Research Article

Decision Tree Model for Rockburst Prediction Based on Microseismic Monitoring

Hongbo Zhao ¹, Bingrui Chen,² and Changxing Zhu³

¹School of Civil and Architectural Engineering, Shandong University of Technology, Zibo, Shandong 255000, China

²Institute of Rock and Soil Mechanics, Chinese Academy of Sciences, Wuhan, Hubei 430071, China

³School of Civil Engineering, Henan Polytechnic University, Jiaozuo, Henan 454000, China

Correspondence should be addressed to Hongbo Zhao; bxhzbzhao@hotmail.com

Received 13 May 2020; Revised 5 January 2021; Accepted 25 January 2021; Published 4 February 2021

Academic Editor: Emanuele Brunesi

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Rockburst is an extremely complex dynamic instability phenomenon for rock underground excavation. It is difficult to predict and evaluate the rank level of rockburst in practice. Microseismic monitoring technology has been adopted to obtain microseismic events of microcrack in rock mass for rockburst. The possibility of rockburst can be reflected by microseismic monitoring data. In this study, a decision tree was used to extract the knowledge of rockburst from microseismic monitoring data. The predictive model of rockburst was built based on microseismic monitoring data using a decision tree algorithm. The predictive results were compared with the real rank of rockburst. The relationship between rockburst and microseismic feature data was investigated using the developed decision tree model. The results show that the decision tree can extract the rockburst feature from the microseismic monitoring data. The rockburst is predictable based on microseismic monitoring data. The decision tree provides a feasible and promising approach to predict and evaluate rockburst.

1. Introduction

Rockburst is a kind of sudden dynamic failure and instability phenomenon of rock mass which usually causes injury to workers and economic losses for rock underground excavation such as mining engineering and tunnel engineering. In China, rockburst is becoming a more and more serious problem for rock engineering with increasing depth of mining and underground rock excavation [1]. In 1966, Cook et al. proposed and applied rock mechanics to study and predict rockburst in mining [2]. Since then, various models have been developed to predict or evaluate the rockburst based on rock mechanics theory in the past decades. Based on rock mechanics, various predictive methods of rockburst have been developed and proposed by the empirical method, experimental method, analytical method, numerical method, and intelligent method [3–21]. Recently, Zhou et al. [22] and Sajjad et al. [23, 24] reviewed the state-of-the-art of theory, predictive method, and data preprocessing of rockburst in brief and classified the various methods into the empirical method, experimental method, analytical method,

intelligent method, and numerical method [22–24]. But, it is difficult to predict and evaluate rockburst accurately based on the above studies due to the unclear mechanism of rockburst and uncertainty and complexity of rock mass materials. Rockburst prediction remains a universal issue for rock underground excavation till now.

Some researchers considered rockburst as microseismic events that result in severe damage to rock mass structure with sudden or intensive acoustic emissions [25–27]. Microseismic monitoring technology has been widely used in rock mechanics and provides a feasible way to predict or prewarn rockburst [28–31]. Feng et al. proposed a neural network prediction model based on the microseismic monitoring information [1]. Ma et al. studied the seismic source, seismogenic period, and scale effect of rockburst and believed that rockburst can be predicted based on the relationship between rock heterogeneity and acoustic emission sequence [32]. Xu et al. applied the ideal-point method to predict rockburst based on the information theory [33]. Currently, microseismic monitoring has been widely used to predict, evaluate, and prewarn the rockburst in rock

underground excavation. Microseismic monitoring also provides a large amount of data about rockburst.

With the development of machine learning, it provides a powerful tool to reveal the mechanism behind data [34, 35]. The decision tree is a supervised machine learning algorithm and is commonly used in various engineering fields [36]. Microseismic monitoring provides a deluge of microseismic data about rockburst. How to extract the rockburst information and knowledge from data is an important challenge to predict or evaluate rockburst. The combination of microseismic monitoring data, machine learning, and rockburst theory offers an exciting new opportunity for expanding our knowledge about rockburst. In this study, a decision tree was adopted to build the predictive model of rockburst through the combining of microseismic monitoring data.

