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Research paper

Rockburst prediction in kimberlite using decision tree with incomplete data

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ABSTRACT

A rockburst is a common engineering geological hazard. In order to predict rockburst potential in kimberlite at an underground diamond mine, a decision tree method was employed. Based on two fundamental premises of rockburst occurrence, σ_θ, σ_c, σ_t, W_{ET} are determined as indicators of rockburst, which are also partition attributes of the decision tree. 132 training samples (with 24 incomplete samples) were obtained from real rockburst cases from all over the world to build the decision tree. The decision tree based on 108 complete samples was built with an accuracy of 73% for 15 validation samples while another decision tree based on 132 samples (with 24 groups of incomplete data) shows an accuracy of 93% for validation samples. Hence, the second decision tree was employed for kimberlite burst prediction. 12 samples from lab tests and a numerical model were used as test samples. The results indicate a moderate burst liability which matches real situations at the diamond mind in question.

1. Introduction

Rockburst is a type of unstable geological hazard in overstressed areas which is in the majority of cases induced by underground mining and constitutes a serious threat to the safety of staff and equipment during underground construction in both mining and civil engineering projects. All mining countries have records concerning rockburst events, including China (Qiang, Yi-Shan, & Yi-Jie, 2005), Germany (Baltz & Hucke, 2008), South Africa (Gibowicz, 2009), Canada (Blake & Hedley, 2003) and Australia (Potvin, Hudyma, & Jewell, 2000). Both the Lubin Copper Basin (Butra & Kudełko, 2011) and the Upper Silesian Coal Basin (USCB) in Poland have experienced severe rockbursts (Korzeniowski, Skrzypkowski, & Zagórski, 2017). In order to prevent rockburst disaster, short-term and long-term prediction methods are proposed to estimate burst liability in engineering projects (Adoko, Gokceoglu, Wu, & Zuo, 2013). However, due to the suddenness and uncertainty of rockbursts, short-term prediction which is usually based on the in-situ site testing methods is usually unreliable. Therefore, long-term prediction of rockburst should be considered as a preliminary prediction of rockburst liability and used during the engineering design stage. Traditionally, researchers put forward several criteria for long-term prediction, such as strain energy storage index (Kidybiński, 1981), energy-based burst potential index (Mitri, Hughes, & Zhang, 2011), elastic strain energy density (Jaeger, Cook, & Zimmerman, 2009), rock brittleness coefficient (Altindag, 2003), etc. However, the occurrence of rockburst relates to many different factors including geologic structure, mining and excavation methods, mechanical properties of rocks, in-situ stress and more. This makes rockburst prediction a highly nonlinear problem (Kabwe & Wang, 2015; Pu, Apel, & Xu, 2018). Consequently, traditional mechanism-based prediction methods are greatly limited when it comes to engineering rockburst prediction (Feng & Zhao, 2002). Some researchers proposed mathematical and statistical methods to solve this problem. Li, Li, He and Yan (2014) used a traditional backpropagation (BP) neural network to estimate rockburst in the Yantai colliery. Zhou, Li and Shi (2012) employed a modified Support Vector Model (SVM) to evaluate rockburst liability in underground openings. Li, Jimenez and Feng (2017) used a Bayesian network structure to predict long-term rockburst occurrence. Each method mentioned above has its own advantages aimed at tackling different types of problems. For example, a neural network is good at predicting with a sufficient amount of data whereas SVM shows highly satisfactory results when it is employed for binary classification problems. The decision tree (Breiman, Friedman, Stone, & Olshen, 1984) is a popular machine learning method, which can be used to classify test samples after training by teaching the samples. The decision tree method has some obvious advantages compared to other machine methods. For example, with a generalized information gain formula, a decision tree can be fed incomplete data and it will implement classification. This method is widely used in indecision analysis.

In this paper, a decision tree model was constructed to evaluate burst liability in two kimberlite pipes at a diamond mine in northern Canada (Sepehri, 2016). The data from literature reviews of more than

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one hundred groups of historical rockburst cases was employed as training samples in the decision tree building, whereas 12 groups of relevant data from kimberlite pipes were used as test samples to obtain the final prediction results.

2. Rockburst decision indicator selection

According to the mechanism of rockburst, two necessary conditions are responsible for its occurrence: (1) the rock has the capability to accumulate strain energy and (2) the environment is favorable to stress concentration (Ortlepp & Stacey, 1994). Some indicators reflect the rock mechanism property (the capability of accumulating strain energy), such as uniaxial compression stress (UCS) or uniaxial tension stress, while some other indicators reflect the environment stress condition, such as maximum tangential stress around an underground opening (Leveille, Sepehri, & Apel, 2017; Lingga & Apel, 2018). In terms of engineering practices, a combination of these indicators, rather than a single indicator, is commonly adopted to comprehensively assess burst liability. For example, in China, four indices corresponding to UCS, elastic strain energy, bursting energy index, and the dynamic failure duration index are considered comprehensively to determine burst liability (Zhao, Guo, Tan, Lu, & Wang, 2017). In this paper, three indicators including the ratio between uniaxial compressive strength (σ_c) and uniaxial tensile stress (σ_t), the ratio between maximum shear stress around the tunnel wall (σ_θ) and uniaxial tensile stress (σ_t), and linear elastic energy (W_{ET}) were chosen to evaluate rockburst liability (Leveille et al., 2017). Additionally, four ranks are introduced for depicting the severity of rockburst (Cai et al., 2016). There are as follows, with increasing severity: no rockburst, moderate rockburst, strong rockburst and violent rockburst. Numbers 1, 2, 3 and 4 represent the different rockburst severity grades, respectively (1 – no rockburst; 2 – moderate rockburst; 3 – strong rockburst; 4 – violent rockburst). The grading criteria for single indicator is listed in Table 1.

