Experimental Investigation on Acoustic Emission Precursors of Rockburst Based on Unsupervised Machine Learning Methods

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Abstract

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Full Text

Preamble

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Full Length Article

Experimental investigation on acoustic emission precursor of rockburst based on unsupervised machine learning method

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Keywords: Rockburst; Acoustic emission; Precursor; Machine learning

The key to achieving rockburst warning lies in the understanding of rockburst precursors. Considering the correlation characteristics of rockburst acoustic emission (AE) parameters, a self-organizing map neural network (SOMNN) based method for rockburst precursor inversion was proposed. The feature of this method lies in a cyclic data segmentation iteration process based on the thinking of "interference signal screening," "key signal extraction," and "precursor signal inversion." The rationality of this method has been verified in three groups of rockburst experiments. The results revealed that rockburst AE precursor signals consist of a series of signals characterized by long duration, high energy, low average frequency, high energy amplitude, and low peak frequency. Subsequently, potential value in long term rockburst warning of the precursor obtained in this study was shown via the comparison of conventional precursors. Finally, a preliminary interpretation for rockburst precursor was proposed under the framework of AE parameters physical significance, and it is revealed that AE precursor signals are likely linked to the creation of large-scale tensile cracks before rockburst.

1. Introduction

With the increase in depth of underground excavations, rockbursts are becoming a significant challenge in rock engineering (He et al., 2018; Konicek and Schreiber, 2018; Mazaira and Konicek, 2015; Feng et al., 2019; Mohammadali et al., 2020; Cai and Brown, 2017). Rockburst is a nonlinear dynamic process in which energy is instantly released by a rock mass along a free surface. It is accompanied by the forceful ejection of rock fragments and loud noise, which can cause severe damage to the excavation area and injuries to the constructor (Waqar et al., 2023; Feng et al., 2017; Mazaira and Konicek, 2015; Kaiser and Cai, 2012). In some cases, it can even lead to surface collapse and local earthquakes. As the depth of the burial increases, the frequency and severity of rockburst also tend to increase (Khosravi and Simon, 2018).

Ensuring the safe construction of deep-buried tunnels relies heavily on early warning of potential rockburst disasters (Basnet et al., 2023; Wojtecki et al., 2022; Khosravi and Simon, 2018). However, the complex nature factors of rock mass make it difficult for traditional empirical criteria to provide accurate warnings. Fortunately, scholars have been able to identify precursor characteristics of rockburst with the use of advanced monitoring equipment like micro-seismic (MS) and AE monitoring. After conducting numerous rockburst experiments, researchers have formed favorable results on the characteristics of AE precursors for rockburst, including a decrease in the b-value (Su et al., 2022), a decrease in the fractal dimension (Yu et al., 2020; Feng et al., 2016; Su et al., 2021), a sudden change in infrared radiation (Sun et al., 2017; Liu et al., 2018; Huo et al., 2020), and a sudden change in the multifractal dimension (Ren et al., 2023). It is worth noting that changes in the process of crack evolution can be considered as precursor phenomena of rockburst. These changes include the occurrence time of the calm period of the tension crack (Wang et al., 2023) and the decreasing cumulative proportion of tension cracks (Liu et al., 2023). However, it is important to keep in mind that these conclusions are based on statistics of a single parameter in the time series.

Machine learning algorithms have become widely used in rock mechanics due to the advancements in computer science and big data analysis in recent years (Beroza et al., 2021; Liu et al., 2023). Machine learning method is considered to be one of the effective ways of rockburst prediction and early warning (Kamran et al., 2022; Wojtecki et al., 2022; Peng et al., 2021). By adjusting the model structure of machine learning (Wojtecki et al., 2022; Ke et al., 2021) and integrating multiple algorithms (Kamran et al., 2022), the risk of rockburst is clearly visualized. In addition, the possibility of short-term prediction of rockburst has also been confirmed based on the machine learning results of in-situ micro seismic data (Yang et al., 2023; Ullah et al., 2022; Liang et al., 2020).

