

Coal-Rock Catastrophic Collapse: Precursors Based on AE and Fiber Bundle Models

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1 **Coal Rock Catastrophic Collapse: Precursors based on AE and**

2 **Fiber Bundle Models**

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17 **Abstract**

18 This paper proposes a new precursor for monitoring coal-rock dynamic disasters based on a
19 fiber bundle model (FBM), which has been validated in the study of material fracture and critical
20 phenomena. First, the FBM was simulated using the Monte Carlo method to analyze the variations
21 of force and energy. The derivative of energy was identified as a precursor characteristic for model
22 failure. The Acoustic Emission (AE) features of coal-rock under uniaxial compression were also

23 analyzed, and a constitutive model for coal-rock damage evolution under uniaxial compression was
24 established using AE ringing count. Furthermore, the derivative of energy was calculated using the
25 constitutive model to verify the simulation results and propose a new precursor indicator for coal-
26 rock collapse. The research results provide useful guidance for preventing coal mine dynamic
27 disasters.

28 **Practical Applications**

29 This study presents a novel methodology for the prediction of engineering geological hazards,
30 focusing specifically on monitoring and preventing rockburst disasters in coal mines. The crucial
31 precursor characteristics of coal and rock damage are unveiled by research findings, offering
32 valuable insights for the accurate forecasting of potential disaster risks. This approach holds
33 substantial promise not only within the coal mining sector but also across various engineering
34 domains, including geotechnical engineering and other fields necessitating meticulous risk
35 assessment. Implementation of this methodology empowers practitioners to refine disaster
36 prediction, proactively ensuring the sustainability and safety of engineering ventures. It is
37 recommended that project teams consider the integration of this innovative indicator alongside
38 widely-adopted microseismic monitoring techniques, thus mitigating the limitations of existing
39 geophysical monitoring methods. This innovative approach is poised to have a profound and
40 transformative impact on the enhancement of geological hazard monitoring and engineering risk
41 management, providing invaluable support for upcoming engineering projects.

42 **Author keywords:** Fiber bundle model; Damage variable; Precursor; Acoustic emission; Coal
43 burst

44 **Introduction**

45 In many regions of the world and especially in China coal is a primary energy source. However,
46 as mining depths increase, coal and rock dynamic disasters such as coal burst and gas outburst have
47 become more severe, posing a serious threat to the safety of underground personnel (Dou et al.,
48 [2014](#); Fan et al., [2020](#); Zhou et al., [2022](#)). The occurrence of coal burst is a complex process that is
49 characterized by suddenness and uncertainty and is often difficult to predict accurately. Therefore,
50 accurate prediction of coal burst is crucial for coal mine safety.

51 Many studies have indicated that during the loading and damage of rock-like materials, a
52 portion of the energy is released in the form of acoustic emission (AE), electromagnetic radiation,
53 charge induction, and other forms (Aggelis, [2011](#); Baddari et al., [2011](#); Carpinteri et al., [2016](#); Ding
54 et al., [2023](#); Li et al., [2016](#)). Therefore, these non-destructive monitoring techniques are widely used
55 in various fields, such as earthquake monitoring, structural damage monitoring, and coal and rock
56 dynamic disaster monitoring (Behnia et al., [2014](#); Carpinteri et al., [2007](#); Donner et al., [2015](#);
57 Lacidogna, et al., [2011](#); Lou et al., [2019](#)). Specifically, the intermittent generation of AE time series
58 reflects the increasing instability of the system, and the analysis of AE characteristic parameters can
59 be used as a precursor to catastrophic events (Biswas et al., [2015](#); Iturrioz et al., [2013](#); Tanzi et al.,
60 [2023](#)). During coal mine monitoring, it has been discovered that traditional non-destructive testing
61 techniques have certain limitations. This is the result of the combined action of dynamic and static
62 loads in deep coal mine rockburst disasters. (Dou et al., [2018](#); He et al., [2019](#)). Acoustic emission
63 can effectively monitor ultrasonic elastic waves caused by mining and blasting disturbances,
64 providing early warning for coal and rock dynamic disasters, such as coal burst. However, for coal
65 and rock dynamic disasters that occur under high static loads, the signals are relatively stable and
66 weak before the occurrence of collapse, making it difficult to detect obvious precursor signals in

67 advance.

