*Intelligent Equipment and Special Robots*
*Q. Zhang (Ed.)*


*doi:10.3233/ATDE240293*

# Research on Coal-Rock Recognition Based on the EMD-EM-BP Model

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**Abstract.** This article presents a coal-rock recognition method based on a BP neural network. It involves testing acoustic emission (AE) signals during the shearing and cutting of coal-rock, analyzing coal-rock characteristics, and applying Empirical Mode Decomposition (EMD) to the AE signals to obtain several Intrinsic Mode Functions (IMFs). Energy moments of the IMFs, with significant correlation coefficients, are then extracted. These energy moments serve as inputs for the BP neural network to identify the acoustic emission signals of coal-rock. Experimental results indicate that after using the EMD algorithm to decompose the AE signals and calculate the energy moments of the IMFs in relation to the original AE signals, distinctive features become apparent. The BP neural network achieves a high accuracy rate of 95% in recognizing coal-rock characteristics. This model offers exceptional recognition precision and lays the theoretical and technological groundwork for realizing automated and intelligent mining in fully mechanized mining operations.

**Keywords.** Coal-rock identification, acoustic emission signals, EMD decomposition, BP neural network

## 1. Introduction

Coal-rock recognition is vital for achieving unmanned coal mining, ensuring high-efficiency, high-quality, and high-output coal mining operations. It is also essential for reducing energy consumption and prolonging the life of coal mining machinery. In-depth research into coal-rock cutting characteristics and interface recognition methods is of paramount importance. During coal and rock cutting, differences in material, hardness, and composition lead to varying cutting resistances. Consequently, as coal mining machinery cuts coal-rock with different proportion distributions, significant acoustic emission phenomena occur due to friction on the drum. Ding Z. W, et al[1-5]. proposed a dynamic coal-rock interface recognition method based on acoustic emission signals, enabling real-time online monitoring of coal-rock cutting ratios. Yu. A M, et al[6-7]. introduced a coal-rock interface perception and recognition method, enhancing recognition accuracy through the fusion of multiple sensor information. This study focuses on testing and extracting acoustic emission signals during coal mining machine cutting as characteristic signals for the coal-rock recognition system. It involves building a recognition model within a concise framework.

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## 2. Theory

### 2.1. EMD

EMD, as an effective analytical method for non-stationary signals, is primarily based on the concept of decomposing a time series signal into Intrinsic Mode Functions (IMFs) of various scales[7]. Each decomposed IMF highlights the local characteristics of the data, enabling a more accurate and effective grasp of the original data's features. Unlike wavelet decomposition, EMD does not require the prior setting of basis functions; instead, it adapts the signal decomposition according to the inherent time-scale characteristics of the data itself.

(1) Assuming $x(t)$ represents the input signal, the first step involves identifying the upper envelope $e_+(t)$ and lower envelope $e_-(t)$ of the signal. Calculate the average envelope line (the mean of the upper and lower envelopes) and denote it as $m_1(t)$. Then, compute the difference between $m_1(t)$ and the original signal, which we'll refer to as $x(t)-m_1=h_1$ .If the computed $h_1$ satisfies the Intrinsic Mode Function (IMF) criteria, then the first IMF component is $h_1$.

(2) If $h_1$ does not meet the IMF criteria, then decompose it as the input signal and repeat the process. Calculate the average envelope and obtain $m_{11}$ as the difference. Evaluate $h_{11}=h_1-m_{11}$ and check if it satisfies the IMF conditions. If it does not satisfy the conditions, continue with step (1) again. Suppose, after the P-th iteration, it meets the criteria and results in $h_{1(k-1)}-m_{1k}=h_{1k}$ ,making $h_{1k}$ satisfy the conditions, that is, $c_1=h_{1k}$.

(3) After extracting $c_1$ from $x(t)$ ,you can obtain $r_1=x(t)-c_1$ and repeat steps (1) and (2) to acquire the next component $c_2$ that satisfies the conditions. Continue this process until you can no longer extract IMF components that meet the criteria. This loop is performed a total of $n$ times, resulting in multiple IMF components and a residual signal $r_n$ along with the original signal $x(t)=\sum_{i=1}^{N} IMF_i + r_n$.

