Prediction of Rockburst Based on Experimental Systems and Artificial Intelligence Techniques

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ABSTRACT: Rockburst is characterized by a violent explosion of a certain block causing a sudden rupture in the rock and is quite common in deep tunnels. It is critical to understand the phenomenon of rockburst, focusing on the patterns of occurrence so these events can be avoided and/or managed saving costs and possibly lives. The failure mechanism of rockburst needs to be better understood. Laboratory experiments are one of the ways. A description of a system developed at the State Key Laboratory for Geomechanics and Deep Underground Engineering (SKLGDUE) of Beijing is described. Also, several cases of rockburst that occurred around the world were collected, stored in a database and analyzed. The analysis of the collected cases allowed one to build influence diagrams, listing the factors that interact and influence the occurrence of rockburst, as well as the relations between them. Data Mining (DM) techniques were also applied to the database cases in order to determine and conclude on relations between parameters that influence the occurrence of rockburst during underground construction. A risk analysis methodology was developed based on the use of Bayesian Networks and applied to the existing information of the database and some numerical applications were performed. Conclusions were established.

1 GENERAL

The rockburst is an event that is caused by high stresses that occur in intact brittle rocks, located generally at great depths, during the excavation of an underground work. This phenomenon can occur in tunnels for transport systems, hydroelectric projects and in mining operations. The rockburst may take such proportions, causing the sudden rupture of rock, with serious consequences in the building process and the people involved in the work (He, 2009; Kaiser, 2009; Tang, 2010; Shiyong et al., 2010, Peixoto et al., 2011).

The experiences from deep level mining have contributed significantly to the understanding of the rock mechanics involved in the phenomenon of rockburst. Methods for prediction of rock stress problems that cause spalling and rockburst have been developed based on experience and the development of rockburst vulnerability indexes (Hudson, 2009; He, 2009). Rockbursts are not easy to predict. Investigations using acoustic emission monitoring are sometimes recommended. Acoustic emissions allow one to monitor the accumulation of cracking and evaluate the tendency for the rock to suffer rockburst (Tang, 2010).

Influence diagrams, containing the major parameters that influence the rockburst can be built as it is presented in Fig. 1 (Sousa, 2010). For prediction of rockburst special reference is also made for the development of a rockburst experimental system at laboratory in the next section (He et al., 2011).

2 TRIAXIAL ROCKBURST SYSTEM

A true-triaxial rock test system was developed at SKLGDUE (He et al., 2010). It is a unique system for rockburst testing which includes the main machine, the hydraulic pressure controlling unit and data acquisition, including forces and displacements, acoustic emission and high speed digital camera recording (Fig. 2). During a test, one surface of the specimen can be unloaded immediately from the true triaxial compression condition, which can simulate the excavation in the field, as it can be seen in Figs. 3 and 4 (He et al., 2011). In the study, two AE (Acoustic Emissions) polarity transducers were used, both with a resonance frequency of about 150 kHZ and a fairly flat response from 100~300 kHZ. The pre-amplification is at 40 dB, gain amplification is 100 and the total amplification is 1000. The data acquisition rate was set to 1 MHz and waveforms could be measured every 1 μs. The recording speed of high speed photograph system is 1000 frame/s under full resolution.

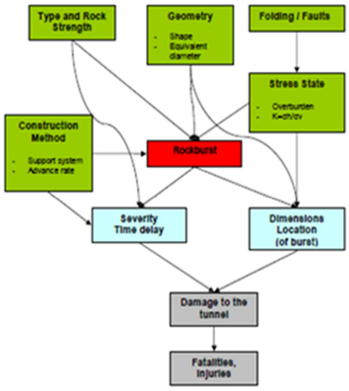


Fig. 1. Influence diagram of rockburst (Sousa, 2010)