2. Decision Tree

A decision tree is a decision support tool that uses a tree-like model of decisions and their possible consequences, including chance event outcomes, resource costs, and utility. Decision tree learning is a method commonly used in machine learning [36]. The goal is to create a model that predicts the value of a target variable based on several input variables. The target variable of classification trees can take a discrete set of values, and the target variable of regression trees can take continuous values (typically real numbers). Each interior node corresponds to one of the input variables; there are edges to children for each of the possible values of that input variable. Each leaf represents a value of the target variable given the values of the input variables represented by the path from the root to the leaf (Figure 1). There are many specific decision tree algorithms such as Iterative Dichotomiser 3 (ID3), Classification and Regression Tree (CART), and CHi-squared Automatic Interaction Detector (CHAID) [37, 38].

In the decision trees, primary splitters (i.e., input variables that appear in the upper levels of the tree) that are directly connected with leaf nodes are considered the most influential factors in determining the value of the target attribute. In this study, the CART algorithm is adopted to build the decision tree model for rockburst prediction. The CART is a classical algorithm that has been commonly utilized to build a decision tree. To develop a CART model, recursive binary splitting is used. To the classification decision tree, the Gini splitting rule was adopted in this study. The strategy of Gini permutations/measurements was also used to determine the importance of each feature in the samples [39].

Consider that the n_k samples' fraction from the ($k = 0, 1$) category out of all the samples at the node τ is expressed as follows:

$$p_k = \frac{n_k}{n}, \quad (1)$$

where p refers to the probability of having a specific data class in a branch of the decision tree model (node τ). The

FIGURE 1: A simple example of the decision tree.

following equation presents the mathematical expression for the Gini impurity i_τ :

$$i_\tau = 1 - \sum_k p_k^2. \quad (2)$$

If the node has only one single class, the equation output becomes zero, that is, the best value for the impurity. For a two-class problem (class 0 and class 1), i_τ is calculated as follows:

$$i_\tau = 1 - p_1^2 - p_0^2. \quad (3)$$

As the samples are separated and sent to subnodes τ_1 and τ_2 , the Gini impurity changes. To define the reduction amount of i_τ , as a result of separating and sending the samples to subnodes τ_1 and τ_2 by a threshold t_θ on feature θ , the following expression can be used:

$$\Delta i_\tau = i_\tau - p_1 i_{\tau_1} - p_2 i_{\tau_2}. \quad (4)$$

Depending on the applied setting (when creating a tree), the ideal strategy is to make enough branches until each branch has a Gini impurity of zero.

Conducting a proper/systematic search over all the available features at the node, the pair $\{\theta, t_\theta\}$ that leads to a maximal Δi_τ is obtained. After this stage, the algorithm records and accumulates a decrease in i_τ for all the nodes (individually for all features). To the decision tree, the Gini importance is an index and can be used to measure the heterogeneity of the node. In the CART algorithm, the Gini importance is calculated using the following expression [39]:

$$I_G(\theta) = \sum_t \sum_\tau \Delta i_\theta(\tau, T), \quad (5)$$

where $I_G(\theta)$ is the Gini importance and T is the number of trees in the model. The Gini importance indicates how often a specific feature θ is employed for a split and how important its general discriminative value is for the classification analysis of the objective function.

To build the tree, the information gain of each possible first split would need to be calculated. The best first split is the one that provides the most information gain. This process is repeated for each impure node until the tree is

complete. In this study, *ski-learn*, which is a minimalist Python library for the decision tree, was adopted to build a decision tree model for rockburst prediction.

3. Decision Tree Model for Rockburst Prediction

It is difficult to predict or evaluate rockburst due to its indistinct mechanism and complicated phenomenon. Though lots of predictive models have been developed in the past decades, there is not a progression for predicting rockburst successfully. With the development of data sciences and machine learning, they provide a good way to obtain knowledge about rockburst from data. Microseismic monitoring technology can provide lots of data about the rockburst phenomenon. Machine learning can extract knowledge and information from the data. In this study, a novel model of rockburst prediction was developed by combining the decision trees and microseismic data.