### 2.2. Energy moment feature extraction

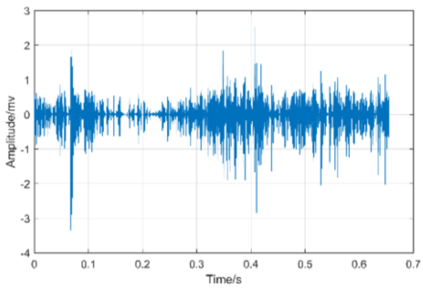
In different operating conditions, the energy of various frequency components varies. Energy moment feature extraction, compared to traditional methods like energy calculation or the computation of energy entropy and sample entropy, goes beyond merely representing energy values numerically. It further captures distribution characteristics, making it a more concise and practical approach. It can delve deeper into uncovering latent feature information. Energy moment feature extraction takes into account the distribution characteristics of energy for each IMF component along the time axis. For non-continuous signals, energy $E_k$ is represented by equation (2).

$$E_k=\sum_{j=1}^{n}(j\Delta t)\,|D_k(j\Delta t)|^2=\Delta t\sum_{j=1}^{n} j\,|D_{kj}|^2 \quad (1)$$

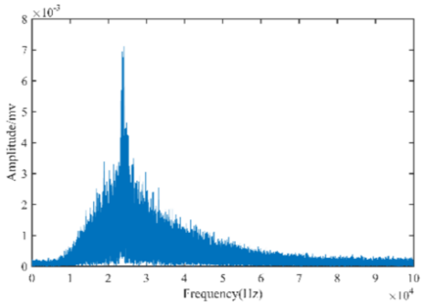
$$j=1,2,\ldots n \quad (2)$$

## 3. Experimental analysis

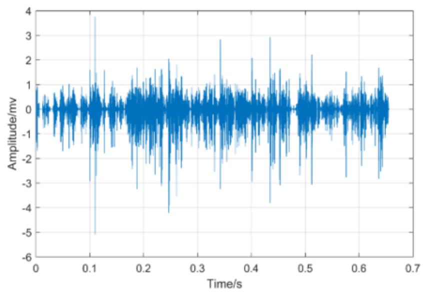
### *3.1. Analysis of Acoustic Emission Signals*



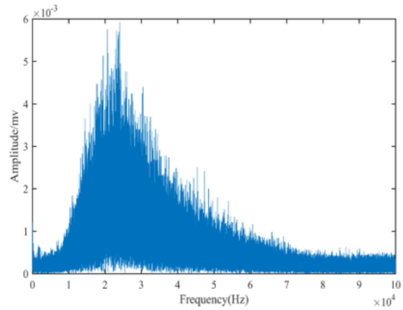

(a)Time-Domain Waveform of Acoustic Emission Signals for Whole Rock




(b)Frequency-Domain Waveform of Acoustic Emission Signals for Whole Rock




(c)Time-Domain Waveform of Acoustic Emission Signals for Whole Coal




(d)Frequency-Domain Waveform of Acoustic Emission Signals for Whole Coal

**Figure 1.** Time-Frequency Domain Waveform of the Two Signal Sets

The time-frequency information of the two collected signal sets is depicted in Figure 1. From the time-domain perspective, it is evident that the acoustic emission signals of the entire rock exhibit a more concentrated impulse characteristic, while in the case of the entire coal, the acoustic emission signals display a relatively dispersed impulse pattern. Furthermore, in the frequency domain, it can be observed that both the entire rock and entire coal acoustic emission signals primarily center around a frequency of approximately 25kHz.

### *3.2. Analysis and Processing of Acoustic Emission Signals*

In order to more accurately identify and distinguish different types of coal and rock, improve the accuracy, robustness, and generalization ability of the recognition algorithm, models with different coal and rock ratios are selected for testing. Following the method proposed in this study, we first decompose the original signal using the Empirical Mode Decomposition (EMD) method, resulting in ten Intrinsic Mode Functions (IMFs). The decomposition results are depicted in Figure 2.