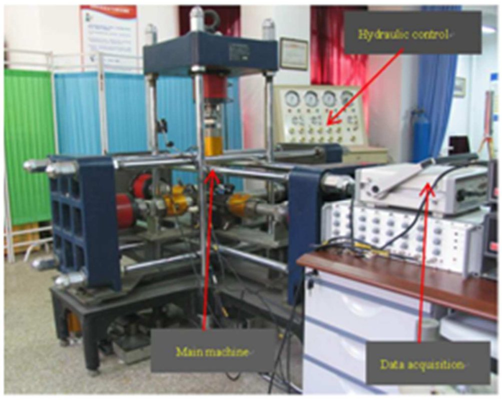


Fig. 2. Rockburst test system

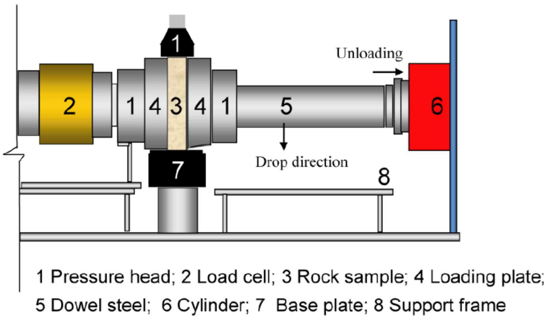


Fig. 3. Illustration of the dropping system for load bar and loading plate (He et al., 2011)

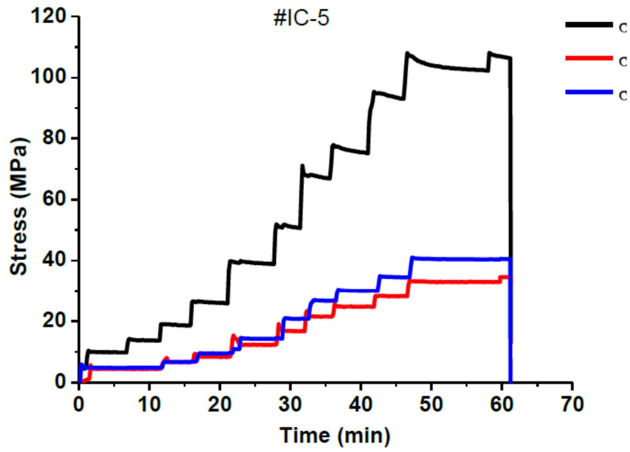


Fig. 4. Loading stress path for instantaneous rockburst (He et al., 2011)

According to laboratory test results and site investigation, the rockburst critical depth is defined by the depth of the place where the first rockburst occurred. Rockburst index can be defined and several formulae can be defined (He, 2009).

3 CONSTRUCTION OF A ROCKBURST DATABASE

The organization of a database of selected cases of rockburst occurred during the construction of several tunnels was performed. To develop the database, it resorted to an extensive research from technical literature, publications and reports of experiences in tunnels. Data were stored and analyzed on the database being the rockburst classified by its proportions and dimensions, its causes and consequences. Then, DM techniques were applied to this database, including Artificial Intelligence (AI).

DM represents a new area of computer science that lies at the intersection of statistics, machine learning, data management and databases, pattern identification and other areas. DM appears as a class of analytical techniques that go beyond statistics and concerns with an automatic search for patterns and relationships that are embedded within the data series that have a scientific value. DM permits to achieve trends and relationships between variables that characterize the system and processes in order to predict their future state. In the present case DM techniques were used to seek, analyze and extract knowledge from a database on rockburst phenomena, in order to discover new and relevant information in the form of rules and relationships between the data (Miranda, 2007).

In order to evaluate and understand what types of undesirable events may occur after the rockburst, we tried to gather a certain amount of information in a database. This would improve the knowledge about what kinds of accidents occur due to rockburst and identify in what circumstances they can happen. A form was elaborated in order to facilitate interaction between experts. Eight fields were considered: (1) occurrence of rockburst; (2) method of construction; (3) geometry of the tunnel; (4) strength of the rock; (5) in situ state of stress; (6) dimensions and location of the rockburst; (7) severity and delay time; and (8) damage in the tunnel. In Table 1, the different information inserted for each field is referred.

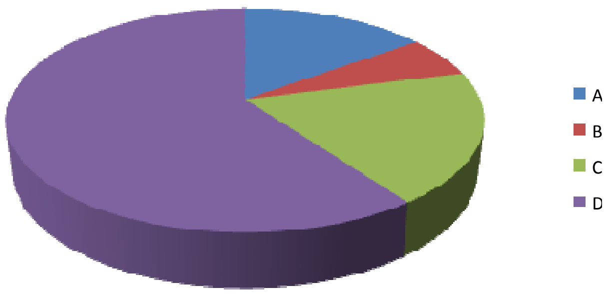
Table 1. Fields considered in the database

