Data-Fusion Based Vulnerability Analysis of Shield Driven Tunnel Suffering from Extreme Soil Surcharging

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Abstract: A new data fusion approach is presented for evaluating the vulnerability curves utilizing multi-source monitoring information. A Bayesian network with continuous variables for a shield driven tunnel involving the loading condition, structural parameters (e.g. stiffness in waist and top joint) and soil parameters (e.g. subgrade reaction and lateral earth pressure) was constructed. Field monitoring data are taken into the Bayesian network to update the uncertain variables. Fragility and vulnerability curves are then drawn using the updated parameters. An example of shield driven tunnel under extreme surcharging is presented to illustrate the proposed methodology. The method is able to integrate the field monitoring information based on the tunnel deformation mechanisms and update the soil and structural parameters.

Keywords: Vulnerability evaluation, shield driven tunnel, data fusion, Bayesian network, field monitoring.

1 Introduction

The vulnerability of building and infrastructure to natural or man-made hazard is often studied with vulnerability and fragility curves (Rossetto 2003; Lagomarsino 2006; Saeidi 2009). Statistical and empirical method with large data scatters are often used to quantify the fragility and vulnerability curves, especially to analysis hazard with large impact range such as the earthquake (Orsini 1999; Saeidi 2012). Numerical simulation is often used to analyze the damage level under different hazard intensity for the urban tunnel due to a lack of data scatters (Argyroudis 2012). However, as most geotechnical problems, geotechnical uncertainties are inevitable in the simulation process (Phoon 1999). This paper proposed a data-fusion based method to make a vulnerability evaluation combining the in-situ monitoring information with the numerical model. Data fusion method is a process of integrating multiple sources of information into a consistent and more accurate representation. The data fusion method has been widely used for hazard assessment such as landslide assessment and dam safety (Chang 2007; Peng 2012; Peng et al. 2014) used a Bayesian network to integrate different kinds of monitoring data and make a global evaluation of slope safety. Soil properties are quantified through the Bayesian inverse analysis and reliability index are updated based on the soil properties.

The objective of this paper is to propose a novel approach which can integrate different geotechnical information to update the fragility and vulnerability curves. Geotechnical uncertainties such as the soil parameter uncertainties, observation uncertainties and model uncertainties are taken into consideration in the data fusion approach. A case study of vulnerability evaluation using the proposed approach is conducted in the third part of the article to make a clear understanding of the main steps.

2 Methodology of the Proposed Vulnerability Assessment

2.1 Framework the proposed method

Both the monitoring information and numerical simulation results were used to evaluate the tunnel performance as shown in Figure 1. In the data fusion approach, a Bayesian network was constructed first including the uncertainty parameters and monitoring information. Then a finite element analysis was conducted to quantify the interrelationship between the uncertainty parameters and monitoring information. Response surface function method was used to improve the computing efficiency. The uncertainty parameters were then updated using the real time monitoring data. Based on the updated uncertainty parameters, the fragility curve and vulnerability curve were figured to make a comprehensive evaluation of the tunnel vulnerability.

2.2 Constructing a Bayesian network

A Bayesian network containing the monitoring data and the uncertainty parameters was shown in Figure 2. Monitoring information such as joint opening and tunnel convergence are taken as the child nodes and the uncertain variables are taken as the parent nodes. There are two kinds of uncertain variables in the proposed Bayesian network. The first kind of uncertain variables is called as objective uncertain variables. This kind of

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uncertain variables determines the mechanical performance of the shield driven tunnel including the lateral earth pressure coefficient $\boldsymbol{K_0}$, the subgrade reaction coefficient $\boldsymbol{K_s}$, the top longitudinal joint bending stiffness $\boldsymbol{k_\theta}$ etc. The second kind of uncertain variables do not influence the performance of the tunnel directly. However, it will have impact on the vulnerability evaluation result of the tunnel such as the loading condition.

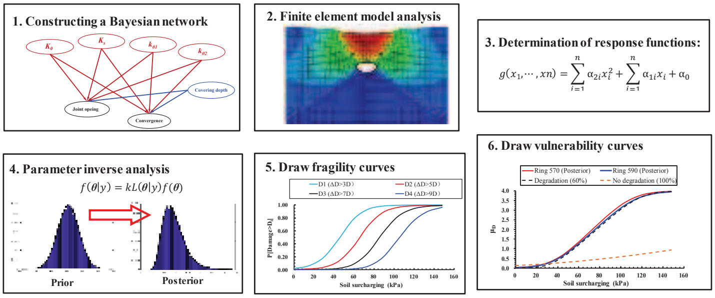

Figure 1 Main steps of the proposed method.

