Dynamic Risk Assessment in Construction Projects Using Bayesian Networks

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Abstract -

This paper presents a systemic Bayesian network (BN) based approach for dynamic risk assessment for adjacent buildings in tunnel construction. This approach consists of four steps in detail, namely, hazard analysis, BN learning and BN-based risk analysis. In the dynamic risk analysis framework, the predictive, sensitivity and diagnostic analysis techniques in the Bayesian inference are used to conduct the feed-forward control in the pre-construction stage, intermediate control in the construction stage and back-forward control in the post-accident stage, respectively. A case relating to dynamic safety risk analysis of some existing buildings adjacent to construction of the Wuhan Yangtze Metro Tunnel in China is presented. Results demonstrate the feasibility of the proposed approach, as well as its application potential. The proposed approach can be used by practitioners in the industry as a decision support tool to provide guidelines on the conservation of adjacent buildings against tunnel-induced damages, and thus increase the likelihood of a successful project in a dynamic project environment.

Keywords -

Dynamic risk assessment; adjacent buildings; tunnel construction; Bayesian network; case study

1 Introduction

In the last ten years, urban tunneling projects have increased substantially as a result of rising populations, space restrictions, and growing environmental concerns. Tunneling excavation in soft ground inevitably leads to ground movement, which may cause adjacent surface buildings to deform, rotate, distort, and possibly sustain unrecoverable damages, especially those founded on shallow foundations [1, 2]. Many existing buildings are aging and do not have complete load-bearing capability as designed, resulting in very low deformation resistance. Thus, the tunnel-induced ground movement may destroy these buildings, unless accurate risk analyses are conducted and appropriate protection measures are implemented [3]. In order to assure the safety and serviceability of adjacent buildings in tunnel construction, it is therefore necessary to explore the safety risk mechanism for the tunnel-induced damage to adjacent buildings.

To prevent heavy casualties and property losses caused by safety violations due to tunnel-induced damages, application of a probabilistic risk assessment (PRA), which is a systematic and comprehensive methodology to evaluate risks associated with a complex engineered technological entity, has been widely reported in literature [4]. However, conventional PRA has the disadvantage of being static and fails to capture the variation of risks as deviations or changes during the life of a continuous process [5]. When associated parameters, such as geological, design and construction parameters are changed with the development of construction projects, the above traditional PRA methods cannot accurately illustrate the updated features of dynamic environments as the construction progress evolves. Accordingly, accurate risk analyses and decision support cannot be conducted in real time as these parameters are updated.

To overcome disadvantages of conventional PRA methods, dynamic risk analysis provides a possible way to cope with the dynamic nature of the risk profile. Dynamic risk analysis is a continuous process of identifying risk, assessing, and determining a way to reduce or eliminate risks in a dynamic manner [6]. Recently, there have been many efforts to simulate the dynamic nature of process behaviors. With the capacity of integrating prior knowledge and sample data, Bayesian network (BN) provides a powerful tool for knowledge representation and reasoning under a dynamic environment [7]. BN allows explicit modeling of changes over time, and can therefore model the evolution of the probabilistic dependencies within a random system. Basically, BN allows designers to easily update the prediction when additional information becomes available, and is especially suitable for engineering applications, where statistical data is often sparse [8].. This paper therefore investigates the possibility of using BN techniques to address the potential dynamic nature underlying the risk analysis and management in tunnel construction. A systemic BN-based approach with detailed step-by-step procedures is proposed for dynamic risk analysis, including predictive, sensitive and diagnostic analysis throughout the overall construction process. A case in relating to the dynamic safety risk analysis of some existing buildings adjacent to construction of the Wuhan Yangtze Metro Tunnel in China is presented. Results demonstrate the feasibility of the proposed approach, as well as its application potential.

2 Methodology

Dynamic risk assessment is a complex activity and requires several steps. Taking advantage of BN inference techniques, a BN-based approach is developed for dynamic risk analysis, making efforts to improve the effectiveness and accuracy of safety management in a dynamic project environment. In the proposed approach, the overall workflow includes the following three steps:

2.1 Hazard analysis

The risk assessment process starts with questions, such as "What can go wrong and how can it go wrong?" The identification of what and how it can go wrong entails defining hazards, risk events, and risk scenarios [9]. Hazard analysis involves determining which risks/risk factors might affect the project safety and documenting these characteristics. The identification is considered a difficult task for a complex system, particularly in tunnel construction. Nevertheless, past experiences provide extensive prior knowledge for risk identification. With the development of tunnel construction practice worldwide, large amounts of scattered knowledge were accumulated [10]. During the hazard analysis process, the failure modes, internal variables, exogenous factors, explicit cause and effect relationships are determined. The main outputs will be used as the input to the BN model in the next step.

