

Research Article

Prediction of the Stability of the Loaded Rock Based on the Acoustic Emission Characteristics of the Loaded Rock Based on Data Mining

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Received 20 July 2021; Accepted 15 September 2021; Published 24 September 2021

Academic Editor: Xuesheng Liu

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The rock masses that occur in nature are damaged and unstable due to the impact of rock burst, coal and gas outbursts, and other human mining activities, posing a major threat to human life and safety. In the light of the early warning of the danger of the loaded rock mass, this paper adopts acoustic emission (AE) device to analyze the AE signal characteristics and damage laws of the loaded rock under different stress levels. Then, based on the AE signal characteristics of the loaded rock, data mining technology is used to construct a model to predict the failure and instability of the loaded rock mass and, finally, verify the reliability of the prediction model based on data mining. The results show that the AE signal characteristics of red sandstone under uniaxial load are related to the magnitude of the bearing stress. Before the plastic deformation stage, the AE energy and the cumulative count per second are both small. After the loaded rock enters the plastic deformation stage, the AE energy and the cumulative count per second both increase sharply. After the AE energy is greater than 500 mV*ms and the cumulative count per second is greater than 150, the loaded rock mass will issue an early warning signal. The research results can provide a reference value for the safe production of the project site and the dangerous early warning of the loaded rock mass.

1. Introduction

Rock masses, as the most common bearing medium in nature, are widely resided in geotechnical engineering such as tunnels, subways, coal mines, mountain roads, and rock slopes [1–6]. The stability of the rock mass is very important to the reliability of the engineering and the safety of the human body. The disasters induced by the instability of the load-bearing performance of large rock masses have the characteristics of sudden instability, wide range of influence, large economic losses, and difficult predictions [7]. This is one of the main balance points that hinder engineering safety and economy, and it is also a hot spot of the current research [8].

The rock mass in geotechnical engineering is subjected to an external load, and the internal cracks gradually expand and penetrate with the increase of the load [9]. The structure of the loaded rock body gradually changed with the increase of the load, and at the same time, it releases elastic waves containing rich rock mechanics characteristics that can be received by the sensor [10]. An in-depth analysis of these waveform signals is necessary to study the stability of the loaded rock body. AE monitoring is based on this principle for continuous and real-time monitoring of the loaded rock mass. Many scholars have used AE monitoring technology to study the mesomechanical characteristics, macroscopic failure laws, and critical failure precursor identification of loaded rocks [11–13]. Some scholars also used numerical

simulation and tomography to analyze the damage law and failure characteristics of the rock during the loading process [14–16]. These research results provide some references for the stability monitoring and risk assessment of the bearing rock mass and also for the safe of geotechnical engineering [17].

Monitoring the stability of the loaded rock mass is mostly based on the analysis of the elastic wave released from the loaded rock mass [18]. The principle is the same as that of the AE monitoring of the load-bearing process of the loaded rock mass. In the indoor test, the AE device is adopted to monitor the stability of the bearing rock, mainly by analyzing the AE signal characteristics of the loaded rock under different stress levels and exploring the information of the damage, fracture mechanism, and critical failure precursor identification of the loaded rock [19–21]. In terms of predicting the failure and instability of the loaded rock mass based on AE monitoring, there are mainly two methods. One way is to construct a damage mechanics model based on the characteristics of the loaded rock including AE ringing count or AE energy and predict its failure and instability limit state by analyzing the magnitude of the load acting on the bearing rock mass [13, 22]. The other method is based on analyzing the characteristics of the AE signal during the failure and instability of the loaded rock mass, and on the basis of the monitored AE signal parameters, the law of critical failure of the loaded rock mass is analyzed to predict the failure and instability [23].