However, these studies are typically based on pre-existing sample data and fall under the category of empirical research. The accuracy of these sample labels and training data can greatly impact the results of supervised machine learning. Unfortunately, in practical engineering, engineering data labels are often unknown, making it difficult to clearly label the categories of these data before rockburst (Su et al., 2022). Consequently, the precursor of rockburst is still unclear. However, unsupervised learning methods differ from supervised machine learning in that they do not require prior knowledge of dataset labels. Instead, these algorithms extract commonalities between unlabeled data sets to uncover correlations within the data. Consequently, unsupervised learning can help achieve the inversion of rockburst precursors by analyzing the interior of acoustic emission big data.

In this paper, an inversion method for rockburst precursor is proposed by a typical unsupervised learning method, and the rationality of this method is verified.

Then, the potential value in rockburst warning of the precursor obtained in this study is analyzed.

2.1. The introduction of binary approximation method

The "binary approximation method" is a widely used mathematical approach to finding solutions or sets of solutions with specific properties. The method involves narrowing down intervals to find a set with property 'a' within a closed interval set P. The specific ideas are as follows: (1) Find a set of closed intervals that includes P. Bisect it to create P1 and P2. (2) Segment P1 and P2, then identify the set P0 that contains property 'a'. (3) Segment P0 again to obtain two closed interval sets, P01 and P02, then identify the set P00 that contains property 'a'. (4) Segment P00 again to obtain two closed interval sets, P001 and P002. (5) Continue segmenting the set according to the above rules until the error between the properties of all point sets in the segmented closed interval set Pn and property a is minimal. The resulting set, Pn, is considered the final answer and is the optimal solution with the property 'a'.

Furthermore, for a multidimensional matrix C composed of multiple parameter sequences, if we want to find the most "special" position in this matrix C, the basic solution idea can also be solved according to this principle. The basic schematic diagram for its calculation is shown in Fig. 1 [Figure 1: see original paper]. The specific ideas are as follows: (1) Divide matrix C into four submatrices C11, C12, C13, and C14 with the same number of columns as C according to a certain classification method. (2) Based on the certain rule proposed in step 1, calculate the similarity or contribution rate between these four submatrices C11, C12, C13, and C14, and find the most special matrix C1i |i = 1 or 2 or 3 or 4 (such as the lowest similarity or the highest contribution rate). (3) Continue to classify the matrix C1i |i = 1 or 2 or 3 or 4 found in the second step again, and divide it into four categories to obtain the four submatrices C21, C22, C23, and C24 of C1i. Among them, C2i |i = 1, 2, 3, and 4 are respectively interpreted as the No.1–4 sub-matrix obtained from matrix C after the second round of clustering. (4) Similarly, follow the rules in step 2 to find the most special matrix C2i |i = 1 or 2 or 3 or 4. (5) Repeat steps 1 to 4 in a cyclic manner, continuously segmenting the most special submatrix until the nth round, when the four submatrices Cn1, Cn2, Cn3, and Cn4 of C(n-1)i cannot be further divided (if all four submatrices are similar or have almost the same contribution rate), the classification will be stopped and matrix C(n-1)i will be considered as the most special position of matrix C.

2.2. Algorithm requirements

Section 2.1 outlines two fundamental principles that should be considered when selecting algorithms. Firstly, the algorithm should be capable of achieving classification goals. Secondly, it should be adaptable to the calculation of high-dimensional data.

Machine learning algorithms can be divided into two categories: unsupervised and supervised learning algorithms. Unsupervised learning algorithms are designed to identify data structures and patterns through algorithms, without any prior knowledge of the data. On the other hand, supervised learning algorithms use algorithms to establish connections between datasets and their corresponding labels. However, these algorithms are often affected by human subjectivity during the classification process, which can result in inaccurate classification. Therefore, unsupervised learning algorithms are more suitable for the calculations in this paper.

Self-organizing map neural network (SOMNN) is a kind of unsupervised learning neural network based on a competitive learning strategy. This method is very suitable for visualizing high-dimensional data. It can map high-latitude data with complex relationships to low-latitude spaces with simple geometric structures and interrelationships while maintaining the topological structure of the input space. Therefore, this study introduced SOMNN into the inversion of precursor features. The SOMNN has a two-layer network structure, including an input layer and a competition layer (output layer), as shown in Fig. 2 [Figure 2: see original paper].

