A NOVEL MODEL FOR RISK ASSESSMENT OF ADJACENT BUILDINGS IN TUNNELLING ENVIRONMENTS

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ABSTRACT

This paper presents a novel model to assess the risk of adjacent buildings in tunnelling environments based on Extended Cloud Model (ECM). ECM is an organic integration of Extension Theory (ET) and Cloud Model (CM), where ET is appropriately employed to flexibly expand the variable range from [0, 1] to (-∞, +∞), and CM is used to overcome the randomness and fuzziness during the gradation of evaluation factors. The risk level of a specific adjacent building is assessed by the correlation with the cloud models. A confidence indicator θ is proposed to illustrate the rationality and reliability of evaluating results. Ten buildings adjacent to Wuhan Metro Line Two (WMLT) are randomly chosen among hundreds of adjacent buildings for a case study. Results have proved to be consistent with the actual situation. Compared with other traditional evaluation methods, ECM has been verified to be a more competitive solution with high calculation accuracy, wide adaptability, as well as simplified computer programming. There are no stringent requirements on the quantity of training data during the modelling process, and the original data can be directly entered into ECM without a normalization procedure, avoiding the potential information loss. ECM can be offered as a decision support tool for the risk assessment in urban tunnelling construction and worth popularizing in other similar complicated projects.

KEYWORDS

Cloud Model; risk assessment; adjacent buildings; complex environments; decision support

INTRODUCTION

Tunnelling excavation is bound to produce significant disturbances to surrounding environments. A major concern induced by tunnelling excavation is the potential damage to surrounding buildings and subsurface structures (Bilotta & Russo, 2010). Tunnel-building interaction is a highly complicated process, and risk assessment of adjacent buildings in tunneling environments (RAABTE) has attracted broad attention in recent years. Numerical analyses have been widely applied to investigate the tunnelling-induced impacts on surrounding environment in engineering practices (Lateb, Masson, Stathopoulos, & B E Dard, 2010). Such numerical analyses could be time consuming and extremely expensive, especially when a large number of adjacent buildings have to be assessed (Chen, Zhu, Liu, & Tang, 2011). In the meantime, comparatively few critical factors are chosen as input parameters in such numerical analyses, regardless of some other relevant factors such as "quality of the construction workers" and "quality of building preservation condition" and so forth.

A comprehensive evaluation method should have the capacity of taking all related factors into account and calculating the contribution of each factor. Current comprehensive evaluation methods can broadly be grouped into the following three categories: Based on fuzzy mathematics theory (Unal, Demir, & Uygunoglu, 2007), such as Fuzzy Analytic Hierarchy Process (FAHP); Based on probability and statistics theory, such as Osculating Value Method (OVM); Based on artificial intelligence approaches (Doukas, Nychtis, & Psarras, 2009), such as Neural Networks (NN). Generally, these methods make significant contributions to RAABTE with their own distinct features. However, due to the imperfection of historical statistical data, limitations of expert knowledge acquirement, as well as the uncertainty of empirical judgment, much randomness and fuzziness exist during the evaluation factors gradation, lowing the credibility of evaluation results to some extent.

Cloud Model (CM), an effective tool in uncertain transforming between qualitative concepts and their quantitative expressions (D. Y. Li, 2000), has the capability of expressing fuzziness and randomness existing in human knowledge representation, knowledge acquirement, as well as knowledge inference. In the past ten years, CM has been widely applied in many areas, such as inexact knowledge representation, intelligence control and system evaluation data mining (Deyi & Changyu, 2004). Meanwhile, Extension Theory (ET) is beneficial for interval parameters repression with the advantage of expanding the valid range from fuzzy set [0,1] to the real axis $(-\infty, +\infty)$ (Das, 2006). ET is objective and simple, and what is more important, it can directly use the original data without a normalization procedure, avoiding the potential information loss (Hu & He, 2006). Based on the organic integration of CM and ET, we propose a novel risk assessment model, namely Extended Cloud Model (ECM) for RAABTE. For the case study, ECM is adopted into the risk assessment of adjacent buildings along the route of Wuhan Metro Line Two (WMLT), providing decision support for the protection of adjacent buildings with different risk levels.

