Decision Making for Optimal Primary-Support Selection to Minimise Tunnel-Squeezing Risk

Yu Chen

Institute for Risk and Uncertainty, University of Liverpool, UK. E-mail: yuchen@liverpool.ac.uk

Edoardo Patelli

Department of Civil and Environmental Engineering, University of Strathclyde, UK.
E-mail: epatelli@liverpool.ac.uk

Peng Zeng

State Key Laboratory of Geohazard Prevention and Geoenvironment Protection, Chengdu University of Technology, China. E-mail: zengpeng1987@hotmail.com

Ben Edwards

School of Environmental Sciences, University of Liverpool, UK. E-mail: edwardsb@liverpool.ac.uk

Tianbin Li

State Key Laboratory of Geohazard Prevention and Geoenvironment Protection, Chengdu University of Technology, China. E-mail: tbli2005@163.com

Michael Beer

Institute for Risk and Reliability, Leibniz University, Germany. E-mail: beer@irz.uni-hannover.de

The excessive deformation caused by tunnel squeezing hazard is a key problem in tunnel construction, especially when tunneling through weak and over-stressed rock masses. Significant losses and delays would arise should an inappropriate selection of tunnel support be made. This paper presents a risk-based decision making framework to select the optimal support scheme in a quantitative manner. A program evaluation and review technique based Monte Carlo simulation procedure, which aims to estimate the cost distribution of different tunnel support schemes, is coupled with a multi-class probabilistic classifier on tunnel squeezing intensity. The risks regarding different scenarios of squeezing intensity and support scheme are expressed in a cost-benefit perspective using a modified Event Tree analysis, where abundant simulations of decision making can be done at one time and the optimal support scheme is hence selected based on votes. Finally, an engineering application is presented to demonstrate the efficiency and practicality of the proposed framework.

Keywords: Tunnel squeezing, decision making, risk assessment, Monte Carlo, cost-benefit analysis.

1. Introduction

Rock squeezing involves excessive plastic deformation of rock masses subjected to stresses exceeding a limit shear stress, which typically occurs when tunneling through weak rock masses or high tectonic-stressed areas (Barla 1995; Jimenez and Recio 2011; Hoek and Marinos 2000). This large convergence is accused of leading to significant budget overruns and construction delays over the tunneling process (Feng and Jimenez 2015; Evert 2001).

In past decades, much progress has been made in the prediction of tunnel squeezing hazard using empirical models based on increasingly accumulated history cases (Feng and Jimenez 2015; Evert 2001). Three categories of predictive models have been summarized by Chen et al. 2019 as: (i) Geomechanical-based methods; (ii) Competence-factor based methods; and (iii) Probabilistic classification methods. In particular, recent years have seen much effort in deriving probabilistic classifiers using Supervised Learning algorithms due to a special merit that those probability outputs can be further involved in a subsequent risk analysis (Jimenez and Recio 2011; Feng and Jimenez 2015; Faber 2007).

Through a quantitative risk assessment, potential problems (i.e. tunnel squeezing) can be iden-

Proceedings of the 30th European Safety and Reliability Conference and the 15th Probabilistic Safety Assessment and Management Conference
Edited by Piero Baraldi, Francesco Di Maio and Enrico Zio
Published by Research Publishing, Singapore.
ISBN: 978-981-14-8593-0; doi:10.3850/978-981-14-8593-0

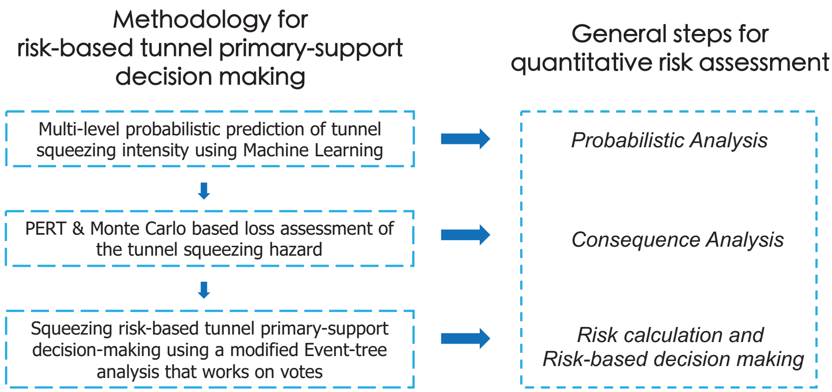

Fig. 1. The flowchart for the dynamic framework for risk-based tunnel primary-support decision making

tified, probability of the occurrence of the hazard and its associated consequences can be evaluated, which would serve as an objective basis for decision making (Faber 2007; Manchao et al. 2015).