Field	Topics
Occurrence of rockburst	undertaking; date; country; localization
Method of construction	excavation; support; advance in relation to front
Geometry of the tunnel	type of shape; equivalent diameter
Strength of the rock	type of rock; UCS (MPa); E (GPa)
In situ state of stress	K_0; relevant faults & discontinuities; folds; water level (m)
Dimensions and location of the rockburst	Orientation; depth (m); shape; height (m); equivalent radius (m)
Severity and delay time	type of accident; delay of the work (hours)
Damage in the tunnel	equipments; primary support

To complete the database, it resorted to an extensive survey of several cases in which they used a form that covered all aspects mentioned above and which constituted the entire 62 cases in the database. Each record in the database is based on the interpretation of articles as well as through a questionnaire completed by an expert. The database has a small number of cases. However, it is a fundamental first step in order to create a more complex model in the future (Peixoto, 2010).

One of the aspects relating to the distribution of cases refers to the functionality of the tunnel, which stands a greater presence for hydroelectric schemes (91%). However, it should be stressed that the majority of cases occurring rockburst are in deep underground mines. The collected data has confined itself to the methods of excavation of NATM, D&B (Drill and Blast) and TBM methods. Over 50% of the cases were drilled using conventional means, i.e., D&B and NATM. Another aspect is the shape of the tunnels. Only two possible cases occurred, circular (66%) and horseshoe shapes (34%). There are a greater percentage of cases with the circular shape due to the use of TBMs.

More than half of the accidents are due to excessive load, where the rockburst is very strong (Fig. 5). The distribution of cases in relation to the primary support shows that 48% of the cases occur for a support consisting of wire mesh and shotcrete. Also high percentages occurred with supports with wire mesh and steel sets. After the occurrence of rockburst, no damage to the equipment exist in most cases, though it was registered a high percentage of cases in which there is no information. In all cases, there was damage to the supports, namely in the shotcrete or steel sets and sometimes, there is total destruction of the support. The predominant shape of the block is like a cone, about 24%, with a small percentage distribution in rough shape of a prism or pyramid. In about 60% of cases it was not possible to obtain a description of the shape of the blocks. It was obtained the distribution of the orientation of rockburst at the periphery of the tunnels, with predominance along the ceiling, about 30%, not existing information in about one quarter of cases (Peixoto, 2010). The rockburst was classified in four types: I – small; II – moderate; III – strong; and IV – very strong, the same classification used at Jinping II hydroelectric scheme (Shiyong et al., 2010; Peixoto, 2010). Type IV rockburst occurred in 48% of the cases, with 21% of situations without classification.



A – light rockburst (15%) C – strong rockburst (19%)
B – moderate rockburst (6%) D – excess of loads (60%)

Fig. 5. Distribution of cases by accident type

4 APPLICATION OF DATA MINING TECHNIQUES

Nowadays, due to the advances in information and communication technologies, there is an extraordinary expansion of data generation that needs to be stored. The data can hold valuable information, such as trends and patterns that can be used to improve decision making and optimize processes. Due to the great potential of this subject there has been an increasing interest in the Knowledge Discovery from Databases (KDD) and Data Mining (DM) fields that led to the fast development of electronic data management methods.

DM is a relatively new area of computer science that lies at the intersection of statistics, machine learning, data management and databases, pattern recognition, AI and other areas. DM consists in the searching and inference of patterns or models in the data which can represent useful knowledge. There are several DM techniques, each one with its own purposes and capabilities, namely Decision Trees and Rule Induction, Neural Networks, Support Vector Machines and BN, Learning Classifier Systems and Instance-Based algorithms (Berthold and Hand, 2003).

The increasing interest on DM led to the necessity of defining standard procedures to carry out this task. In this context, the two most used methodologies in DM are the CRISP-DM (Cross-Industry Standard Process for Data Mining) and the SEMMA (Sample, Explore, Modify, Model, and Assess). The CRISP-DM methodology was developed by a group of companies. It is described as an iterative and interactive hierarchic model which develops in several phases (Chapman et al., 2000). The SEMMA methodology was developed by the SAS Enterprise Miner institute which is a company that delivers services in the areas of DM and decision support (Miranda, 2007).

The main issue of the DM task is building a model to represent data. In this step of the KDD process, learning occurs by adopting a search algorithm for training. This process occurs over a training set until a given criteria is met. After training, the model is built and its quality is normally evaluated over a test set not used for training. There are several different models but there is no universal one to efficiently solve all the problems. Each one presents specific characteristics (advantages and drawbacks) which make them better suited in a certain case. Some of the major modeling techniques applied in this study is referred (Decision Trees - DT, K-Nearest Neighbors – K-NN, Artificial Neural Networks - ANN and Support Vector Machines - SVM).