The above two methods to assess the stability of the loaded rock mass in geotechnical engineering not only enrich the theoretical system but also provide some references for the safe production of the project. The first method provides a quantitative damage mechanics model for the prediction of the stability of the loaded rock mass. The prediction method is simple and convenient and has a wide range of applications. The second method is mainly to analyze the law of AE signal parameters in the whole process from the loaded rock to failure and instability. Then, in the process of monitoring the loaded rock mass, the possibility of instability is judged according to the characteristic parameters of the AE signal. However, the above two methods still have room for further research. Due to differences in lithology types, occurrence environments, and the degree of influence of mining activities, as well as the discrete nature of rock strength, these two methods are not accurate enough to predict the stability of the rock mass at the engineering site [24, 25]. Therefore, it is necessary to adopt a more reasonable and reliable method to predict the failure and instability of the loaded rock mass.

With the rapid development of computer technology and the improvement of industrial informatization, data mining technology has been widely used in the field of engineering, which has greatly promoted the innovation of industrial technology and industrial intelligence [26, 27]. Therefore, combining the AE technology based on data mining to analyze the stability and early warning of the loaded rock has a wide range of application prospects. Data mining technology first appeared in the 1980s [28]. It is mainly a process of extracting potentially useful information

and knowledge that is hidden in and people do not know in advance from a large amount of unclear, incomplete, and random practical application data [29, 30]. Data mining could generally be divided into descriptive mining and predictive mining. Descriptive mining describes the general characteristics of the data in the database and expresses the acquired knowledge in a form that conformed to the data law. Predictive mining is to make speculative judgments based on current data to predict the future. With the continuous integration of data mining and engineering, it could discover many types of patterns such as characterization and differentiation, association analysis, classification and prediction, cluster analysis, outlier analysis, and evolution analysis [31, 32]. The knowledge representations obtained based on data mining mainly include decision trees, knowledge bases, network weights, and formulas.

In recent years, data mining has played an extremely important role in the fields of aerospace engineering [33], marine engineering [34], and earthquake engineering [35]. In terms of predicting the stability of rock masses, the application of data mining technology is currently less. As far as the stability of the loaded rock mass is concerned, by analyzing the AE signal characteristics of the loaded rock or the response law of the coal and rock mass before the coal mine dynamic disaster occurred, the judgment basis of the critical precursor before the failure of the loaded rock mass is constructed. Based on the waveform signals monitored during rock mass instability in the past in geotechnical engineering, the AE characteristics and wave patterns before rock mass failure and instability are analyzed, and the criteria for rock mass failure and instability are constructed [36]. This method could be combined with existing safety accidents to predict the damage and instability of the loaded rock mass. It is safe and economical, and the prediction accuracy is also high. It is a prediction method worthy of popularization.

This paper adopted AE to monitor the rock under uniaxial load, analyzed the characteristic parameters of AE of the loaded rock, and further explored the damage evolution. Then, according to the damage evolution of the loaded rock, the AE signal characteristics of all the loaded rocks in this test were analyzed. Based on the data mining technology, the basis for determining the parameters of the AE signal before the loaded rock was damaged and unstable was constructed. Finally, the accuracy of the prediction model was verified based on data mining technology.

2. Experimental Equipment and Process

The rock selected in this article was red sandstone, purchased from Hunan Jingcheng Rock Processing Co., Ltd., China. All rock samples were prepared into standard cylindrical samples with a diameter of 50 mm and a height of 100 mm after being cut and polished indoors according to the standards of the International Society for Rock Mechanics. The flatness error of both ends of the red sandstone should be controlled below 0.01 mm, and the nonparallelism of the two ends should be less than 0.05 mm. Partial rock samples are shown in Figure 1.



FIGURE 1: Partial red sandstone samples.

The experimental equipment mainly included two sets of equipment: loading device and AE monitoring device. The loading device adopted the rock mechanics test system produced by Shanghai SANSI Technology, as shown in Figure 2. The AE device adopted the DS-5 AE signal detector produced by Beijing Soft Island Technology, as shown in Figure 3. In this test, the AE device was first used to monitor the loading process of red sandstone under uniaxial load. As shown in Figure 4, each loaded sandstone adopted 8 sensor probes for real-time monitoring of the AE signal in the sandstone and saved the AE signal parameters. In order to ensure the accuracy of the test results and reduce the error caused by the deviation of the AE sensors, the layout coordinates of each sensor must be the same for different sandstone specimens.