In the SOMNN, the output layer neurons are arranged in a two-dimensional matrix format, and each neuron has a weight vector. When the network receives an input vector, it identifies the winning neuron in the output layer. This winning neuron determines the position of the input vector in the low-dimensional space. Upon receiving a training sample, each output layer neuron measures the distance between the sample and its own weight vector. The neuron with the smallest distance is declared the best matching unit. The weight vectors of the best matching unit and its neighboring neurons are then modified to reduce the distance between these weight vectors and the current input sample. This process is repeated until convergence is achieved.

3.1. Specimens' preparation

In this study, rockburst experiments were conducted on red sandstone, gneiss, and slate from three different engineering sites, including mines and traffic tunnels. Table 1 presents the basic physical parameters of these three types of rocks, and Fig. 3 illustrates the size of the processed sample, which is 30 × 60 × 150 mm.

3.2. Experimental system and loading path design

He et al. (2007) conducted the rockburst experimental system in the State Key Laboratory for GeoMechanics and Deep Underground Engineering. The testing system consists of loading equipment, AE monitoring, and high-speed photograph system. By applying true triaxial loading, sudden and rapid unloading can be achieved on one side, creating a stress state and geometric boundary conditions for rockburst. The loading system has a maximum working pressure of 450 kN.

The AE signals are monitored using Micro-II AE system produced by the American Physical Acoustics Corporation (PAC). The sampling rate is set to be 1 MPS, and the threshold is set at 40 dB. The AE sensors (Nano 30) are uniformly placed on the diagonal of the sample side. Before the experiment, an ultrasonic coupling agent was applied to the surface of the AE sensor, then tightly connected to the sample surface with spring pressure in the prefabricated holes found on the side plate (as shown in Fig. 4 [Figure 4: see original paper]).

In Fig. 5 [Figure 5: see original paper], the stress loading path of rockburst is depicted (He et al., 2018). The entire loading process can be categorized into five stages. The first stage pertains to the loading process until reaching the preset stress level and the loading rate is 0.1 MPa/s. The second stage represents the clamping process after reaching the preset stress level, imitating the stress state of sandstone before excavation. The third stage involves unloading σh to 0 MPa with the unloading rate of 0.1 MPa/s, simulating the excavation and unloading process of the rock mass. The fourth stage is the process of holding the load after unloading. Finally, the fifth stage involves loading σV to rockburst with the loading rate of 0.1 MPa/s, which is used to simulate rockburst caused by stress concentration.

Table 2 illustrates the specific preset stress level and loading/unloading rates for three groups of different rockburst experiments.

3.3. Macroscopic destructive phenomenon

3.3.1. Dynamic ejection process of rockburst

In Fig. 6 [Figure 6: see original paper], the failure process of three groups of rockbursts is displayed. Upon unloading, there are no visible macroscopic cracks on the surface of sandstone and gneiss specimens. However, when σv increases, macroscopic cracks quickly form on the surface, and debris is expelled in a short time. In the case of slate, there are no apparent macroscopic cracks on the surface during unloading. As σv increases, macroscopic cracks gradually appear on the surface, and flaky debris bulges. With further increases in σv, the bulging flakes break and erupt along the free surface.

3.3.2. Failure mode of rockburst

As displayed in Fig. 7 [Figure 7: see original paper], specimens after rockburst are photographed to show the failure mode of the rockburst. Gneiss and red sandstone all have noticed "V" shaped rockburst pit. The interior of these rockburst pit have a serrated, stepped shape and will be covered in rock powder. However, slate rockburst only have localized rockburst pits on the free surface. In all three groups of experiments, several parallel tensile cracks distribute along the free surface. In addition, these tensile cracks are also penetrated by macroscopic shear cracks, indicating the tensile-shear-coupling failure characteristics of rockburst.