EXTENDED CLOUD MODEL (ECM)

Extension Theory

The extension set, first introduced in 1983 by Cai (Cai, 1983), extends the fuzzy set from [0, 1] to $(-\infty, +\infty)$. Consequently, the extension set allows to define a set including any data in the domain and has the capability of solving contradictory problems which cannot be solved by the cantor set or fuzzy set (Cai, 1983). In the extension theory, the matter-element (R) contains three fundamental elements: matter name (N), matter characteristics (C) and values of matter characteristics (V) (Cai, 1999). The matter-element can be described as $R=[N, C, V]$. Assuming a multi-dimensional matter-element $C=[c_1,c_2, \ldots, c_n]^T$ associated with a characteristic region $V=[v_1,v_2, \ldots, v_n]^T$ and a range of classical intervals $v_i=\langle a_{pi}, b_{pi}\rangle$ (i=1,2,...,n). The classical domain $v_i=\langle a_{pi}, b_{pi}\rangle$ stands for the defined interval values in traditional extension analysis. Few studies have taken randomness and fuzziness into full consideration during the interval gradation, which would significantly affect the accuracy and effectiveness of the final evaluation results.

Cloud Model and ECM

Cloud Model (CM) is a qualitative and quantitative transformation model proposed by Deyi Li (D. Li, Cheung, Shi, & Ng, 1998), which can use linguistic value to represent the uncertain conversion between a qualitative concept and its quantitative value. A cloud model can be characterized with three digital characteristics $C=(Ex, En, He)$. The expected value "Ex" represents the typical point which best characterizes the quality concept. The entropy "En" is the uncertainty distribution of the concept representing the range of values that could be accepted in the domain. The hyper-entropy "He" is a measure of the uncertainty of the entropy "En", which represents the randomness of all points of the concept (Tseng, Hwang, & Su, 2011). For example, the factor "*Neighbouring Relation*" plays a significant role in tunnelling excavation's impact on the building damage. "*From 6 meters to 12 meters*" is the common expression to describe the status of "*Adjacent*" for the "*Neighbouring Relation*", as seen in Fig. 1.

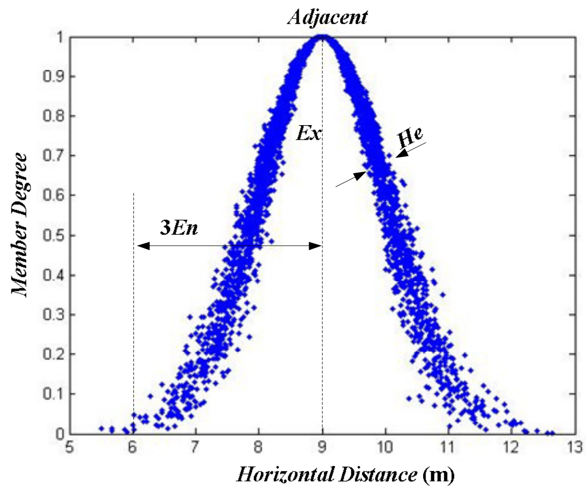

Fig. 1--Cloud model "*Adjacent*" for the "*Neighbouring Relation*"

In the risk analysis and evaluation progress in complex environments, much randomness and fuzziness exist during the gradation of the evaluation factors. Taking advantages of both ET and CM, a novel risk assessment model, Extended Cloud Model (ECM), is proposed to effectively deal with the uncertainty in evaluation factors gradation. The core of ECM is to adopt the normal cloud model (*Ex*, *En*, *He*) into the representation of interval values, instead of the classical domain v_i=<a_{pi}, b_{pi}>.

RISK ANALYSIS OF ADJACENT BUILDINGS IN TUNNELLING ENVIRONMENTS

Influence variables

Owing to the highly complicated tunnel-building interaction, the building subsidence varies widely with the differences along spatial and temporal factors in surrounding environments. Tunnel-induced building damages are of major interests for urban tunnel construction. Keshuan et al. (Keshuan & Lieyun, 2008) pointed out that the tunnelling–building interaction causes a significant influence on the distribution of damages in the building. Based on engineering practices and theoretical analysis, four types of parametric variables concerning the safety issues on adjacent buildings induced by tunnelling excavation are presented, including tunnel related variables: geological variables; building related variables; and technical & managerial variables.