For the sake of enhancing the effect of AE monitoring, evenly spread petroleum jelly on the ceramic surface of the sensor probe to collect the signal, then stuck it to the pre-designed monitoring point, and fix the probes with rubber bands, as shown in Figure 4. For the sake of reducing the binding effect of the rubber band, the pretightening force of the rubber band was released until it can just wrap the four probes outside the sandstone, and then the sensor probes were fixed. Before the start of the test, the pencil lead was used as the analog source to conduct a positioning test and a sound velocity measurement test to detect the response of the sensors to the signal source and to exclude the interference of mechanical noise such as external impact and friction. The test would start after the debugging was normal. The AE monitoring experiment and uniaxial loading experiment were developing simultaneously, and the loading rate of 5000 N/s was applied. Every sandstone adopted 8 sensors to receive the AE signals of the loaded sandstone in real-time monitoring. The amplifier was set to be 40 dB, the threshold of each channel was set to be 100 mV, and the frequency was 3 MHz. During the test, the uniaxial loading test and the AE monitoring test of the AE equipment were performed simultaneously.

By analyzing the characteristics of the AE signal of red sandstone under uniaxial load, an early warning system based on the parameters of the AE signal of the loaded rock



FIGURE 2: Rock mechanics test system.

is constructed based on the data mining technology. Finally, it was verified according to the constructed early warning system. The detailed technical route is shown in Figure 5.

3. AE Signal Characteristics of Sandstone under Uniaxial Loading

Among the AE parameters obtained by monitoring red sandstone under uniaxial load based on AE, parameters such as the cumulative count of AE events, AE energy, and stress can intuitively characterize the damage evolution of the loaded rock. With time as the independent variable, the cumulative count of AE events, AE energy, and stress as the dependent variables, the AE characteristic curve of the rock during the whole process from uniaxial load to failure was drawn, as shown in Figure 6.

The rock under uniaxial load mainly underwent four mechanical characteristic stages, which were the compaction and closure stage, the elastic stage, the plastic deformation stage, and the failure and instability stage in sequence. The physical structure of the rock was closely related to its diagenetic environment and physical properties [37]. In addition, after a long period of geological history, the physical structure of the rock had also undergone some changes. Under the action of the load, the primary pores in the rock were first compacted and closed. The mechanical characteristic of this stage was that the strain increases faster and the stress changes less; that is, the elastic modulus of the rock is smaller. In this stage, the primary pores in the loaded rock were compacted and closed, and the AE event was emitted at the same time. Due to the primary pores being compacted and closed at a small scale, the AE energy was relatively small at this stage. However, due to the large number of primary pores in the rock, the number of AE events was also large, and AE events were intensively emitted in a short period of time.

After most of the primary pores in the rock were compacted and closed, the gravel in the loaded rock played a major role in resisting the load. From this time until the plastic deformation stage, the deformation of the loaded rock can be restored with the removal of external load. This loaded stage was also called the elastic stage. It could be



FIGURE 3: AE device.

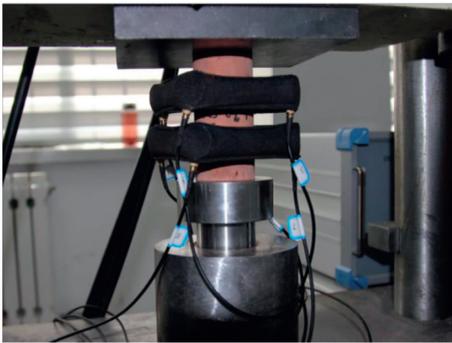


FIGURE 4: Layout of AE probes.

known from the mechanical properties of the rock that the deformation of the loaded rock in the elastic stage was mainly the elastic deformation of sand and gravel. There were no larger or more fractures in the rock, only partially unclosed primary pores and a small amount of gravel damage. Therefore, the AE energy of the loaded rock in the elastic stage was larger than that of the primary pores in the compacted and closed stage, but the number of AE events per second was smaller.