Table 1
Grading criteria of rockburst intensity.

	σ_θ/σ_c	σ_c/σ_t	W_{ET}
No rockburst	< 0.3	> 40	> 5
Moderate rockburst	0.3–0.5	26.7–40	3.5–5.0
Strong rockburst	0.5–0.7	14.5–26.7	2.0–3.5
Violent rockburst	> 0.7	< 14.5	< 2.0

Based on the rules of machine learning (Michalski, Carbonell, & Mitchell, 2013), the training set is a set of samples used for learning, which are to fit the parameters of the classifier. The validation set is a set of samples used to tune the parameters of a classifier. The test set is a set of samples used only to assess the performance of a fully specified classifier. The training set and validation set include samples with labels while the test set includes samples without labels (labels of test samples show our expected prediction results). In this paper, the training set consists of 132 samples (every training sample is a real rockburst case) which has three attributes and a corresponding label. The validation set consists of 15 labeled samples (from real rockburst cases) with the same three attributes. In general, the number of training samples should be more than validation samples. The test set consists of 12 samples which are from 12 different locations at a diamond mine.

From the literature (Zhou et al., 2012), 132 historical rockburst cases were collected from all over the world to form the training set for this study. Of this data, 108 samples are complete which means that the three indicators σ_c/σ_t, σ_θ/σ_t, W_{ET} are all complete while the other 24 samples are incomplete which means some indicators are missing. The decision tree model is good at dealing with discrete attributes which are not continuous attributes. Based on the grading criteria of rockburst intensity in Table 1, we could discretize the original data. Table 2 shows the original data and corresponding discretization results.

3. Basic theory of a decision tree

A decision tree is defined as a classification procedure that recursively partitions a data set into smaller subdivisions on the basis of a set of tests defined at each branch (or node) in the tree (Friedl & Brodley, 1997). The root node includes test samples, while leaf nodes correspond to decision results. Every internal root registers an attribute test. The goal of a decision tree study is to build a decision tree with a strong generalization ability which can deal with unclassified samples. Fig. 1 is a sketch map of a decision tree. The labels (A, B, C) at each leaf node refer to the class label assigned to each observation.

The key issue for decision tree building is to select the optimal partition attribute for the root node and internal node. In general, as the partition proceeds, it is hoped that samples in branch nodes belong to the same category as far as possible, which means the “purity” for nodes is higher and higher. The most typical algorithm for choosing partition attribute is the ID3 algorithm (Quinlan, 1986), which employs information gain as a partition criterion.

It was assumed that in sample set D the proportion of the kth sample is p_k (k = 1, 2, … $|y|$). Information entropy can be defined by formula (1)

$$Ent(D) = -\sum_{k=1}^{|y|} p_k \log_2 p_k \tag{1}$$

The smaller the value of $Ent(D)$ the higher the purity of sample set D. If discrete attribute a has V values $\{a^1, a^2, \ldots, a^V\}$ and attribute a is adopted to partition D, then V nodes are generated. D^v is the vth node which contains all samples in set D whose values are all equal to a^v. Formula (1) can be used to calculate the information entropy of D^v. Due to different numbers of samples on different branch nodes, every node is allocated a weight $|D^v|/|D|$, which means a node with more samples has greater influence. Now, information gain for the partition when using attribute a to sample set D can be defined as formula (2). In general, greater information gain means greater "purity gain" when using attribute a to partition. Hence, the attribute with maximum information gain is chosen to partition every node (Mingers, 1989).

$$Gain(D, a) = Ent(D) - \sum_{v=1}^{V} \frac{|D^v|}{|D|} Ent(D^v) \tag{2}$$

4. The decision tree building process

4.1. Rockburst prediction based on complete data

In our case study, a decision tree model was built based on 108 completed samples. According to formula (1), $|y|$ = 4 (rockburst can be divided into four categories). In 108 samples, 18, 32, 44 and 14 samples show no, moderate, strong and violent rockbursts respectively. Hence, the information entropy for root node D can be calculated as following:

Table 2
Original data from actual rockburst cases and discretization results (* means data missing).