A DT is a direct and acyclic flow chart that represents a set of rules distinguishing classes or values in a hierarchical form. These rules are extracted from the data, using rule induction techniques, and appear in an "If-Then" structure, expressing a simple and conditional logic. Source data is splitted into subsets, based on the attribute test value and the process is repeated in a recursive manner (Berry and Linoff, 2000). The technique that uses K-NN is based on the predictions for a specific observation, in weighing the characteristics of k observations that are similar (Peixoto, 2010). ANN was conceived to imitate the biological networks of neurons found in the brain. They are formed by groups of connected artificial neurons in a simplified but very similar structure to the brain neurons. Like the biological structures, these networks can be trained and learn from a set of examples to find solutions to complex problems, recognize patterns and predict future events. The acquired knowledge can then be generalized to solve new problems. This means that they are self-adaptive systems. Finally, the technique of SVM was originally designed for data classification. The vectors that characterize it permit to define the position of the input variables that are used by the algorithm to define the distance between classes. This technique makes the nonlinear transformation of data into a multidirectional space where it will be an image of the data that allows a linear separation (Peixoto et al., 2011).

The environment R (R Development Core Team, 2010) was applied using RMiner software developed by Cortez (2010). In Table 2 are presented the three groups where data was organized. The goal was to predict the type of rockburst expected using some important characteristics related to the underground work. The data was splitted in training and testing sets for the holdout method application. In this case, two thirds of the data was used for training and one third for testing.

Given the presence of continuous quantitative variables in the database measures were implemented to assess their variability. One of the measures used was the average value which is a measure of location of the center of the sample. To obtain a measure of variability we used the standard deviation. Then, the measurements for the three groups were obtained for both training data and for test data.

Different DM techniques were applied (DT, K-NN, ANN and SVM), being obtained the accuracy to each group, for both types of data (training and test), (Peixoto, 2010). For the test set, the ANN technique presents more percentage of accuracy as illustrated in Fig. 6. Its accuracy varies from 72% (Group 2) to 86% (Group 3) which can be considered very good since the database presented only a few cases for training. The application of DM techniques permitted also to obtain the importance of the variables in the models. Fig. 7 illustrates the importance of variables for the ANN algorithm.

For the K-NN technique, the most relevant variables are TSUP, H, FALH and Deq. In the ANN case, the relevant variables are TSUP, E and Deq. For the DT technique, only E is a relevant variable, while for the SVM technique, E and K are the most important. As a conclusion, the DT model presents the worst results and less accuracy for the three groups. The K-NN model presents an acceptable performance. Group 3 presents the best successes and better accuracy.

5 APPLICATION OF BAYESIAN NETWORKS (BN)

A BN, also known as belief network, is a graphical representation of knowledge for reasoning under uncertainty. Over the last decade, BN have become a popular model for encoding uncertain expert knowledge in expert systems (Sousa, 2010). BN can be used at any stage of a risk analysis, and may substitute both fault trees and event trees in logical tree analysis. While common cause or more general dependency phenomena pose significant complications in classical fault tree analysis, this is not the case with BN. They are in fact designed to facilitate the modeling of such dependencies. Because of what has been stated, BN provide a good tool for decision analysis, including prior analysis, posterior analysis and pre-posterior analysis. Furthermore, they can be extended to influence diagrams, including decision and utility nodes in order to explicitly model a decision problem.

Table 2. Generated groups

Parameter	Symbol	Group 1 (46)	Group 2 (46)	Group 3 (46)
Length of occurrence (m)	L(m)	Yes	Yes	Yes
Type of excavation	TESC	Yes	Yes	Yes
Type of support	TSUP	Yes	Yes	Yes
Type of rock	TROC	Yes	Yes	Yes
UCS (MPa)	σ_c(MPa)	Yes	Yes	Yes
E (GPa)	E(GPa)	Yes	Yes	Yes
Height folds (m)	H (m)			Yes
Equivalent radius (m)	Req (m)		Yes	
K_0	K			Yes
Faults	FALH		Yes	Yes
Folds	DOBR	Yes	Yes	Yes
Shape of tunnel	FORM	Yes	Yes	Yes
Equivalent diameter (m)	Deq (m)	Yes	Yes	Yes