In the context of tunneling risk assessment which involves significant uncertainties regarding geologic conditions and construction performance, the exceptional risks brought by specific hazard need to be quantitatively assessed so that appropriate construction strategies can be selected, guided by a principle of minimal risk (Einstein 2004; Sousa and Einstein 2012). However, such problems of decision-making under uncertainty in construction projects have not been sufficiently studied so far (Špačková et al. 2013; Manchao et al. 2015).

Specifically, for the excessive convergence caused by tunnel squeezing, in spite of noticeable advancements in predictive models, however, an ultimate goal of construction contractors is to select an appropriate support scheme in response to the potential squeezing problem. Therefore, in this paper, a comprehensive methodology, which combines a multi-class probabilistic classifier and a risk-based decision making framework, is proposed to quantitatively select the optimal support scheme.

Fig. 1 shows the flowchart of the proposed risk-based decision making framework. It illustrates the roles of the key steps constituting this framework (left column) in the overall architecture of a quantitative risk assessment in tunneling (Huang and Zhang 2015; Degn Eskesen et al. 2004) (right column).

2. A probabilistic prediction on tunnel squeezing intensity

A probabilistic classification problem is a classical Supervised learning problem that makes predictions through a model trained on known observations and their categories (as inputs). Often a probability distribution over classes is associated with each prediction (as outputs).

Recently, much effort has been made in constructing probabilistic models to classify the degree of tunnel squeezing using many Supervised Learning algorithms, such as Logistic Regression (Jimenez and Recio 2011), Naive Bayes (Feng and Jimenez 2015), Support Vector Machine (Sun, Feng, and Yang 2018), Decision Trees (Chen et al. 2019). Although many of these methods can indeed output a probability distribution over classes, via which the class with the highest probability is predicted; however, not all those classification models are naturally probabilistic, and some, notably naive Bayes classifiers, decision trees and boosting methods, actually in principle produce distorted class probability distributions (Niculescu-Mizil and Caruana 2005). Therefore, it should be specifically pointed out that when those probability estimates are intended to be further used in the subsequent parts of risk analyses, probability calibrations are necessary.

3. Risk-based decision making on tunnel support selection

3.1. *Loss assessment for tunnel squeezing*

Despite there are several established probabilistic models for the purpose of tunnel construction risk that have paid special attention to the uncertainties of the construction time and cost (Isaksson and Stille 2005; Moret and Einstein 2016; Špačková et al. 2013); however, those exceptional cost caused by undesired events such as geological hazards should be separately considered and have not been sufficiently modeled (Isaksson and Stille 2005; Sousa and Einstein 2012).

From the experience of many tunnel squeezing cases, three main kinds of direct loss can be identified should an improper support be used when squeezing happen: (i) the original initial support would mostly be destroyed by the excessive deformation; for example, the shotcrete linings cracked, rock bolts snapped and steel sets compromised; (ii) the original support being demolished and the squeezed part of rock masses being re-excavated to maintain the designated cross-section shape; (iii) A new and stronger set of support being reinstalled. An implicit assumption is made here: although the original support set may not be fully damaged as it depends on the intensity of the squeezing and the mechanical interaction between the rock masses and the lining, which requires more complicated modeling, we assume the damaged support cannot function well so that new support need to be reinstalled. As such, the economic loss due to the squeezing hazard can be expressed as Eq. (1):

$$E_{Total\ Loss} = E_{da} + E_{re} + E_{ex} \tag{1}$$

where E_{da} is the loss of the previously installed support set; E_{ex} represents the expense incurred by demolishing and re-excavating; E_{re} is the cost of the newly-installed support set.