After the elastic deformation of the loaded rock increased to its elastic limit, the cracks in the loaded rock began to gradually expand. The deformation of the loaded rock during the yield deformation stage was mainly caused by the cracking of the transition surface between the gravel and the mineral matrix. Under the action of the load, on the one hand, the transition surface between the gravel and the mineral matrix gradually cracked and emitted AE events. On the other hand, the mineral matrix began to crack and expand with the tip effect of the gravel and emitted AE events. Under the action of the above two mechanical factors, there were more AE events and greater AE energy in the loaded rock. Compared with the compacting and closing stage of the primary pores and the elastic stage, the number of AE events and the AE energy of the loaded rock in the plastic deformation stage were much larger. But at this time, the loaded rock only produced cracks and propagated inside, there was no obvious change on the outside, and it still had the ability to continue to bear the load.

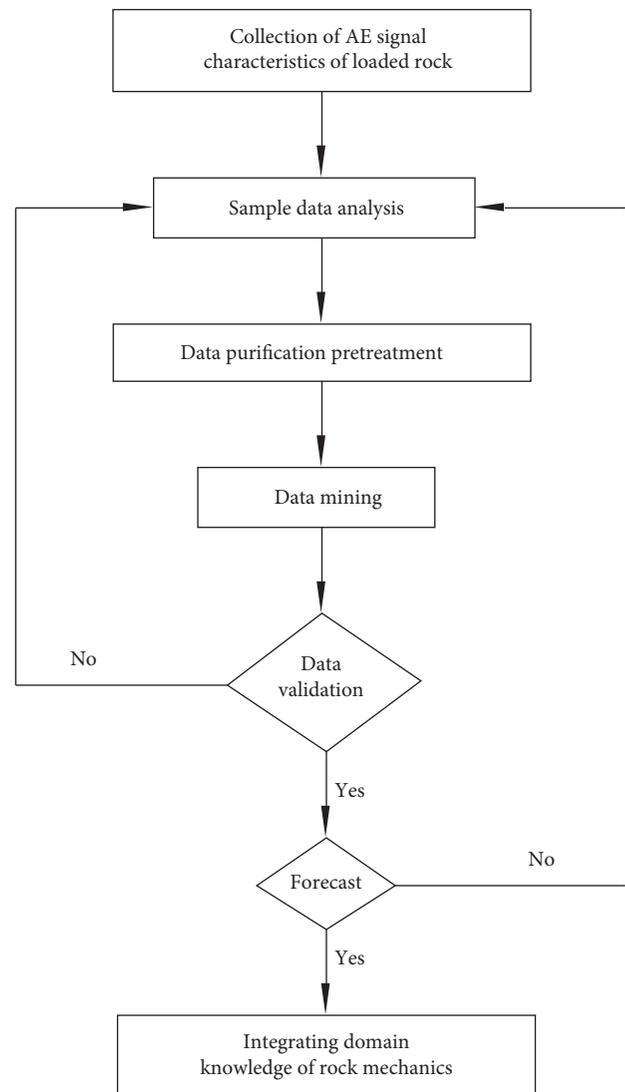


FIGURE 5: Detailed technical route of data mining.

As the load continued to increase, the size of the cracks in the loaded rock increased rapidly and expanded rapidly, which induced secondary cracks. At this time, the number of cracks in the loaded rock increased exponentially. The cracks

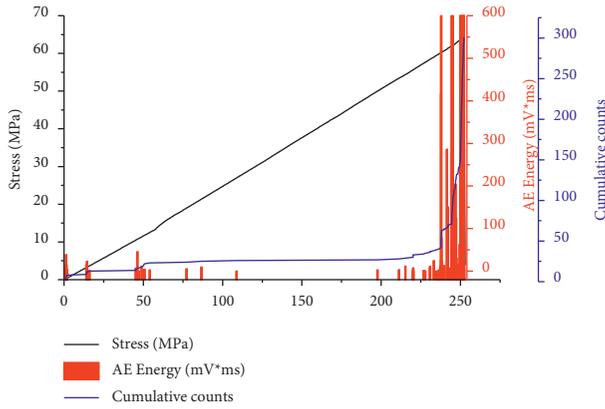


FIGURE 6: AE characteristic curve of rock under uniaxial load.

