Engineering 3 (2017) 552–558

Contents lists available at ScienceDirect

Engineering

journal homepage: www.elsevier.com/locate/eng

Research
Efficient Exploitation of Deep Mineral Resources—Article

The Use of Data Mining Techniques in Rockburst Risk Assessment

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ARTICLE INFO

Article history:
Received 28 April 2017
Revised 6 July 2017
Accepted 7 July 2017
Available online 31 July 2017

Keywords:
Rockburst
Data mining
Bayesian networks
In situ database

ABSTRACT

Rockburst is an important phenomenon that has affected many deep underground mines around the world. An understanding of this phenomenon is relevant to the management of such events, which can lead to saving both costs and lives. Laboratory experiments are one way to obtain a deeper and better understanding of the mechanisms of rockburst. In a previous study by these authors, a database of rockburst laboratory tests was created; in addition, with the use of data mining (DM) techniques, models to predict rockburst maximum stress and rockburst risk indexes were developed. In this paper, we focus on the analysis of a database of *in situ* cases of rockburst in order to build influence diagrams, list the factors that interact in the occurrence of rockburst, and understand the relationships between these factors. The *in situ* rockburst database was further analyzed using different DM techniques ranging from artificial neural networks (ANNs) to naive Bayesian classifiers. The aim was to predict the type of rockburst—that is, the rockburst level—based on geologic and construction characteristics of the mine or tunnel. Conclusions are drawn at the end of the paper.

1. Introduction

Accidents and related problems can occur frequently in deep underground mines and other underground structures. Thus, it is essential to develop and implement risk analysis procedures to minimize their occurrence. Risk has a complex nature and results from the combination of two sets of factors: first, the events and their impacts; and second, the vulnerability factors that determine the probability of an event having a certain impact or consequence [1–3].

Many researchers have collected, analyzed, and published reports on accident cases that have occurred in tunnels during construction and exploration [2,4]. Rockburst is one example of an accident that can occur during tunneling. It is a result of overstress of the rock mass or of the intact brittle rock, and happens when stresses exceed the compressive strength of the material. The impacts of rockburst range from spalling to sudden and violent failure of the rock mass. Depth is an important factor in the occurrence of this phenomena, since the stress exerted on the rock increases with depth.

In mining activities, other types of events have also been identified and classified, such as heat hazards and other events related to blasting cavities. Blasts, gas explosions, and fire are the most common hazardous events in China. In deep mining activities, major problems are also associated with large deformations and overstressing of the rock mass, which are caused by excavations at great depth, and which may result in rockburst. Comprehensive investigations of deep mining mechanics are thus of great interest [5].

Risk assessment can be managed with the aim of avoiding problems in underground construction. Risk management procedures can be significantly improved by using systematic techniques throughout the project's life. By using such techniques, potential problems can be clearly identified such that appropriate risk mitigation measures can be implemented in a timely manner. As a result, risk management became an integral part of most underground construction projects during the late 1990s [1,2,6].

During the construction of some of the underground structures of the Jinping II hydropower scheme in China, engineers were faced with the occurrence of several rockbursts [7–9]. As a result, a large study was conducted by the authorities to evaluate the accidents

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http://dx.doi.org/10.1016/J.ENG.2017.04.002

and to come up with mitigation measures and guidelines for construction under circumstances that are prone to rockburst. This study included the establishment of a database containing information regarding rockburst and a description of the events that had occurred, and led to the use of data mining (DM) techniques to determine the probability of occurrence of rockburst and its characteristics (i.e., type, location, depth and width, and time delay) [10–14].

We analyzed these events and concluded that the main mechanisms in rockburst are usually associated with local underground geometry, such as pillars and openings, and with the ground conditions [15,16]. Rockbursts are classified as strain bursts, pillar bursts, or fault slip bursts [17,18]. They usually occur during mining operations; however, they can also happen during the construction of civil underground structures, such as deep tunnels. In these cases, the most common phenomenon is strainbursting, although buckling and face crushing may also take place. In addition, impact-induced rockburst created by blasting, caving, and adjacent tunneling should be considered for less stressed and deformed rock formations.

