-induced effects on adjacent underground buried pipelines are of considerable importance for geotechnical practice. Due to a lack of sufficient data, it is difficult to have an exact estimation of the failure rate of the occurrence probability of undesired events. This paper uses FBN to provide an alternative means to facilitate the safety risk analysis of pipeline damage induced by tunneling excavation. A novel and systemic decision support approach with detailed step-by-step procedures is proposed on a basis of FBN, including risk mechanism analysis, BN model establishment, fuzzification and defuzzification, and fuzzy Bayesian inference. A conceptual causal model involving eleven influential variables can be jointly used to graphically demonstrate the cause-effect relationships in tunnel-induced pipeline damage. The probability distribution of the consequence occurrence can be calculated using Bayesian inference under both prior knowledge and given evidence circumstances. The most likely causes leading to accident occurrence can also be identified by means of sensitivity analysis, providing effective support for safety assurance of the pre-existing pipelines in the pre-construction and construction stages accordingly. A case study is presented to analyze the safety performance of the underground buried pipelines adjacent to the construction of Wuhan Yangtze River Tunnel. The results demonstrate the feasibility of the proposed FBN approach and its application potential, and the comparison between the FBN and BN based risk analysis is further discussed according to the results. Also, the proposed safety decision support approach is worth popularizing in other similar projects, such as emergency management, coal mining, disaster prevention, and so forth, and to increase the likelihood of a successful project in a complex project environment.

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REFERENCES