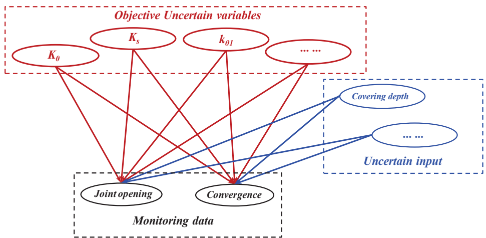

Figure 2 Bayesian network of the proposed method.

2.3 Determination of response functions using the FEM method

After establishing the Bayesian network in Figure 2, the next step is to quantify the inter-relationships in the causal network. Theoretically, given the value of major uncertainty parameters K_0, K_s, $k_{\theta 1}$ and $k_{\theta 2}$, the value of joint opening and convergence can be calculated using the finite element analysis. However, for the sake of computing efficiency, response surface function method should be used to simplify the inter-relationship between uncertainty parameters and monitoring information. Peng (2014) suggested that polynomial function is suitable for the geotechnical problem.

$$g(x) = \sum_{i=1}^{m} \alpha_{3i} x_i^3 + \sum_{i=1}^{m} \alpha_{2i} x_i^2 + \sum_{i=1}^{m} \alpha_{1i} x_i + \alpha_0 \tag{1}$$

where x is the vector of uncertainty parameters, α3i, α2i, α1i, α0 are the regression coefficients of polynomial function. This polynomial function will be used in the next MCMC simulation instead of using the finite element directly for calibrating the likelihood function. According to the research by Peng, the interaction terms in Eq. (1) are neglected. And the fitting result without interaction terms will be studied later.

2.4 Updating the uncertain variables

The tunnel vulnerability evaluation is conducted by updating the uncertainty parameters with in-situ monitoring information. According to Eq. (1), the monitoring data can be expressed using the uncertainty parameters. Considering that the uncertainty of loading condition, the surcharging load x_5 is taken as an input random variable with normal distribution that do not need to update. Then the posterior distribution of $\boldsymbol{x}$ can be expressed using the Bayes' theorem:

$$f(\boldsymbol{x}|\boldsymbol{y}) = kL(\boldsymbol{x}|\boldsymbol{y})f(\boldsymbol{x}) = \frac{L(\boldsymbol{x}|\boldsymbol{y})f(\boldsymbol{x})}{\int_{-\infty}^{+\infty} L(\boldsymbol{x}|\boldsymbol{y})f(\boldsymbol{x})d\boldsymbol{x}} \tag{2}$$

where k is a constant that makes the probability density function valid. $f(x)$ is the prior distribution of $\boldsymbol{x}$. The likelihood function can be determined based on the response function

$$L\left(\theta|\boldsymbol{y}\right)=f\left(\boldsymbol{y}|\theta\right)=\varepsilon_1 g(\theta)+\varepsilon_2 \tag{3}$$

where ε_1 is the model error and ε_2 is the observation error. The model error is often assumed to have a no bias normal distribution with mean value of zero and standard deviation of 0.2 times the measurement (Zhang and Chu 2009; Zhang et al. 2009). Considering that the integration process in Eq. (2) is time consuming, the Markov Chain Monte Carlo method is taken to improve the computing efficiency. In this case, the Metropolis-Hasting (MH) algorithm is used to make a sample.

2.5 Vulnerability evaluation

Theoretically, given a set of random parameter x, the structural response of tunnel can be quantified using the finite element method analysis. Wang et al. (2013) studied the transverse deformation mechanism of shield tunnels under a soil surcharging and suggested to take the horizontal convergence as the assessment index of tunnel. Hence, the tunnel horizontal convergence is chosen as the vulnerability index in this case. The tunnel damage condition is divided into several damage degrees based on the vulnerability index. The vulnerability index might change with different loading conditions. Therefore, the exceeding probabilities of different tunnel damage degrees can be calculated using the following equation:

$$P\left[Damage \geq D_i\right]=1-\sum_{j=1}^{i-1}\frac{N(D_j)}{n} \tag{4}$$

where P[Damage>D_i] represents the probability that the damage of tunnel is higher than damage degree D_i; n is the total number of sample; $N(D_i)$ is the number of sample of damage degree D_i. The fragility curve is usually fitted using a lognormal function or function as Eq. (5):