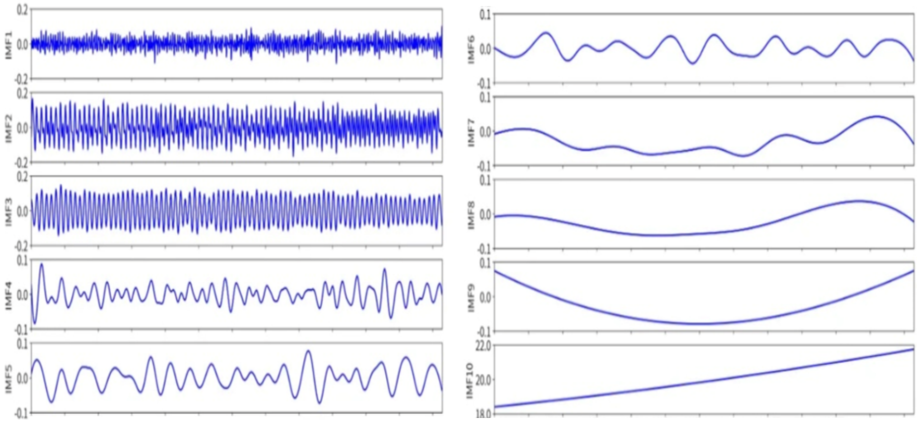
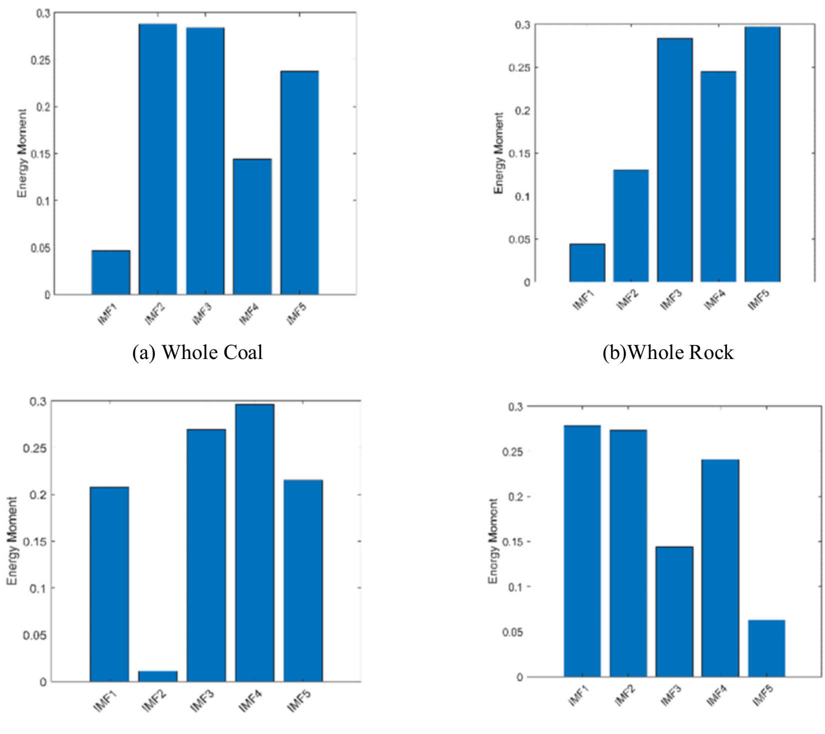



**Figure 2.** EMD decomposition results

Using the Empirical Mode Decomposition (EMD), the acoustic emission signals were decomposed, and the top five IMFs based on correlation coefficients were selected. These IMFs were then used to extract effective IMFs for leakage signal analysis under different operating conditions. The energy moments of these selected IMFs were calculated and normalized. The resulting energy moment feature vectors are depicted in Figure 3, ordered by increasing correlation coefficients.