E_{da} and E_{ex} are essentially the costs of different support schemes (as denoted by C_i). For these costs incurred by an routine tunnel activity (i.e. building primary support) are often modeled as random variables in tunnel construction risk analysis, due to the uncertainties in risk factors such as price fluctuation, labor efficiency and supply delay of construction materials etc. (Moret and Einstein 2016; Isaksson and Stille 2005). As such, this activity is broken down by all the basic operations in a sequential order. And to represent the variability of the prices related each operation, a PERT distribution is used to model the unit price of each construction operation. The PERT distribution has been widely adopted in recent years for estimating the effect of uncertainty of costs or durations in project management, for its easiness that only three estimates (i.e. the optimistic, the most likely, and the most pessimistic) are required (Golenko-Ginzburg 1988). When compared to a triangular distribution which is also based on these three point estimates, the PERT distribution is more suitable for occasions where much historical data have been documented (Covert 2013), such as the tunneling process in this study.

In the PERT distribution, the mean and standard deviation are defined as Eq. (2):

$$\mu = \frac{a + \gamma m + c}{\gamma + 2}, \ \sigma = \frac{c - a}{6} \tag{2}$$

where a is the optimistic value, m is the most likely value and c is the most pessimistic value; an additional scale parameter γ controls the shape and the default value is 4. The shape of the a PERT distribution can be seen in Fig. 2 where the data from Miyaluo No.3 tunnel in section 4 is used as an illustration.

For the re-excavation expense E_{re} which obviously depends on the volume of squeezed rock masses, the estimation of the degree of squeezing is of great importance in this regard. And E_{re} can be estimated through the multiplication of the squeezed volume by the mucking rate (see Eq. (3)). Moreover, the mucking operation is also a routine activity during tunneling whose unit price (mucking rate r_m) can also be modeled as a PERT distribution.

$$E_{ex} = V \cdot r_m, V = \pi[R^2 - (\frac{2R - u_a}{2})^2] \tag{3}$$

where V represents the squeezed volume that needs to be re-excavated and removed, r_m is the mucking rate, R is the equivalent radius of the tunnel (Feng and Jimenez 2015) and u_a is the potential convergence of the tunnel face of interest, which can be either predicted by an empirical regression model (Feng et al. 2019) or, in a simpler way, be considered as a random variable following a uniform distribution so that it is assigned to the mean value of the convergence range defined by the predicted corresponding squeezing intensity (see Hoek and Marinos 2000). The squeezing intensity is predicted by the proposed probabilistic classifier.

3.2. *Risk-based tunnel primary support decision making*

In tunneling practices, a few support schemes, as alternatives, would be recommended based on past experiences and expert judgements for construction convenience. A decision on what support scheme to use is closely related to the potential extent of convergence. The probabilistic multi-class squeezing prediction thus provides the estimation on the likelihood of different extents of convergence. However, as an integral part of

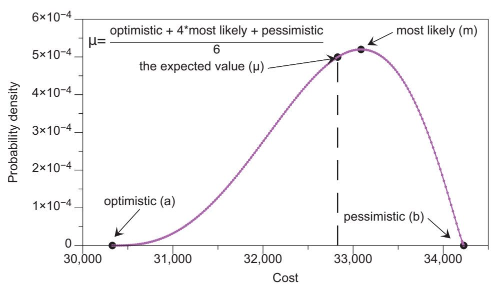

Fig. 2. The cost for the regular support scheme C_0 per linear meter

Table 1. Utility expressions for the example of a medium type support scheme

Alternative	Outcome	Probability[a]	Description	Utility value[b,c]
A2-Medium type support	non-squeezing	p_0	waste	$C_2 - C_0$
	slight-squeezing	p_1	waste	$C_2 - C_1$
	mediate-squeezing	p_2	just right	0
	severe-squeezing	p_3	inadequate	$C_2 + C_3 + E_{ex}$

Note: [a]represents the multi-class probability prediction of the squeezing intensity in a certain tunnel face; [b]C_i represents the cost of the support scheme i; [b]E_{ex} stands for the re-excavation expense when various squeezing hazard happens.

the risk component, the calculation of the consequence brought by the squeezing is clearly based on the scenarios concerning different combinations of squeezing intensity and support schemes. In principle, a relatively stronger support type (say a medium type support as shown in Table 1), with a higher-than-normal cost, would likely to handle a minor squeezing situation, but probably inadequate to hinder a severe squeezing and too conservative for a normal convergence. In either case, an economic loss or waste would arise. Therefore, a modified Event Tree Analysis (ETA) is adopted herein to probabilistically model each possible outcome of squeezing associated with each support alternative, with each scenario characterized by a branch, see Eq. (4).