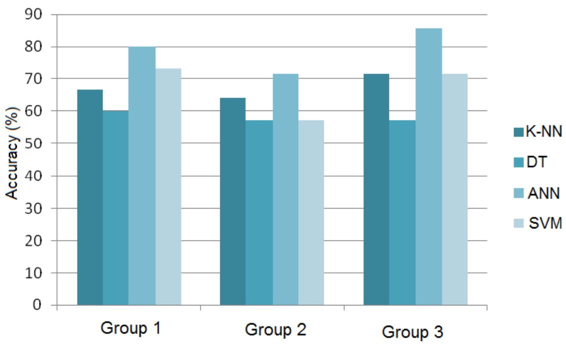


Fig. 6. Comparison of accuracies for different techniques

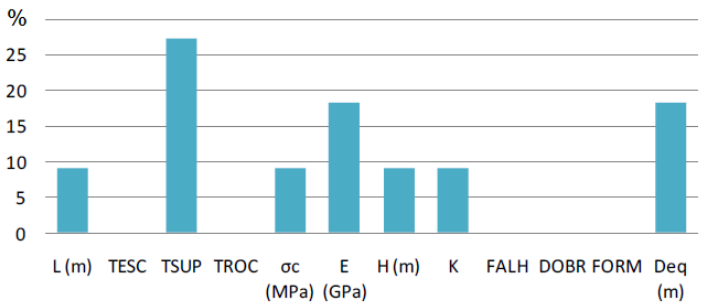


Fig. 7. Importance of variables with ANN

A BN is a concise graphical representation of the joint probability of the domain that is being represented by the random variables, consisting of (Sousa, 2010):

- A set of random variables that make up the nodes of the network.
- A set of directed links between nodes. (These links reflect cause-effect relations within the domain.)
- Each variable has a finite set of mutually exclusive states.
- The variables together with the directed links form a directed acyclic graph (DAG).
- Attached to each random variable A with parents $B_1, \ldots, B_n$ there is a conditional probability table $P(A = a \mid B_1 = b_1, \ldots, B_n = b_n)$, except for the variables in the root nodes. The root nodes have prior probabilities.

Humans are normally better at providing structure than probabilities. Therefore, when possible, it is good to use data to obtain the conditional probability tables. The structure is normally given by experts and the conditional probability tables can be estimated through available data. When there is a good amount of data available and not enough domain knowledge it is also possible to learn the network structure from data. Learning is basically to search over a space of models to find the one that suits best the data available.

Despite the limited amount of cases from the rockburst database, a BN was learned, trained with 30 of the most well documented cases available. The algorithm used for the learning of model 31 was the “greedy thick thinning” with a uniform prior. For detailed information on the greedy thick thinning algorithm please refer to Heckerman, 1997. Note that because no cases where no rockburst occurred where collected one is not able to learn a network that will allow you to predict whether or not a rockburst will occur under certain geological and construction related scenarios. However, with the data available one was able to learn a BN that has the goal of predicting what type of event (overbreak, slight rockburst, median rockburst and strong rockburst), and where, would occur under certain circumstances (geological, construction method, etc). The learned BN is presented in Fig. 8. The BN was then tested on 20 cases, which were not included in the training. For each tested case the probability of type of occurrence was determined. The type of occurrence with the highest probability was then compared to the actual type of occurrence. The accuracy of the results was of 65%.

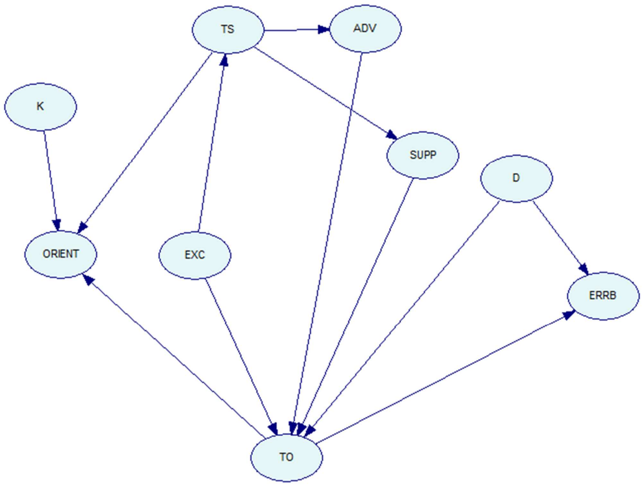


Fig. 8. Learned rockburst BN ($K = \sigma_h/\sigma_v$, TS = Tunnel Shape, ORIENT = Orientation / location of the rock burst, ADV=Advance Rate, SUPP=Type of Support; D=depth; EXC=Excavation method; ERRB=Equivalent Radius of the Rockburst; TO = type of occurrence)