Number	σ_θ/σ_c (Attribute A)	Discretization result	σ_c/σ_t (Attribute B)	Discretization result	W_{ET} (Attribute C)	Discretization result	Rockburst ranking
1	0.53	3	15.04	3	9	1	Strong
2	0.41	2	29.73	2	7.3	1	Moderate
3	0.38	2	17.53	3	9	1	Moderate
4	0.32	2	24.11	3	9.3	1	Strong
5	0.34	2	23.97	3	6.6	1	Strong
6	0.27	1	21.69	3	5	2	Strong
7	0.44	2	26.87	2	5.5	1	Moderate
8	0.38	2	28.43	2	5	2	Strong
9	0.82	4	18.46	3	3.8	2	Strong
10	0.77	4	17.5	3	5	2	Violent
11	0.32	2	21.69	3	5	2	Strong
12	0.38	2	21.67	3	5	2	Strong
13	0.36	2	24.14	3	5	2	Strong
14	0.42	2	21.69	3	5	2	Strong
15	0.1	1	23	3	5.7	1	No
16	0.35	2	20.5	3	5	2	Strong
17	0.11	1	31.23	2	7.4	1	No
18	0.23	1	27.78	2	7.8	1	No
19	0.43	2	13.98	4	7.44	1	Strong
20	0.4	2	0.147	4	7.1	1	Strong
21	0.55	3	0.148	4	6.4	1	Strong
22	0.54	3	14.19	4	6.16	1	Violent
23	0.404	2	15	3	7.08	1	Strong
24	0.547	3	11.4	4	6.43	1	Strong
25	0.26	1	14.34	4	2.9	3	Moderate
26	0.58	3	13.18	4	6.27	1	Violent
27	0.45	2	17.53	3	5.08	1	Moderate
28	0.39	2	20.86	3	4.63	2	Strong
29	0.28	1	28.9	2	3.67	2	Moderate
30	0.2	1	36.04	2	2.29	3	No
31	0.19	1	47.93	1	1.87	4	No
32	0.66	3	13.2	4	6.83	1	Violent
33	0.22	1	33.75	2	2.89	3	Moderate
34	0.63	3	4.48	4	3.17	3	Moderate
35	0.444	2	8.976	4	4.86	2	Moderate
36	0.902	4	6.841	4	2.15	3	Moderate
37	0.564	3	9.498	4	6.11	1	Moderate
38	0.697	3	12.05	4	2.85	3	Moderate
39	0.402	2	16.04	3	3.5	3	Moderate
40	0.439	2	13.13	4	2.12	3	Moderate
41	0.58	3	24.4	3	6.31	1	Strong
42	0.13	1	6.67	4	1.39	4	No
43	0.37	2	24	3	5.1	1	Moderate
44	0.45	2	11.2	4	2.03	3	Moderate
45	0.64	3	24.4	3	6.31	1	Strong
46	0.19	1	6.67	4	1.39	4	No
47	0.48	2	24	3	5.1	1	Strong
48	0.65	3	11.2	4	2.03	3	Strong
49	0.74	4	24.4	3	6.31	1	Violent
50	0.23	1	6.67	4	1.39	4	No
51	0.61	3	24	3	5.1	1	Strong
52	1	4	11.2	4	2.03	3	Violent
53	0.283	1	9.68	4	1.92	4	No
54	0.627	3	10.7	4	3.62	2	Violent
55	0.697	3	11.7	4	2.78	3	Strong
56	0.479	2	10.1	4	1.1	4	No
57	0.34	2	23.97	3	6.6	1	Violent
58	0.11	1	27.22	2	7	1	No
59	0.23	1	25.25	3	7.6	1	Moderate
60	0.72	4	13.59	4	1.6	4	No
61	0.13	1	18.75	3	3.6	2	No
62	0.35	2	24.58	3	8	1	Moderate
63	0.27	1	24.74	3	9	1	Violent
64	0.32	2	18.96	3	5.6	1	Violent
65	0.1	1	21.43	3	4.7	2	No
66	*	*	20	3	3.1	3	Strong
67	*	*	26.8	2	0.85	4	Moderate
68	*	*	25.7	3	0.9	4	Violent
69	*	*	28.9	2	3.2	3	Violent
70	*	*	28.9	2	3.2	3	Violent
71	*	*	28.9	2	3.2	3	Strong
72	*	*	19.2	3	3.1	3	Violent
73	*	*	22	3	2	3	Strong
74	*	*	20.4	3	2	3	Moderate

(*continued on next page*)

Table 2 (*continued*)

Number	σ_θ/σ_c (Attribute A)	Discretization result	σ_c/σ_t (Attribute B)	Discretization result	W_{ET} (Attribute C)	Discretization result	Rockburst ranking
75	0.464	2	20.4	3	2	3	Moderate
76	*	*	26.8	2	0.85	4	Moderate
77	0.29	1	26.8	2	0.85	4	Moderate
78	*	*	19.7	3	0.85	4	Strong
79	*	*	19.7	3	2.3	3	Moderate
80	0.436	2	19.7	3	2.3	3	Moderate
81	*	*	19.7	3	2.3	3	Strong
82	*	*	19.7	3	2.3	3	Moderate
83	*	*	19.7	3	2.3	3	Moderate
84	*	*	27.3	2	3.1	3	Strong
85	*	*	27.3	2	3.1	3	Strong
86	*	*	24.3	3	4.6	2	Moderate
87	*	*	23.6	3	4.9	2	Moderate
88	*	*	21.3	3	5.3	1	Strong
89	*	*	23.8	3	4.8	2	Moderate
90	*	*	21.2	3	5.5	1	Strong
91	*	*	28.6	2	6.8	1	Violent
92	*	*	24.6	3	7.3	1	Strong
93	0.112	1	29.4	2	2.04	3	No
94	0.139	1	31.4	2	2.19	3	Moderate
95	0.151	1	28.1	2	2.11	3	Moderate
96	0.155	1	27.9	2	2.26	3	Moderate
97	0.23	1	7.52	4	1.5	4	No
98	0.23	1	10.22	4	2.5	3	Strong
99	0.23	1	11.52	4	4.6	2	Strong
100	0.22	1	14.45	4	5.2	1	Strong
101	0.29	1	9.8	4	3.7	2	Strong
102	0.44	2	20.3	3	8.1	1	Violent
103	0.62	3	8.26	4	1.8	4	Moderate
104	0.64	3	17.51	3	7.2	1	Violent
105	0.56	3	9.74	4	7.27	1	Strong
106	0.62	3	14.05	4	5.76	1	Strong
107	0.55	3	11.11	4	3.97	2	Strong
108	0.81	4	16.71	3	5	2	Moderate
109	0.56	3	24.41	3	6	1	Moderate
110	0.43	2	45.9	1	1.7	4	No
111	0.42	2	29.9	2	2.4	3	Moderate
112	0.56	3	34.3	2	1.9	4	Moderate
113	0.6	3	28.3	2	3.4	3	Strong
114	0.53	3	21	3	3.6	2	Strong
115	0.66	3	21.5	3	4.1	2	Strong
116	0.52	3	17.8	3	4.3	2	Strong
117	0.57	3	25.6	3	3.8	2	Strong
118	0.61	3	25.6	3	3.7	2	Strong
119	0.56	3	29.2	2	4.8	2	Strong
120	0.71	4	32.2	2	5.5	1	Violent
121	0.49	2	49.5	1	4.7	2	Strong
122	0.46	2	45.5	1	5.2	1	Strong
123	0.47	2	55	1	5	2	Strong
124	0.26	1	42.9	1	3.7	2	Moderate
125	0.31	2	36.1	2	3.2	3	Moderate
126	0.31	2	42.8	1	1.8	4	No
127	0.34	2	28.3	2	3	3	Moderate
128	0.49	2	49.5	1	4.7	2	Strong
129	0.61	3	25	3	3.7	2	Strong
130	0.55	3	31.3	2	4.6	2	Strong
131	0.69	3	32.1	2	5.9	1	Violent
132	0.5	2	50.9	1	5.2	1	Strong

