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The Influence of Bayesian Networks Structure on Rock Burst Hazard Prediction with Incomplete Data

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Abstract

Rock burst is often induced by the superposition of static and dynamic loads that produces failure with a sudden and violent release of elastic energy accumulated in rock and coal masses during underground activities. Casualties, deformation of the supporting structures and damage of the equipment on site are some of its consequences, hence producing a need to study its prediction. A novel application of Bayesian networks (BNs) to predict rock burst is proposed in this paper. In order to analyze the influence of the network structure, several networks are constructed with five parameters: Tunnel depth (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}). The Expectation Maximization algorithm is employed to learn from a data set of 135 rock burst case histories with incomplete data, whereas belief updating is carried out by the Junction Tree algorithm. 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, and the influence of the network structure on the classification results, as well as the advantages and limitations of different network structures, are discussed. Results suggest that BNs are able to satisfactorily deal with incomplete data, hence becoming a useful tool to predict the rock burst hazard at the initial stages of underground work.

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Keywords: Rock burst; BN-Bayesian networks; Naïve Bayes classifier; Tree augmented Naïve Bayes classifier; BN augmented Naïve Bayes classifier; Incomplete data; Cross-validation

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1. Introduction

Rock burst is a sudden and violent release of elastic energy accumulated in rock and coal masses that occurs during underground activities. Casualties, deformation of the supporting structures and damage of the equipment on site are some of its consequences, hence producing a need to study its prediction [1, 2].

Long-term predictions of rock burst aims to preliminary assess, during the initial stages of a project, the likelihood of rock burst occurring during the project, so that they can serve for decision making. This work focuses on long-term prediction of rock burst. Data mining methods and artificial intelligence have often been applied for this since the seminal work of [3]. Methods such as Back Propagation Neural Network, SVM, Random Forests, Cloud models and fuzzy technologies have been studied by many researchers [4-7].

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 difficulty, we propose a Bayesian network (BN) [8] to predict rock burst, as BNs have the advantage of naturally dealing with the conditional dependency relationships between the observed or unobserved variables of a statistical model, hence making them an interesting choice in inference, classification and decision making [9]. Although BNs have been widely employed in geotechnical engineering [10-12], they have not yet been employed to predict rock burst. In addition, as BNs depend on the structure of conditional relationships, we test three different classifier structures to assess their influence on the BN results and performance.

2. Parameters chosen for the BN and data set description

2.1. Inputs in the BN

For the long-term prediction considered herein, we consider five parameters with 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 rock (UCS) (σ_c) and elastic energy index (W_{et}). A brief description of these parameters is presented below.

2.2. Description of the database

Many rock burst case histories including data from different types of underground projects from all over the world have been compiled by [4]. Additional rock burst data of coal tests have been collected from [13]. Such sources have allowed us to compile a new database of rock burst case histories to be employed in our analysis. It contains 135 case histories, among which 83 correspond to rock burst cases and 52 to non-rock burst. Table 1 shows the statistics (number of available and missing data, minimum and maximum values, means and standard deviations) of the five parameters chosen to predict rock burst with the established BN. (It also proposes intervals for analysis, which will be discussed later.)

Table 1. Descriptive statistics of the input parameters for case histories within the database and the interval applied for the BN.

Parameter	Available	Missing	Min	Max	Mean	Standard deviation	Set of intervals with count	State of each parameter
H [m]	119	16	100	1140	705.97	274.53	[100, 200]/4, (200, 400]/20, (400, 705]/22, (705, 1140]/73	Shallow, Medium, Deep, Very deep
MTS [MPa]	100	35	2.6	167.2	56.28	33.21	[2.6, 28]/16, (28, 57.5]/42, (57.5, 167.2]/42	Low, Medium, High
UCS [MPa]	134	1	2.9	263	97.32	54.69	[2.9, 69.15]/44, (69.15, 119]/42, (119, 263]/48	Low, Medium, High
UTS [MPa]	123	12	0.38	19.2	5.68	3.58	[0.38, 3.29]/41, (3.29, 6]/36, (6, 19.2]/46	Low, Medium, High
W_{et}	117	18	1.1	9.3	4.41	2.05	[1.1, 2.2]/26, (2.2, 4.7]/38, (4.7, 9.3]/53	Low, Medium, High