3.1. Microseismic Monitoring and Microseismic Data about Rockburst. The stress of the surrounding rock mass will be altered and redistributed with the underground structure excavation. The rock mass will release the stored elastic energy in the form of microseismic events with the appearance and development of microcracks when the redistributed stress is greater than the strength of the rock masses. This phenomenon is called acoustic emission [40]. Passive acoustic emission detection technology, which takes advantage of the local strain energy quickly released in engineering materials, is also known as the microseismic monitoring technology. Some researchers noticed an anomalous increase in microseismic events before the occurrence of rockburst. To date, microseismic monitoring technology has been an important tool to predict and avoid rockburst. The predictive method and model of rockburst have been developed and applied to rock underground excavation based on microseismic monitoring data [41–44]. In this study, a decision tree was adopted to predict rockburst by building the relationship between rockburst and microseismic information.

The occurrence of rockburst is related to microseismic monitoring information. To predict rockburst based on microseismic monitoring data, it is critical to reasonably determine the key parameters of microseismic data which can represent the rockburst. Feng et al. developed and proposed a predictive model based on microseismic monitoring using neural networks [1]. In this study, the number of microseismic events, microseismic energy, microseismic apparent volume, and development time were selected to predict rockburst. Various studies of rockburst rank have been conducted in the last decades. Russnes proposed and classified the rockburst intensity into four ranks, i.e., none, weak, moderate, and severe [45]. Brauner classified the rockburst into three ranks based on the intensity of destruction to the surrounding rock mass [46]. Tan classified the rockburst into four ranks based on lots of laboratory tests and field investigations [47]. Cai et al. developed the four ranks of rockburst

to evaluate the rockburst liability [48]. The four ranks method of rockburst classification has been widely used in mining, tunnel, and other rock engineering. So, the four ranks of rockburst were adopted in this study. The input of the decision tree was the number of microseismic events, microseismic energy, microseismic apparent volume, and development time, respectively. The output is the ranks of rockburst, i.e., no rockburst, moderate rockburst, strong rockburst, and violent rockburst. Numbers 1, 2, 3, and 4 were adopted to represent the different ranks of rockburst in the decision tree model (1-no rockburst, 2-moderate rockburst, 3-strong rockburst, and 4-violent rockburst).

3.2. Datasets. Learning samples are critical to the model effect of the decision tree. In the literature, lots of researchers collected plenty of case histories and laboratory tests' results and evaluated the potential of rockburst using different predictive models such as empirical models, numerical models, and intelligent models. In this study, the datasets were collected from the literature based on the previous works [1]. The datasets consist of 173 samples which have four influencing factors and a corresponding rank (label) of rockburst. The dataset was divided into 153 training samples and 20 test samples. Figures 2 and 3 show the relationship between rockburst rank and microseismic feature parameters. It is obvious that their relationships are very complex, and it is impossible to be characterized using the traditional mathematical model. Therefore, the decision tree model was adopted to evaluate the rockburst rank based on microseismic data. Table 1 lists the testing samples.

3.3. Rockburst Prediction. To verify and illustrate the rockburst predictive model based on a decision tree, the above samples were used to train a decision tree model using the CART algorithm. The samples were divided into learning samples and testing samples. The number of learning and testing samples were 153 and 20, respectively. The performance of the decision tree was evaluated, and the predicted results were compared with the real rank of rockburst. The results show that the decision tree model can be used to predict rockburst. It also presented the microseismic monitoring parameter's affection for rockburst. It proved that the decision tree provides a good tool to predict and evaluate rockburst based on microseismic monitoring technology with the supplementation of microseismic data.