The focus of this paper is on rockburst risk assessment, on the different types of rockburst events, and on their consequences to underground mining and construction. Two rockburst databases that were assembled by these authors are discussed. The first consists of a collection of rockburst laboratory experiments that were performed at the State Key Laboratory for GeoMechanics and Deep Underground Engineering (SKL-GDUE) in Beijing and that were the object of a publication in the journal of *Engineering Geology* for geological and geotechnical hazards [6]. The second consists of worldwide *in situ* cases of rockburst that occurred during mining and deep underground construction. The latter database was analyzed, and a list of factors that interact and influence the occurrence of rockburst was determined, along with the relationships between these factors. Finally, different DM techniques were applied to the rockburst databases with the aim of developing predictive models of rockburst index and type. The results are presented in detail in Sections 3 and 4, and the different techniques are compared.

2. Data mining modeling in geoengineering

The prediction of geotechnical formation behavior in geoengineering is complex, particularly during excavations in mining engineering. This complexity is related to uncertainties in the rock mass characterization. In important projects, a large amount of geotechnical data can assist in reducing uncertainties concerning the establishment of design values for the parameters [19]. In the case of rockburst occurrence, the problems are even more difficult to evaluate.

Such data can hold information on trends and patterns that can be used in decision-making and to optimize processes. Therefore, it is necessary to define standard ways of collecting, organizing, and representing data. DM techniques are automatic tools from artificial intelligence and pattern-recognition fields that enable the discovery of potential knowledge [20–23]. DM is an area of computer science that lies at the intersection of statistics, data management and databases, machine learning, artificial intelligence, pattern recognition, and other areas.

The formal and complete analysis process is called knowledge discovery from databases (KDD). KDD establishes the main procedures for transforming data into knowledge. The KDD process follows the steps indicated in Fig. 1 [20]: collection of a target dataset, data warehousing, transformation of the data into adequate forms for the DM process, selection of a DM tool, relationship identification of DM (classes, clusters, associations), interpretation of results, and consolidation of discovered knowledge.

Several DM techniques exist, each with its own purposes and capabilities. These include decision trees (DTs) and rule induction,

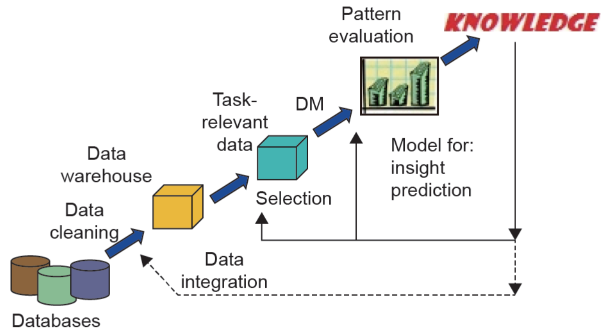

Fig. 1. DM and the knowledge-discovery process [20].

neural networks, fuzzy modeling, support vector machines (SVMs), k-nearest neighbors (k-NN), Bayesian networks (BNs), instance-based algorithms, and learning classifier systems, among others [24–27].

Studies using a formal KDD framework are still uncommon in rock mechanics-related activities; however, when applied, they can provide important insight into the most influential parameters in the behavior of rock masses. An important example of such applications is a study done for the Deep Underground Science and Engineering Laboratory, which is located at the former Homestake gold mine in the United States [28]. Here, innovative regression models using different DM techniques were developed to analyze the strength and deformability of the host rock mass and to determine geomechanical indexes for the project [29]. One of the most important tasks in the KDD process is the DM step, which consists of choosing a learning algorithm for training and ultimately building a model that represents the data. Once the training phase is completed, the obtained model is evaluated using a test dataset that was not used during the learning process. The results consist of several different models; there is no universal model that can be used to efficiently solve all the problems.