$$u(A_i) = \sum_{j=1}^{n} p_i \cdot u(\theta_j),\ u(\theta_j) \sim PERT(\mu, \sigma, \gamma) \tag{4}$$

where A_i is the support alternative i; p_i and $u(\theta_j)$ respectively represents the probability and the utility value of the outcome θ_j, which represents the potential squeezing intensity in this analysis. Moreover, the utility expression here is considered in a cost-benefit perspective that both waste and damage are modeled as monetary loss. Table 1 demonstrates the logic between the support alternative and the possible squeezing intensity via the example of a medium type support scheme. Likewise, other support schemes can also be represented in the tree structure.

To reflect the uncertainties of this decision problem, compared to a classic deterministic event tree analysis, the utility outcome at each branch $u(\theta_j)$ is indeed a probability distribution that approximately follows a certain PERT distribution with a mean μ and a standard deviation σ, since the cost of supports C_i and re-excavation expense E_{ex} are modeled as random variables. As a result, for a given probability distribution $\vec{p_i}$, when Monte Carlo simulation is integrated to sample a random value in each branch, abundant simulations of decisions can be made, as opposed to a one-time decision in a traditional ETA. All these simulations of decisions could serve as votes to the final choice. Fig. 3, based on an example of a real tunnel case which would be elaborated in section 4, displays the whole structure of the tree as well as the utility expression for each scenario.

4. An Illustrative case

A tunnel case previously studied by Chen et al. 2019 to dynamically and probabilistically compute its tunnel squeezing intensity is revisited here. In this paper, we extend this analysis to further calculate the potential consequence and hence choose the optimal support scheme.

Located in southwest China, Miyaluo No.3 tunnel has a length of 3.6 km and a maximum overburden of 319m. A significant proportion of the grounds through which it is excavated are heterogeneous rock masses with inter-bedded layers of phyllite and thinly slate.

Table 2 lists the parameters of PERT distributions for the constituent components/operation of a tunnel support scheme, which are referenced from the budgetary norms of highway project in China (MTPRC 2007). The last row of Table 2, used to calculate the re-excavation expense, is referenced from Guan et al. 2014. Besides, four support schemes distilled from the tunneling experiences in squeezing grounds in southwestern China are adopted herein (Li, Meng, and Wang 2016), see Table 3. Table 3 indeed specify the quantity of materials required by each operation to construct a support scheme, suggesting that the cost distribution C_i can be therefore estimated by combining the quantitiy value and the unit price parameters (Table 2). As an example, Fig. 2 plots the PDF (probability density function) of the cost of the "regular support scheme" per linear meter. Also, the re-excavation expense E_{ex} can be obtained by combining the mucking rate, modeled as a PERT distribution (Table 2), and the squeezed volume, derived by a corresponding relationship between the squeezing intensity and the convergence, see Hoek and Marinos 2000. In this way, the utility value associated with each branch in Fig. 3 can be modeled by PERT distribution via the linear expression of C_i and E_{ex}.

For the study tunnel range from location ZK163+105 to ZK163+120, the tunnel face ad-

Table 2. PERT distribution parameters for the unit prices regarding the operations involved in a support set

Operation	Type	Unit	Most likely	Optimistic	Pessimistic	Mean	Std dev
Steel sets	structural steel	set	1436	1000	2000	1457.33	166.67
Steel mesh	-	t	4579	4000	5200	4586.00	200.00
Rock bolts	hollow	$100m$	4564	4000	5000	4542.67	166.67
	AAP[a]	$100m$	5485	5000	6000	5490.00	166.67
Shotcrete	-	$10m^3$	7933	7500	8500	7955.33	166.67
Mucking[b]	rock masses	$100m^3$	5703	5649	5858	5719.83	34.83

Note: [a]automatic anchor pole; [b]the re-excavation and mucking process of the squeezed rock masses;