$$\begin{aligned} Ent(D) &= -\sum_{k=1}^{|y|} p_k \log_2 p_k \\ &= -\left(\tfrac{18}{108}\log_2\tfrac{18}{108} + \tfrac{32}{108}\log_2\tfrac{32}{108} + \tfrac{44}{108}\log_2\tfrac{44}{108} + \tfrac{14}{108}\log_2\tfrac{14}{108}\right) \\ &= 1.861 \end{aligned}$$

Then, based on formula (2), information gains for attributes A, B, C could be obtained respectively. For example, in the case of rockbursting study (σ_θ/σ_c) could be used as attribute A. After discretization, attribute A has four possible values 1, 2, 3 and 4. Then attribute A is used to partition sample set D. After partition, four subsets can be obtained D^1 ($\frac{\sigma_\theta}{\sigma_c} = 1$), D^2 ($\frac{\sigma_\theta}{\sigma_c} = 2$), D^3 ($\frac{\sigma_\theta}{\sigma_c} = 3$), D^4 ($\frac{\sigma_\theta}{\sigma_c} = 4$). D^1 which includes 29 samples (No. 6, 15, 17, 18, 25, 29, 30, 31, 33, 42, 46, 50, 53, 58, 59, 61, 63, 65, 77, 93, 94, 95, 96, 97, 98, 99, 100, 101, 124) and where no rockburst (No. 15, 17, 18, 30, 31, 42, 46, 50, 53, 58, 61, 65, 93, 97) takes the proportion of 14/29; moderate rockburst (No. 25, 29, 33, 59, 77, 94, 95, 96, 124) takes the proportion of 9/29; strong rockburst (No. 6, 98, 99, 100, 101) takes the proportion of 5/29 and violent rockburst (No. 4) takes the proportion of 1/29. Formula (1) was adopted to calculate information entropies for four generated branch nodes by using attribute A to partition root node D. It is usually agreed that $p_k = 0$, $\sum p_k \log_2 p_k = 0$.

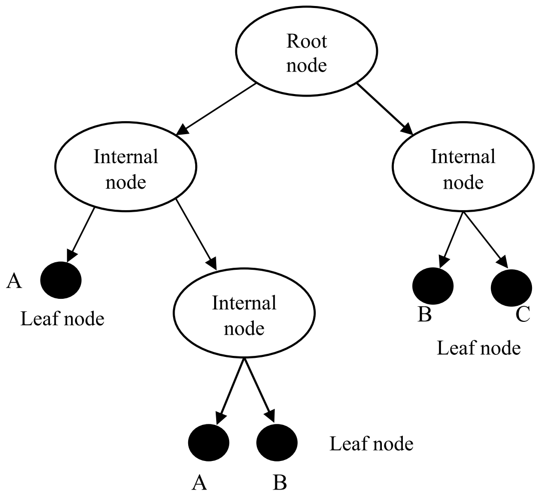

Fig. 1. Sketch map of a typical decision tree.

$$
\begin{aligned}
Ent(D^1) &= -\left(\tfrac{14}{29}\log_2\tfrac{14}{29} + \tfrac{9}{29}\log_2\tfrac{9}{29} + \tfrac{5}{29}\log_2\tfrac{5}{29} + \tfrac{1}{29}\log_2\tfrac{1}{29}\right)\\
&= 1.635\\
Ent(D^2) &= -\left(\tfrac{3}{39}\log_2\tfrac{3}{39} + \tfrac{15}{39}\log_2\tfrac{15}{39} + \tfrac{18}{39}\log_2\tfrac{18}{39} + \tfrac{3}{39}\log_2\tfrac{3}{39}\right)\\
&= 1.615\\
Ent(D^3) &= -\left(\tfrac{0}{32}\log_2\tfrac{0}{32} + \tfrac{6}{32}\log_2\tfrac{6}{32} + \tfrac{20}{32}\log_2\tfrac{20}{32} + \tfrac{6}{32}\log_2\tfrac{6}{32}\right)\\
&= 1.33\\
Ent(D^4) &= -\left(\tfrac{1}{8}\log_2\tfrac{1}{8} + \tfrac{2}{8}\log_2\tfrac{2}{8} + \tfrac{1}{8}\log_2\tfrac{1}{8} + \tfrac{4}{8}\log_2\tfrac{4}{8}\right)\\
&= 1.75
\end{aligned}
$$