68 The statistical analysis of fracture and damage in heterogeneous materials has drawn wide
69 attention from statistical physicists, and has also led to the study of phase transitions and critical
70 phenomena in statistical physics related to the fracture behavior of materials (Alava et al., 2006;
71 Pradhan et al., 2008). Recently, there have been some reports discussing the critical phenomena of
72 material collapse (Batoool et al., 2022; Dębski et al., 2021; Diksha & Biswas, 2022; Pradhan et al.,
73 2019). Pradhan et al.(2019) used a fiber bundle model to analyze the relationship between force,
74 elastic energy, and displacement during the tensile failure process of materials. According to this
75 theory, the slope of elastic energy and displacement reaches its maximum value before the
76 catastrophic failure of the material, which can be used as a precursor point for material catastrophic
77 failure. Dębski et al. (2021) used the discrete element method to simulate the failure process of the
78 fiber bundle model and confirmed the relationship between energy release and the maximum value
79 of the derivative of elastic energy. Diksha & Biswas (2022) applied the fiber bundle model to
80 analyze disordered solids and conducted a systematic analysis of avalanche size and energy release
81 time series generated by the fiber bundle model using supervised machine learning. Roy (2023)
82 numerically studied the failure process of disordered systems under external forces using the fiber
83 bundle model. Diksha et al. (2023) simulated the process of fiber bundle fracture and believed that
84 a measure of how unequal avalanche sizes are is potentially a crucial indicator of imminent failure.
85 The obtained results can predict failure time. These research results not only expand the application
86 of the fiber bundle model, but also provide new ideas for predicting and controlling coal rock
87 dynamic disasters.

88 Despite extensive scholarly research, there is limited exploration regarding the application of

89 the fiber bundle model to coal and rock materials, particularly concerning the existence of a
90 maximum energy derivative phenomenon preceding catastrophic failure. Further experimental
91 verification is needed. Previous studies have primarily utilized the Weibull distribution in the fiber
92 bundle model, focusing predominantly on the shape parameter k , while the significance of the scale
93 parameter λ has been overlooked. This paper addresses this research gap through a comprehensive
94 investigation involving theoretical analysis, simulation, and experimental validation. In this work,
95 the Monte Carlo method was employed to establish a fiber bundle model where elastic elements
96 share the load, simulating the process of material fracture. Laboratory uniaxial compression tests on
97 coal are performed, and a constitutive model of coal rock damage is developed based on AE ringing
98 count. Validation of simulated results is conducted against experimental data.

99 **Fiber Bundle Model**

100 **Establishment of Fiber Bundle Model**

101 The fiber bundle model (FBM) (Peirce FT, 1926) is a simulation tool with a simple principle
102 and the ability to reflect profound evolution processes, as shown in Fig. 1. The fibers are parallel to
103 each other and fixed between parallel loading plates. A load parallel to the fibers can be applied to
104 both ends of the fiber bundle by the loading plates until the stress threshold of the fiber bundle and,
105 therefore, the rupture is reached. When a certain stress threshold is exceeded, some fibers will
106 collapse, and the load they originally carried will be shared by the remaining unbroken fibers.

107 [Fig. 1 about here]

108 Assuming that the model consists of N parallel fiber bundles jointly bearing an external force F
109 applied to the system, the relationship between the stress σ and the strain ε of each fiber is given
110 by:

111
$$\sigma = \mu\varepsilon, \tag{1}$$

112 Where μ is the elastic constant. If a portion of fibers breaks, the load is distributed evenly among
113 the remaining fibers. This type of loading model is called the equal-load-sharing (ELS) scheme
114 (Daniels, 1945). Since ELS has a mathematical analytical form, it is helpful to study material failure
115 problems in conjunction with the model. Therefore, the subsequent model only considers the
116 distribution form of ELS. The strength of fibers is usually determined by the threshold x they can
117 withstand. It is assumed that the strength of fibers follows a Weibull distribution, where the
118 cumulative distribution function $P(x)$ is given by (Zheng et al., 2019):

119
$$P(x) = 1 - \exp\left(-\left(\frac{x}{\lambda}\right)^k\right), \tag{2}$$

120 its corresponding probability density function is:

121
$$p(x) = \frac{k}{\lambda} \left(\frac{x}{\lambda}\right)^{k-1} \exp\left(-\left(\frac{x}{\lambda}\right)^k\right), \tag{3}$$

122 Where k is shape parameter and λ is scale parameter. The parameter k determines the shape of the
123 Weibull distribution. For a specific material, it can describe the brittle or plastic characteristics. The
124 parameter λ determines the location and scale of the Weibull distribution, which can affect the
125 strength and failure properties. Different materials have different physical properties and lifetime
126 behaviors, which can lead to different shape parameters and scale parameters.