Risk level gradation

Based on the practical experience, numerical simulation tests and analysis, we divide the safety status of each evaluation factor into five levels, R1~R5. The higher the level, the higher the risk for each factor. Table 1 presents the risk level gradation of 14 evaluation factors in RAABTE, where the information resource of factors (c_1, c_2, …, c_8) comes from field monitoring data, and that of factors (c_9, c_{10}, …, c_{14}) comes from expert evaluation by the hundred-mark system (Wang et al., 2012). During the RAABTE, ECM is employed to assess the final comprehensive Risk level which is divided into the following five levels "I, II, III, IV, V". The higher the level, the higher the risk for a specific adjacent building.

Table 1--Risk level gradation of the evaluation factors related to RAABTE.

Variables	Factors	Description	*R1*	*R2*	*R3*	*R4*	*R5*
Tunnel related variables	c_1	Cover Depth (m)	[20,40]	[14,20]	[10,14]	[5,10]	[0,5]
	c_2	Cover-span Ratio	[3,5]	[2,3]	[1,2]	[0.5,1]	[0,0.5]
	c_3	Ground Loss Ratio (%)	[0,0.5]	[0.5,1]	[1,1.5]	[1.5,2]	[2,4]
Geological variables	c_4	Friction Angle (°)	[25,45]	[15,25]	[10,15]	[5,10]	[0,5]
	c_5	Compression Modulus (MPa)	[40,60]	[20,40]	[10,20]	[5,10]	[0,5]
	c_6	Soil Cohesion (KPa)	[20,25]	[15,20]	[10,15]	[5,10]	[0,5]
	c_7	Poisson's Ratio	[0.4,0.5]	[0.3,0.4]	[0.2,0.3]	[0.1,0.2]	[0,0.1]
Building related variables	c_8	Neighbouring Relation (m)	[30, 50]	[20,30]	[12,20]	[6,12]	[0,6]
	c_9	Historical Value (score)	[80,100]	[60,80]	[40,60]	[20,40]	[0,20]
	c_{10}	Building Intact Conditions (score)	[80,100]	[60,80]	[40,60]	[20,40]	[0,20]
	c_{11}	Structure Configuration (score)	[80,100]	[60,80]	[40,60]	[20,40]	[0,20]
Technical & managerial variables	c_{12}	Construction Technologies (score)	[80,100]	[60,80]	[40,60]	[20,40]	[0,20]
	c_{13}	Management Team (score)	[80,100]	[60,80]	[40,60]	[20,40]	[0,20]
	c_{14}	Monitoring Engineers (score)	[80,100]	[60,80]	[40,60]	[20,40]	[0,20]

RISK ASSESSMENT BASED ON ECM

Step 1: Cloud model of evaluation factors

Each evaluation factor in RAABTE as seen in Table 1 has five closed double-restriction intervals, represented by [$c_{\min}$, $c_{\max}$]. In fact, much randomness and fuzziness exist during the boundary-setting of each interval. ECM is employed to restore the uncertainty in double-restriction setting. The transformation from the double-restriction interval [$c_{\min}$, $c_{\max}$] can then be transferred to a normal cloud model (*Ex*, *En*, *He*). For example, the status of "*Neighbouring Relation*" is divided into five levels, namely *R1*"*Extremely Far*", *R2*"*Far*", *R3*"*Medium*", *R4*"*Adjacent*" and *R5*"*Extremely Adjacent*". Then the normal cloud model of "*Neighbouring Relation*" (c_8) is shown in Fig. 2.

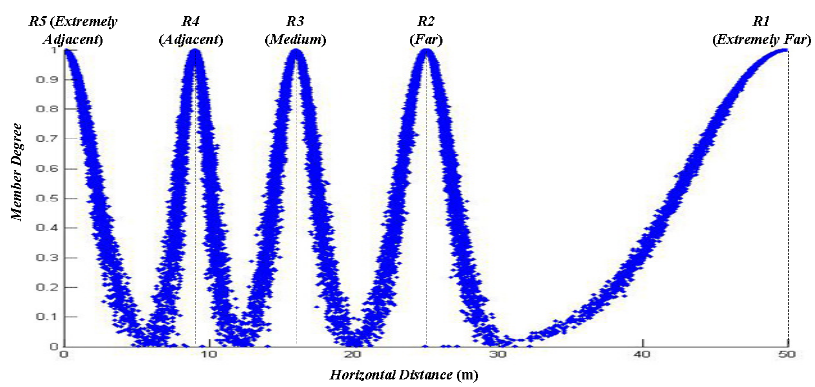

Fig. 2--Normal cloud model of "Neighbouring Relation"