A brief overview of the most relevant algorithms applied in previous studies is presented here. A DT is a tree-like graph that represents a set of rules for classifying data. These rules can be learned by using a class-labeled training dataset [27]. Artificial neural networks (ANNs) are a deep-learning technique that is modeled after the way in which neurons operate within the human brain [29]. ANNs are formed by groups of artificial neurons connected in layers; signals travel from the first (input) layer to the last (output) layer, forming a structure that is similar to that of brain neurons. These networks, which can be learned from data, are particularly useful in complex applications to recognize patterns and predict future events. SVMs are supervised learning models that are normally used for data classification and regression analysis. Given categorized training data, SVMs determine an optimal plane that defines the decision boundaries, that is, the distance between classes [19]. Finally, BNs are graphical representations of the joint probability of a certain domain under certain simplifying assumptions [2,29].

Rockburst is affected by different factors. The influence diagram in Fig. 2 [2] lists the factors that affect the probability of a rockburst and its potential consequences. Influence diagrams such as this are very important in the design of DM models for the analysis of accidental events such as rockburst.

Successful applications of DM to different types of problems already exist in the field of geoengineering [19]. Concerning rockburst phenomena, DM techniques were successfully applied to a rockburst laboratory test database obtained from tests at SKL-GDUE, China [6]. The developed triaxial rock test machine used to model the rockburst is presented in Fig. 3 [6,30]. This equipment forms a true triaxial testing scheme; during the test, one surface of the specimen can be immediately unloaded from the true triaxial compression condition. In this way, it is possible to simulate the stress condition of the rock mass at the free excavation boundary in an underground excavation [30].

The database included a total of 139 cases with samples from different rock types located in China, Italy, Canada, and Iran. Two indexes were developed and used: σ_{RB}, the rockburst maximum stress, and I_{RB}, the rockburst risk index. The meaning of these indexes is described in detail in the publication of He et al. [6]. DM techniques were applied to the rockburst database to infer prediction models of the indexes σ_{RB} and I_{RB}. σ_{RB} is the rupture stresses that are obtained in rockburst tests, while I_{RB} is related to the rockburst critical depth [6]. New models were established using multiple regression (MR), ANNs, and SVM algorithms.

3. *In situ* rockburst database and data mining

In situ cases of rockburst that have occurred during tunnel construction/mining were collected via extensive research into publications and reports, and were organized into a database. The rockburst cases were classified according to their geometric characteristics, causes, and consequences. DM techniques were then applied to the database, with the aim of developing rockburst predictive models [31]. In order to understand the circumstances in which rockbursts occur, their magnitude, and the different consequences of rockburst, we gathered as much information as possible on different aspects of the cases that could provide relevant information about the occurrence of the rockburst. For this purpose, a form was created that included eight fields, each with one or more variables. The eight fields included: ① rockburst occurrence, ② construction procedure, ③ tunnel shape or geometry, ④ rock strength, ⑤ *in situ* existing stresses, ⑥ location and dimensions of the rockburst, ⑦ severity and time delay, and ⑧ damage in the tunnel and associated equipment. The database contains 60 cases—a relatively small number. However, we believe that it constitutes an important first step in the development of more complex models in future. One important feature of the database is that most of the collected rockburst cases (91%) occurred during the construction of hydroelectric underground power schemes. It is important to emphasize that a large number of the cases in which rockburst took place were located in deep underground mines. The collected data is confined to drill-and-blast and tunnel-boring machine excavation methods, and the shapes of the tunnels where the rockburst cases occurred were either circular (67%) or horseshoe (33%).

Different levels of rockburst were classified, as shown in Table 1, following the experience gained at the Jinping II hydropower scheme in China [9]. Fig. 4 gives the distribution of cases in the database by rockburst type. In this figure, the Overbreak situation corresponds to levels C and D.

Several DM techniques were applied to the database, including DT, k-NN, ANN, and SVM, with the aim of developing rockburst predictive models. The R environment [32] and the rminer package developed by Cortez [33] were used for the implementation of all DM