127 At a certain moment, n fibers are assumed to be broken. The damage variable d is defined as:

128
$$d = \frac{n}{N}, \tag{4}$$

129 As N approaches infinity, the Δ at each step becomes very small, so the loading process can be
130 considered quasi-static. On the other hand, for larger N values, the damage factor d can be treated
131 as continuous, so it can be approximated by $P(x)$.

132 Considering the strain ε of each fiber bundle as representative of the strain in the process of

133 coal compression, the constitutive relationship between the stress and strain of coal rock,
 134 considering the damage variable, can be expressed as:

$$135 \quad \sigma(\varepsilon) = E\varepsilon(1 - P(\varepsilon)), \quad (5)$$

136 Where σ is the stress and E is the elastic modulus.

137 Strain is considered as the control parameter, and construct the energy E^e as:

$$138 \quad E^e(\varepsilon) = \frac{E}{2}\varepsilon^2(1 - P(\varepsilon)). \quad (6)$$

139 **Warning Sign of Collapse**

140 From the above formula, the maximum values of functions (5) and (6) regarding stress and
 141 strain energy are sought. By setting the derivative of stress and energy, the following is obtained:

$$142 \quad \frac{d\sigma(\varepsilon)}{d\varepsilon} = E(1 - \varepsilon_c p(\varepsilon_c) - P(\varepsilon_c)) = 0, \quad (7)$$

$$143 \quad \frac{dE^e(\varepsilon)}{d\varepsilon} = \frac{E}{2}[2\varepsilon_m(1 - P(\varepsilon_m)) - \varepsilon_m^2 p(\varepsilon_m)] = 0, \quad (8)$$

144 From which the following values are obtained:

$$145 \quad \varepsilon_c = \lambda k^{-\frac{1}{k}}, \quad (9)$$

$$146 \quad \varepsilon_m = \lambda \left(\frac{2}{k}\right)^{\frac{1}{k}} = \varepsilon_c 2^{\frac{1}{k}} > \varepsilon_c, \quad (10)$$

147 In this context, ε_c is defined as the strain when the stress reaches its maximum value, also
 148 known as critical strain. On the other hand, ε_m represents the strain when the energy reaches its
 149 maximum value.

150 From the above analysis, it can be concluded that energy has a maximum value, but it always
 151 appears after the critical strain ε_c . when plotting $dE^e/d\varepsilon$, which is the derivative curve of energy with
 152 respect to strain, it is always possible to observe a maximum value. By calculating the second
 153 derivative of energy with respect to the strain and setting the derivative function equal to zero, the
 154 following is obtained:

155
$$\frac{d^2E(\varepsilon)}{d\varepsilon^2} = \frac{E}{2} \left[2 \left(1 - P(\varepsilon_p) \right) - 4\varepsilon_p p(\varepsilon_p) - \varepsilon_p^2 p'(\varepsilon_p) \right] = 0, \quad (11)$$

156 By substituting Eq. (2) and (3) into Eq. (11), the following is obtained:

157
$$\frac{E}{2} \exp \left(- \left(\frac{\varepsilon_p}{\lambda} \right)^k \right) \left(k^2 \left(\left(\frac{\varepsilon_p}{\lambda} \right)^k - 1 \right) \left(\frac{\varepsilon_p}{\lambda} \right)^k - 3k \left(\frac{\varepsilon_p}{\lambda} \right)^k + 2 \right) = 0, \quad (12)$$

158 From which the following value is obtained:

159
$$\varepsilon_p = \lambda 2^{-\frac{1}{k}} \sqrt[2k]{\frac{k^2 - \sqrt{k^2 + 6k + 1}k + 3k}{k^2}},$$

160
$$= \varepsilon_c k^{-\frac{1}{k}} 2^{-\frac{1}{k}} \sqrt[2k]{k^2 - \sqrt{k^2 + 6k + 1}k + 3k} < \varepsilon_c. \quad (13)$$

161 In Eq. (13) the term $k^{-\frac{1}{k}}$ is less than or equal to 1, and the term $2^{-\frac{1}{k}}$ is less than 1. Meanwhile, It

162 is observe that $\sqrt[2k]{k^2 - \sqrt{k^2 + 6k + 1}k + 3k}$ is always less than 1, irrespective of the value of k .