2.2 BN learning

A BN model is defined by two components: structure and parameters. The structure is a graphical and qualitative illustration of the relationships among the nodes using directed arcs, while the parameters represent the quantitative probabilistic relationships among the nodes using probabilities. In this stage, a BN model is developed to simultaneously integrate the structure of the system, the variables and causal mechanisms (or interdependencies) analyzed by the last step. The design of a BN model involves determining the network structure and its parameters. There are two procedures in this step, as follows:

(1) Structure learning. Structure learning aims to determine the proper DAG, confirming the relationship between nodes. Every variable in the real-world situation is represented by a Bayesian variable. The BN variables (nodes) should be first created according to the results of hazard identification in the last step. Then the network structure can be developed by creating the directed edges from the node corresponding to fault causes to the node representing its consequence, which is indicative of a conditional dependency between the variables it links. In the meantime, considered as one of the most commonly used techniques for risk and reliability studies, FTA is a logic diagram that displays the interrelationships between a potential critical event and the causes in a system. Thus, the approved fault trees in construction fields can be applied to provide effective prior knowledge for BN structure learning.

(2) Parameter learning. Parameter learning aims to determine the conditional probability distribution of each node under the established BN structure [11, 12]. The conditional probability tables can be determined by learning the parameters on the database using a learning algorithm. For instance, the K2 algorithm is a well-known algorithm for BN parameter learning [13, 14], and can be adapted under the established BN structure. Also, expert judgment is an alternative when certain database information is unavailable.

2.3 BN-based risk analysis

When the established BN model is validated within the acceptable range, the BN model can be used to conduct various types of analysis. Ren et al. [15] indicated that the most important use of BN 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 occurrence of accidents. In this paper, we mainly discuss the predictive, sensitivity and diagnostic analysis using the Bayesian inference.

(1) Predictive analysis

Predictive analysis aims to capture the probability distribution of the risk event (T) under a combination of root nodes (X_1, X_2... X_n). The states of each root node and intermediate node can be treated as evidence input into the BN model. Compared with traditional FTs/ETs, the Bayesian inference in BN models does not need to get minimal cut sets, which increases greatly the computational efficiency. The probability distribution of T, represented by $P(T=t)$, can be calculated by Eq. (1). At the same time, in light of actual observations of events, for instance, X_i is observed to stay in the state of q_i ($X_i = x_i^{q_i}$), and the probability distribution of T, represented by $P(T = t | X_i = x_i^{q_i})$, can be calculated by

Eq. (2) under given evidence. Both $P(T=t)$ and $P(T=t|X_i=x_i^{q_i})$ can serve as indicators to evaluate the risk of T, assisting construction decision makers to take proper preventive measures in advance.

$$P(T=t)=P(T=t|X_1=x_1,X_2=x_2,\dots,X_n=x_n) \times P(X_1=x_1,X_2=x_2,\dots,X_n=x_n) \quad (1)$$

$$t=\{t_1,t_2,...,t_P\},\ x_i=\{x_i^1,x_i^2,...,x_i^{Q_i}\},\ i=1,2,\dots,n$$

$$P(T=t|X_i=x_i^{q_i})=\frac{P(T=t,X_i=x_i^{q_i})}{P(X_i=x_i^{q_i})} \quad (2)$$

$$t=\ t_1,t_2,...,t_P\ ,\ x_i=\ x_i^1,x_i^2,...,x_i^{Q_i}\ ,\ i=1,2,\dots,n$$

where, t stands for the state of a risk-prone event T with P states; $\{t_1,t_2,...,t_P\}$ is a range of P states for the risk event T; x_i stands for the state of risk factor X_i with Q_i states; $\{x_i^1,x_i^2,...,x_i^{Q_i}\}$ is a range of Q_i states for a root node X_i; $P(T=t|X_1=x_1,\dots,X_n=x_n)$ represents the conditional probability distribution of T; and $P(X_1=x_1,\dots,X_n=x_n)$ represents the joint probability distribution of the root nodes.

(2) Sensitivity analysis

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 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 makes 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). In light of actual observations of events, for instance, X_i is observed to stay in the state of q_i ($X_i=x_i^{q_i}$), and $SPM(X_i)$ can be calculated by Eq. (4) under given evidence. $SPM(X_i)$ can be used as an indicator to measure the degree of sensitivity of the root node X_i in the accident occurrence. Factors that are very sensitive to the accident occurrence should be given more attention during the construction process to reduce the risk limit.

$$SPM(X_i)=\frac{1}{Q_i}\sum_{1}^{Q_i}\left|\frac{P(T=t|X_i=x_i)-P(T=t)}{P(T=t)}\right| \quad (3)$$

$$SPM(X_i)=\frac{1}{Q_i-1}\sum_{1}^{1,\dots,q_i-1,q_i+1,\dots,Q_i}\left|\frac{P(T=t|X_i=x_i)-P(T=t|X_i=x_i^{q_i})}{P(T=t|X_i=x_i^{q_i})}\right| \quad (4)$$