It is important to also check, in the cases the model does not accurately predict the type of occurrence, which type of occurrence is predicted. For that a confusion matrix is presented in Table 3 for training data set. Each row of the matrix represents the predicted type of occurrence, while each column represents the actual type of occurrence. One benefit of a confusion matrix is that it is easy to see if the model is confusing two type of occurrence. The type of occurrence Overbreak was predicted accurately for all the cases. The slight rockburst was mistaken by overbreak and moderate rockburst 16.7% of the cases, respectively. Fifty percent of the moderate rockbursts were mistaken by slight rockbursts. Finally, the strong rockburst was mistaken 14% by moderate rockburst and about 29% by slight rockburst.

Table 3. Confusion matrix

	Overbreak	Slight Rockburst	Moderate Rockburst	Strong Rockburst
Overbreak	100.0%	16.7%	0.0%	0.0%
Slight Rockburst	0.0%	66.7%	50.0%	28.6%
Moderate Rockburst	0.0%	16.7%	50.0%	14.3%
Strong Rockburst	0.0%	0.0%	0.0%	57.1%

The results of the analysis show the potential of BN as predictors of events such of rockbursts. The results are promising; despite the fact of the limited amount of cases, and the fact the database contains only cases where events occurred. If cases where no event occurred were also documented and available, one could train a BN that would predict whether or not an event (and what type) will occur on a certain section of a tunnel / mine.

6 NUMERICAL ANALYSIS OF ROCKBURST

The rockburst develops due to the high stresses in rock masses. There appears, therefore, the need to develop appropriate computational tools that serve as methods of prediction and control of the rockburst. 3D numerical models were developed in order to study the damage induced in the primary support by the rockburst using the software FLAC3D (Peixoto, 2010). The model was developed for a simplified situation corresponding to a TBM high pressure tunnel from Jinping II Hydroelectric scheme (Jiang et al., 2009; Shiyong et al., 2010).

The 3D numerical model is illustrated at Fig. 9, considering a tunnel with 12 m in diameter. A sequential excavation was executed on 72 m, where the first 24 m are excavated with 3m advances and the remaining 48m are excavated with 1m advances. A depth of 1500 m was considered and the ratio between the average horizontal in situ stress and the vertical one was set to 0.5. The in situ vertical stress was set to 20.25 MPa. The rock mass was considered homogeneous with a deformability modulus of E=20GPa, a Poisson ratio of ν=0.2, a cohesion of 3 MPa, a friction angle of 33° and a tensile strength of 0.1 MPa. The primary support was considered as continuous, including in an approximate way the shotcrete and bolting, with a thickness of 20 cm. Shell elements were considered with E_c=10.5 GPa and ν_c=0.25 (Peixoto, 2010).

For the simulation of rockburst, it was considered an unstable block fetched from the database, with a depth of approximately 3m as shown in Fig. 10. The location of rockburst was considered at the level of the side walls. A perturbation method was assumed considering that the rockburst occurs when the stiffness of the block is zero. An equivalent load was applied to the removed block using a multiplying factor to the weight of the block that represents the dynamic effect of the rockburst. The factors 1.0 and 1.2 were considered and they were obtained based on analytical solutions (Brady and Brown, 2004).