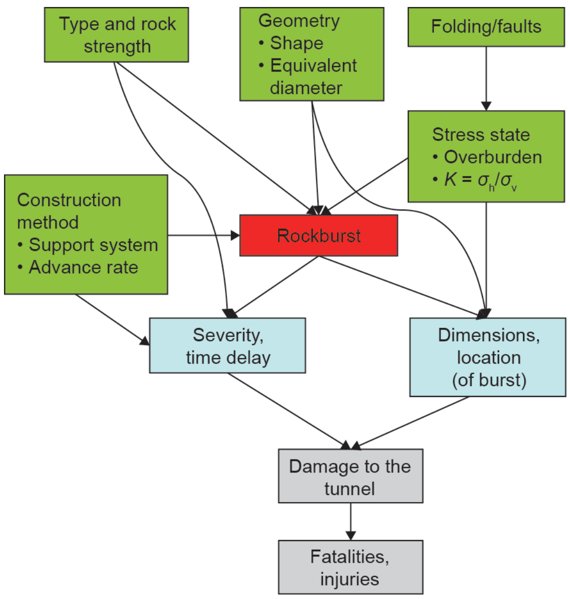

Fig. 2. Influence diagram of rockburst [2].

Fig. 3. Rockburst laboratory testing system.

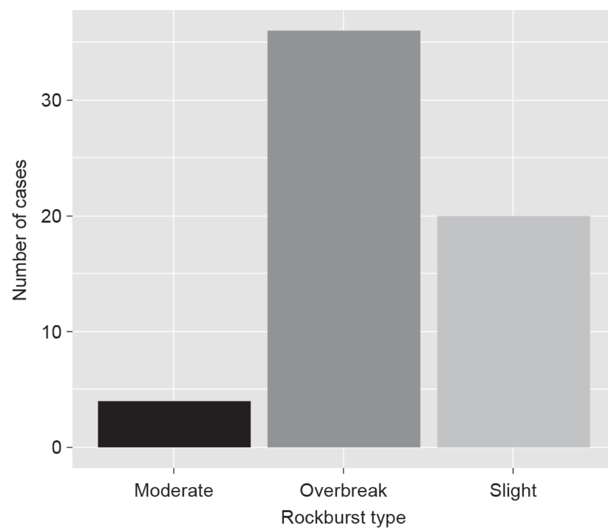

Fig. 4. Distribution of cases by rockburst type.

Table 1
Classification of different levels of rockbursts.

	Level A	Level B	Level C	Level D
Description	Slight	Moderate	Strong	Very strong
Duration	Sporadic explosion	Long duration	Fast	Sudden
Block depth (m)	< 0.5	0.5–1.0	1.0–2.0	> 2.0
Impact in excavation	Small	Certain impact	Reasonable impact	Large impact

techniques.

For the prediction of *in situ* rockburst type, a set of nine variables was considered:

- L: Length of occurrence (m)
- *TESC*: Type of excavation
- *TSUP*: Type of support
- *UCS*: Unconfined compressive strength (MPa)
- E: Young's modulus (GPa)
- K: horizontal vs. vertical stresses ratio K_0
- *FORM*: Shape of the tunnel
- D_{eq}: Equivalent diameter (m)
- R_{eq}: Equivalent radius (m)

The aim of this analysis was to develop models that would allow the prediction of the type of rockburst, given certain conditions and characteristics related to the underground work. For validation purposes, a leave-one-out method [34] was applied under 20 runs. The leave-one-out method consists of sequentially using one case to test the model, while the remaining cases are used to determine the model's structure. As a result, all data is used for training and testing. By using this method, N models are fitted, where N is the number of available data points. The final generalization estimate is evaluated by computing evaluation metrics for all N test samples.

For the evaluation and comparison of the models, we used three classification metrics based on a confusion matrix (Fig. 5): recall, precision, and F_1 score. The recall measures the ratio of how many cases of a certain class were properly captured by the model. In other words, the recall of a certain class is given by

$$\text{Recall} = \frac{\text{True positives}}{\text{True positives} + \text{False negatives}} \tag{1}$$

On the other hand, the precision measures the correctness of the model when it predicts a certain class. More specifically, the precision of a certain class is given by

$$\text{Precision} = \frac{\text{True positives}}{\text{True positives} + \text{False positives}} \tag{2}$$

The F_1 score represents a tradeoff between the recall and precision for a given class. It corresponds to the harmonic mean of precision and recall, according to the following expression:

$$F_1 \text{ score} = \frac{2\text{Precision} \times \text{Recall}}{\text{Precision+Recall}} \tag{3}$$

For all three metrics, a higher value indicates better predictions.