(3) Diagnostic analysis

Compared to the traditional PRA-based methods, such as FTA, ETA and NN, the feature of the backward reasoning technique is unique and matchless in BN inference [16]. Diagnostic analysis aims to obtain the posterior probability distribution of each risk factor using the BN's backward reasoning technique when an accident or failure (T) occurs. Posterior probability distribution of risk factor X_i, represented by $P(X_i=x_i|T=t)$, can be calculated by Eq. (5). The distribution of posterior probabilities can provide reliable references for fault diagnosis. X_i is more likely to become the direct cause of an accident or failure (T) when $P(X_i=x_i|T=t)$ is close to 1.

$$P(X_i=x_i|T=t)=\frac{P(X_i=x_i)*P(T=t|X_i=x_i)}{P(T=t)} \quad (5)$$

3 Data and modelling

3.1 Risk identification

Tunnel-soil-building interaction is considered as a complex process, where various influential factors are involved. Tunnel-induced building damage has attracted broad attention due to the development of urban transit systems. According to engineering practice and expert estimates regarding the safety of adjacent buildings against tunnel-induced damages, a typical multi-level and multi-attribute framework has been structured, consisting of the following four types of variables:

(1) Tunnel related variables (B1): The variables related to the tunnel structure have a significant influence on disturbances in surrounding environments, such as *Covering Depth* (X1), *Cover-span Ratio* (X2) and *Tunnel Diameter* (X3). These three variables are usually treated as crucial parameters for the simulation of tunnel excavation in finite element models [17], and can produce notable impacts on the foundation deformation of adjacent buildings.

(2) Geological variables (B2). As an intermediary in tunnel-building interaction, the soil plays an important role in tunnel-induced building damages. The tunnel excavation in soft ground inevitably leads to the soil displacement which can subsequently affect the surface or subsurface structures [18]. Such parameters as *Friction Angle* (X4), *Compression Modulus* (X5), *Soil Cohesion* (X6) and *Poisson's Ratio* (X7) are four variables that are frequently used to illustrate geological features of the soil.

(3) Building related variables (B3). Most old buildings are aging and do not have complete load-bearing capability as designed initially, and some kinds of structural damages are likely to occur in the process of long-term operations [19, 20]. The structural health condition of an existing building provides a basis as to how much additional deformation or load it is able to bear, which is very important for the safety of adjacent buildings in tunnel construction. Such parameters as *Building Value* (X9), *Building Intact Conditions* (X10) and *Structure Configuration* (X11) are all related to the quality of the building health condition. Furthermore, the *Horizontal Distance* (X8) between the tunnel structure and the adjacent building is another factor that should be included, since the magnitude of the tunnel excavation effect appears to be slowed down as the building foundation is further away from the tunnel structure [21].

(4) Mechanical variables (B4). In the process of shield-driven tunneling excavation, engineers pay close attention to the measurement of some mechanical variables, to maintain the face stability of the excavation and minimize settlements [22]. Some pressure and speed sensors are installed on the top and middle of the cutter head. These monitored parameters, including *Driving Speed* (X12), *Thrust Force* (X13), *Cutter Torque* (X14), *Cutter Speed* (X15), *Cut Slurry Pressure* (X16), *Soil Pressure* (X17), *Grouting Pressure* (X18) and *Grouting Amount* (X19), are very sensitive to geologic conditions, and should be adjusted to adapt to the changing surrounding environments.

3.2 Risk modelling

In tunnel construction practice, the daily measurement of ground settlement is reviewed as a basic means for the safety assurance of surface and subsurface buildings. According to some technical specifications in China, such as "Technical code for monitoring measurement of subway engineering (DB11/490-2007)", the ground settlement should be controlled within 30 mm, and the nearby buildings are regarded unsafe if exceeding this control standard. However, the actual observed value turns out to be random due to the uncertainties and complexities underlying complex project conditions, and a single predicted value is met with significant limitations. In this situation, we use the fuzzy set theory to divide the predicated value into several ranges. The safety status of shield tunnel construction can then be assessed by analyzing the chance of the predicted value among different ranges. As to ground settlement with a general distribution range of 0~70 mm, we divide its predicated value into the following five ranges, namely, I (*Very Safe*, 0~20 mm), II (*Safe*, 20~30 mm), III (*Dangerous*, 30~40 mm), IV (*Very Dangerous*, 40~50 mm) and V (*Extremely Dangerous*, 50~70 mm). Each range corresponds to one risk level in regard to the tunnel-induced building damage (*T*). Between 2006 and 2013, researchers at Huazhong University of Science and Technology developed some safety control systems for metro tunnel construction and operation tasks for Shenyang, Zhengzhou, Shenzhen and Wuhan Metro systems. The researchers have also developed early warning web-based systems for safety control of each project. Large amounts of monitoring records have been accumulated during the work progress on these projects [23, 24]. According to the BN learning process as mentioned in Section 2, the accumulated 1000 training samples are used to conduct the TIBDN, as seen in Fig. 1.

