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Stability assessment of hard rock pillars using two intelligent classification techniques: A comparative study

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ABSTRACT

One of the most challenging safety problems in underground hard rock mines is pillar stability during mining operation. This paper presents an assessment of J48 and SVC application for pillar stability prediction in underground hard rock mines. Based on a database compiled from various hard rock mines and using these algorithms, two stability graphs are developed. The performance assessment of models indicates that both models can predict pillar stability with acceptable accuracy. In comparison with logistic regression model, the prediction capability of J48 and SVC models is better, but the J48 model shows superiority over two other models.

1. Introduction

Pillars can be defined as the in situ rock between two or more underground openings. In underground hard rock[1] mines, pillars are required to support the overburden and to provide a safe, stable working environment for mining personnel and equipment. Unstable pillars can result in rock sloughing from the pillar ribs and can lead to the collapse of the roof if one or more pillars should fail. Thus, pillar stability is an essential prerequisite for safe and economic working conditions in hard rock mines.

In conventional approaches, pillar stability is assessed by calculation of safety factor. The pillar safety factor is defined as the ratio of pillar strength to pillar load. The pillar fails when the ratio is less than 1, because the pillar is loaded beyond its peak resistance. The pillar load can be estimated using several different ways, including the tributary area theory and numerical modeling methods. Furthermore, strength of pillars can be determined by two different methods, namely, empirical equations derived from back analyses of failed and stable cases, and numerical modeling tools using appropriate failure criteria (Martin and Maybee, 2000; Kaiser et al., 2010; Malan and Napier, 2011). Some of these empirical equations presented by Hedley and Grant (1972), Von Kimmelmann et al. (1984), Krauland and Soder (1987), Potvin et al. (1989), Sjoberg (1992) and Lunder and Pakalnis (1997).

In past years, many researches have been conducted to assess the hard rock pillars stability. Ozbay et al. (1995) presented a comprehensive review of empirical pillar design methods in South Africa hard rock mines. York et al. (1998) developed guidelines for the design of pillar systems for shallow and intermediate depth, tabular, hard rock mines based on field observations and numerical modeling of Africa mines. Schubert and Villaescusa (1998) presented a new approach for hard rock pillar design at the McArthur River mine, Australia. Iannacchione (1999) examined seventy-two stone mines in US and developed pillar design guidelines based on field observations. Aksoy and Onargan (2006), Esterhuizen and Ellenberger (2007), Mortazavi et al. (2009), Elmo and Stead (2010), Li et al. (2013), Dehghan et al. (2013), Kun (2014), Kortnik (2015), Murphy et al. (2016) used numerical modeling for pillar stability assessment. Griffiths et al. (2002) and Cauvin et al. (2009) investigated the underground pillar stability based on probabilistic methods. Deng et al. (2003) proposed a pillar design approach by combining finite element methods, neural networks and reliability analysis. Gonzalez-Nicieza et al. (2006) presented a new formulation for hard rock pillar design based on modification of existing empirical formulae on the basis of the RMR (Bieniawski's Rock Mass Rating). They concluded that this new formulation determines the safety factor of pillars with greater reliability. Tawadrous and Katsabanis (2007) used artificial neural networks for predicting the stability of crown pillars. Carter (2014) explained use of the empirical Scaled Span methodology for surface crown pillar stability assessment. Zhou et al. (2011) presented two models for predicting pillar stability applying support vector machine and Fisher discriminant analysis techniques. Esterhuizen et al. (2011a, 2011b) carried out a survey of pillars performance in 34 different stone mines in the Eastern and Midwestern United States between 2005 and 2009. This survey led to the development of applicable guidelines for designing stable pillars and roof spans

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[1] Hard rock can be considered to include most igneous and metamorphic rocks and well-indurated sedimentary rocks such as limestones, dolomites, and sandstones (Kendorski, 2007).

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in stone mines. A software package titled Stone mine pillar design (S-pillar) was developed for easy application of these guidelines (Esterhuizen and Murphy, 2011). Tomory et al. (2014) and Wattimena (2014) developed graphs for predicting of hard rock pillars stability using logistic regression. Idris et al. (2015) performed a stochastic assessment of pillar stability at Laisvall mine using artificial neural network. Zhou et al. (2015) developed several models for pillar stability prediction in hard rock mines using six supervised learning methods: linear discriminant analysis, multinomial logistic regression, multilayer perceptron neural networks, support vector machine, random forest, and gradient boosting machine. Most of these models are black box, i.e. these models do not show a transparent and understandable relationship between inputs and output.

The main purpose of this study is to develop robust and transparent models for stability assessment of hard rock pillars. To achieve this purpose, the J48 and support vector classification (SVC) techniques are used to develop two graphs for pillar stability prediction. Although these techniques have been successfully applied in many domains, the application in mining and rock mechanics is limited based on literature surveys. Unlike most soft computing methods, which are opaque, J48 and SVC algorithms can provide a comprehensible and easy to use graph.