Step 2: Correlation calculation

Correlation is used to measure the relative approach degree between a specific building and the cloud models of each level "$R1$, $R2$, $R3$, $R4$, $R5$". Correlation calculation plays a vital role in RAABTE when ECM is adopted. Assuming a specific building denoted as P, p_i (i=1,2,…n) represents the actual value of ith evaluation factor for the building P.

In the risk assessment process, original data can be entered into ECM without a normalization procedure. Compared with the cloud model of the j level denoted as R_j (Ex_{ij}, En_{ij}, He_{ij}) (j=1,2,3,4,5), the actual value p_i is viewed as a cloud droplet. Its correlation denoted as q_{ij} (i=1,2,3…, n; j =1,2,3,4,5) can then be calculated using Eq. (1), where, En_{ij}' is a random number produced by the cloud generator which satisfies $En_{ij}'\sim N(En_{ij}, He_{ij}^2)$. The correlation matrix of the specific building P is represented by Q.

$$q_{ij} = \exp\left(-\frac{\left(p_i - E_{xij}\right)^2}{2\left(E_{nij}^{'}\right)^2}\right) \quad (1)$$

Step 3: Weight setting

The contribution of each evaluation factor varies noticeably in RAABTE, causing an driving force for weight setting of each factor. Assuming the weight of each factor c_i (i=1,2,...,n) turns out to be λ_i by Analytic Hierarchy Process and ξ_i by Entropy-weight Method respectively, the final comprehensive weight w_i can be calculated by Eq. (2). See more references on Analytic Hierarchy Process and Entropy-weight Method to Li et al. (S. Li & Li, 2009) and Wu et al. (Wu & Zhang, 2011) accordingly. All comprehensive weight values constitute the weight matrix W in the index system related to RAABTE.

$$w_i = \frac{\lambda_i \times \xi_i}{\sum_{i=1}^{n}(\lambda_i \times \xi_i)} \quad (2)$$

Step 4: Evaluation result and confidence indicator

With the help of the weight matrix W and the correlation matrix Q, the comprehensive evaluation vector denoted by $B=W*Q$. The weighted mean method can then be employed to conduct the final comprehensive risk level K, as seen in Eq. (3). The value of K can be divided into the following five ranges [0,1]; (1,2]; (2,3]; (3,4]; (4,5], denoted as the level of "I, II, III, IV, V" accordingly.

$$K = \frac{\sum_{j=1}^{5}(b_j \times j)}{\sum_{j=1}^{5} b_j} \quad (3)$$

Due to the randomness existing in the correlation calculation of matrix Q, a series of the K set (K_1, K_2, ..., K_m) appears after repeated computations using Eq. (1)~(3) for m times. As for K set, the expectation denoted by $Ex(K)$ and standard deviation denoted by $En(K)$ can then be calculated by Eq. (4). A confidence indicator θ is proposed to measure the reliability of evaluation results, which is calculated by Eq. (5). θ is one when the evaluation result is perfectly reliable.

$$\begin{cases} Ex(K) = \dfrac{K_1 + K_2 + \ldots\ldots + K_m}{m} \\ En(K) = \sqrt{\dfrac{1}{m}\sum_{i=1}^{m}\left(K_i - Ex(K)\right)^2} \end{cases} \quad (4)$$

$$\theta = 1 - \frac{En(K)}{Ex(K)} \tag{5}$$

CASE STUDY

In order to relieve the pressure of urban traffic jam across the Yangtze River, the construction of Wuhan Metro Line Two (WMLT) runs mainly underground on a northwest-southeast alignment between the Hankou and Wuchang districts, as seen in Fig. 3. Owing to the crowded buildings along the tunnel route, as well as the complicated tunnelling environments, the safety control of existing buildings adjacent to WMLT faces extreme difficulty.