3.4. AE characteristics

3.4.1. b-value evolution process of rockburst

B. Gutenberg and C. F. Richter (1944) proposed that the fracture scale can be evaluated by the b-value of earthquake frequency-magnitude relationship. Equation (1) shows the calculation of b-value.

$$\log N = a - bm$$

where m is the earthquake magnitude; N is the number of earthquakes with magnitude in the range of Δm. During rockburst, an increasing b-value shows small-scale crack development, while a decreasing b-value shows large-scale crack development (Zafar et al., 2022; Su et al., 2022). Fig. 8 [Figure 8: see original paper] shows the evolution process of b-value for rockburst experiments. Sandstone is considered as an example to describe the b-value evolution process of rockburst.

At the first stage, b-value hold a stable evolution process, indicating a stable expand process of micro-cracks. At the second stage, a silent emission signal is generated, and the crack does not expand due to the load-preserving in at this stage. At the third stage, with the unloading of σh to 0 MPa, a slight decrease in the b value is caused. The result indicates that considerable damage within the rock was caused by the unloading effect. At the fourth stage, a silent emission signal is generated, and the crack does not expand due to the load-preserving in at this stage. At the fifth stage, the AE b-value initially remains unchanged, but then shows a significant downward trend before rockburst implying large scales are formed before rockburst.

3.4.2. AE energy evolution process of rockburst

The time distribution of AE energy in the rockburst experiments is similar with each other, as shown in Fig. 9 [Figure 9: see original paper]. At stage I, a large number of AE signals were generated due to the micro-cracks closed and expanded. Stage II is a load-holding stage with no force changes, the AE energy remains unchanged. In stage III, due to the rapid unloading of σh to 0 MPa, the stress state changes strongly, and the AE energy shows a sudden increase, indicating that the rapid unloading causes damage to the specimen. At stage V, along with the increase of the σv, the internal crack inside extends throughout and forms a large number of AE signals, the AE energy shows a violent rise, reflecting that rockburst failure is a process of intense energy release.

4.1. Pre-processing of AE

4.1.1. Selection of AE parameters

Acoustic emission (AE) is defined as 'transient elastic stress waves produced by a release of energy from a localized source' (Hardy, 2005). And an 'AE Hit' is recorded once the electrical signal generated by the sensor crosses the pre-decided threshold value (Datt et al., 2020). The waveform signal of each AE hit can be analyzed to extract characteristic parameters such as rise time, count, energy, and amplitude (Fig. 10 [Figure 10: see original paper]).

The relationship between the characteristic parameters of the AE signals is not always consistent. To make data mining more efficient and prevent redundancy, it's important to assess the correlation between these parameters. Thus, the correlation coefficient is used as an indicator to evaluate the correlation between AE parameters. The calculation formula is shown in Eq. (2) and the evaluation interval in Eq. (3) (Zhang et al., 2021).

$$r = \frac{COV(X,Y)}{\sqrt{D(X)}\sqrt{D(Y)}}$$

where, COV (X, Y) is the covariance between the AE parameter X and Y, and D (X) and D (Y) are the variances of the AE parameters X and Y, respectively.

$$\begin{cases} |r| \geq 0.8; & \text{highly correlated} \\ 0.5 \leq |r| < 0.8; & \text{moderately correlated} \\ 0.3 \leq |r| < 0.5; & \text{lowly correlated} \\ |r| < 0.3; & \text{basically unrelated} \end{cases}$$

The correlation calculation results of AE parameters for rockburst experiment are shown in Fig. 11 [Figure 11: see original paper]. In this study, AE parameters with a correlation coefficient below 0.5 are considered to have a low correlation. Considering red sandstone as an example (Fig. 11 (b)), the correlation coefficients between the rise time, count, energy, and duration were greater than 0.5. Therefore, it can be considered that there is a moderate correlation between these parameters. Consequently, one of these parameters (rise time, count, or duration) is sufficient. Meanwhile, it can be observed that the correlation coefficients between amplitude, average frequency, absolute energy, and peak frequency were less than 0.3. This indicates that there were completely unrelated sets of these parameters (amplitude, average frequency, absolute energy, and peak frequency). Therefore, the final selection of the five AE parameters comprised the duration, amplitude, average frequency, absolute energy, and peak frequency.