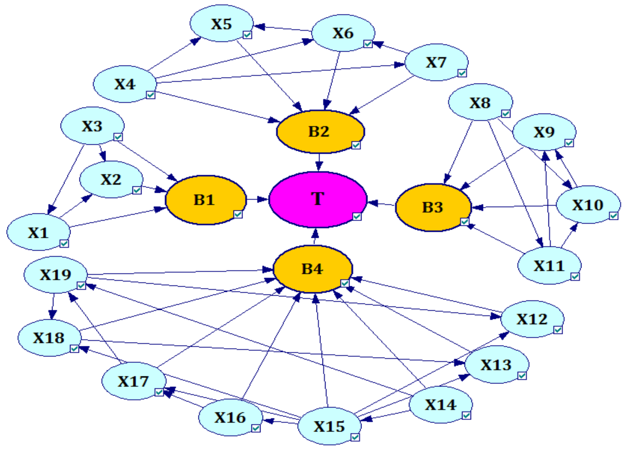

Fig. 1. An established risk network for TIBDN.

4 Results

A case of three surface buildings adjacent to the construction of the Wuhan Yangtze Metro Tunnel (WYMT) in China is presented in this research. WYMT, known as "the first metro tunnel across the Yangtze River in China", is an important route connecting two large cities, comprising the metropolitan area of Wuhan, namely Wuchang and Hankou. According to the site investigation, there are 35 buildings within 30 m offset the tunnel centerline in total, among which 11 buildings are located directly above the tunnel structure. Due to the complex failure mechanism of tunnel-induced building damage and poor geological conditions, the safety risk analysis and management of existing building adjacent to WYMT is considered a challenging task. In this case study, three buildings, denoted by $B^{1\#}$, $B^{2\#}$ and $B^{3\#}$, are randomly chosen and taken as examples to present the detailed computation process.

Each risk event has a life cycle, namely before, during and after an accident or failure. Therefore, safety analysis of risk-prone events can be divided into three stages in the overall work process: namely, feed-forward control in the pre-construction stage, intermediate control in the construction stage and back-forward control in the post-accident stage. Taking advantage of powerful reasoning features in the Bayesian inference, predictive, sensitivity and diagnostic analysis techniques are used to conduct the safety control of the above three stages, respectively. In this way, TIBDN is offered as a decision support tool, and thus, real-time and effective support can be available for decision makers in a dynamic manner in the entire life cycle of risk-prone events.

4.1 Feed-forward control

Feed-forward control aims to determine the probability distribution of the tunnel-induced building damage (*T*) using the predictive analysis technique of the Bayesian inference in the pre-construction stage of tunnel construction. Since most of the important decisions are made in the pre-construction stage, this stage plays a significant role in guaranteeing the safety of the tunnel construction and adjacent buildings. To be specific, in the conceptual design, a deep understanding about the factual situation related to the potential safety status of adjacent buildings is lacking, since no definite information about the tunnel construction is provided. However, in this situation (defined by *Scenario A*), prior probabilities of root nodes (X_i) can be entered into TIBDN as input evidence. The probability distribution of *T* within each risk level can then be obtained using Eq. (1), as seen in Table 1. The results indicate that the potential safety status of *T* corresponds to a level of IV (*Very Dangerous*) under *Scenario A*, since $P'(T=\text{IV}) > P'(T=\text{III}) > P'(T=\text{V}) > P'(T=\text{II}) > P'(T=\text{I})$. *Scenario A* can be viewed as a general situation where all existing nearby buildings are involved. In this way, the impact of the tunnel excavation on general existing buildings can be assessed without much given information.

During the construction survey and design phases, the values of other influential variables for a specific building can be obtained. In the preliminary design phase, the state of root nodes (X1-X19) can be determined (see Table 1), and subsequently used as given evidence in the Bayesian inference. For simplification, the situation regarding $B^{1\#}$, $B^{2\#}$ and $B^{3\#}$ can be represented by *Scenarios B*, *C* and *D*, respectively. Thus, we list the variable values of each scenario, enter their current variable states (I, II,...,V) into TIBDN as given evidence, and then calculate the probability distribution of the risk event (*T*) using Eq. (2). The results as seen in Table 1 indicate that the safety risk of all these three buildings is rated at a level of III (*Dangerous*). In other words, in locations of the mentioned three surface buildings, the ground settlement induced by tunneling excavation is likely to fall into a range of 30-40 mm, which is still beyond the allowed safe range of the safety control standard. Thus, to reduce the risk limit, the construction decision makers will make some further adjustments and optimizations based on the previous scheme according to the calculated results. Using the same Bayesian inference process, the updated calculation results of the probability distribution of *T* are shown in Table 1. As one might expect, the safety risk of these three buildings then tends to decrease to a level of II (*Safe*). In this way, the construction scheme can be optimized continuously until the high potential safety risk is under control.