163 Therefore, it follows that ε_p is always smaller than ε_c . Here, ε_p is defined as the corresponding strain

164 when the $dE^e/d\varepsilon$ reaches its maximum value. The above analysis shows that the strain ε_p is always

165 found before ε_c . As far as coal rock is concerned, when the sample reaches the ε_c in the compression

166 failure process, most of the samples will be destroyed in a short period of time, showing strong

167 brittle characteristics. Therefore, the strain ε_p can be used as a precursor of coal rock collapse.

168 Compared with previous studies (Dębski et al., 2021; Pradhan et al., 2019), this paper considers the

169 shape parameter k and scale parameter λ of Weibull distribution at the same time, so that the coal-

170 rock loading process can be simulated with greater accuracy.

171 Monte Carlo method

172 In this section, the fracture process of the FBM is simulated to verify the conclusions obtained

173 above. To simulate the process of fiber bundle fracture, Monte Carlo method (James, 1980; Kroese

174 et al., 2014) is applied. Monte Carlo simulations use random samples to estimate the probability

175 distribution and expected values of a system or process. They are useful when dealing with complex

176 systems or those with inherent randomness or uncertainty. Since the fracture of fiber bundles can be

177 modeled using the Weibull distribution, Monte Carlo simulations can be utilized to reproduce the
178 Weibull distribution of fiber bundles and model the process of fiber fracture. Since the Monte Carlo
179 method mainly uses random numbers to solve the calculation problems of the FBM, the simulation
180 process of the FBM can be represented by mathematical variables. The simulation steps can be
181 described in mathematical language as follows:

- 182 (1) Generate a random matrix A of size $m \times n$ from a Weibull distribution.
- 183 (2) Initialize a non-zero matrix B of size $m \times n$ to store load increments, with all values set to an
184 equal constant.
- 185 (3) Determine a loading rate v .
- 186 (4) Compute the number of non-zero elements a in array B , locate the positions of these
187 elements within B , increase their values by $c=v/a$, and update the resulting array as B .
- 188 (5) Compare the elements of arrays A and B . If an element in array B is greater than the
189 corresponding element in array A , set both elements in arrays A and B to 0 at same position, resulting
190 in new arrays A and B . Otherwise, arrays A and B remain unchanged.
- 191 (6) Repeat steps 4 and 5 until all elements in array A are 0. End the simulation.

192 In the simulation process described above, the number of elements in matrix A represents the
193 number of fibers in the bundle, and each element is assigned a Weibull distribution to represent the
194 strength of the fiber. The values in matrix B simulate the changing load values. By comparing the
195 values in matrix B with the corresponding positions in matrix A , when there exists an element in B
196 that is greater than that in A , the element in A at the corresponding position is assigned to zero,
197 indicating that a fiber has broken. Steps 4 and 5 are repeated, simulating the entire process of fiber
198 bundle fracture. The simulation ends when all elements in matrix A become zero, indicating that all

199 fibers have fractured.

200 **Simulation Results**

201 Setting $m=500$, $n=100$, and the fiber quantity $N=5 \times 10^4$. Having a sufficient number of fibers
202 can avoid abnormal simulation results. The loading rate is set to $V=500$, which depends on the
203 number of fibers and the simulation effect. Too high rate can cause the fiber bundle to be completely
204 destroyed in a few cycles, while too low rate means that the fibers will break one by one, which is
205 not consistent with the actual situation. In the Monte Carlo method described above, the first step is
206 to determine the free matrix A that follows the Weibull distribution. From Equation (2) and Eq. (3),
207 it can be seen that the parameters that affect the Weibull distribution function are the scale parameter
208 λ and the shape parameter k . The maximum likelihood estimation method is used to estimate the
209 parameters of the Weibull distribution, with detailed solution process available in (Cohen, 1965).
210 Let us assume that x_1, x_2, \dots, x_n are the strengths of the samples measured, and based on the Weibull
211 probability density function given in Eq. (3), the likelihood function can be expressed as
212 (Murshudov et al., 1997):

$$213 \quad L(x_i, \lambda, k) = \prod_{i=1}^n \frac{k}{\lambda} \left(\frac{x_i}{\lambda}\right)^{k-1} \exp\left(-\left(\frac{x_i}{\lambda}\right)^k\right). \quad (14)$$

214 Based on the actual sample test results, the uniaxial compressive strength of 8 coal samples
215 were calculated in this paper. The values of the uniaxial compressive strengths are respectively 12.15,
216 12.35, 9.7, 8.67, 7.5, 6.25, 10.25, and 11.27 MPa. The calculated values of the scale parameter and
217 shape parameter are $k=5.75$ and $\lambda=10.58$, respectively. In particular, when the shape parameter is 1
218 and 2, the Weibull distribution corresponds to the exponential distribution and Rayleigh distribution,
219 respectively, whose simulation under these two conditions has been discussed by the authors.