(a) Whole Coal (b)Whole Rock

(c) Coal-Rock Ratio of 4:1 (d) Coal-Rock Ratio of 2:1

**Figure 3**. Distribution of energy moment feature vectors

By comparing the energy moment distribution characteristics of the aforementioned acoustic emission signals, it is evident that under different coal-rock ratios, the energy distribution among the various IMFs varies, showcasing the ability to characterize different coal-rock conditions. In summary, this study selected normalized energy moment feature vectors as inputs for the recognition model, with different coal-rock ratios as the outputs.

### *3.3. BP Neural Network Recognition*

The BP (Backpropagation) neural network algorithm primarily consists of two main steps: forward propagation of information and backward propagation of errors. The network structure comprises an input layer, a hidden layer, and an output layer. The number of neurons in the input and output layers is determined by the number of input and output feature parameters, respectively. Meanwhile, the number of neurons in the hidden layer is determined based on problem requirements and the number of neurons in the input and output layers. The calculation formula for this is as follows:

$$P = \sqrt{m + \mathrm{n}} + a \tag{3}$$

Where $p$, m, n represents the number of neurons in the hidden layer, $a$ is an integer ranging from 0 to 10. In this study, we are performing Empirical Mode Decomposition (EMD) processing on acoustic emission signals from four different coal-rock ratios and extracting five feature values. Therefore, the number of neurons in the input and output layers is set to 5 and 4, respectively. We conducted sampling of the acoustic emission signals for the four coal-rock ratios at a sampling rate of 20,000 Hz, resulting in 200 samples for both the training and testing datasets, with an 8:2 ratio. The sample information for the coal-rock dataset is presented in Table 1. The recognition results obtained by inputting the sample data into the convolutional neural network are provided in Table 1 as well.

**Table 1.** Sample Information for Coal-Rock Acoustic Emission Signal Dataset

| Coal-Rock Conditions | Number of Training Samples per Group | Number of Testing Samples per Group | Class Labels |
|---|---|---|---|
| **Whole Rock** | 50 | 10 | 1 |
| **Coal-Rock Ratio of 4:1** | 50 | 10 | 2 |
| **Coal-Rock Ratio of 1:2** | 50 | 10 | 3 |
| **Whole Coal** | 50 | 10 | 4 |

Based on the proposed theory, a coal-rock recognition model was established, and the model's recognition results are depicted in Figure 4. It is evident that the model achieved a recognition rate of 95%, indicating that the proposed model can effectively distinguish different coal-rock conditions based on acoustic emission signals.

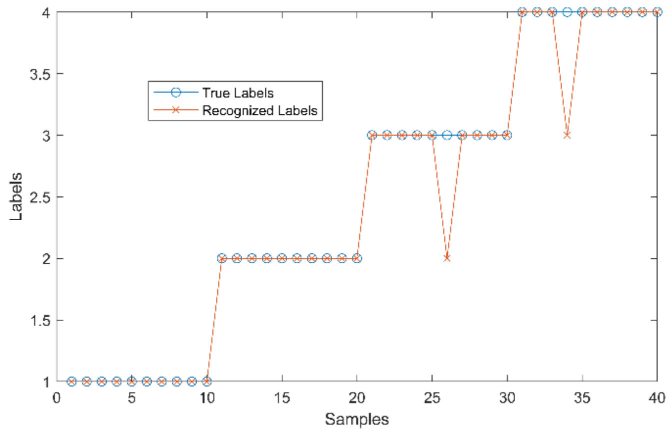



**Figure 4:** Recognition Results

## 4. Conclusion

In addressing the problem of coal-rock recognition based on acoustic emission signals, this study has undertaken several key steps. Firstly, it analyzed the time-frequency domain characteristics of acoustic emission signals from different coal-rock conditions. Subsequently, it introduced a feature extraction method based on Empirical Mode Decomposition (EMD) and energy moments. Furthermore, a coal-rock model was established using a Backpropagation (BP) neural network. Finally, the recognition model was trained and validated using various acoustic emission signals from different coal-rock conditions. The experimental results demonstrate that the feature extraction method proposed in this study can accurately distinguish between different coal-rock ratios. This lays the theoretical foundation and technological groundwork for achieving automation and intelligent mining in fully mechanized mining faces.

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