Based on formula (2), information gain for attribute A can be calculated.

$$
\begin{aligned}
Gain(D, A) &= Ent(D) - \textstyle\sum_{v=1}^{4} \tfrac{|D^v|}{|D|} Ent(D^v)\\
&= 1.861 - \left(\tfrac{29}{108} \times 1.635 + \tfrac{39}{108} \times 1.615 + \tfrac{32}{108} \times 1.33 + \tfrac{8}{108} \times 1.75\right)\\
&= 0.315
\end{aligned}
$$

Similarly, information gains for attribute B and attribute C can be calculated.

$$Gain(D, B) = 0.153$$

$$Gain(D, C) = 0.438$$

It is clear that maximum information gain takes place for attribute C (W_{ET}). Hence, attribute C was chosen as the partition attribute for root node D. Fig. 2 shows the partition result for the root node based on attribute C.

Afterwards, branch nodes are partitioned using the other two attributes A and B. Finally, the decision tree for rockburst prediction was built as shown in Fig. 3.

In order to verify the accuracy of this model, 15 groups of data from literature (Yun-hua, Xin-rong, & Jun-ping, 2008) were chosen as a validation set. This data is based on real rockburst cases from engineering projects. Each group of data includes the same three rockburst attributes and a corresponding burst severity. Table 3 shows the actual rockburst result and prediction result by the decision tree. Of the 15 groups of validation data, 11 groups were accurately predicted. The prediction accuracy was 73%.

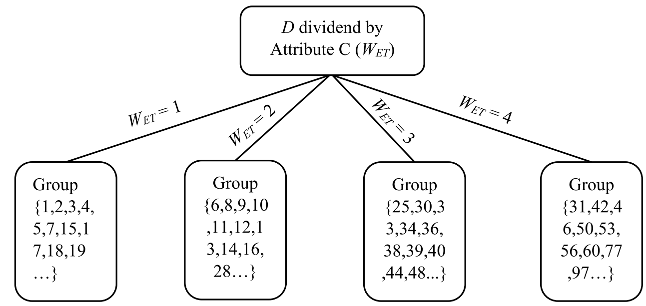

Fig. 2. The partition of root node based on W_{ET}.

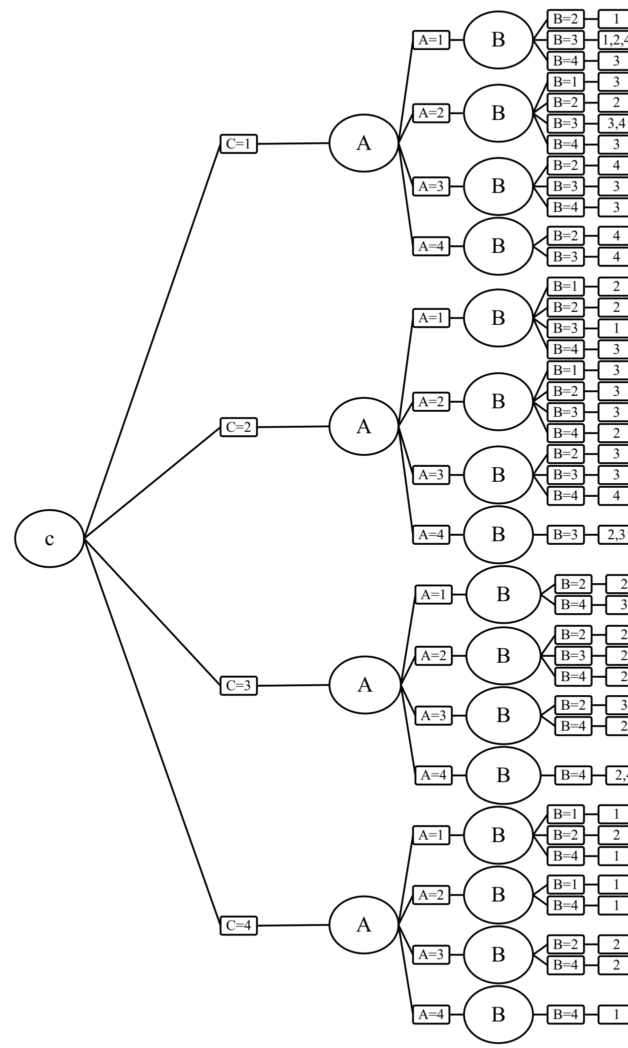

Fig. 3. Decision tree based on complete data.

4.2. Rockburst prediction based on incomplete data

The decision tree built in chapter 4.1 was based on 108 complete samples from 132 original samples. In other words, 24 incomplete samples were not taken into consideration. In this chapter a decision tree with 132 original samples will be built including the 24 incomplete samples.

Table 3
The practical rockburst result and prediction result by the decision tree.