Table 1. Probability distribution of the tunnel-induced building damage in different scenarios.

Stages	Scenarios	Evidence {X1,X2,…,X19}	$P(T=\text{I})$	$P(T=\text{II})$	$P(T=\text{III})$	$P(T=\text{IV})$	$P(T=\text{V})$
Conceptual design	*A*	Prior probabilities	0.017	0.082	0.316	0.432	0.151
Preliminary design	*B*	{III, II, V, II, IV, III, III, V, III, II, I, III, III, IV, III, II, II, III, IV}	0.088	0.144	0.257	0.224	0.287
	C	{V, IV, V, II, V, IV, V, V, IV, IV, IV, IV, II, V, III, II, IV, III, IV}	0.072	0.176	0.354	0.257	0.141
	D	{II, III, V, III, V, I, III, V, III, IV, IV, IV, III, V, III, IV, II, II, IV}	0.108	0.169	0.308	0.259	0.155
Optimized preliminary design	*B*	{III, II, V, II, IV, III, III, V, III, II, I, II, II, III, III, II, II, III, III}	0.150	0.269	0.177	0.246	0.158
	C	{V, IV, V, II, V, IV, V, V, IV, IV, IV, I, II, III, III, II, II, III, III}	0.017	0.432	0.316	0.082	0.151
	D	{II, III, V, III, V, I, III, V, III, IV, IV, II, II, II, III, II, II, III, III}	0.088	0.224	0.257	0.144	0.287

4.2 Intermediate control

Intermediate control aims to identify critical and sensitive factors in occurrence of construction failures using the sensitivity analysis technique of the Bayesian inference. In the construction stage, some variables, including tunnel related variables (B1), geological variables (B2) and building related variables (B3), have been determined and cannot be changed as a matter a fact, and thus, engineers pay much more attention to mechanical variables (B4) which have flexibility to be adjusted in order to maintain the face stability of the excavation and minimize settlement. In the intermediate control, the most sensitive mechanical variables can be identified as key check points in the process of shield-driven tunneling excavation.

With regard to general surface buildings in *Scenario A* (prior probability) of this case, the values of all influential variables are unknown, and Eq. (3) can be used to calculate the performance sensitivity of all root nodes *PSM* (X_i) (i=12,13,...,19). The results as seen in Fig. 2 (a) indicate that X15 (*Cutter Speed*), X14 (*Cutter Torque*) and X12 (*Driving Speed*) become the top three sensitive factors when the tunnel-induce building damage (T) falls into a risk level of V (*Extremely Dangerous*), since X15> X14 > X12> X16 > X13 > X17> X19 > X18 in the sensitivity analysis results in case of $P(T\text{=V}) = 1$. As seen in Fig. 6 (a), X15, X14 and X12 are more likely to become the most sensitive factors when T falls into a risk level of IV (*Very Dangerous*). Meanwhile, when T falls into a risk level of III (*Dangerous*), X13, X15 and X12 turn out to be the top three sensitive factors. In general, under the prior probability situation, X12, X13, X14 and X15 should be considered as the critical check factors for real-time measurement and adjustment until the high potential safety risk (P(T=III, IV or V)) is under control.