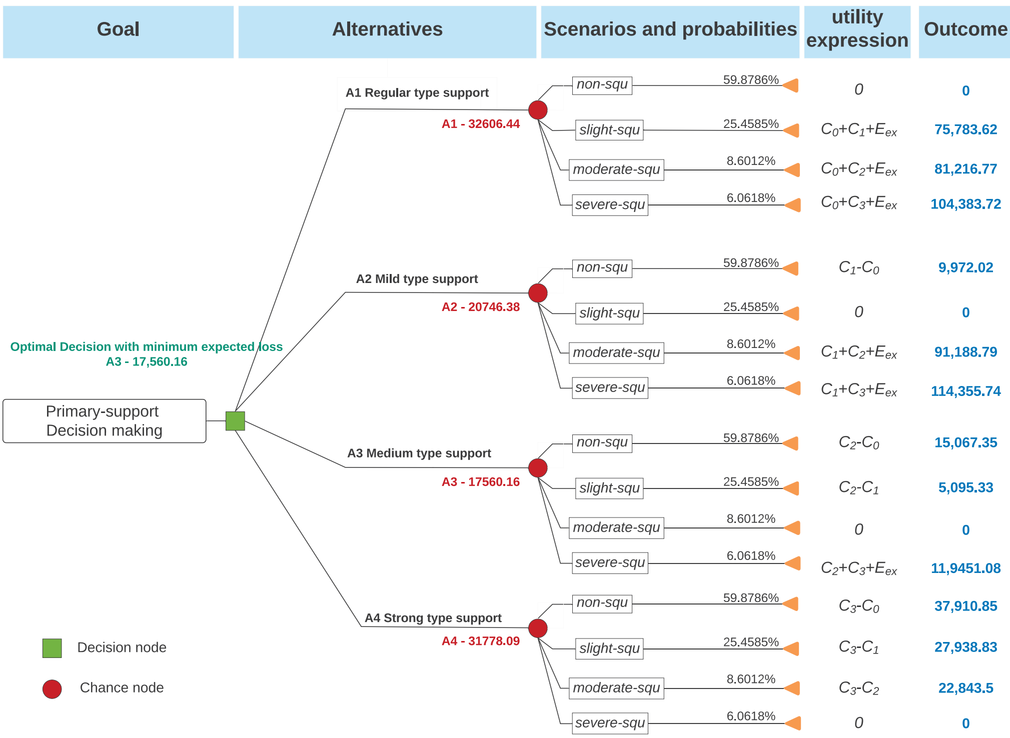

Fig. 3. The modified event tree analysis for location ZK163+120. The red number next to the chance node represents the expected loss value of each alternative, thereby an optimal decision can be made by choosing the least value as shown by the green number next to the decision node. The probability distribution over the four squeezing intensity is derived by a logistic classifier; The outcome values shown herein are random samples from Monte Carlo simulations as the the utility expression for each branch is modeled as a PERT distribution.

vanced roughly 1.8m a day and a consecutive 7-day in situ observations, which uses Schmidt Hammer test on surrounding rocks at each excavated tunnel face, have been documented, see Chen et al. 2019 for details. An example of the ETA analysis at location ZK163+120 is shown in Fig. 3, where a whole tree structure, the probability distributions over squeezing intensity derived by the trained logistic classifier, as well as a static series of sampled results of the utility outcome from 10000 Monte Carlo simulations are featured.

To fulfill the goal of primary-support decision making for a certain tunnel face to be excavated, four alternatives are identified (i.e. the southwestern-China support schemes), with each further linked to four possible squeezing scenarios associated with four squeezing intensities defined in Chen et al. 2019.

Table 3. Alternatives for primary-support schemes

Support scheme	Shotcrete (cm)	Rockbolts length (m)	Rockbolts spacing (cm)	Mesh (mm)	Structural steel type	Structural steel spacing (cm)
Regular	24	3	120*80	ϕ8@20	I18	80
Mild	26	5	100*100	ϕ8@20	I18	80
Medium	28	5	100*80	ϕ8@20	I22b	60
Strong	28	5	100*60	dual ϕ8@20	I22b	50

As a result, for the 10000 simulations of the event tree analysis, Fig. 4 shows the distribution of the expected outcomes for the alternative A4 (i.e. the severe type support) as an illustration while the distribution for other alternatives can likewise be drawn. Of the 10000 votes shown in Fig. 5, approximately 2/3 of the decisions end up picking the ”severe support type”.