Number	σ_θ/σ_c	σ_c/σ_t	W_{ET}	Actual rockburst severity	Prediction severity
1	0.32	37.31	8.3	3	3
2	0.29	35.74	7.3	4	4
3	0.22	26.56	7.3	4	4
4	0.51	14.87	10.0	2	1
5	0.38	17.55	10.0	3	3
6	0.09	21.43	5.1	4	4
7	0.27	26.38	5.2	2	2
8	0.72	3.3	18.81	2	2
9	0.32	22.70	9.2	2	2
10	0.37	23.95	5.0	2	2
11	0.43	21.89	5.0	2	2
12	0.45	26.71	5.5	3	2
13	0.34	20.12	5.5	2	3
14	0.4	25.71	5.5	2	2
15	0.81	18.38	5.5	1	2

The information gains for attribute A, B, C is calculated and root node D is partitioned by the attribute which has the maximum information gain. For Attribute A, 24 group samples are missing data. The definition of information gain (formula (2)) can be generalized as follows:

$$Gain(D, a) = \rho \times Gain(\widetilde{D}, a) = \rho \times \left[Ent(\widetilde{D}) - \sum_{v=1}^{V} \tilde{r}_v Ent(\widetilde{D}_v) \right] \tag{3}$$

From formula (1), the below was obtained:

$$Ent(\widetilde{D}) = -\sum_{k=1}^{|y|} \widetilde{p}_k \log_2 \widetilde{p}_k \tag{4}$$

$\widetilde{D}$ refers to a subset of D which has the complete data for attribute A.

$$\rho = \frac{The\ number\ of\ samples\ in\ \hat{D}}{The\ number\ of\ samples\ in\ D} \tag{5}$$

It is assumed that attribute A has V possible values. $\widetilde{D}_v$ refers to a subset of $\widetilde{D}$, where the value of attribute a is a^v. And $\widetilde{D}_k$ refers to a subset of $\widetilde{D}$, which belongs to kth class ($k = 1, 2, \ldots |y|$). We had

$$\widetilde{p}_k = \frac{The\ number\ of\ samples\ in\ \widetilde{D}_k}{The\ number\ of\ samples\ in\ \widetilde{D}} \quad (1 \le k \le |y|) \tag{6}$$

$$\tilde{r}_v = \frac{The\ number\ of\ samples\ in\ \widetilde{D}_v}{The\ number\ of\ samples\ in\ \widetilde{D}} \quad (1 \le v \le V) \tag{7}$$

Based on formulas (3)–(7), information gains for attribute A, B, C could be calculated and then root node D could be partitioned by the maximum information gain attribute. For attribute B and C, all samples are complete which means the information gains for B and C are the same as in chapter 4.1.

$$Gain(D, A) = 0.258$$

$$Gain(D, B) = 0.153$$

$$Gain(D, C) = 0.438$$

Hence, attribute C was still chosen to partition root node D. Then following the same calculation process, the decision tree based on incomplete data was built as follows (Fig. 4).

As before, the samples in Table 2 were used as verification samples. This decision tree, built of 15 groups verification samples, correctly predicted 14 groups of rockburst severities. The prediction accuracy rose to 93%, 20 percent more than the decision tree based on complete data. This is because the first decision tree used in chapter 4.1 was based on 108 complete pieces of data while the second was based on 132 samples. This decision tree included 108 complete samples and 24 incomplete samples, which meant that the input data of the second decision tree contained all the information used to build the first decision tree and an additional 24 samples. The more training samples provided to the decision tree, the higher the accuracy the tree showed (Hall, Chawla, & Bowyer, 1998). Hence, the decision tree based on incomplete data in chapter 4.2 will be employed to predict rockburst severity in kimberlite pipes at a diamond mine.

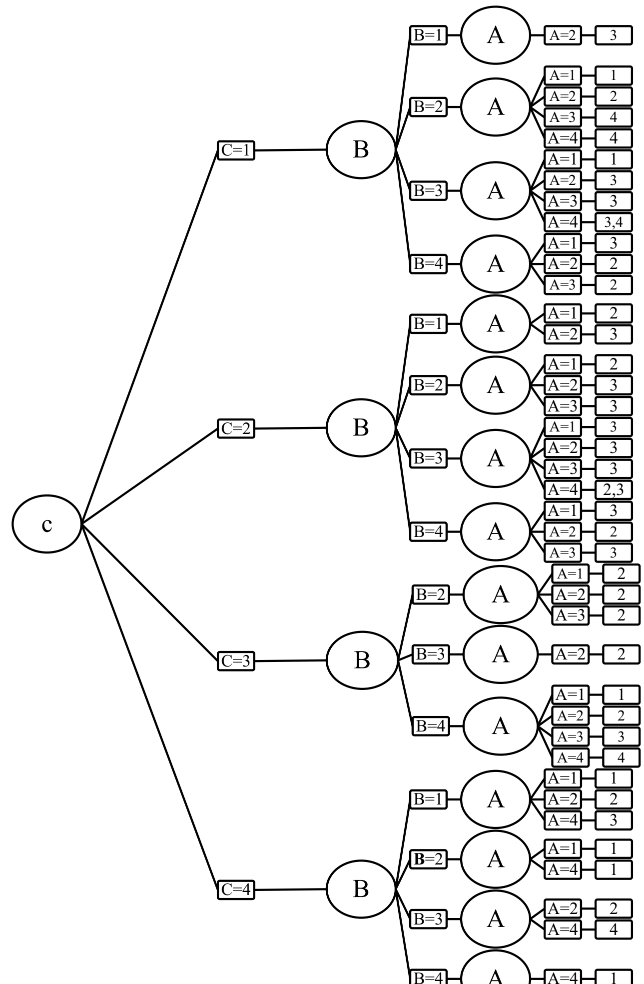

Fig. 4. Decision tree based on incomplete data.