3.4. Decision Tree Model for Rockburst Prediction. The structure of the decision tree is shown in Figure 4 based on the training samples. 20 test samples were used to verify the decision tree model. Table 1 lists the predicted results and their comparison with the real rank of rockburst. The predicted rank of 18 samples is in excellent agreement with the real rank, and 2 samples (nos. 4 and 14) are not classified correctly. The error ratio is about 10%. To further verify the decision tree model, it was used to determine the rockburst rank of eight real case histories [1]. The results are listed in Table 2. Two case histories were not predicted correctly. The

FIGURE 2: The relationship between rockburst rank and microseismic parameters.

error in prediction occurred at the neighboring rank for the nos. 4 and 14 test samples and nos. 3 and 7 case histories. As we know, the mechanism of rockburst is not clearly understood till now. The relationship between rockburst and microseismic data is also not clear and remains uncertain. It is difficult to distinguish the rank of rockburst which falls in between two neighboring ranks. With the increasing of microseismic monitoring data, the prediction precision can be improved. Thus, the decision tree has the capacity of predicting rockburst based on microseismic monitoring information. The proposed method provides a good way to evaluate the rockburst rank.

3.5. Important Feature in Microseismic Data. Due to the unclear mechanism of rockburst, it is difficult to select the proper microseismic parameters and present the relationship between the rockburst rank and the selected microseismic parameters. Based on the decision tree model of rockburst, Shapley additive explanations (SHAP) was used to evaluate the important feature of microseismic data. The important feature order is microseismic energy, number of microseismic events, microseismic apparent volume, and development time, respectively (Figure 5). Figure 6 shows the impact of each sample and its input on the rockburst rank. The proposed

FIGURE 3: Bivariate relationship of microseismic parameters with the rockburst rank.

TABLE 1: Predicted results of test samples using the decision tree.

No.	Number of events	Microseismic energy (LgE/J)	Microseismic apparent volume (LgV/m ³)	Development time (day)	Rockburst rank	
					Real	Prediction
1	17	3.172	5.015	10	2	2
2	2	1.94	3.25	1	1	1
3	42	6.284	5.05	7	4	4
4	21	5.848	4.834	11	3	4
5	6	5.561	4.043	6	2	2
6	22	5.859	4.895	10	4	4
7	5	2.435	3.878	10	1	1
8	7	4.381	4.132	4	2	2
9	13	4.408	4.428	6	2	2
10	44	5.459	4.865	15	4	4
11	8	5.204	3.977	3	2	2
12	14	5.841	4.622	6	3	3
13	17	4.754	4.397	9	3	3
14	15	3.486	5.03	7	1	2
15	18	5.295	4.703	10	3	3
16	10	5.322	4.238	7	3	3
17	49	6.419	4.995	4	4	4
18	14	4.818	4.266	11	3	3
19	4	5.82	3.728	7	1	1
20	24	4.748	4.66	6	3	3

FIGURE 4: Structure of the decision tree model.

TABLE 2: Predictive results of eight case histories.

No.	Number of events	Microseismic energy (LgE/J)	Microseismic apparent volume (LgV/m ³)	Development time (day)	Rockburst rank	
					Real	Prediction
1	29	5.513	4.777	5	4	4
2	15	6.587	5.152	9	4	4
3	10	4.886	4.105	6	3	2
4	17	4.944	4.598	10	3	3
5	19	5.865	4.263	7	3	3
6	7	4.834	4.116	13	2	2
7	5	5.17	4.594	6	2	3
8	1	1.67	4.033	1	1	1

FIGURE 5: The important feature order of microseismic parameters based on SHAP.

FIGURE 6: Impact on rockburst of different microseismic parameters based on SHAP.

FIGURE 7: Impact of MS energy on rockburst.

model shows that microseismic energy and the number of microseismic events have a higher impact on rockburst. Figures 7 and 8 show the impact of microseismic energy and the number of microseismic events on the rank of rockburst, respectively. It shows that the rank level of rockburst is higher with the higher microseismic energy and the larger number of microseismic events. It is well in

agreement with the rockburst theory. It shows that the knowledge extracted from data meets the rockburst theory. It proved that it is feasible to build a rockburst predictive model based on microseismic monitoring data. And, it also proved that the decision tree captures well the relationship between rockburst rank and microseismic feature parameters.

FIGURE 8: Impact of the number of MS events on rockburst.

(a)

FIGURE 9: Continued.