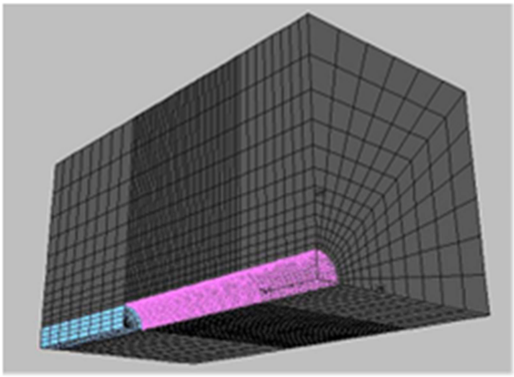


Fig. 9. 3D numerical model with primary support

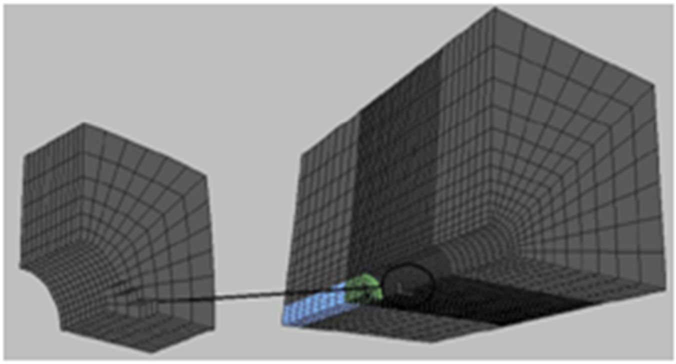


Fig. 10. Detail of a block where the rockburst occurred

Fig. 11 presents displacements for the critical section with the occurrence of the rockburst considering the most critical situation with a factor of 1.2. The calculated displacements were calculated in several rings at the primary support. Fig. 12 shows, for three sections, displacements obtained in the primary support considering the most severe situation with a factor of 1.2.

The results show that the primary support is clearly affected by the occurrence of the rockburst. The elastoplastic model without rockburst presents a maximum displacement of about 16mm, while in the models with rockburst the maximum value is about 30mm and the tensile stresses obtained generate the collapse of the support. It was a preliminary study and more refined numerical studies will allow taking conclusions with interest in the design of the provisional supports and particularly with consideration of special bolts.

7 CONCLUSIONS

The main conclusions of the study are:

- In the construction of deep tunnels, some events can occur, like squeezing, swelling, spalling and rockburst that cause changes in the behavior of rock masses, which may lead to rupture of the supports and, consequently, undermine the efficiency of the construction process and cause fatalities during construction.
- The occurrence of rockburst can reach such proportions that important volumes of rock can fall with high energy. These phenomena were reported in deep underground structures, such as mining and hydroelectric developments, which requires the development of appropriate support systems to minimize the consequences in terms of costs involved in the delay of the works and accidents with people.
- A database with rockburst accidents was created with cases involving hydraulic and hydroelectric projects and mines. Data analysis showed that a considerable percentage of accidents occur due to excessive loads and at depths generally greater than 1000 m. In similar situations, the occurrence of rockburst is more frequent in the case of TBM tunnels compared with excavations carried out by NATM or D&B methods.
- The application of various AI techniques, in particular DM, based on data, identified the importance of various parameters involved in the rockburst. Special attention was given to the development of influence diagrams and the use of BN, which allow replacing with advantage, other techniques to better address the uncertainties involved in the phenomenon of rockburst.
- A preliminary analysis of the phenomenon using 3D numerical models to assess the damage caused in support was performed, that permitted to establish a methodology for assessing the effects induced in the supports.

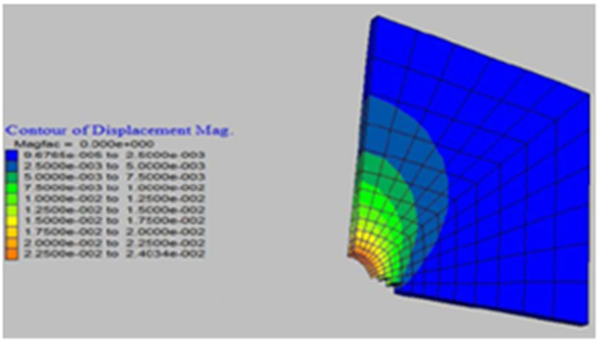


Fig. 11. Displacements in the rock mass with rockburst

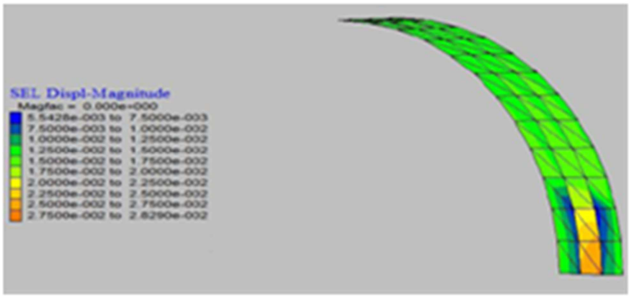


Fig. 12. Displacements in the primary support

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