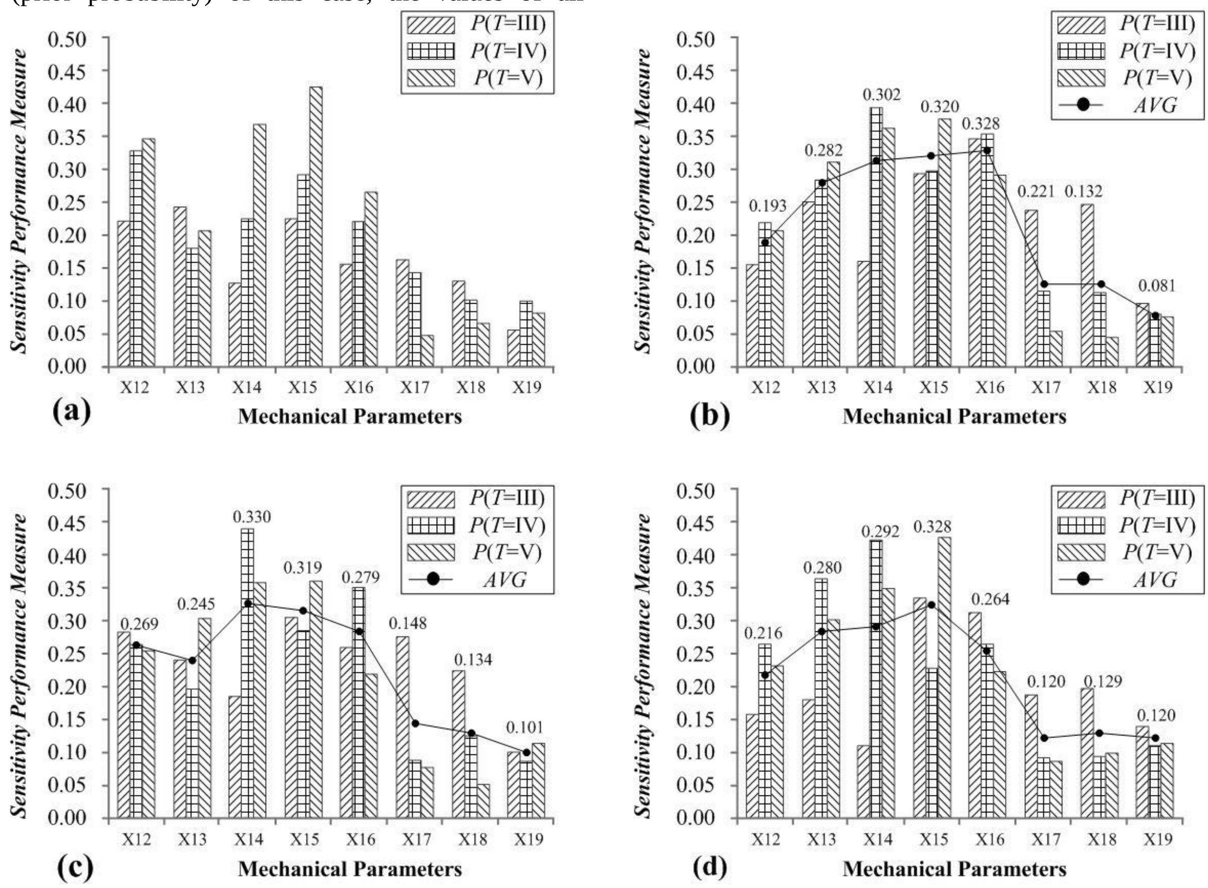

Fig. 2. Results of sensitivity analysis for mechanical parameters in: (a) *Scenario A* (Prior probabilities); (b) *Scenario B*; (c) *Scenario C*; and (d) *Scenario D*.

With regard to specific buildings in *Scenarios B*, *C* and *D* of this case (see Table 1), the values of all influential variables are determined and entered into TIBDN as given evidence, and Eq. (4) can then be used to calculate the performance sensitivity of all root nodes *PSM* (X_i) (i=12,13,...,19). The results as seen in Fig. 2 (b)-(d) indicate that there are some changes in the sensitivity of root nodes when the states of influential variables are observed, and contribution of each root node (X_i) to the leaf node (T) varies in different scenarios. In order to simplify the sensitivity analysis, the sensitivity of each variable can be evaluated in terms of average sensitivity measure (as shown in a polyline in Fig. 2 (b)-(d)), given the tunnel-induced building damage (T) lies in a high risk level (P(T=III, IV or V)). In *Scenario B*, X16, X15 and X14 can be considered as the most sensitive variables to the occurrence of a high safety risk level of T, as seen in Fig. 2 (b). In *Scenario C*, X14, X15 and X16 can be regarded as the top three sensitive variables in case of a high safety risk level of T, as seen in Fig. 2 (c). In *Scenario D*, X15, X14 and X13 should be the top three sensitive variables in case of a high safety risk level of T, as seen in Fig. 2 (d). As a consequence, key check points should be updated given the observed states of influential variables are different among existing buildings. Accordingly, the major focus of concern for safety management strategies can be updated among different scenarios during the construction process.

4.3 Back-forward control

In current construction practice, construction managers are likely to invite domain experts to join an expert group meeting in case of an accident, and then the experts discuss proposing some control measures. This is likely to miss the critical opportunity of handling problems, causing more serious losses. Back-forward control aims to identify the suspected causes using the diagnostic analysis technique of the Bayesian inference, in order to facilitate the real-time fault diagnosis once an accident occurs.