4.1.2. Elimination of interference AE signals

During rockburst experiments, a significant number of these signals are generated. However, many of these signals are low energy and low amplitude, and are caused by locally small-scale cracks (Hardy, 2005; Zhang, 2018). As a result, these signals will cause interference with the extraction of precursor signals. Correctly filtering out these interference signals is crucial to optimize the iteration of AE precursor parameters. Based on this approach, this paper utilizes the k-means clustering algorithm to eliminate AE interference signals. The basic steps are as follows: (1) Centroids (clustering centers) are selected by randomly sampling K from N data documents. (2) Classify each data document as belonging to the closest centroid. (3) Recalculate class centroids until they no longer change to achieve clustering goal. (4) To determine outlier clusters, the distance and relative distance between the sample point in each cluster and its centroid need to be calculated. Compare the calculated distance to a set threshold. If the distance is greater than the threshold, it is considered an outlier cluster. If the distance is less than the threshold, it is considered a non-outlier point cluster. (5) Calculate the contribution rates of the two data clusters separately, considering the clusters with large numbers and small contribution rates as interference signals.

Based on these steps, the k-means clustering algorithm is conducted to extract key AE parameters. During the calculation, the number of clusters is set to 3. After the clustering algorithm iteration is complete, a statistical analysis of the results under different thresholds is performed to get a reasonable threshold. As shown in Fig. 12 [Figure 12: see original paper], 99.82% of AE samples are accounted for when the threshold is set to be 15–20. Once the threshold was set, the contribution rate of AE inside and outside the threshold was calculated by Eq. (4), and the results are displayed in Fig. 13 [Figure 13: see original paper].

$$CR = \frac{E_i}{\sum_{i=1}^{n} E_i}$$

where, E_i represents the AE cumulative energy values within and outside the threshold, respectively.

As shown in Fig. 13, only 0.18% of AE samples are located outside the threshold, but the contribution rate of them is 97.39% of the total. In other words, these AE samples which account for only 0.18% of the total, can effectively represent 97.39% of the AE samples. Consequently, we incorporate AE samples outside the threshold into rockburst precursor calculations.

4.2. Extraction of AE precursor for rockburst

4.2.1. Parameters setting of SOMNN

Before the calculation, a preliminary attempt was made to determine the number of iterations of the SOMNN algorithm. Sandstone is considered as an example; during the first round, the number of iterations and classification results are shown in Fig. 14 [Figure 14: see original paper]. Based on Fig. 14, it is evident that the clustering results of SOMNN become stable after 108 iterations during a single round of iteration. The basic structure of the SOM neural network is displayed in Fig. 15 [Figure 15: see original paper] at this point.

4.2.2. The iteration process of AE precursors

During iterative calculations, the AE key parameter matrix D_k calculated in section 4.1 is used as the input set to the established neural network model. The contribution rate Eq. (4) is used as the judgment criterion for each iteration round. An example of this process is shown in Fig. 16 [Figure 16: see original paper] represented by sandstone rockburst, which provides a schematic diagram of the iteration and discrimination process of sandstone acoustic emission precursor parameters. The iterative process is explained as follows:

First round: After the first iteration, the sub-matrix, D11, with the highest contribution rate 99.99976% is selected as the input matrix for the next iteration.

Second round: During the second round of iteration, four sub-matrices (D21~D24) are obtained. And D24 had the highest contribution rate of 98.85876%. As a result, D24 is chosen as the input matrix for the next iteration.

The third and fourth rounds: The iterative and discriminative processes in these rounds are consistent with the previous two rounds.

Fifth round: After the fifth iteration, the contribution rates for the sub-matrix D51~D54 are as follows: 7.921285%, 12.0476%, 44.84685%, and 35.18426%. It is clear that D53 has the highest contribution rate, but since it only has 4 data points, it cannot be further divided. Therefore, the calculation is stopped.

As shown in Fig. 17 [Figure 17: see original paper], the number of iterations round of AE precursors for gneiss, sandstone, and slate rockburst is given. It can be seen that after 5, 5, and 6 rounds of iteration, the sandstone, gneiss, and slate meters have respectively reached a stable state.