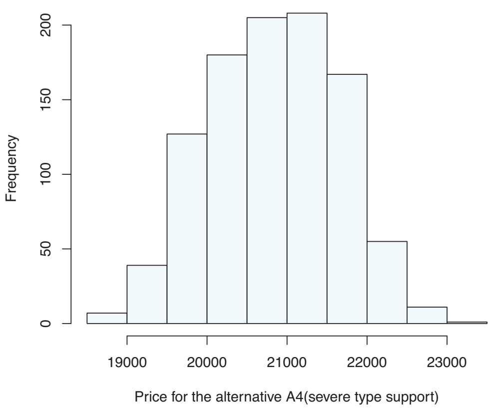

Fig. 4. Distribution of the expected loss with respect to the severe support scheme (A4) in 10000 Monte Carlo simulations

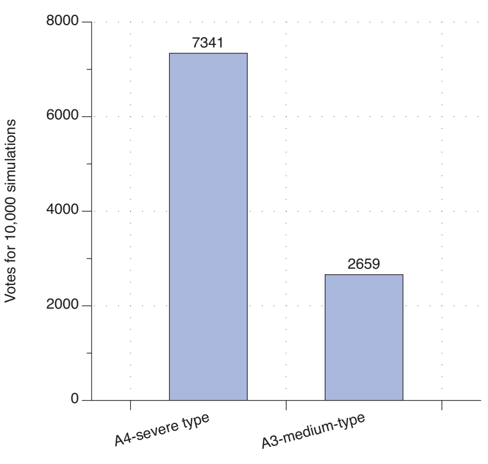

Fig. 5. Distribution of the votes for support alternatives in 10000 Monte Carlo simulations

5. Conclusion

This paper presents a risk-based decision making methodology to select the optimal support scheme in a quantitative manner.

In particular, the cost variance of each support scheme is modeled by a PERT distribution; the risk with respect to all possible outcomes of tunnel-squeezing intensity is represented by a modified Event Tree analysis: (i) each branch, which expresses a scenario of the possible tunnel squeezing intensity and the support alternative, is characterized with a probability and a utility value; (ii) the utility value, defined to reflect the monetary loss in a cost-effective way, is actually a probability distribution, as opposed to a single value; (iii) the distribution of votes to each support alternative, as outputs of the event tree, can be drawn via Monte Carlo simulations on the PERT distributions.The probability estimates over tunnel-squeezing intensities can be derived by most supervised learning algorithms, but attention should be paid that some algorithms produce distorted class probability distributions that cannot be directly used in further risk analysis, such as Naive Bayes, decision trees and boosting methods.

However, it should be emphasised that although a quick and useful selection of support scheme can be recommended by this methodology for construction convenience, it is still suggested that: when a high probability of severe squeezing or a large consequence is predicted, a more sophisticated analysis based on numerical simulations is necessary to confirm a final support design.

References

Barla, G. 1995. “Squeezing rocks in tunnels.” *ISRM News Journal* 2 (3): 44–49.

Chen, Yu, Tianbin Li, Peng Zeng, Junjie Ma, Edoardo Patelli, and Ben Edwards. 2019. “Dynamic and Probabilistic Multi-class Prediction of Tunnel Squeezing Intensity.” *Rock Mechanics and Rock*

Engineering: Manuscirpt submitted for publication.

Covert, R. 2013. "Analytic Method for Probabilistic Cost and Schedule Risk Analysis, Final Report." *prepared by Raymond Covert, for National Aeronautics and Space Administration (NASA) Office of Program Analysis and Evaluation (PA&E) Cost Analysis Division (CAD):* 186–187.

Degn Eskesen, Søren, Per Tengborg, Jørgen Kampmann, and Trine Holst Veicherts. 2004. "Guidelines for tunnelling risk management: International Tunnelling Association, Working Group No. 2." *Tunnelling and Underground Space Technology* 19 (3): 217–237. doi:10.1016/j.tust.2004.01.001.

Einstein, H. 2004. "Decision aids for tunneling: Update." *Transportation research record,* no. 1892: 199–207.

Evert, Hoek. 2001. "Big Tunnels in Bad Rock." *Journal of Geotechnical and Geoenvironmental Engineering* 127, no. 9 (September): 726–740. doi:10.1061/(ASCE)1090-0241(2001)127:9(726). https://doi.org/10.1061/(ASCE)1090-0241(2001)127:9(726).

Faber, Michael Havbro. 2007. "Risk and safety in civil engineering." *Lecture Notes. Swiss Federal Institute of Technology, Zurich.*

Feng, Xianda, and Rafael Jimenez. 2015. "Predicting tunnel squeezing with incomplete data using Bayesian networks." *Engineering Geology* 195:214–224. doi:10.1016/j.enggeo.2015.06.017. http://linkinghub.elsevier.com/retrieve/pii/S0013795215300028.