were quickly connected, and the main cracks in the rock were formed and penetrated. In the meantime, the rock lost the ability to resist deformation, and obvious cracks can be seen on the surface of the loaded rock. The macroscopic deformation characteristics of the loaded rock were caused by the mesostructure changes gradually accumulated under the load. Therefore, during the failure and instability stage of the loaded rock, both the AE energy and the cumulative count of AE events reach the maximum, and the AE events emitted per second also reached the maximum.

4. Predicting the Destruction of the Loaded Rock Based on Data Mining

From the characteristics of the AE signal of the rock under uniaxial load, it could be known that before the elastic limit, the AE energy value of the loaded rock and the growth rate of the accumulative count were both small. Rock is a brittle material. It could be seen from the mechanical properties of rock that its bearing capacity was greatly reduced after the rock undergoes plastic deformation. Taking the bearing state of the rock mass at this time as an early warning basis not only was safe in geotechnical engineering but also provided sufficient time for the dangerous relief of the loaded rock mass. If the strength limit or the area close to the strength limit was used as the criterion, at this time, the cracks in the loaded rock body were intricate and the rock mass structure was extremely unstable, and it is very easy to break and lose stability, which brought great hidden dangers to the safety of the project and the safety of human life. Therefore, this paper took the loaded rock into the plastic deformation stage as the criterion to predict the failure and instability of the loaded rock.

By analyzing the AE characteristics of all loaded rocks, it could be known that when the loaded rock entered the plastic deformation stage, the AE energy was greater than $500 \text{ mV} \cdot \text{ms}$, the cumulative count per second also reached the maximum, and all were greater than 150, as shown in Figure 7. When choosing the early warning criterion, this paper chose two AE parameters, AE energy and accumulative count of AE per second, as the judgment basis. After the cracks of the loaded rock were compacted and closed, the

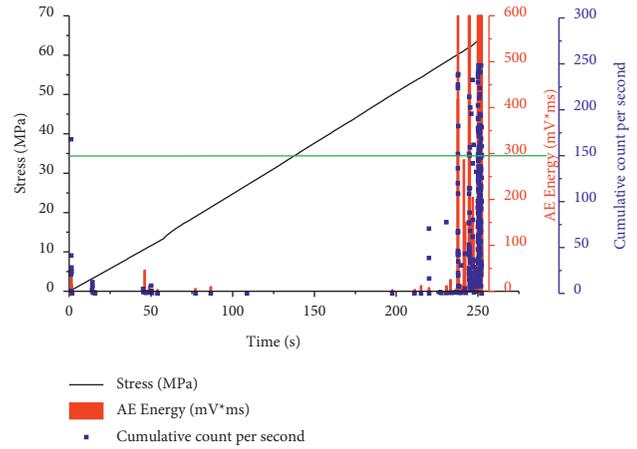


FIGURE 7: Characteristic map of early warning value of loaded rock.

primary pores in the rock were compacted and closed within a short time. In the meantime, the cumulative AE count per second was also relatively large, but the AE energy was generally small. Therefore, it was not reliable to rely solely on the cumulative count of AE per second as the criterion. In addition, there were many types of rocks, the physical structures in different types of rocks were different, and the size and scale of cracks under load were also different. Therefore, the AE energy of the AE event emitted by the rock under uniaxial load in the yield stage was also different. Thus, it was unreasonable to rely solely on the magnitude of AE energy as the criterion for the failure and instability of the loaded rock. In summary, this paper chose the cumulative count per second and AE energy as the criteria for predicting the failure and instability of the loaded rock.