Fig. 5. View of a typical open stope at the analyzed underground diamond mine.

Table 4
Original data and prediction results at a diamond mine.

Group	σ_θ/σ_c	σ_c/σ_t	W_{ET}	Prediction severity	Corresponding ranking
1	0.37	31.4	3.3	3	Strong
2	0.35	18.9	1.7	2	Moderate
3	0.38	21.2	2.3	3	Strong
4	0.62	25.1	3.2	2	Moderate
5	0.64	18.6	2.5	2	Moderate
6	0.4	40	1.5	2	Moderate
7	0.88	30.1	5.2	2	Moderate
8	0.44	25.6	2.5	4	Violent
9	0.32	22.9	2.8	1	None
10	0.2	28.5	1.2	2	Moderate
11	0.4	24.2	2.3	2	Moderate
12	0.51	17.1	2.2	2	Moderate

5. Rockburst prediction in kimberlite with a decision tree

Kimberlite is a volcanic and volcanoclastic rock that sometimes bears diamonds. The analyzed case study comes from an underground diamond mine located in northern Canada. The statistical simulation of the rockburst potential of kimberlite was performed on rock samples obtained from two kimberlite pipes at this mine (Fig. 5).

To determine the rock burst potential, twelve groups of kimberlite specimens from twelve different locations were collected from North and South pipes for rock mechanics test. Each group contained fifteen cylinder specimens which were divided into three sets of five specimens each. The three sets of specimens were used to perform a UCS test, uniaxial tensile test and hysteresis loop test. When each rock specimen was collected, the in-situ stresses at each rock collection location were estimated. This was done by extracting the in-situ stress data from the FEM model built at the University of Alberta from data supplied by the mine. This model could be used for the prediction of mining induced stresses around underground excavations (Sepehri, Apel, & Liu, 2017). Table 4 shows the original data and prediction results.

Based on the decision tree prediction, eight locations showed "moderate" burst liability, while two locations showed "strong" burst liability. The remaining two locations registered "none" and "violent" burst liability. At least three cases of brittle and surficial failure occurred at the mine and were attributed to localized high stress accumulation and were classified as strain bursts. According to field observation and evaluation, these failures could be regarded as moderate rockbursts, which verify the prediction results.

6. Conclusion

The decision tree model is introduced to predict burst liability in kimberlite, which avoided analyzing the complex mechanism of rockburst. 132 groups of original rockburst data were used as the training sample for the decision tree, and two decision tree models were built. One was based on 108 complete samples while the other was based on the full range of data (with the additional 24 incomplete samples). Decision trees are capable of using incomplete data which can avoid data waste.

Three indicators including $\frac{\sigma_\theta}{\sigma_c}$, $\frac{\sigma_c}{\sigma_t}$, W_{ET}, were chosen as partition attributes of the decision tree model. These factors combine two fundamental conditions of rockburst occurrence, these being energy condition and rock mechanical condition. Based on these three indicators, a decision tree model with high generalization ability could be built and used in different rockburst predictions in different locations.

In this case study, the constructed decision tree was used to predict kimberlite burst liability at a diamond mine. 12 groups of original data derived from lab tests and a numerical model were adopted as test samples. The results showed that of the 12 samples, 8 samples have a moderate burst liability, which is in line with practical rockburst situations at this diamond mine.

Conflict of interest

None declared.

Ethical statement

Authors state that the research was conducted according to ethical standards.

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References

Adoko, A. C., Gokceoglu, C., Wu, L., & Zuo, Q. J. (2013). Knowledge-based and data-driven fuzzy modeling for rockburst prediction. *International Journal of Rock Mechanics and Mining Sciences, 61*, 86–95. https://doi.org/10.1016/j.ijrmms.2013.02.010.

Altindag, R. (2003). Correlation of specific energy with rock brittleness concepts on rock cutting. *Journal of The Southern African Institute of Mining and Metallurgy, 103*(3), 163–171.

Baltz, R., & Hucke, A. (2008). Rockburst prevention in the German coal industry. In S. S. Peng,, Ch Mark,, G. Finfinger,, S. Tadolini,, A. W. Khair,, & K. Heasley, (Eds.). *Proceedings of the 27th International Conference on Ground Control in Mining, July 29–31, 2008* (pp. 46–50). Morgantown, VA: Dept. of Mining Engineering, College of Engineering and Mineral Resources, West Virginia University.

Blake, W., & Hedley, D. G. (2003). *Rockbursts: Case studies from North American hard-rock mines.* Littleton, CO: Society for Mining, Metallurgy, and Exploration, Inc.

Breiman, L., Friedman, J., Stone, C. J., & Olshen, R. A. (1984). *Classification and regression trees.* CRC Press.

Butra, J., & Kudełko, J. (2011). Rockburst hazard evaluation and prevention methods in Polish copper mines. *Cuprum,* (4), 5–20.

Cai, W., Dou, L., Si, G., Cao, A., He, J., & Liu, S. (2016). A principal component analysis/fuzzy comprehensive evaluation model for coal burst liability assessment. *International Journal of Rock Mechanics and Mining Sciences, 81*, 62–69. https://doi.org/10.1016/j.ijrmms.2015.09.028.

Feng, X., & Zhao, H. (2002). Prediction of rockburst using support vector machine. *Journal of Northeastern University (Natural Science),* (01), 57–59 (in Chinese).

Friedl, M. A., & Brodley, C. E. (1997). Decision tree classification of land cover from remotely sensed data. *Remote Sensing of Environment, 61*(3), 399–409. https://doi.org/10.1016/S0034-4257(97)00049-7.