$$P\left[Damage \geq D_i\right]=\frac{1}{1+e^{\alpha i+\beta}} \tag{5}$$

where both α and β are the regression coefficients. The vulnerability curve presents the relationship between the damage expectation and loading condition. When the horizontal convergence is taken as the vulnerability index, the vulnerability curve can be transferred from the above fragility curve using the following equation:

$$\mu_D=\sum P_i D_i \tag{6}$$

where μ_D is the damage expectation under a particular loading condition, D_i is the damage degree and P_i is probability of exceeding D_i. Lagomarsino (2006) suggested that use the hyperbolic tangent function is well fitted for the fragility curve as the following function:

$$\mu_D=a[b+\tanh(ci+d)] \tag{7}$$

where μ_D is also the damage expectation, and a, b, c and d are the regression coefficients.

3 Illustrative Example

In this section, an example is presented to show how to fuse all kinds of information and how to make a vulnerability evaluation. The data is collected from a specific site of Shanghai Metro Line 2. And different kinds of uncertainty will be taken into consideration in the proposed approach, including the model uncertainty, the soil property uncertainty and the observation uncertainty.

3.1 Project information

The present case is an interval tunnel of extension line of Shanghai Metro Line 2. The tunnel suffered from an extreme surcharge during the operation period in 2010. The monitoring information including the covering depth, horizontal convergence and joint opening were collected after the surcharging accident. Same to most of Shanghai metro line, the shield driven interval tunnel was excavated using the earth pressure balance method. The internal tunnel has an outer diameter of 6.2m, a wall thickness of 0.35m and a longitudinal width of 1.2m. The single ring consists of six concrete segments, which can be denoted as segments F, L1, L2, B1, B2 and D from top to bottom. The tunnel has an average cover depth of 17.5m. The dumped soil with a height of 2m to 7m caused serious extreme surcharge which was discovered by the metro company in May of 2010. In this case, the surcharge soil with a unit weight of 18kN/m^3 was transverse the vertical pressure.

3.2 Establishing Bayesian network

A Bayesian network was established as shown in Figure 2, containing the uncertain variables of soil and structure. According to relevant numerical simulation results and several literature review, the monitoring data of horizontal convergence and longitudinal joint opening are sensitive to four uncertain variables, namely the lateral earth pressure K_0, subgrade reaction K_s, bending stiffness of top longitudinal joint $k_{\theta 1}$ and bending stiffness of waist longitudinal joint $k_{\theta 2}$.

3.3 Determining response surface functions

After establishing the Bayesian network, a numerical model conducted by finite element method was established using the ABAQUS finite element analysis software. A load structure model was chosen due to its simplicity and wide acceptance as shown in Figure 4. Parameter P_1 is the vertical pressure of the covering soil. Q_0 denotes the vertical load of soil surcharging. The segments are simulated using the beam elements. The longitudinal joints are modeled as the Rotating spring elements. Uncertainty parameters K_0, K_s, $k_{\theta 1}$ and $k_{\theta 2}$ were chosen as the input parameters of the numerical model, and structural responses of horizontal convergence and joint opening are taken as the output data. Important parameters such as bolt stress, joint opening can also be calculated using the finite element method. So the lateral earth pressure P_3 and P_4 can be calculated using Q_0, P_1, and K_0.

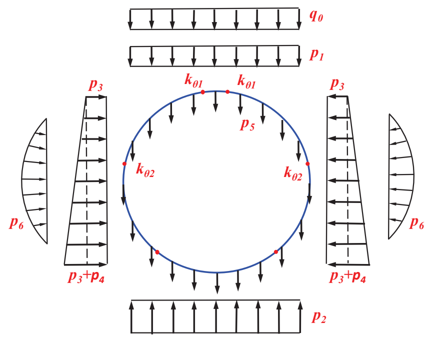

Figure 3. Schematic diagram of the load structure model of a shield-driven tunnel cross-section.