Fig. 6 shows and compares the DM models' performance for *in situ* rockburst prediction based on recall, precision, and F_1 score. Except for the Moderate rockburst level, all models presented a very good response, with F_1 scores very close to 100%. The low performance in predicting the Moderate class was expected, since only a

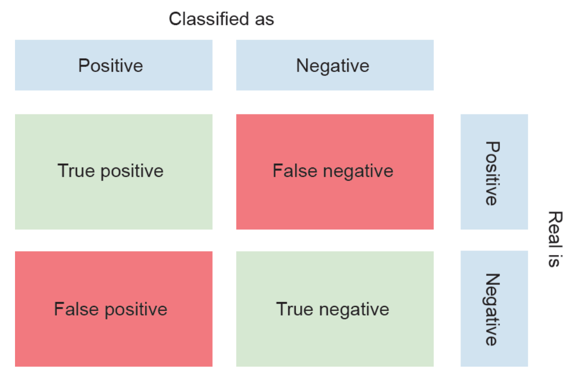

Fig. 5. Establishment of a confusion matrix.

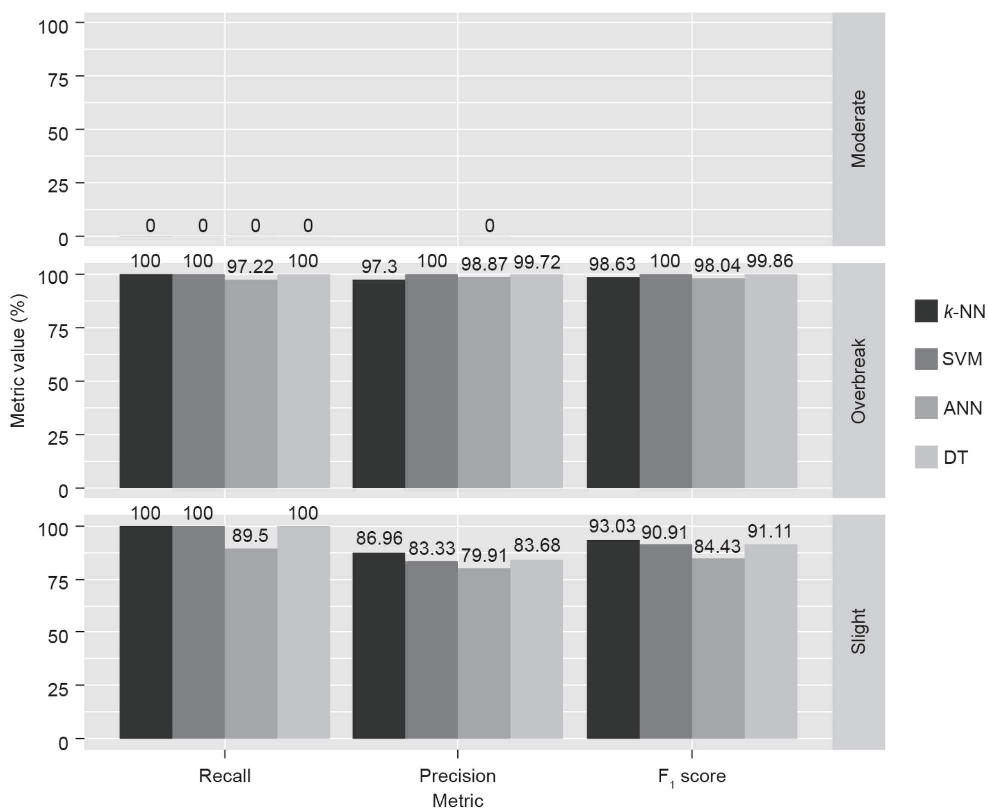

Fig. 6. Comparison of DM models' performance for *in situ* rockburst prediction based on recall, precision, and F_1 score metrics.

few records were available for this class in the database for model training (around 7%, as shown in Fig. 4). However, we are confident that it will be possible to improve the model's response once more data for this class becomes available.