220 Based on the analysis in Section 2.1, The force F , energy E^e , and energy derivative $dE^e/d\varepsilon$ of

221 the FBM during the simulated fracture process can be easily obtained, along with their relationship
222 curve, as shown in Fig. 2.

223 [Fig. 2 about here]

224 In Fig. 2, the horizontal axis represents the number of cycles in the simulation process,
225 indicating the number of iterations. The vertical axis shows the normalized dimensionless energy
226 and force values. It can be seen from Fig. 2 that the model can be considered stable before the force
227 reaches its maximum value, and it becomes unstable after the force reaches its maximum value,
228 which is consistent with the actual situation. The strain ε_m in the figure represents the strain at the
229 maximum energy, which appears in the unstable phase, while the strain ε_p represents the strain at
230 the maximum derivative of energy, which appears before the critical strain ε_c . The simulation results
231 are consistent with the theoretical analysis. As the model enters the unstable phase after the force
232 reaches its maximum value, the fibers subsequently accelerate fracture, so it is believed that the ε_p
233 can be used as a precursor to model failure, and also as a precursor indicator for coal collapse.

234 **Test Equipment and Test Procedure**

235 **Sample preparation**

236 A study was conducted on four coal samples from Xinjiang province, China. To ensure
237 consistency, all samples were prepared in accordance with the suggested shape and size by the
238 International Society for Rock Mechanics (ISRM), which have a cylindrical with a diameter of 50
239 mm and a height of 100 mm. Both ends of the sample had a flatness error of less than 0.02 mm.
240 Table 1 presents the basic parameters of the coal samples tested.

241 [Table 1 about here]

242 **Test equipment**

243 In this study, the experimental system consisted of a loading system, an acoustic emission (AE)
244 system, as shown in Fig. 3. An MTS C45.104 testing machine was used in the loading system, with
245 a maximum load capacity of 300 kN. The AE instrument utilized a PCI-Express8 multi-channel AE
246 system manufactured by American Physical Acoustics Company, along with nano 30 miniature
247 sensors. The sensor has a frequency range of 125~750 kHz, and it is equipped with a 2/4/6 voltage
248 preamplifier that allows for a selectable range of 20, 40, and 60 dB. The AE threshold was set to 40
249 dB to minimize the impact of ambient noise, and the sampling rate was set to 1 MHz. Prior to the
250 start of the experiment, tight contact between the specimen and the upper and lower loading heads
251 of the testing machine was ensured. Additionally, a pre-load of 50 N was applied to the specimen to
252 mitigate potential errors caused by its unevenness. All samples underwent uniaxial compression
253 tests at a displacement-controlled rate of 1 mm/min. The stress-strain curves are presented in Fig. 4.

254 [Fig. 3 about here]

255 **Experimental Results**

256 **Strength and deformation characteristics**

257 After conducting uniaxial compression tests, the strength and elastic modulus of coal
258 specimens can be calculated, as shown in Table 1. Figure 4 presents the stress-strain curve of coal
259 specimens under uniaxial compression conditions. It can be observed that the stress curves of
260 samples C-1 and C-2 drop sharply after reaching compressive strength, indicating an instantaneous
261 failure characteristic. In the laboratory, it has been observed that when a sample experiences
262 macroscopic failure, coal fragments can be ejected from the face, and even a phenomenon called
263 "coal burst" can occur, where the coal specimen completely explodes. In contrast, the curves of C-
264 3 and C-4 did not show a sharp drop after reaching the compressive strength of the coal specimen.

265 Instead, the stress decreased to a certain value, then increased, and then decreased again until failure
266 occurred, exhibiting a gradual failure characteristic. This is because after the coal sample reaches
267 its peak strength, localized damage occurs, the stress adjusts, and a relatively stable structure is
268 formed, and the remaining part still has a certain load-bearing capacity.

