



Fuzzy comprehensive Bayesian network-based safety risk assessment for metro construction projects

Z.Z. Wang*, C. Chen

School of Civil Engineering, Dalian University of Technology, Dalian, PR China



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ABSTRACT

This paper presents a systemic decision-support approach to safety risk analysis for metro construction projects under uncertainty using a fuzzy comprehensive Bayesian network (FCBN), which combines the fuzzy comprehensive evaluation method (FCEM) and a Bayesian network (BN). The results of the safety risk assessment based on the FCBN are composed of three aspects: risk probability, risk loss, and risk controllability. In this assessment, two of the aspects—risk loss and risk controllability—are calculated in terms of intervals or fuzzy numbers. Through the application of the FCEM, the levels of risk loss and risk controllability are then estimated. The risk probability is calculated from the BN, in which the relationships among the dependent variables are expressed in the form of a directed graph. A comprehensive safety risk assessment allows engineers to assess potential safety hazards and provides a basis for dynamic early risk warning and control ahead of metro construction, which is acquired by combining the FCEM and the BN. A case study relating to safety risk analysis in the construction of the Dalian Metro in China is used to verify the feasibility of the approach as well as its application potential. A comparison of the results with the actual construction state shows its effectiveness in estimating the risk level of a metro construction project under uncertainty. The proposed approach provides a powerful tool with which planners and engineers can systematically assess and mitigate the inherent risks associated with metro construction.

1. Introduction

The metro has become a popular solution for relieving the pressure on surface transportation systems worldwide, especially in developing countries such as China. However, metro construction is typically complicated and is associated with large potential risks. In recent years, the issue of safety risk analysis and management in metro construction has grown to be a public concern because of its close relationship with public safety. Many accidents and undesirable events are related to uncertainties regarding in situ ground conditions, which results in complicated and high-risk construction work. Therefore, it is essential to develop safety risk assessment systems in order to avoid or mitigate these occurrences (He, 2015).

Risk analysis is a tool designed to establish a proactive safety strategy by investigating potential risks (Labib and Read, 2013). In recent decades, risk-analysis methods also were adapted for tunnel safety. In state-of-the-art systems, risk analyses are not considered as stand-alone tools; they are incorporated into a complex risk-management system, which forms part of the decision-making process (Rundmo et al., 2011). Sturk et al. (1996) aimed to assess risks during

tunnel construction and to support the decision-making process with a case study that used failure modes, effects analysis, and fault tree analysis as separate risk-analysis tools. On the other hand, Hong et al. (2009) used event tree analysis for similar purposes. Eskesen et al. (2004) presented general guidelines for performing risk management in tunnels. Fang et al. (2011, 2012) provided an environmental risk-management procedure for underground projects based on construction process mechanics. There also were numerous research studies on risk assessment attempting to illuminate and formulate answers covering all possible risks created by tunneling and underground construction (Choi et al., 2004; Seo et al., 2008).

Both the fuzzy comprehensive evaluation method (FCEM) and the Bayesian network (BN) are regarded as effective tools for facilitating knowledgeable reasoning in uncertain environments. In conventional BN analysis, the occurrence probability of root nodes is always regarded as the crisp value. However, in construction engineering fields, it is difficult or nearly impossible to obtain exact values for probabilities due to a lack of sufficient data (Zhang, 2014; Wu et al., 2015). In addition, risk loss and risk controllability evaluations are also difficult to obtain. The fuzzy comprehensive evaluation method (FCEM) provides a

* Corresponding author.

E-mail address: wangzhengzheng@dlut.edu.cn (Z.Z. Wang).

powerful tool for solving engineering problems under uncertainty by utilizing intervals or fuzzy numbers (Horcik, 2008).

In the past five years, our research group, based at Centre for Tunnel Research at the Dalian University of Technology, has undertaken major research in risk management for many metro engineering projects (e.g., Beijing, Tianjin, Chengdu, Shenyang, and Dalian Metros). We have found that the origins of risks in metro construction often stem from unanticipated obstructions, natural or manmade; soil and groundwater conditions differ from those anticipated; ground behavior differs from what is ordinarily expected; and misinterpretation of ground conditions have led to inappropriate construction methods or equipment choices. Furthermore, some methods of tunneling are inherently riskier than others or may cause excessive ground movements, and sensitive existing structures may make use of such construction methods in their vicinity undesirable. Therefore, it is important to conduct risk analysis during metro construction.

This paper investigates the possibility of merging the FCEM and a BN using fuzzy comprehensive Bayesian networks (FCBN) to provide a powerful tool with which planners and engineers can systematically assess and mitigate the inherent risks associated with metro construction. The results of the safety risk assessment were arrived at through comprehensive evaluation and are composed of three aspects: risk probability, risk loss, and risk controllability. A case study concerning the safety analysis for the construction of the Dalian Metro in China also was used to verify the feasibility of the approach, as well as its application potential.