4.3. Extraction result of AE precursor for rockburst

In Fig. 18 [Figure 18: see original paper], there is a comparison of the precursor signal and the original signal's interval distribution characteristics. The precursor signals have a clustering feature in their distribution. To save space, a sandstone rockburst is used as an example in this paper. The duration's distribution range is from 9999 to 100000 s, which accounts for almost the whole interval of 99%–100%. The amplitude's distribution range is from 87 to 100 dB, which accounts for approximately 87%–100% of the entire range. The absolute energy distribution range is from 10^6.81 to 10^8.35 aJ, accounting for roughly 76.21%–100% of the entire range. The average frequency and peak frequency are generally concentrated in a lower distribution range. The distribution range of the average frequency is from 152 to 257 kHz, accounting for approximately 15.2%–25.7% of the entire interval. The distribution range of the peak frequency is from 156 to 195 kHz, accounting for approximately 31.2%–39.0% of the entire interval. This finding indicates that the precursor signal of a rockburst is a low frequency, and long high-energy signal with high amplitude, duration.

4.4. Temporal distribution of AE precursor for rockburst

Fig. 19 [Figure 19: see original paper] shows the time distribution of AE precursor parameters for rockburst. The calculated AE precursor signal appears continuously before the rockburst, proving the temporal precursor capacity. To further validate the rockburst prediction effect of AE precursors obtained in this paper, some key time points are connected to analyses. For red sandstone rockburst, the first AE precursor signal appears at 4375.87 s. At this point, there is 68.23 s until the rockburst occurs. For gneiss and slate, the occurrence time of precursor signals is 3504.18 s and 4116.28 s, respectively, which is 82.03 s and 228.73 s earlier than the rockburst. In summary, the AE precursor signals inverted in this paper have the potential to be used for rockburst time warnings.

5.1. The physic characteristics reflected by AE precursors

5.1.1. Amplitude-frequency characteristics

The AE main frequency value is directly related to the scale of micro-fractures. Generally speaking, the generation of large-scale rupture is indicated by a high-amplitude, low-frequency signal (Stefano and Adrienn, 2013). Based on the analysis of Section 4.3, amplitude-frequency distribution range of AE precursor signals for three groups of rockburst experiments is listed in Table 3 .

The results show that the main frequency range of AE precursor signals falls between 156 and 195 kHz, 104–253 kHz, and 88–148 kHz (after normalization, the range is 0.31–0.39, 0.20–0.50, and 0.18–0.30) for red sandstone rockburst, gneiss rockburst, and slate rockburst, respectively. In addition, the corresponding amplitude ranges are 87–100 dB, 82–100 dB, and 91–100 dB (after normalization, the ranges are 0.87–1.00, 0.82–1.00, and 0.91–1.00) for red sandstone rockburst, gneiss rockburst, and slate rockburst, respectively. Based on these results, it can be concluded that the rockburst precursor signals in this paper are characterized by high-amplitude and low-frequency AE signals, which correspond to the generation of large-scale fractures.

5.1.2. Fracture type

The AE parameters, RA value (amplitude/rise time), and AF value (average frequency) can be utilized to determine the types of microcracks resulting from rock fracture. Tensile cracks are shown to have high RA values and low AF values, while shear cracks have low RA and high AF values (Ohno and Ohtsu, 2010; Ohtsu et al., 2007) as seen in Fig. 20 [Figure 20: see original paper]. Generally speaking, the slope (k) of the straight line plotted on the AF-RA coordinate system can be used to distinguish between the tensile and the shear microcracks (the tensile and the shear micro-cracks are positioned above and below the straight line, respectively).

In this paper, k was calculated as the ratio between the maximum values of AF and RA (Yue et al., 2020), that is to say, k = max (AF)/max (RA). Fig. 21 [Figure 21: see original paper] displays the distribution of RA-AF values for these three types of rockbursts. Based on the k-value division results, it is evident that the AE precursor parameters demonstrate the characteristics of high RA and low AF, indicating that the AE precursor signals of rockburst have the traits of tensile fracture.