269 According to the coal specimen crack propagation process, the stress-strain curve can be
270 divided into four stages: (1) compaction stage: at the beginning of loading, the stress is small, and
271 the coal specimen has a faster axial strain rate due to the presence of many primary cracks. (2)
272 Linear elastic stage: after the compaction stage, the stress of the coal sample begins to steadily
273 increase and secondary cracks appear, at which point the stress-strain curve is approximately a
274 sloping straight line. (3) Crack propagation stage: the stress reaches its yield limit, cracks begin to
275 accelerate and form multiple crack clusters. (4) Failure stage: the coal sample reaches its maximum
276 load-bearing capacity, the cracks merge and penetrate, and instantaneous or gradual failure
277 characteristics begin to appear

278 [Fig. 4 about here]

279 **AE Behaviors**

280 The characteristics of AE signals are closely related to the deformation and failure process of
281 coal specimens under uniaxial compression and can reflect the evolution of damage during loading.
282 Figure 5 shows the relationship between stress-time and AE ring-down counts for specimens C-1,
283 C-2, C-3, and C-4 during uniaxial compression. It can be observed that during the compaction stage,
284 the AE ring-down counts are very low and can be ignored. This is because the initial cracks inside
285 the coal specimens are closed and compacted. Only a small amount of low-energy AE signals are
286 generated from some rough surfaces, mixed with some noise. As the coal specimens develop tiny

287 cracks during the mid-loading stage, the AE signals gradually increase. During the crack
288 propagation stage and failure stage, the density of AE signals increases as the cracks accelerate and
289 propagate, leading to a rapid increase in AE ringing counts.

290 From Fig. 5, it can be observed that the AE ringing counts become extremely active when the
291 stress reaches its peak value, and the maximum value of AE ringing counts is achieved at the stress
292 peak. This is because the specimen immediately generates a significant stress drop when reaching
293 the stress peak, indicating that macroscopic cracks have occurred and released significant energy.
294 Additionally, the ringing counts increase significantly with every stress drop, as shown in Fig. 5(c)
295 and Fig. 5(d). The above analysis demonstrates that there is a good correlation between AE ringing
296 counts and coal damage under uniaxial compression.

297 [Fig. 5 about here]

298 **Damage evolution model of coal based on AE characteristics.**

299 Heiple et al. (1981) conducted long-term research on material damage and fracture processes
300 using AE technique and found that the AE ring-down counts are one of the features that can better
301 describe the changes in material damage among multiple parameters of AE. This is because it is
302 proportional to the strain energy released by particle dislocations and movement, fracture, and crack
303 propagation in the material. Therefore, this paper uses the AE ringing count and the cumulative AE
304 ringing count to establish a coal damage evolution model. The damage variable of the material was
305 originally proposed by Kachanov (1958). According to the definition of the damage variable,
306 assuming that the cumulative AE ringing count when all N fibers in the material are broken is C , the
307 average AE ringing count C_0 when each fiber is damaged is calculated as:

$$308 \quad C_0 = \frac{C}{N}, \quad (15)$$

309 When n fibers are broken, the cumulative AE ringing count at this moment is C_n , which can be
310 expressed as:

$$311 \quad C_n = C_0 n = C \frac{n}{N}, \quad (16)$$

312 Therefore, the damage variable based on ringing counts can be defined as:

$$313 \quad d = \frac{C_n}{c}, \quad (17)$$

314 There are many microcracks and voids randomly distributed inside the coal. According to the
315 statistical damage theory, it is assumed that the failure probability of the coal microstructure follows
316 the Weibull distribution. The microstructure size includes enough voids and cracks and can also be
317 considered as small enough to adopt the concept of continuum mechanics (J. Zhou & Chen, 2013).
318 The probability density function of the Weibull distribution is shown in Eq. (3).

319 The damage variable d defined above has a value range of 0 to 1, which represents the
320 cumulative degree of microscopic damage in the material. Here, 0 represents an undamaged material,
321 while 1 represents a completely damaged material. However, after the test is stopped, the specimen
322 still has a certain bearing capacity, but the calculated value of the d is 1, which does not match the
323 actual situation. To eliminate this influence, a critical damage can be introduced to modify the
324 damage variable d based on the effect of load on AE. When the test stops, the damage variable d is
325 controlled by the critical damage, which is more in line with the actual situation. Therefore, the
326 modified damage variable can be expressed as:

$$327 \quad d = d_0 \frac{C_n}{c} = d_0 \left(1 - \exp\left(-\frac{\varepsilon}{\lambda}\right)^k \right), \quad (18)$$

