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Predicting rock burst hazard with incomplete data using Bayesian networks

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ABSTRACT

Rock burst is a dynamic process of sudden, rapid and violent release of elastic energy accumulated in rock and coal masses during underground activities. It can lead to casualties, to failure and deformation of the supporting structures, and to damage of the equipment on site; hence its prediction is of great importance. This paper presents a novel application of Bayesian networks (BNs) to predict rock burst. Five parameters —Buried depth of the tunnel (H), Maximum tangential stress of surrounding rock (MTS) (σ_θ), Uniaxial tensile strength of rock (UTS) (σ_t), Uniaxial compressive strength of rock (UCS) (σ_c) and Elastic energy index (W_{et})— are adopted to construct the BN with the Tree augmented Naïve Bayes classifier structure. The Expectation Maximization algorithm is employed to learn from a data set of 135 rock burst case histories, whereas the belief updating is carried out by the Junction Tree algorithm. Finally, the model is validated with 8-fold cross-validation and with another new group of incomplete case histories that had not been employed during training of the BN. Results suggest that the error rate of the proposed BN is the lowest among the traditional criteria with capability to deal with incomplete data. In addition, a sensitivity analysis shows that MTS is the most influential parameter, which could be a guidance on the rock burst prediction in the future.

1. Introduction

Rock burst is a sudden and violent release of elastic energy accumulated in rock and coal masses that occur during the underground activities. It produce ejection of rock fragments, which could lead to casualties, to failure and deformation of the supporting structures, and to damage of equipment (Brauner, 1994; Ortlepp and Stacey, 1994; Dou et al., 2012; Cai, 2013). Its economic consequences in the civil and mining engineering sectors are significant. For instance, taking data from China as an example, more than 13,000 accidents associated with rock burst, with casualties exceeding 16,000, have been reported to have occurred in metal mining between 2001 and 2007 (Zhou et al., 2012). Similarly, significant problems have occurred in coal mining due to rock burst. Two examples are Qianqiu Coal mine in Henan province (3rd November, 2011, with 10 people killed and 75 trapped underground), and Sunjiawan Coal mine in Liaoning Province (14th February, 2005, with a serious gas explosion induced by rock burst that killed 214 people) (Li et al., 2015). It is therefore expected that, with the increasing complexity and depth of future underground projects, additional challenges due to rock burst must be addressed, so that there is a need to further test methods that are commonly employed in current practice (see Table 1), and to develop new multi-disciplinary methods to predict and control rock burst hazards during mining and other underground activities (Dou et al., 2012).

Rock burst prediction can be divided into two categories: long-term and short-term predictions (Peng et al., 2010). Long-term predictions aim to preliminary qualify, during the initial stages of a project, the likelihood of rock burst occurring during the development of the project, so that can serve a guidance for decision making in relation to excavation and control methods; whereas short-term predictions aim to predict the location and time of rock burst occurrence based on data —such as information about drilling bits, micro seismic monitoring, and acoustic emission— collected at the engineering site. (see e.g., Cai et al. (2001), Lu et al. (2012) and Ma et al. (2015)) This work focuses on long-term prediction of rock burst.

Data mining methods and artificial intelligence have often been applied for long-term prediction of rock burst since the seminal work of Feng and Wang (1994). For instance, Zhang et al. (2011) employed a Particle Swarm Optimization-BP Neural Network; Zhou et al. (2012) and Peng et al. (2014) proposed a rock burst

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Table 1
A summary of previous criteria for rock burst prediction.

Proposed by	Equation	Parameters	Rock burst discrimination
Russenes criterion (Russenes, 1974)	σ_θ/σ_c	σ_θ, σ_c	>0.2
Hoek criterion (Hoek and Brown, 1980)	σ_c/σ_θ	σ_θ, σ_c	$\leqslant$3.5
Rock brittleness coefficient (Wang et al., 1998)	σ_c/σ_t	σ_c, σ_t	$\leqslant$40
Depth prediction critical (Hou and Wang, 1989)	$H_{cr} = 0.318\sigma_c(1-\mu)/(3-4\mu)\,\gamma$	σ_c, μ, γ	N/A
Elastic energy index (Wang et al., 1998)	W_{et}	W_{et}	>2.0

Note: σ_θ is the maximum tangential stress of surrounding rock, MPa, σ_c is the uniaxial compressive strength of rock, MPa, σ_t is the uniaxial tensile strength of rock, MPa, μ is the Poisson's ratio, γ is the weight of the rock mass, W_{et} is elastic energy index.

classification based on support vector machines; Li and Liu (2015) employed the random forest approach; and Liu et al. (2013) employed cloud models with attribution weight. Others have employed fuzzy technologies (see e.g., Liu et al. (2008), Guo and Jiang (2009), Yu et al. (2009) and Adoko et al. (2013)) to infer rock burst and its risks; and Bai et al. (2009) developed a Fisher discriminant analysis model (FDA) for rock burst prediction in deep rock engineering.