5.2. Analysis of rockburst warning capability

Recently, scholars have used AE systems to propose rockburst precursors based on the b-value and AE energy. To assess the effectiveness of these precursors, the occurrence times of each parameter are statistically analyzed and presented in Table 4 . The results show that the rockburst precursor proposed in this paper (RPPP) appeared the earliest, with occurrence times of 4375.88s, 3504.18s, and 4116.22s in sandstone, gneiss, and slate rockburst, respectively. The b-value decrease was the second precursor, occurring at 4376.72s, 3560.44s, and 4158.80s in these three rock burst tests. The precursor based on sudden energy increase was the latest. In other words, RPPP holds the earliest occurrence time, meaning the longest rockburst warning time.

According to the identification capacity of rockburst precursor, studying the decrease in AE b value and identifying precursor phenomena has been challenging. Although the overall b value showed a downward trend before rockburst, there were still fluctuations process, making it difficult to confirm the decrease point, and resulting in inaccurate rockburst warnings. This paper proposes a new method for identifying precursor phenomena (RPPP) using feature extraction of AE signals. The method involves determining thresholds for all parameters, including duration, amplitude, absolute energy, average frequency, and peak frequency. Once all these parameters reach the threshold range of the precursor simultaneously, a rockburst warning signal can be given. This new approach greatly improves the reliability of the rockburst warning.

5.3. Discussion on the rationality of rockburst precursor

Table 4 shows that the RPPP occurred before the AE b-value decreased. However, the duration of the RPPP corresponds to the evolution process of the AE b-value from increasing to decreasing. An increasing b-value shows small-scale crack development, while a decreasing b-value shows large-scale crack development. Therefore, the occurrence time of the RPPP also corresponds to the process of micro-cracks penetrating and forming macroscopic cracks within the rock specimen. Meanwhile, this phenomenon also indicates the foresight and accuracy of the precursors inverted in this paper.

In addition, similar conclusions have been proposed in other studies regarding micro-seismic signals of rockburst. For instance, Liang et al. (2020) found that the downward shift of frequency band energy distribution can serve as a precursor of rockburst. Additionally, Lu et al. (2013) noted that micro-seismic precursor signals of rockburst display an increase in energy and have a trend of towards low-frequency bands. These results also indicate that high-energy and low-frequency signals are indeed an abnormal signal feature before rockburst. According to their study, the findings of this paper on spectrum shift rockburst precursors (AE signals characterized by long duration, high energy, low average frequency, high energy amplitude, and low peak frequency) are valuable for research. However, it is important to notice that there are distinctions between indoor rockburst experiments and rockburst on-site. Further research is necessary to determine how to utilize the RPPP for on-site warning.

6. Conclusion

In this study, an inversion method for rockburst precursor was proposed based on the SOM neural network. Subsequently, the characteristic attributes of rockburst AE precursors were summarized based on precursor inversion results of gneiss, red sandstone, and slate rockburst. Finally, the potential long-term rockburst warning value of the AE precursor signals obtained in this research was discussed. The main conclusions of the study are: (1) In this study, an inversion method for rockburst precursor was proposed based on the SOM neural network. The feature of this method lies in a cyclic data segmentation iteration process. In the rockburst precursor inversion of three lithologies (including gneiss, red sandstone, and slate), the precursor signals were obtained at 82.03s, 68.23, and 228.73s before rockburst, verifying the rationality and universality of this method. (2) Compared with the precursor judged by b-value and AE energy, the precursor obtained in this study has the earliest occurrence time. This result also reflects the advantages of precursors obtained in this study in long-term warning of rockburst. (3) The physical significance of rockburst precursor obtained in this study has been interpreted from the perspective of fracture scale and crack type, and it is preliminarily judged that the precursors obtained in this study are related to the formation of large-scale tensile cracks before rockburst.

CRediT authorship contribution statement

Jie Sun: Data curation, Formal analysis, Investigation, Methodology, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Dongqiao Liu:** Conceptualization, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing. **Pengfei He:** Conceptualization, Investigation, Supervision, Validation, Visualization, Writing – original draft. **Longji Guo:** Supervision, Validation, Visualization. **Binghao Cao:** Conceptualization, Data curation, Supervision, Validation, Writing – original draft. **Lei Zhang:** Conceptualization, Software, Supervision, Validation, Visualization, Writing – original draft. **Zhe Li:** Supervision, Validation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Note: Figure translations are in progress. See original paper for figures.