With regard to general surface buildings in *Scenario A* of this case, Eq. (5) is used to calculate the posterior probability distribution of the risk factors (X12-X19), given that the tunnel-induced building damage (T) lies in a high risk level, that is P(T=IV)=1 as an example. The results as seen in Fig. 3 (a) indicate that X14=IV (with a 45.2% chance) and X19=IV (with a 46.9% chance) are most likely to occur in case of P(T=IV)=1. For this reason, the fault diagnosis should concentrate on these two factors, and the practical check confirms our deduction. As a consequence, both X14=IV and X19=IV can be entered into TIBDN as additional evidence for the subsequent diagnostic analysis. The results as seen in Fig. 3 (b) show that both X12=I and X13=IV are more likely to occur in the second diagnosis cross, which should be the focus of practical diagnosis in the next cross.

With regard to specific buildings in *Scenarios B*, *C* and *D* of this case, the values of all influential variables are determined and entered into TIBDN as given evidence, and Eq. (5) can then be used to calculate the posterior probability distribution of the risk factors (X12-X19), given T lies in a high risk level of IV (*Very Dangerous*), as an example. The results in relating to $B^{1\#}$, $B^{2\#}$ and $B^{3\#}$ are shown in Fig. 4 (a), Fig. 5 (a) and Fig. 6 (a), respectively. The suspected causes leading to an occurrence of P(T=IV)=1 can be easily detected, and the practical check against these suspected causes is followed subsequently. According to the similar Bayesian inference, the observed values of the suspected causes are then entered into TIBDN as additional evidence for the next diagnostic analysis and the posterior probability distribution of other variables are shown in Fig. 4 (b), Fig. 5 (b) and Fig. 6 (b), respectively. In general, the diagnostic analysis results can provide new evidential information for the diagnostic analysis of the next cross, and the posterior probabilities of relevant factors can be updated in a dynamic manner. In this way, the evolution route of accidental occurrence can be extracted in real time, and at the same time, the high dependency on domain experts can be reduced.

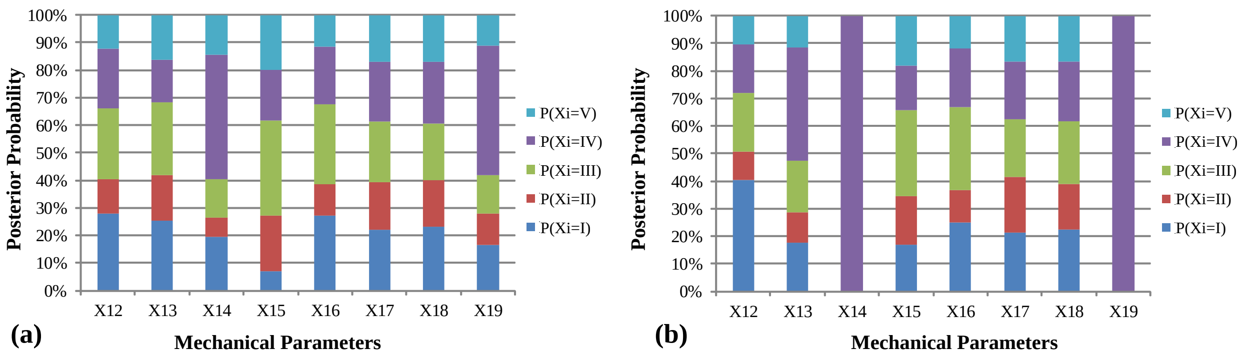

Fig. 3. Fault diagnosis under *Scenario A* in: (a) the first diagnosis cross P(T=IV); and (b) the second diagnosis cross P(T=IV|X15=X19=III).

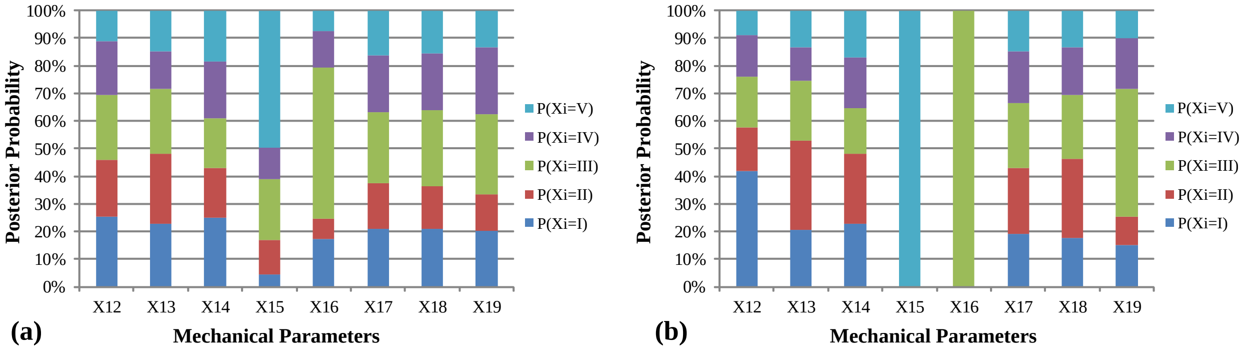

Fig. 4. Fault diagnosis under *Scenario B* in: (a) the first diagnosis cross *P*(*T*=IV); and (b) the second diagnosis cross *P*(*T*=IV|X15=V, X16=III).