According to Eq. (1), the response function is given using a second-order polynomial function:

$$\boldsymbol{y} = \boldsymbol{g}(\boldsymbol{x}) = \sum_{i=1}^{m} \alpha_{2i} x_i^2 + \sum_{i=1}^{m} \alpha_{1i} x_i + \alpha_0 \tag{8}$$

where $\boldsymbol{y}$ is the monitoring data vector, $\boldsymbol{x}$ is the monitoring data vector (i.e. x_1=K_0, x_2=K_s, x_3=$k_{\theta 1}$, x_4=$k_{\theta 2}$ and x_5=*surcharging load* in this case), α_{2i}, α_{1i}, α_0 are the regression coefficients of polynomial function. Figure 4 compares the numerical results by FEM and the data using response function. The predictions match well with the numerical results. The R^2 of convergence and joint opening are 0.9988 and 0.9949, respectively.

3.4 Quantification of the Bayesian network

Given that the average horizontal convergence in Shanghai Metro Line 2 is 30mm (Huang et al. 2017), the initial variables for a normal working tunnel is assumed to have a joint lognormal distribution as shown in Table 1. Prior distribution of convergence and joint opening calculated using the Monte Carlo method are also shown in Table 1. Tunnel performance may have a remarkable decrease after an extreme soil surcharging accident. The prior distribution of the variables before the accident is decreased to 30% of the normal variables. As an example, the convergence of Ring 418 reached 155.1mm under a soil surcharging of 61.2kPa with the prior variables. Uncertain parameters (i.e. K_0, K_s, $k_{\theta 1}$ and $k_{\theta 2}$ in this study) were updated using the Markov Chain Monte Carlo simulation. The prior distribution of the parameters were assumed to follow a lognormal distributions with mean value and standard deviation as shown in Table 1. Hence, the updated parameters are following a joint lognormal distribution. Using the response functions in Eq. (1), the horizontal tunnel convergences and joint opening under different loading conditions were updated with the uncertain parameters. The posterior distributions of the convergence and joint opening are shown in Table 1. Through trial calculation, the uncertain parameters after soil surcharging were about 60% of the initial data. So the mean value of the prior distribution is assumed to be 60% of the initial data. And the coefficient of variance is assumed to be 2%. It can be seen that the standard deviations were increased remarkably after taking the different uncertainties into consideration.

Table 1. The updated variable using Bayesian network

Variable	Parameter	Normal	Ring 570 (Prior)	Ring 570 (Posterior)	Ring 590 (Prior)	Ring 590 (Posterior)
K_s (kPa/m)	mean	3000	1795	1760	1792	1706
	std	60	36	231	36	219
K_0	mean	0.65	0.32	0.30	0.32	0.30
	std	0.01	0.01	0.04	0.01	0.04
$k_{\theta 1}$ (kN・m/rad)	mean	22.5	13.5	12.1	13.4	12.3
	std	0.5	0.4	1.8	0.4	2.0
$k_{\theta 2}$ (kN・m/rad)	mean	9.00	5.39	5.68	5.38	5.14
	std	0.18	0.16	1.08	0.16	0.78
Soil surcharging (kPa)	mean	0.0	108.4	108.3	97.8	97.8
	std	3.7	3.7	3.7	3.7	3.8
Convergence (mm)	**measured**	-	**201.8**	-	**172.5**	-
	mean	28.6	175.9	210.1	169.7	180.5
	std	16.8	10.8	12.9	10.5	11.6
Joint opening (mm)	**measured**	-	**21.9**	-	**19.4**	-
	mean	5.6	17.6	20.5	17.2	18.1
	std	1.4	0.9	1.1	0.9	1.0