Another outcome of the application of the abovementioned DM techniques is the possibility of obtaining the importance of each of the model variables through sensitivity analysis [35]. Hence, and according to the ANN model, the relevant variables are *K*, *TSUP*, and *L*, which have a total influence of around 57% (Fig. 7).

4. Application of the Bayesian network classifiers

BNs, which are graphical representations of joint probability distributions under certain simplifying assumptions [2,36], were also applied to the database. The techniques used included: naive Bayesian classifiers, which are simple probabilistic classifiers based on Bayes' theorem, and which are a particular class of BN with assumed independence between predictors; tree-augmented naive Bayesian (TAN) classifiers, which are an extension of naive Bayesian classifiers in which each attribute variable has one parent variable between the other attributes; and augmented naive Bayesian (ANB) classifiers, which are semi-naive structures.

Several sensitivity studies were performed to determine the most influential variables in the prediction of rockburst type. These were found to be: ① *TSUP*, ② *K*, ③ *UCS*, ④ D_{eq}, and ⑤ *ORIENT* (only for the naive Bayesian and the TAN models; note that *ORIENT* refers to the orientation of the burst in the periphery of the excavation). The "best" BN classifiers are indicated in Fig. 8.

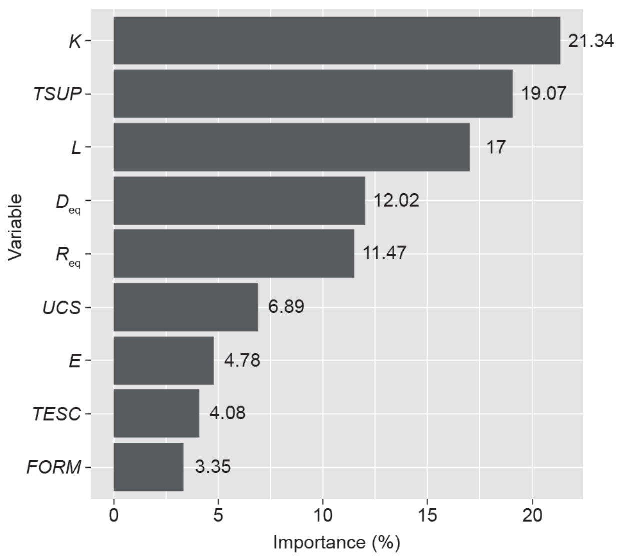

Fig. 7. Importance of variables according to the ANN model.

The networks were validated using a five-fold cross-validation method. The results of the different models are shown in Fig. 9. One can observe that the application of a TAN classifier results in a slightly improved classification compared with the application of the other two models. This is expected, as a TAN classifier normally has a better classification performance than a standard naive Bayesian classifier. Naive BNs are very simple representations of a problem; although this can be an advantage, the independence assumption that is made in these models is often incorrect and unrealistic. TANs are improved versions of naive BNs that consider dependence between attributes in the models; they are therefore normally more realistic than naive BNs. The downside is that the process of adding dependencies between variables in order to capture correlations between the attributes increases the computational complexity.

Finally, the confusion matrix for the naive Bayesian model and for the TAN model (i.e., the lowest and highest accuracy of the "best" models) are presented in Table 2 and Table 3, respectively. One can observe that the naive Bayesian model classifies all cases of Overbreak correctly. It also classifies 83% of Strong rockbursts correctly, and classifies 25% and 87.5%, respectively, of Moderate and Slight rockbursts correctly. The TAN model performs slightly better, classifying Overbreak and Strong rockbursts correctly in all cases. However, like the naive Bayesian model, this model cannot accurately classify all Moderate and Slight rockbursts; it correctly classifies only 80% and 87.5% of these cases, respectively. This result may be explained by the small number of cases in these two categories; we believe that extending the database in future may help to improve the overall accuracy of the models.

5. Conclusions

Several effective design methods are available to deal with ground fall in mining. However, this is not the case for rockbursts or for seismicity-related mine design problems. Modeling analyses have become a fundamental tool for assessing potential undesirable events, and their cost is only a small fraction of the potential benefits to excavation operations. A large variety of numerical analysis methods can and have been applied to underground engineering in order to assess the potential for the occurrence of rockburst. Monitoring of seismic events and visualization techniques in deep tunnels and mining activities are very useful tools for predicting potentially hazardous situations in order to assist the construction team in time.