328 Where d_0 is the critical damage, which is multiplied by the damage variable d to obtain a modified
329 d that can reflect the residual strength of the coal, making the obtained model closer to the actual
330 situation. The critical damage d_0 reflects the damage condition of the specimen after loading. To

331 simplify calculations, d_0 is taken as:

$$332 \quad d_0 = 1 - \frac{\sigma_p}{\sigma_r}, \quad (19)$$

333 Where σ_p represents peak strength and σ_r represents residual strength.

334 As described in Section 4.2, due to the presence of inherent cracks and a relatively high porosity
335 in coal, there is a compression stage during the compression process, resulting in fewer AE signals.
336 Additionally, compared with the crack propagation and failure stages, the AE signals during the
337 elastic stage are also minimal. If only the AE signals are used to construct the damage evolution
338 model, it will lead to significant discrepancies between the model and the actual curve for both the
339 compression and linear elastic stages. To mitigate this effect, the concept of compaction coefficient
340 K (the ratio of the stress-strain derivative to the elastic modulus E) is introduced in this study (Gu
341 et al., 2019). Since the derivative curve of stress-strain relationship approximates a logarithmic
342 function (Liu et al., 2016), K can be described as:

$$343 \quad K = \begin{cases} \log_n \left(a \frac{\varepsilon}{\varepsilon_s} + 1 \right), & 0 \leq \varepsilon < \varepsilon_s, \\ 1, & \varepsilon \geq \varepsilon_s \end{cases}, \quad (20)$$

344 here, n is a constant obtained through experiments, ε_s is the yield strain. The coal damage model
345 established in this paper can be expressed as follows:

$$346 \quad \sigma = KE\varepsilon(1 - d). \quad (21)$$

347 **Damage model validation**

348 To verify the accuracy and effectiveness of the proposed damage model, this paper applies the
349 model to experimental data of actual coal and compares the results. The parameters of the
350 compression coefficient K were obtained by fitting the stress-strain curve of uniaxial compression,
351 as shown in Table 2. Similarly, based on the relationship between time and strain, as well as time
352 and AE ringing counts, the relationship between strain and cumulative AE ringing counts can be

353 obtained and fitted using the Weibull distribution function. The fitting curve is shown in Fig. 6.
354 From Fig. 6, it can be seen that the Weibull distribution function fits the cumulative ringing count
355 very well, indicating that the curve follows the Weibull distribution. The damage variable
356 parameters k and λ can be accurately obtained using the acoustic emission ringing count. The fitting
357 parameters of each sample obtained by fitting using Eq. (18) are shown in Table 2, where R^2
358 represents the degree of curve fitting.

359 [Fig. 6 about here]

360 [Table 2 about here]

361 The theoretically calculated stress-strain curve obtained from Eq. (21) is in good agreement
362 with the actual stress-strain curve, as shown in Fig. 7. This indicates that the coal damage
363 constitutive model established in this paper is relatively reasonable. From Fig. 7, it can also be
364 observed that the stress-strain curve described by Eq. (21) is generally slightly higher than the
365 experimental values. This is due to the fitting error of the compression coefficient K . Compared to
366 rocks such as granite and marble, coal has a relatively higher porosity. During uniaxial compression,
367 the linear elastic stage of the curve is not significant, and the curve is concave upwards. This leads
368 to some errors in the calculation of the elastic modulus E and affects the fitting of the compression
369 coefficient K . Therefore, the obtained theoretical compression coefficient is relatively larger,
370 resulting in a slightly higher strength than the experimental values.

371 In Fig. 7, the variation curve of the damage variable d with strain is also plotted. It can be
372 observed that before the specimen enters the yield stage, the d is between 0 and 0.1. This indicates
373 that only a small amount of AE signals are collected before the yield stage, and it also proves that
374 the degree of damage to the specimen is small during this stage.

[Fig. 7 about here]

Early warning indicator

According to the established coal damage constitutive model, the energy can be calculated by the following equation:

$$E^e(\varepsilon) = K \frac{E}{2} \varepsilon^2 (1 - P(\varepsilon)). \quad (22)$$

Based on the results of simulation analysis using the FBM presented in Section 2, it can be inferred that the maximum energy occurs after the critical strain ε_c , while the maximum energy derivative occurs before the ε_c . To further validate this conclusion through experiments, Figure 8 shows the stress-strain, energy-strain, and energy derivative-strain curves based on the coal damage constitutive model. It is evident that the energy derivatives of all four specimens reached the maximum value before the maximum stress was reached. The stress-strain curve shows that coal, as a material with high plastic deformation capacity, exhibits significant deformation during uniaxial compression but quickly collapses after reaching the peak stress, as evidenced by the occurrence of obvious coal burst phenomena in specimens C-1 and C-2, indicating strong impact tendency. Therefore, the maximum energy derivative can be used as a precursor indicator of impact ground pressure. For coal specimens with gradual damage characteristic, such as C-3 and C-4, the maximum energy derivative can also be used as a precursor indicator of the sample entering the unstable stage.