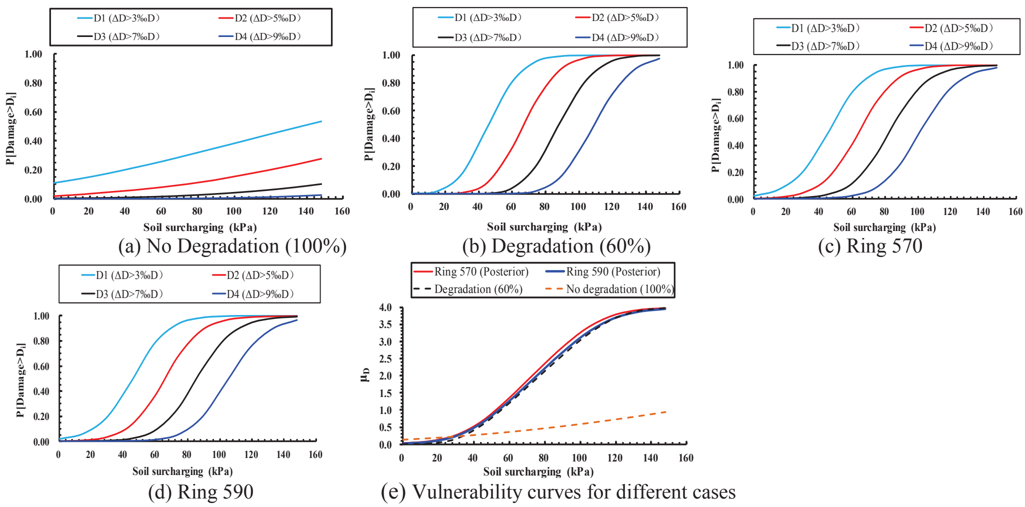

Figure 4. Fragility curves and vulnerability curves: (a) No Degradation (100%); (b) Degradation (60%); (c) Ring 570; (d) Ring 590; (e)Vulnerability curves for different cases.

3.5 Vulnerability evaluations

As mentioned before, tunnel convergence is chosen as the vulnerability index. The damage is assumed to have 4 levels. According to the tunnel convergence statistics by (Shen et al. 2015), tunnel horizontal diameters conformed to lognormal distribution. The average convergence of tunnel in Shanghai Metro Line is 32mm (5‰D_{out}). The convergence of the tunnel has been divided into 4 levels based on the statistical results. In order to reflect the damage caused by a surcharging process, the initial convergence of the case without degradation is supposed to be 5‰D_{out}. The initial convergence of the other three cases are the average convergence under soil surcharging of 0 kPa. The thresholds of each vulnerability levels are 3‰D_{out}, 5‰D_{out}, 7‰D_{out}, 9‰D_{out} in addition to the initial convergence 5‰D_{out}. Figure 4 shows the probabilities of exceeding each damage levels under soil surcharging from 0 kPa to 148kPa. Assuming that the major variables (i.e. K_0, K_s, $k_{\theta 1}$ and $k_{\theta 2}$ in this study) do not have a degradation in the soil surcharging process, the exceedance probability curves are keeping at a relative low level. However, with the accumulation of structure damage, major variables will have a decrease and the exceedance probability curves increase. Figure 4(b) is the fragility curves that the average value of major variables degraded to 60% of the initial mean value. The probability distributions in Figure 4(b) are taken as the prior distribution for Bayesian updating. As above mentioned, in situ monitoring data consisting convergence and joint opening are taken to make the updating. The fragility curves of Ring 570 and Ring 590 are shown in Figure 4(c) and Figure 4(d) respectively. Vulnerability curves can be drawn using Eq. (7) based on the fragility curves in Figure 4. The vulnerability curve is at a low level if the major variable keeps invariable. The curve increases remarkably when the parameters reduce to 60% of the initial value. The curves of Ring 570 and Ring

590 are close to the degradation case. So, it is reasonable to take 60% degradation parameters as prior distribution. As shown in Table 1, the measured convergence of Ring 570 is 117% times that of Ring 590. However, the soil surcharging is only 111% that of Ring 570. From the updated vulnerability in Figure 4(e), Ring 570 is slightly higher than that of Ring 590. It can be induced that the tunnel of Ring 590 has better anti-deformation ability than that of Ring 570. From the perspective of damage and stiffness relationship, the tunnel structure in Ring 570 suffered more damage than that of Ring 590.

4 Conclusion

The paper presents a data-fusion based method for vulnerability evaluation utilizing multi-source monitoring information. The following conclusions can be drawn:

1. A Bayesian network is constructed by considering different relevant uncertain variables including the lateral earth pressure K_0, subgrade reaction K_s, bending stiffness of top longitudinal joint $k_{\theta 1}$ and bending stiffness of waist longitudinal joint $k_{\theta 2}$. The prior probabilities are quantified with finite element analysis and the simplified response functions.
2. Numerical simulation and monitoring data can be taken into account in the vulnerability evaluation of the shield driven tunnel. Markov Chain Monte Carlo simulation is used to update the Bayesian network with the in-situ monitoring information. The uncertain variables decreased remarkably after a Bayesian updating approach. Fragility curves and vulnerability curves are drawn based on the updated parameters.
3. The fragility curves and vulnerability curves indicate that the vulnerability will increase after an extreme soil surcharging. The vulnerability curves of Ring 418 and Ring 590 are much higher than that of the initial conditions.

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