Decision tree is currently the most extensive data mining classification algorithm. It is mainly used to deal with the classification and prediction of noncontinuous variables and can be described in a tree-shape or IF-THEN form. It is a convergent classifier or prediction model. The decision tree maximizes the difference of dependent variables by continuously refining and categorizing the input information, finally classifies the data into disjoint branches, and establishes the strongest classification on the value of dependent variables. Compared with clustering algorithms such as neural network clustering, Gaussian mixture clustering, and k-means, decision trees have many advantages. The decision tree model can be described by graphs or rules and is interpretable for the reasoning process. Since the scale of the decision tree has nothing to do with the size of the data set, the amount of calculation will not increase with the amount of data. Owing to the failure and instability of the loaded rock mass which has brought significant losses to human life safety and economy, the stability of the loaded rock mass should be given an early warning and reasonable measures to relieve the danger before the failure and instability. Therefore, this paper chooses a decision tree to classify the alarm information in order to provide decision support for the fault tracking program of the dispatcher. The decision tree classification algorithm is a supervised learning method; it takes training samples as input and supervised model as

classification rules, generates decision trees through induction algorithms, and then performs predictive analysis on unfamiliar data sets. Combining with the mechanical characteristic parameters of the loaded rock, an early warning is made for the failure and instability of the loaded rock. The specific judgment process is shown in Figure 8.

5. Reliability Test

In this paper, a prediction model for the failure and instability of the loaded rock is constructed based on data mining, but the reliability of the model still needs to be certificated. A total of 20 red sandstone samples were used in this test. The first four groups of 16 sandstone samples were selected in part by establishing a prediction model based on data mining. The remaining 4 red sandstone samples were used to verify the reliability of the model. By analyzing the AE parameters of the remaining four sandstones under uniaxial loads, it is judged whether the prediction model of the failure and instability of the loaded rock based on data mining is reliable as shown in Figure 9.

It can be seen from the experimental results in Figure 9 that, in the area before the elastic limit of the loaded rock, although there are very few points with a cumulative count greater than 150 per second, the AE energy at this point is less than $500 \text{ mV}^* \text{ms}$. In addition, there are points where the AE energy is greater than $500 \text{ mV}^* \text{ms}$, but the cumulative count per second at this point is less than 150. The prediction model constructed by data mining shows that neither of the above two points can make the loaded rock issue a dangerous warning. Combined with the mechanical characteristic curve of the loaded rock, it can be seen that the loaded rock at these two points is in the elastic deformation stage and has not yet undergone plastic deformation. At this time, the loaded rock is not in a dangerous state. In the stage where the primary pores are compacted and closed, when there are more primary pores in the loaded rock, the cumulative count per second in this stage is larger. In the stage of elastic deformation, when the gravel and the mineral matrix resist the load and deform together, they can be regarded as an element in the microscopic view. The rock is composed of several such elements. As the load increases, the transitional interface between the gravel and the mineral matrix will initiate cracks under tension to emit AE signals. When the scale of the gravel is large, or the energy stored by the gravel from deformation under the action of the load is large, the continued increase of the load may cause the transition surface between the gravel and the mineral matrix to crack on a larger scale. But this is only a special case, not a common phenomenon in the loaded rock at this stage. Therefore, the AE energy is greater than $500 \text{ mV}^* \text{ms}$ and the cumulative count per second is less than 150.

It can also be known from the experimental results in Figure 9 that when the loaded rock enters the plastic deformation stage, the cumulative count per second is greater than 150, and the AE energy is greater than $500 \text{ mV}^* \text{ms}$. At this time, the threshold for forecasting the warning is

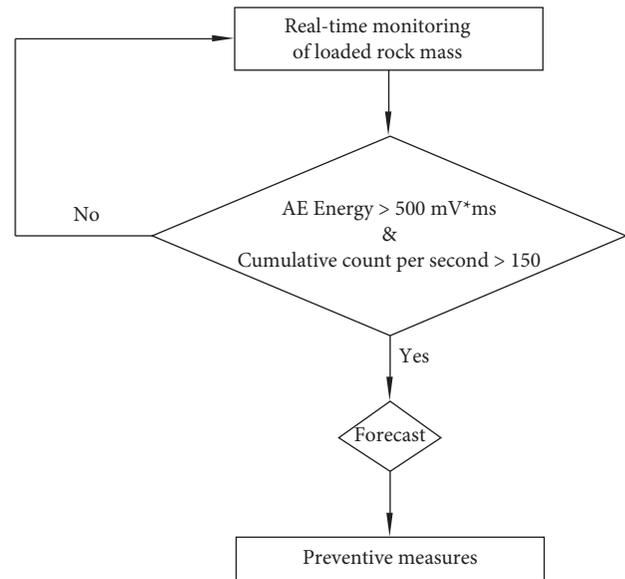


FIGURE 8: Early warning process of loaded rock based on data mining.