Feng, Xianda, Rafael Jimenez, Peng Zeng, and Salvador Senent. 2019. "Prediction of time-dependent tunnel convergences using a Bayesian updating approach" [in English]. *Tunnelling and Underground Space Technology* 94:103118. doi:10.1016/j.tust.2019.103118. https://linkinghub.elsevier.com/retrieve/pii/S0886779819301968.

Golenko-Ginzburg, Dimitri. 1988. "On the Distribution of Activity Time in PERT." *Journal of the Operational Research Society.* ISSN: 0160-5682. doi:10.1057/palgrave.jors.0390808.

Guan, Zhenchang, Tao Deng, Yujing Jiang, Cheng Zhao, and Hongwei Huang. 2014. "Probabilistic estimation of ground condition and construction cost for mountain tunnels." *Tunnelling and Underground Space Technology* 42:175–183. doi:10.1016/j.tust.2014.02.014. http://linkinghub.elsevier.com/retrieve/pii/S0886779814000248.

Hoek, Evert, and Paul Marinos. 2000. "Predicting tunnel squeezing problems in weak heterogeneous rock masses." *Tunnels and tunnelling international* 32 (11): 45–51.

Huang, Hongwei, and Dongming Zhang. 2015. "Quantitative Geotechnical Risk Management for Tunneling Projects in China." *Geotechnical Safety and Risk V:* 61–75.

Isaksson, Therese, and Håkan Stille. 2005. "Model for estimation of time and cost for tunnel projects based on risk evaluation." *Rock Mechanics and Rock Engineering* 38 (5): 373–398.

Jimenez, R, and D Recio. 2011. "A linear classifier for probabilistic prediction of squeezing conditions in Himalayan tunnels." *Engineering Geology* 121 (3): 101–109.

Li, Tianbin, Lubo Meng, and Lansheng Wang. 2016. *Tunnel stability under high geostress and prevention of rock burst and squeezing hazard.* 200–205. Beijing: Science Press.

Manchao, He, R Leal e Sousa, André Müller, Eurípedes Vargas, L Ribeiro e Sousa, and Chen Xin. 2015. "Analysis of excessive deformations in tunnels for safety evaluation." *Tunnelling and Underground Space Technology* 45:190–202. doi:10.1016/j.tust.2014.09.006. http://www.sciencedirect.com/science/article/pii/S088677981400159X.

Moret, Yvonne, and Herbert H Einstein. 2016. "Construction Cost and Duration Uncertainty Model: Application to High-Speed Rail Line Project" [in English]. *Journal of construction engineering and management* 142 (10): 5016010–5016013. doi:10.1061/(ASCE)CO.1943-7862.0001161. http://ascelibrary.org/doi/10.1061/%7B%5C%%7D28ASCE%7B%5C%%7D29CO.1943-7862.0001161.

MTPRC. 2007. *Budgetary Norms of Highway Project in China. JTGTB0602. Ministry of Transportation of PR China. (in Chinese).*

Niculescu-Mizil, Alexandru, and Rich Caruana. 2005. "Predicting good probabilities with supervised learning." In *ICML 2005 - Proceedings of the 22nd International Conference on Machine Learning,* 625–632. ISBN: 1595931805. doi:10.1145/1102351.1102430.

Sousa, Rita L, and Herbert H Einstein. 2012. "Risk analysis during tunnel construction using Bayesian Networks: Porto Metro case study." *Tunnelling and Underground Space Technology* 27 (1): 86–100. doi:10.1016/j.tust.2011.07.003.

Špačková, Olga, Eva Novotná, Michal Šejnoha, and Jiří Šejnoha. 2013. "Probabilistic models for tunnel construction risk assessment." 62-63:72–84. doi:10.1016/j.advengsoft.2013.04.002.

Sun, Yang, Xianda Feng, and Lingqiang Yang. 2018. "Predicting Tunnel Squeezing Using Multiclass Support Vector Machines" [in English]. *Advances in Civil Engineering* 2018 (11): 1–12. doi:10.1155/2018/4543984. https://www.hindawi.com/journals/ace/2018/4543984/.