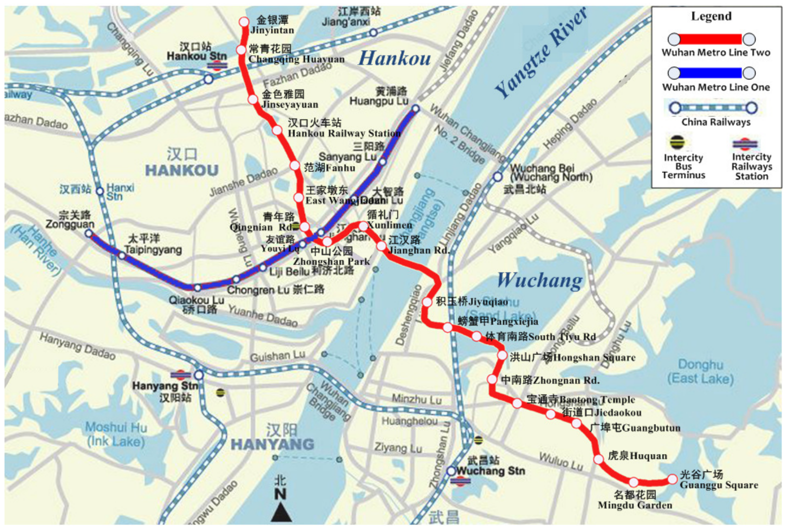

Fig.3--Metro map of Wuhan Metro Line Two (WMLT).

Among hundreds of crowded buildings adjacent to WMLT construction, ten buildings (*1#*, *2#*,..., *10#*) were randomly chosen for the case study. A systematic investigation was first carried out, covering all the evaluation factors in RAABTE. Values of 14 evaluation factors were then obtained for those ten adjacent buildings, as seen in Table 2. Using Eq. (1)~(5), evaluation results of ten adjacent buildings were presented in Fig.4. The analysis was made as follows:

Table 2--Values of 14 evaluation factors in RAABTE for ten adjacent buildings.

Factors \ ID	*1#*	*2#*	*3#*	*4#*	*5#*	*6#*	*7#*	*8#*	*9#*	*10#*
c_1	13.19	26.13	4.88	18.49	14.05	18.79	16.12	15.26	4.82	7.56
c_2	2.20	4.36	0.81	3.08	2.34	3.13	2.69	2.54	0.80	1.26
c_3	2.8	0.4	2.7	2.2	2.1	1.4	2.6	2.4	2.6	2.2
c_4	21	30	20	25	35	40	15	12	15	10
c_5	5.7	15.7	6.6	16.7	4.9	6.7	5.6	6.3	4.7	3
c_6	12	16	20	22	20	20	13	8	6	21
c_7	0.21	0.27	0.21	0.44	0.31	0.20	0.21	0.22	0.06	0.23
c_8	3.0	35.0	3.4	6.0	18.0	6.0	3.0	4.1	2.6	4.0
c_9	55	86	50	82	81	45	60	55	35	55
c_{10}	78	86	85	90	75	78	48	30	35	35
c_{11}	82	87	95	85	35	82	84	60	20	30
c_{12}	75	86	80	36	79	80	75	56	25	11
c_{13}	76	90	76	40	76	84	76	70	60	30
c_{14}	83	83	85	30	65	83	81	76	44	40

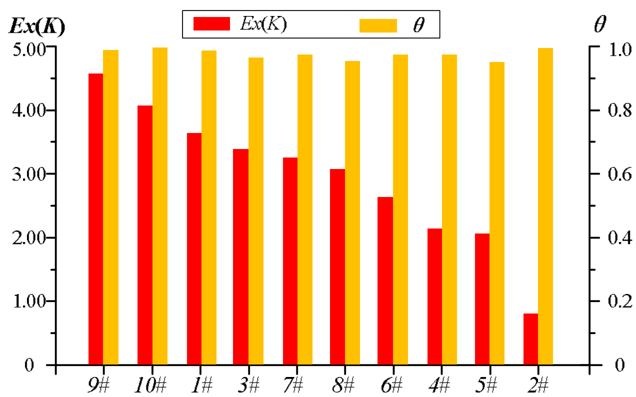

Fig. 4--Evaluation results of ten adjacent buildings.