Rockbursts are a type of event that can range from minor spalling to significant volumes of rock falling or being ejected with high energy, with devastating consequences. These phenomena are commonly reported in deep underground mining structures, but can also occur in deep tunnels such as the Jinping II hydropower scheme. This paper emphasized the importance of a rockburst triaxial experimental system for the prediction of these types of events,

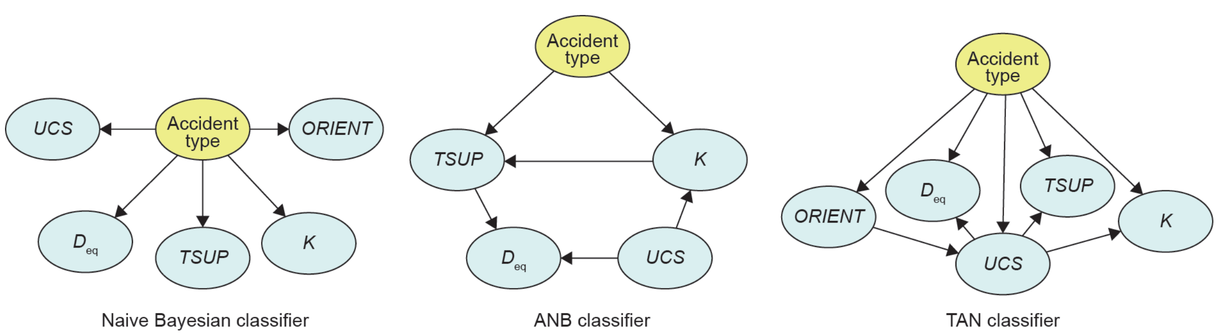

Fig. 8. Bayesian network classifiers. Accident type: type of rockburst; *TSUP*: type of support; *K*: horizontal vs. vertical stresses ratio K_0; D_{eq}: equivalent diameter of the tunnel; *UCS*: unconfined compressive strength; *ORIENT*: orientation of the burst in the periphery of the excavation.

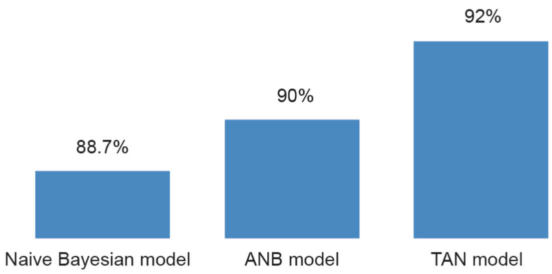

Fig. 9. Comparison of the accuracy between naive Bayesian classification models.

Table 2
Confusion matrix for the naive Bayesian model.

		Classified as			
		Overbreak	Slight	Moderate	Strong
Real is	Overbreak	37	0	0	0
	Slight	0	7	1	0
	Moderate	1	3	1	0
	Strong	0	0	2	10

Table 3
Confusion matrix for the TAN model.

		Classified as			
		Overbreak	Slight	Moderate	Strong
Real is	Overbreak	37	0	0	0
	Slight	0	7	1	0
	Moderate	0	1	4	0
	Strong	0	0	0	12

both in mining and in other deep underground projects. In addition, a previous analysis of rockburst test results allowed these authors to develop predictive models to estimate rockburst maximum stress and risk indexes.

A database of rockburst accidents that have occurred in mines and other underground works around the world, such as underground hydropower systems, was created for this study. Data analysis showed that a considerable percentage of accidents occur as a result of excessive loads, generally at depths greater than 1000 m. The application of various DM techniques yielded different predictive models that focused on the determination of rockburst level, given geologic and construction-related parameters. All the developed models showed a high accuracy rate, allowing the importance of the several parameters involved in the prediction of rockburst level to be identified. In the case of BN classifiers, the models also allowed the relationship between these variables to be identified.

Compliance with ethics guidelines

Luis Ribeiro e Sousa, Tiago Miranda, Rita Leal e Sousa, and Joaquim Tinoco declare that they have no conflict of interest or financial conflicts to disclose.

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