This paper is organized as follows: a description of used database is given in Section 2. Development of J48 and SVC models are described in Section 3. Evaluation of models' performances is outlined in Section 4. In Section 5, the performances of proposed models are compared with similar previous models. Finally, the summary of the work and concluding remarks are presented in Section 6.

2. Description of database

As mentioned before, the aim of this study is to develop two graphs for assessing hard rock pillar stability using J48 and SVC algorithms. To develop these graphs, the database complied by Lunder (1997) is used. This database contains 178 hard rock pillar cases from various mine sites: Elliot Lake uranium mines in Canada, Mount Isa mines in Australia, Selebi-Phikwe mines in Southern Africa, Black Angel mine in Greenland, open stope mines in Canada, Zinkgruvan mine in Sweden, Westmin Resources Ltd.'s H-W mine in Canada (Lunder, 1994). The database has been presented in Wattimena (2014) in details and a summary of that is indicated in Table 1. As can be seen in the table, the database includes two input parameters, i.e. the pillar width to height ratio (w/h) and the ratio of average induced pillar load over the UCS of the intact rock (PL/UCS), and one output parameter, i.e. pillar stability condition (PS). Pillar stability condition has been classified into 3 categories; stable, unstable and failed based on presented definitions in Table 2. The database contains 60 stable, 50 unstable and 68 failed cases.

3. Development of stability graphs

Since the output parameter of database (PS) is categorical, classification techniques should be used for developing stability graphs. In this paper, J48 and SVC are used as efficient classification techniques and two graphs are developed for assessing pillar stability. In both graphs, w/h and PL/UCS are considered as independent (input) variables and PS as dependent (output) variable, which is coded as 0 for stable, 1 for unstable and 2 for failed pillars. The train-and-test technique, which is one of the most common approaches to establish learning algorithms for a given database, is used to develop the models. In this method, a database is randomly divided into two categories (i.e., the train and the test datasets). After training the model using the train datasets, the model is tested by the test datasets. In this study, 85% of the database (151 datasets) is used to train the models and the remaining 15% (27 datasets) for testing the models.

Table 1
A summary of original database description.

Data type	Parameter	Symbol	Value
Input	Pillar width to height ratio	W/h	0.31–4.5
	Average pillar load to UCS of intact rock ratio	PL/UCS	0.11–0.67
Output	Pillar stability condition	PS	0 for stable pillar 1 for unstable pillar 2 for failed pillar

3.1. Stability graph based on SVC algorithm

Support vector machine (SVM) is a supervised learning model that is used for regression (SVR) and classification (SVC) problems (Shi, 2014). More details about the SVM models and their mathematics are given in Vanpik (1999) and Shi (2014). SVM was first developed to deal with classification problems which the objective is to find an optimal hyperplane that separates two classes (binary classification). Since in the real world, most of problems are multi-category, traditional two-class SVC is unable to be applied in the multi-classification problems. Several approaches have been developed to overcome this deficiency and one of them transforms the multi-class SVC into several two-class SVCs. In this approach, the multi-class SVC methods are grouped into two categories: one-against-one and one-against-all algorithms (Ma and Guo, 2014). Hsu and Lin (2002) explained these two methods in details and concluded that one-against-one is a better approach.

In this paper, LIBSVM toolbox developed by Chang and Lin (2011) was used for constructing the SVC model. The LIBSVM, an integrated software tool, was run in the Matlab environment. LIBSVM implements the one-against-one approach and employs Radial Basis Function (RBF) kernel as the kernel function because of its superiority over the other functions. Application of SVC to any classification problem requires the determination of several user-defined parameters. Two main parameters that need to be determined are regularization parameter (C) and the kernel width (γ). The values of these parameters greatly affect the training and generalization capability of the SVC. In LIBSVM software, C and g are obtained via a grid searching method coupled with cross validation (Chang and Lin, 2011). The obtained graph by LIBSVM software based on train datasets is shown in Fig. 1. As can be seen, this graph contains three distinct zones: stable zone (green), unstable zone (blue) and failed zone (pink). It is evident that increase of w/h and decrease of PL/UCS cause the pillar to locate in stable zone and in contrast decrease of w/h and increase of PL/UCS put the pillars in failed zone. These results are in good agreement with engineering judgments.

3.2. Stability graph based on J48 algorithm

The J48 algorithm is the Java implementation of the C4.5 algorithm (Witten and Frank, 2005). C4.5 is one of the most-used algorithms in classification tasks. C4.5 decision tree is an extension of ID3 algorithm, which was developed by Quinlan (1993). This algorithm can handle numeric attributes, missing values, and noisy data (Nefeslioglu et al., 2010). C4.5 is used to construct the decision (classification) trees. The decision tree uses a graph like tree and acts as decision support system. A tree structure consists of a root node, internal nodes, and leaf nodes. The root node contains all the input data. An internal node can have two or more branches and is associated with a decision function. A leaf node indicates the output of a given input vector and denotes the class label. The main advantage of decision trees is that they are easy to construct and the resulting trees are readily interpretable (Bui et al., 2014).

C4.5 consists of tree building and tree pruning steps. The C4.5 algorithm, builds decision trees from a set of training data using the information entropy concept. The tree is generally constructed in a top-