(1) From the perspective of risk rank, the top two adjacent buildings, the *9#* ($Ex(K)$=4.53) and *10#* ($Ex(K)$=4.14) were both attached to the Level V (*Extremely High Risk*), which turned out to be the core protected buildings during the practical construction progress. It is necessary to carry out field test experiments and conduct reinforcement parameter analysis, aiming to provide support in both construction scheme optimization and emergency response proposals. Furthermore, the confidence indicator θ of each building is substantially approaching one, indicating all calculated results are efficient with high reliability.

(2) From the perspective of comprehensive safety conditions, six adjacent buildings (including *9#*, *10#*, *1#*, *3#*, *4#*, *7#*) out of ten were attached to Level IV or above. Therefore, we had sufficient reasons to believe, the comprehensive risk of all adjacent buildings along the tunnel route was markedly high, rather than low or median. In fact, this deduction was consistent with the actual situation. WMLT, known as "the first metro tunnel across the Yangtze River in China", came across several complicated technical challenges, such as complicated geological structure, high water pressure and shallow covering depth. Consequently, gradation of evaluation factors in such complex

tunnelling environments were worked out with some fairly conservative views, contributing to the high risk level to some extent.

DISCUSSION

In order to further verify the feasibility of the proposed method ECM, three typical evaluation methods among the aforementioned three categories, namely FAHP, OVM and NN, are chosen to conduct the evaluation results on the basis of the previous case study respectively. Results as seen in Table 3 are analyzed as follows:

Table 3--Comparison of evaluation results by four different methods.

ID	FAHP (Risk Level)	OVM (Risk Level)	NN (Risk Level)	ECM		
				Ex(K)	Risk Level	θ
1#	4	4	4	3.62	4	0.9881
2#	2	2	2	1.33	2	0.9977
3#	4	4	4	3.43	4	0.9790
4#	3	3	3	2.16	3	0.9852
5#	3	2	3	2.07	3	0.9602
6#	3	3	3	2..62	3	0.9802
7#	4	4	4	3.21	4	0.9813
8#	4	4	3	3.03	4	0.9627
9#	5	5	5	4.53	5	0.9995
10#	5	5	5	4.14	5	0.9990

(1) The evaluation results calculated by ECM are fairly consistent with other three traditional evaluation methods, indicating the proposed method is considerably reliable and efficient. The lone exceptions are the *5# Building* ($Ex(K)$=2.07) and *8# Building* ($Ex(K)$=3.03), which are theoretically attached to Level III and IV respectively. Actually, these two adjacent buildings both show off considerable tends to move towards Level II and III respectively. The deflections inevitably exist due to the slight difference on risk-taking attitudes or data processing modes among different evaluation methods. However, this appearance is acceptable and understandable in risk assessment of real projects.

(2) With respect to the practical calculation process in risk assessment, ECM turns out to be a more competitive solution surpassing other three traditional evaluation methods. Owing that the safety status of each evaluation factor does not have a linear relation with its actual value, 38 subordinate functions are structured for 14 evaluation factors in RAABTE when adopting FAHP. When adopting OVM and NN into RAABTE, high requirements need to be met with both the quantity and quality of training data. However, the progress of obtaining such huge amounts of training data is laborious associated with high costs in the engineering practices. On the contrary, the proposed risk assessment method ECM is objective and impartial without demanding huge amounts of training data. In the meantime, ECM can directly use the original data without a normalization procedure, effectively avoiding the potential information loss.

CONCLUSIONS

Taking advantages of both Extension Theory (ET) and Cloud Model (CM), a novel risk assessment method ECM is proposed to efficiently deal with the uncertainty existing in evaluation factors gradation. Compared with other traditional evaluation methods, such as FAHP, OVM and NN, ECM has been verified to be a more competitive solution with high calculation accuracy, wide adaptability, as well as simplified computer programming. ECM can directly use the original data without a normalization procedure, avoiding the potential information loss. There is no need of large amounts of training data in the modelling process. Meanwhile, the evaluation result can be worked out effectively associated with a confidence indicator θ. This proposed method can be offered as a decision support tool for the risk assessment in urban tunnelling construction and is worth popularizing in other similar complicated projects.

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