Gibowicz, S. J. (2009). Seismicity induced by mining: Recent research. *Advances in Geophysics, 51*, 1–53. https://doi.org/10.1016/S0065-2687(09)05106-1.

Hall, L. O., Chawla, N., & Bowyer, K. W. (1998). Decision tree learning on very large data sets. *Paper presented at 1998 IEEE International Conference on the Systems, Man, and Cybernetics*.

Jaeger, J. C., Cook, N. G., & Zimmerman, R. (2009). *Fundamentals of rock mechanics* (4th ed.). Malden: Blackwell Publishing.

Kabwe, E., & Wang, Y. (2015). Review on rockburst theory and types of rock support in rockburst prone mines. *Open Journal of Safety Science and Technology, 5*, 104–121. https://doi.org/10.4236/ojsst.2015.54013.

Kidybiński, A. (1981). Bursting liability indices of coal. *International Journal of Rock Mechanics and Mining Sciences & Geomechanics Abstracts, 18*(4), 295–304. https://doi.org/10.1016/0148-9062(81)91194-3.

Korzeniowski, W., Skrzypkowski, K., & Zagórski, K. (2017). Reinforcement of underground excavation with expansion shell rock bolt equipped with deformable component. *Studia Geotechnica et Mechanica, 39*(1), 39–52.

Leveille, P., Sepehri, M., & Apel, D. B. (2017). Rockbursting potential of kimberlite: A case study of Diavik diamond mine. *Rock Mechanics and Rock Engineering, 50*(12), 3223–3231. https://doi.org/10.1007/s00603-017-1294-z.

Li, N., Jimenez, R., & Feng, X. (2017). The influence of Bayesian networks structure on rock burst hazard prediction with incomplete data. *Procedia Engineering, 191*, 206–214. https://doi.org/10.1016/j.proeng.2017.05.173.

Li, H., Li, Z., He, R., & Yan, Y. (2014). Rock burst risk evaluation based on particle swarm optimization and BP neural network. *Journal of Mining and Safety Engineering, 31*(2), 203–231 (in Chinese).

Lingga, B. A., & Apel, D. B. (2018). Shear properties of cemented rockfills. *Journal of Rock Mechanics and Geotechnical Engineering,* 1–10. https://doi.org/10.1016/j.jrmge.2018.03.005.

Michalski, R. S., Carbonell, J. G., & Mitchell, T. M. (2013). *Machine learning: An artificial intelligence approach.* Springer Science & Business Media.

Mingers, J. (1989). An empirical comparison of pruning methods for decision tree induction. *Machine Learning, 4*(2), 227–243. https://doi.org/10.1023/A:1022604100933.

Mitri, H. S., Hughes, R., & Zhang, Y. (2011). New rock stress factor for the stability graph method. *International Journal of Rock Mechanics and Mining Sciences, 48*(1), 141–145. https://doi.org/10.1016/j.ijrmms.2010.09.015.

Ortlepp, W., & Stacey, T. (1994). Rockburst mechanisms in tunnels and shafts. *Tunnelling and Underground Space Technology, 9*(1), 59–65. https://doi.org/10.1016/0886-7798(94)90010-8.

Potvin, Y., Hudyma, M., & Jewell, R. J. (2000). Rockburst and seismic activity in underground Australian mines-an introduction to a new research project. *ISRM international symposium, 19–24 November, Melbourne, Australia*. International Society for Rock Mechanics and Rock Engineering.

Pu, Y., Apel, D., & Xu, H. (2018). A principal component analysis/fuzzy comprehensive evaluation for rockburst potential in kimberlite. *Pure and Applied Geophysics, 175*(6), 2141–2151. https://doi.org/10.1007/s00024-018-1790-4.

Qiang, S., Yi-Shan, P., & Yi-Jie, L. (2005). The typical cases and analysis of rockburst in China. *Coal Mining Technology, 10*(2), 13–17 (in Chinese).

Quinlan, J. R. (1986). Induction of decision trees. *Machine Learning, 1*(1), 81–106. https://doi.org/10.1007/BF00116251.

Sepehri, M. (2016). *Finite element analysis model for determination of in-situ and mining induced stresses as a function of two different mining methods used at Diavik diamond mine* (Doctoral dissertation). Canada: University of Alberta, Department of Civil and Environmental Engineering.

Sepehri, M., Apel, D., & Liu, W. (2017). Stope stability assessment and effect of horizontal to vertical stress ratio on the yielding and relaxation zones around underground open stopes using empirical and finite element methods. *Archives of Mining Sciences, 62*(3), 653–669. https://doi.org/10.1515/amsc-2017-0047.

Yun-hua, Z., Xin-rong, L., & Jun-ping, Z. (2008). Rockburst prediction analysis based on v-SVR algorithm. *Journal of China Coal Society, 33*(3), 277–282 (in Chinese).

Zhao, T.-b., Guo, W.-y., Tan, Y.-l., Lu, C.-p, & Wang, C.-w. (2017). Case histories of rock bursts under complicated geological conditions. *Bulletin of Engineering Geology and the Environment,* 1–17. https://doi.org/10.1007/s10064-017-1014-7.

Zhou, J., Li, X., & Shi, X. (2012). Long-term prediction model of rockburst in underground openings using heuristic algorithms and support vector machines. *Safety Science, 50*(4), 629–644. https://doi.org/10.1016/j.ssci.2011.08.065.