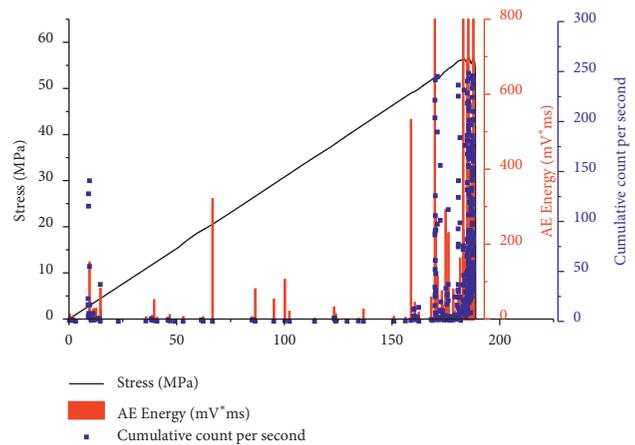


FIGURE 9: Reliability verification of the predictive model.

reached. By verifying the red sandstone samples of the control group, it is concluded that the prediction model based on data mining is reasonable.

6. Discussion

This experiment is carried out on sandstones with higher tightness only, and no experimental research has been carried out on rocks with other lithologies. Rocks with different lithologies have different AE signal characteristic parameters under the action of loads. Although the overall change trend is the same, there are still some differences in the size of the AE parameters in different loading stages. Therefore, it is necessary to analyze the AE signal or microseismic signal law of the rock mass under the load in advance in order to combine the risk warning of the rock

mass in the actual project. In addition, the conditions for the occurrence of rock masses in actual engineering are more complicated, and rock masses at different locations are affected by human excavation activities to different degrees. Only relying on the two acoustic parameters in the article cannot provide accurate early warning. Monitoring should be strengthened and more monitoring equipment, such as strain gauges and displacement gauges, should be used. The multiparameter joint early warning method is adopted to improve the accuracy.

The part of the verification model in this article is based on the characteristics of the AE signal of the loaded rock for verification and analysis. In actual engineering applications, real-time monitoring of the bearing rock mass can be adopted, and data can be analyzed in real-time. When the acoustic parameters or microseismic data of the loaded rock mass exceed the threshold, an alarm is triggered, and the on-site staff promptly withdraw and take reasonable measures to relieve the danger.

7. Conclusions

This paper took the AE signal parameters of red sandstone under uniaxial load as the research object, adopted the method of data mining, and used the AE energy and cumulative count per second as the early warning indicators. In addition, experiments were also used to verify the constructed prediction model. The experimental conclusions obtained are mainly as follows:

- (1) The AE signal characteristics of red sandstone under uniaxial load are related to the magnitude of the load stress. Before the elastic deformation stage, the AE energy and the cumulative count per second are both small. When the loaded rock enters the plastic deformation stage, the AE energy and the cumulative count per second both increase sharply.
- (2) Taking the AE energy of the loaded rock and the cumulative count per second as the threshold value, a hazard early warning model is constructed based on data mining. After the AE energy is greater than 500 mV*ms and the cumulative count per second is greater than 150, the loaded rock mass will issue a dangerous warning.

Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

Conflicts of Interest

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

Acknowledgments

The project was supported by the Independent Research Fund of the State Key Laboratory of Mining Response and Disaster Prevention and Control in Deep Coal Mines (no.

SKLMRDPC20ZZ06) and the program in the Youth Elite Support Plan in Universities of Anhui Province (no. gxyq2020013).

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