[Fig. 8 about here]

Discussion and Conclusions

Although a simple FBM was adopted, in all the analysis results, whether it was the simulation of the FBM or the laboratory experiment, the precursor point before catastrophic failure of the material was consistently observed, that is, the maximum value of energy derivative was observed

397 before the catastrophic collapse of the coal specimen. The coal damage constitutive model based on
398 AE ringing count has also shown good agreement with the experimental curve. This seems to solve
399 the problem of predicting coal specimen collapse well. However, some existing issues need to be
400 further discussed to make the conclusions more reasonable.

401 First of all, there is a simulation issue. MATLAB was utilized to simulate the random fracture
402 of the FBM, but it is difficult to simulate the real situation of coal failure. This is because using the
403 Monte Carlo method to abstract FBM as an iterative process of random arrays ignores the structure
404 and size of the coal sample, as detailed in Section 2.3. The advantage of doing so is that the model
405 is simple and can intuitively evolve the fracture process, but it is also difficult to simulate the
406 complex failure process of coal. Precursor indicator obtained through energy changes allow us to
407 consider collapse from the point of view of coal specimen stress state, but this result is not always
408 correct. For instantaneously damaged coal specimens, such as C-1 and C-2, the stress-strain curve
409 shows that the failure occurs in a short time after reaching the peak stress, and the strain at the
410 maximum value of the energy derivative can be regarded as the precursor indicator of catastrophic
411 failure. But for coal specimens with the gradual failure characteristic, such as C-3 and C-4, the strain
412 at the maximum energy derivative can only be considered that the specimen is about to enter the
413 unstable stage. This also indicates that if there is a maximum value in the energy derivative due to
414 damage, it cannot be immediately judged as the final catastrophic failure. On the other hand, if a
415 small damage leads to the conclusion of catastrophic failure, this judgment is completely wrong.

416 In fact, this shows that the collapse of coal mass cannot be judged solely by the energy
417 derivative. The development of AE technique can to some extent compensate for this deficiency.
418 For example, the AE b-value (Carpinteri, et al., 2009). The magnitude of the b-value can indicate

419 changes in micro-cracks of different scales in coal rock masses, reflecting the degree of damage to
420 the coal rock mass. Many studies have reported this conclusion (Fritschen, 2010; Mondal & Roy,
421 2019; X. Zhou et al., 2023). Therefore, b -value and energy derivative can be used to judge whether
422 coal rock mass will collapse, to better predict rock burst.

423 The FBM proposed in this paper has certain limitations. The equal-load-sharing model is
424 employed, which means that the force acting on the FBM is evenly distributed among the unbroken
425 fibers. This is primarily because this type of model can be solved analytically. However, microcracks
426 in coal samples also significantly influence the development of local cracks, making the equal-load-
427 sharing model inadequate. Therefore, further work is required to enhance the model and improve its
428 ability to simulate real-world scenarios. Given the above comments, The research conclusions can
429 be summarized as follows:

430 1) The FBM established by Monte Carlo method can quantitatively describe the process of
431 fiber fracture, and the evolution of the FBM can correspond well with the AE ringing count of coal
432 under uniaxial compression. The simulation results that there is a maximum value of the energy
433 derivative before the catastrophic failure of the model.

434 2) A damage constitutive model of coal under uniaxial compression based on AE ringing count
435 was established, laying a foundation for better understanding the evolution law of coal damage and
436 revealing the intrinsic mechanism of coal damage.

437 3) Through analyzing the results of uniaxial compression tests on coal specimens, it is found
438 that the energy derivative has a maximum value before the catastrophic failure of coal specimens,
439 which can serve as a precursor for the collapse of coal specimens under uniaxial compression and
440 provide theoretical guidance for the prevention and control of coal mine dynamic disasters.

441 **Data Availability Statement**

442 Some or all data, models, or code that support the findings of this study are available from the
443 corresponding author upon reasonable request.

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