One of the main difficulties to predict rock burst with existing methods is that data are difficult to obtain and often incomplete. To overcome this problem, we propose a Bayesian network (BN) (Pearl, 1986) to predict the occurrence of rock burst, as BNs have the advantage of naturally dealing with the conditional dependency relationships between the observed or unobserved random variables of a statistical model, hence making them an interesting choice in inference, classification and decision making problems (Aguilera et al., 2011). Although BNs have been widely employed in geotechnical engineering (Jimenez-Rodriguez and Sitar, 2006; Medina-Cetina and Nadim, 2008; Xu et al., 2011; Huang et al., 2012; Schubert et al., 2012; Song et al., 2012; Sousa and Einstein, 2012; Špačková et al., 2013; Borg et al., 2014; Feng and Jimenez, 2015), they have not yet been employed to predict rock burst.

2. Parameters chosen for the BN and data set description

2.1. Inputs in the BN

Several theories —such as the 'strength theory', the 'rigidity theory' and the 'energy theory'— were proposed since the 1950s to explain the mechanism leading to rock burst occurrence, and for its long-term prediction considered herein. After that, new 'burst liability' theories that employ the elastic energy index, the burst energy release index and the duration of dynamic fracture to predict rock burst were developed (Dou et al., 2006); and many other criteria have been proposed to predict rock burst (see Table 1 for a summary of the most commonly used ones). As most criteria only considered no more than three input parameters and hence cannot comprehensively utilize all the information about different parameters that can be collected nowadays, the proposed BN can be a powerful approach to naturally deal with data sets comprising several variables, as well as with missing data and with the conditional dependency relationships between variables. Therefore, using such previous works as guidance, we consider five parameters that have potential influence on rock burst: buried depth of the tunnel (H), maximum tangential stress at the surrounding rock (MTS) (σ_θ), uniaxial tensile strength of rock (UTS) (σ_t), uniaxial compressive strength of the rock (UCS) (σ_c) and elastic energy index (W_{et}). A brief description of these parameters, and about the case with which information about them can be acquired, are presented below.

2.1.1. Buried depth of the tunnel

Observations in real cases indicate that rock burst occurs mainly in deep rock engineering and most works consulted during the literature review agree in the observation that tunnel depth is an important factor that can affect rock burst. Therefore, and although in-situ rock stress would probably be a better predictor, the lack of information about in-situ stress in many projects, as well as the difficulties to accurately estimate in-situ rock stress at early stages of a project without expensive and time consuming in-situ tests, make us to select the buried depth of the tunnel as an alternative. (Note also that, as the excavation depth increases, the in-situ stress —which is often estimated by λH with λ being the unit weight of the rock mass— also increases.) H is also commonly reported in case histories, so that information about H is only missing in 16 out of the 135 cases in the data set.

2.1.2. Maximum tangential stress of the surrounding rock

The maximum tangential stress is often used to predict the fracture angle of rock (Aliha and Ayatollahi, 2012). For instance, Ryder (1988), in his study of the influence of excess shear stress on rock burst–prone conditions, concluded that the fault-slip and shear fracture modes played a dominant role in Africa metal mines. Whereas Qian (2014) proposed two modes of rock burst dynamic failure: one 'strain mode' resulting from the rock failure and one 'sliding mode' caused by the fault-slip and shear fracture events. Qian (2014) also analyzed two rock burst accidents in coal mines in China, stating that the instability due to rock burst occurrence could also be classified as 'fault-slip' and 'shear fracture' modes. Therefore, previous studies clearly illustrate that the maximum tangential stress can significantly influence the occurrence of shear fracture instabilities in tunnels, hence becoming an important parameter for rock burst prediction. It is also a widely available parameter, as only 35 cases in the data set do not report this parameter.

2.1.3. Uniaxial compressive and tensile strength

The uniaxial compressive strength and the uniaxial tensile strength are two other parameters that can influence rock burst, and they have often been applied for such task. Both are also commonly available parameters, and only one UCS and twelve UTS values are missing from the database.

2.1.4. Elastic energy index

The Elastic energy index, W_{et}, is defined as the proportion of retained strain energy to that dissipated during a single loading-unloading cycle under uniaxial compression (Kidybiński, 1981; Singh, 1988). This parameter is related to the rock burst hazards, and Wang et al. (1998) developed a rock burst prediction criterion based on W_{et}.W_{et} values can be easily obtained through laboratory tests as well as with direct (double-hole method) or indirect (rebound method) in-situ evaluations. Only 18 cases (out of 135) in the database do not report a W_{et} value or information to compute it (Singh, 1988).

2.2. Description of the database

Many rock burst case histories comprising data from different types of underground projects from all over the world have been compiled by Zhou et al. (2012). Additional rock burst data of coal tests have been collected from Zhao et al. (2007) and some unpublished technical reports. Such sources have allowed us to compile a