FIGURE 9: Continued.

FIGURE 9: Impact of MS parameters on rockburst. (a) Number of MS events. (b) MS energy. (c) MS apparent volume. (d) Development time time.

FIGURE 10: Continued.

FIGURE 10: Interactive impact of the energy and events' number of MS on rockburst.

FIGURE 11: Interactive impact of the energy and apparent volume of MS on rockburst.

FIGURE 12: Interactive impact of the energy and events' number of MS on rockburst. (a) Average no rockburst. (b) Average weak rockburst. (c) Average moderate rockburst. (d) Average strong rockburst.

3.6. Impact of the Single Microseismic Parameters on Rockburst. The microseismic parameters have an impact on the rank level of rockburst. Different values of microseismic parameters reflect the different potential of rockburst. Figure 9 shows the relationship between the microseismic parameters and the rank level of rockburst. The rank level of rockburst increases from no rockburst to strong rockburst with the increasing microseismic events' number (Figure 9(a)). Similar findings were observed for microseismic energy and microseismic apparent volume. No obvious correlation was found between the development time and the rockburst rank. But to the development time, there are no distinct relations to rockburst. It also implied that development time is not significant to evaluate rockburst rank and is stated in Section 3.5.

3.7. Interactive Impact of the Microseismic Parameters on Rockburst. The mechanism of rockburst is unclear, and the relationship between rockburst and microseismic parameters is very complex and uncertain. The interaction between microseismic parameters was evaluated based on the decision tree model. Figure 10 shows the interactive impact of microseismic energy and the number of events on rockburst. It showed that the value of energy and the number of events of microseismic are smaller for the scenario of no rockburst (class 0). But, the impact on rockburst is very complex, nonlinear, and uncertain for rockburst (class 1-2). The interactive impact of microseismic energy and microseismic apparent volume on rockburst are similar to the above case (Figure 11). With the increase of microseismic energy and

microseismic events' number, the potential of rockburst will increase, but their relationship is nonlinear and complex (Figure 12). It proved the rockburst phenomenon is very complex, and it is difficult to propose a predictive model based on traditional methods but the decision tree provides a good way to evaluate it.

4. Conclusions

Rockburst is an extremely serious geological disaster to the rock underground excavation. It is difficult to predict rockburst using traditional methods based on rock mechanics. In this study, a decision tree was adopted to predict and evaluate the rank level of rockburst based on microseismic monitoring data. The relationship between rockburst and microseismic feature parameters was represented using the decision tree. The proposed method was applied to 20 test samples and eight case histories. The results proved that the relationship between the rockburst and the microseismic data is complex, uncertain, and nonlinear. It also showed that the decision tree model is a reasonable and feasible way to predict rockburst based on microseismic monitoring technology. It provides a scientific and rational approach to evaluate the rank level of rockburst for rock underground excavation. The following conclusions can be drawn:

- (1) Rockburst is a complex dynamic instability phenomenon of the rock mass. It is difficult to predict, evaluate rockburst, and understand the mechanism of rockburst only based on rock mechanics.

- (2) Microseismic monitoring technology provides a good way to understand rockburst and its mechanism. Rockburst is predictable through understanding the relationship between microcrack in the rock mass and microseismic data feature.
- (3) With the development of data science and machine learning technique, the decision tree model provides a good way to utilize microseismic monitoring data to extract knowledge about rockburst. The decision tree model can improve our understanding of the rockburst and evaluate effectively the rockburst rank despite the complexity.
- (4) The decision tree model captured well the relationship between rockburst and microseismic features parameters. It has been proved more powerful and flexible than the traditional model based on rock mechanics. The decision tree offers exciting new opportunities for expanding our knowledge about rockburst with the microseismic monitoring technology.
- (5) A decision tree is a kind of interpretable machine learning algorithm which can reveal the complicated and uncertain mechanism of the model based on data. The decision tree model provides a promising approach to understand rockburst through learning from microseismic monitoring information.

Data Availability

All data and models generated or used during the study are available upon request from the corresponding author.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (Grant no. 51874119).

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