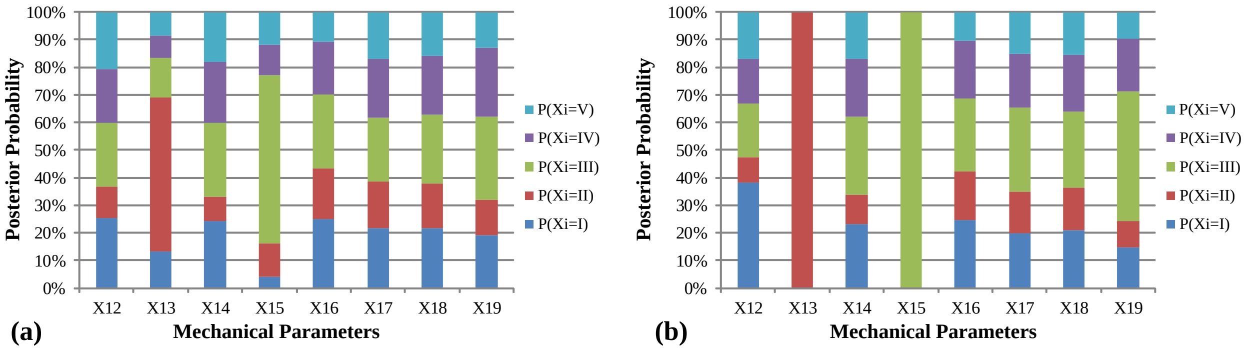

Fig. 5. Fault diagnosis under *Scenario C* in: (a) the first diagnosis cross *P*(*T*=IV); and (b) the second diagnosis cross *P*(*T*=IV|X13＝II, X15=III).

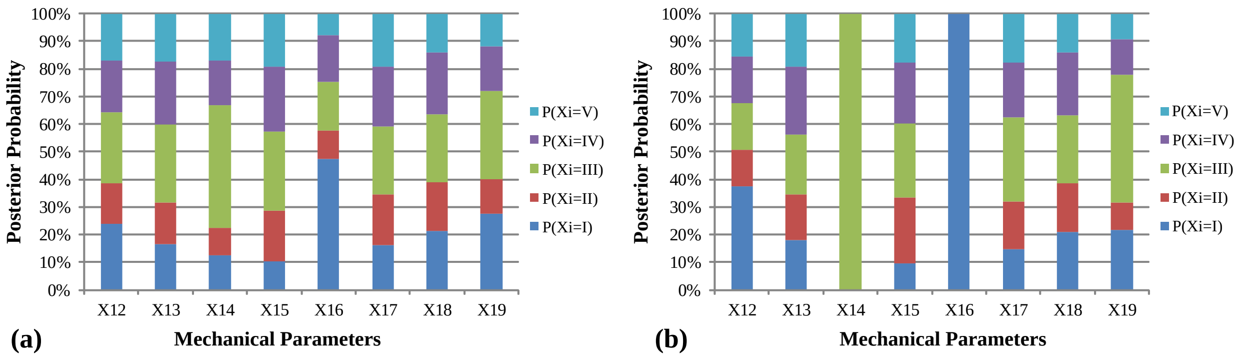

Fig. 6. Fault diagnosis under *Scenario D* in: (a) the first diagnosis cross *P*(*T*=IV); and (b) the second diagnosis cross *P*(*T*=IV|X14＝III, X16=I).

5 Conclusions

In the past ten years, tunnel construction has presented a powerful momentum for rapid economic development worldwide, especially in China. Tunnel excavation produces a significant disturbance to adjacent buildings, and safety violations occur frequently due to complex tunnel-soil-building interactions. This paper presents a systemic BN-based approach with detailed step-by-step procedures regarding dynamic risk analysis for adjacent buildings in tunnel construction. A case in relating to the safety risk analysis of some existing buildings adjacent to construction of the Wuhan Yangtze Metro Tunnel is used to verify the applicability of the proposed approach.

There are also some limitations to the developed systematic approach. Large quantities of monitoring records which serve as training and testing samples have been obtained from web-based systems developed for this research. Numerous engineering technicians have participated in the monitoring work, making an essential contribution to securing regularly scheduled input for the daily monitoring data into the system from project sites. This process is laborious and susceptible to human error. Future work will focus on developing a real-time intelligent monitoring system using automatic data acquisition technologies.

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