2. Methodology

2.1. Fuzzy comprehensive evaluation method

The FCEM was first introduced by Zadeh in an effort to deal with uncertainty due to imprecision and vagueness. The FCEM is a statistical method that uses fuzzy mathematics to achieve scientific evaluation of qualities through consideration of all factors of the evaluated object. The FCEM provides a basis for generating powerful problem-solving techniques with wide applicability, especially in the field of decision-making. The first step of the FCEM is to determine the evaluation factor sets, which are collections of evaluation factors for evaluation objects. If there are n elements, we can express them as $U = \{u_1, u_2, \dots, u_n\}$. The second step is to determine the review sets that represent a collection of different fuzzy assessments (e.g., excellent, good, average, and poor). The review sets can be divided into m levels, according to the actual situation, and expressed as $\{V_1, V_2, \dots, V_m\}$. Third, we need to apply certain methods to the evaluation of each factor's weight, such as using nine scales of 1–9 and their reciprocals to compare and calibrate the relative importance of each evaluation factor in influencing factors sets. By means of the square-root method, the judging matrix and the weight of each evaluation factor are computed. When evaluating the judgment matrix, we need to test the degree of consistency to guarantee that the matrix is fully consistent with the index CI :

$$CI = (\lambda_{\max} - n) / (n - 1), \quad (1)$$

where λ_{\max} is the maximal characteristic root of the matrix, and n is the order of the matrix. A smaller CI results in better consistency.

Next, the CI is divided by RI , which is defined as the average random consistency ratio and yields the testing result CR :

$$CR = CI / RI, \quad \text{where } CR < 0.1. \quad (2)$$

Then, the calculated weight values can be expressed as follows:

$$W = (w_1, w_2, \dots, w_n). \quad (3)$$

The next step is to construct the membership degree matrix, \mathbf{R} , which is used to present the object's evaluation results. The membership degree vector \mathbf{R}_i can be expressed as follows:

$$\mathbf{R}_i = (r_{i1}, r_{i2}, \dots, r_{im}), (i = 1, 2, \dots, n), \quad \text{where } \sum_{j=1}^m r_{ij} = 1, \quad (4)$$

where r_{ij} refers to the likelihood that the plurality of evaluation subjects calculate v_j in the aspect of u_i for some specific evaluation objects.

The membership degree matrix \mathbf{R} can be expressed as follows:

$$\mathbf{R} = (\mathbf{R}_1, \mathbf{R}_2, \dots, \mathbf{R}_n)^T = (r_{ij}). \quad (5)$$

Finally, we can calculate the results of comprehensive evaluation, \mathbf{B} , based on determining the weight vector, \mathbf{W} , and the membership degree matrix, \mathbf{R} (Zhang, 2014):

$$\mathbf{B} = \mathbf{W} \cdot \mathbf{R} = (w_1, w_2, \dots, w_n) \cdot \begin{bmatrix} r_{11} & r_{12} & \dots & r_{1m} \\ \vdots & \vdots & \ddots & \vdots \\ r_{n1} & r_{n2} & \dots & r_{nm} \end{bmatrix}. \quad (6)$$

Here, it is necessary to apply a normalized treatment to \mathbf{B} to determine the final comprehensive evaluation result. This calculation is introduced as follows:

$$b'_i = b_i / \sum_{j=1}^m b_j. \quad (7)$$

2.2. Bayesian networks

Bayesian networks are based on a basic knowledge of probability theory and graph theory, which are used to evaluate problems with strong uncertainty. Bayesian Networks are composed of two parts: a directed acyclic graph (DAG) and an associated joint probability distribution (JPD) (Zhu, 2003). A general BN intuitively represents a complex network of nodes and direct edges. Each node represents a variable, and the state of each node corresponds to the probability of the occurrence of risk factors. The direct edges present association relationships among the variables. A DAG contains conditional independence assumptions, which can be modeled by means of engineering models, expert judgment, or other known relations (Spackova, 2013). The JPD of the BN model mainly refers to the conditional probability table set of a Bayesian network. Each node has a conditional probability table (CPT), which is used to represent the relationship between the node and its parent node.

The Bayesian Network can be expressed as follows:

$$N = \{(V, X), P\}, \quad (8)$$

where V represents the network nodes, X represents a directed acyclic graph, and P represents the conditional probability distribution of the nodes. The discrete node variables $V = \{E_1, E_2, \dots, E_n\}$ represent a set of variable nodes in a network. Each node is attached to a conditional probability table that contains the conditional probability of the parent node. The intrinsic goal of the Bayesian network is to study parameter optimization through the calculation of the prior probability and the posterior probability for a specific network structure (Langseth and Portinale, 2007).

Assuming that the node $V = \{E_1, E_2, \dots, E_n\}$ satisfies the mutual conditions, the conditional probability distribution can be defined as follows:

$$P(E_1, E_2, \dots, E_n) = \prod_{i=1}^n P(E_i | \text{parents}(E_i)), \quad (9)$$

where $P(Y = y_i | X = x_i) = P(X = x_i) \times P(Y = y_i | X = x_i)$.

According to the premise of independent conditions, the edge probability is

$$P(Y) = \sum_i P(X = x_i) \times P(Y = y_i | X = x_i). \quad (10)$$

Thus, the Bayesian formula can be written as follows:

$$P(X = x_i | Y = y_i) = \frac{P(X = x_i) \times P(Y = y_i | X = x_i)}{P(Y = y_i)}. \quad (11)$$

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