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## Article

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# Rockburst proneness evaluation and borehole pressure relief technology for deep heterogeneous rock masses: A case study of Sanshandao Gold Mine

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## Abstract

Deep mining faces severe rockburst hazards under high in-situ stress, and rock mass heterogeneity hampers loading-unloading tests and rockburst evaluation. This study combines theoretical derivation, laboratory tests, PFC2D numerical simulation and field monitoring. First, a uniaxial compressive strength prediction model based on density and P-wave velocity was established and calibrated against 30 heterogeneous rock specimens, providing individualized peak loads for loading-unloading tests. Second, multi-parameter rockburst proneness indices were integrated through game-theory combination weighting and a standard normal cloud model, indicating moderate-to-strong rockburst proneness in the deep rock mass of the Sanshandao mining area. Third, pressure relief boreholes with four diameters (0.05–0.20 m) were simulated by PFC2D with a Weibull heterogeneous strength field calibrated to the Sanshandao specimens. A Pressure Relief and Surrounding-rock Stability Efficiency Index (PRSEI) was proposed, and the 0.10 m borehole achieved the maximum PRSEI (0.466) with critically connected plastic zones and moderate incremental damage, verifying the field scheme (0.10 m diameter, 1.0 m spacing). This study provides a quantitative basis for rockburst evaluation and pressure-relief optimization in deep heterogeneous rock masses.

**Keywords:** deep heterogeneous rock masses; rockburst proneness; uniaxial strength prediction; game-theory combined weighting and cloud model; borehole pressure relief; PFC2D numerical simulation

## 1. Introduction

With the continuous exhaustion of shallow mineral resources, deep mining has become the mainstream development direction of the global mining industry, and rockburst disasters induced by high in-situ stress have become a major bottleneck restricting its safe production [1]. More than 112 metal mines worldwide have reached a mining depth of over 1000 m, with South Africa's Mponeng Gold Mine exceeding 4350 m; in China, over 16 metal mines have entered the deep mining stage below 1000 m [2,3]. As mining depth increases, in-situ stress rises sharply, and coupled with complex geological structures and mining disturbance, the occurrence probability and intensity of rockburst increase substantially [4]. Different from homogeneous rock masses, deep rock masses show prominent heterogeneity due to variable mineral composition and developed joints, which causes dramatic strength fluctuation of rock samples in the same mining area and makes it difficult to accurately assess rockburst proneness and formulate targeted disaster prevention measures [5-7]. For deep metal mines represented by Sanshandao Gold Mine, the coupling of high stress and rock heterogeneity further aggravates rockburst hazards, so research on rockburst proneness evaluation and pressure relief technology for deep heterogeneous rock masses is urgently needed.

During the excavation of deep buried rock masses, the high elastic energy stored in surrounding rocks is released rapidly [8]. The heterogeneity of rock internal structures and mechanical properties results in uneven energy release and stress redistribution, which readily triggers instantaneous dynamic fracturing and eventually induces rockburst disasters [9-11]. Currently, rockburst proneness evaluation mainly relies on indoor rock

mechanics tests [12], in which the rockburst proneness index and deformation brittleness index are determined by loading-unloading tests [13-15]. Nevertheless, the obvious strength variability of heterogeneous rock masses brings great difficulties to the determination of peak load in such tests, making rock strength prediction an essential prerequisite. Many scholars have conducted extensive research on rock strength prediction: Kahraman [16] established empirical equations for predicting uniaxial compressive strength from rock physical properties; Xia et al. [17] proposed a mechanical parameter estimation method combining P-wave velocity and the Hoek-Brown criterion; Lin [18] predicted the compressive failure strength of rock via uniaxial compression tests; and Kochukrishnan [19] developed regression strength prediction models using ultrasonic pulse velocity and other parameters. Although these studies laid a solid foundation, most existing models are developed for specific rock types or purely based on statistical regression methods, and few can address the prominent strength dispersion of deep heterogeneous rock masses or provide a reliable peak load reference for loading-unloading tests in rockburst assessment.

The evaluation criteria differ among various rockburst proneness indices, and single-index assessment often produces contradictory results for the same group of rock specimens. For this reason, multi-index comprehensive evaluation has become an effective way to improve the reliability of rockburst proneness assessment. Shu [20] established a fuzzy comprehensive evaluation model based on the analytic hierarchy process (AHP) and fuzzy mathematics. Armaghani [21] developed a hybrid prediction model that outperformed traditional algorithm-optimized support vector machine (SVM) models at all rockburst hazard levels. Song [22] combined the Mann-Kendall trend test (MKT) with multi-index fusion for real-time quantitative rockburst risk assessment. Wu [23] integrated unascertained measurement and evidence theory to address the fuzziness and uncertainty in rockburst prediction. Shi [24] adopted a trapezoidal fuzzy multi-criteria decision-making (MCDM) method combining subjective and objective weights, verified in Kaiyang Phosphate Mine. Wang [25] established a rockburst liability evaluation model based on weighted fuzzy sets with an optimal evaluation accuracy of 97.64%. Zhao [26] proposed three distance-based MCDM methods with hesitant fuzzy sets (HFS) for rockburst risk evaluation, verified in a deep shaft of Xincheng Gold Mine. Overall, most existing fuzzy comprehensive evaluation methods presume that rock strength can be accurately acquired by conventional laboratory tests and are therefore not applicable to deep heterogeneous rock masses, where the severe strength dispersion makes the accurate determination of the peak load of loading-unloading tests difficult.

In addition, the normal cloud model, which can simultaneously characterize both the fuzziness and randomness of uncertain information, has been increasingly applied to rockburst proneness evaluation. Li et al. [27] established the cloud model as a cognitive model that transforms a qualitative concept into a quantitative representation through three digital characteristics, namely expectation, entropy and hyper-entropy. Li et al. [28] further improved the cloud model for rockburst tendency prediction by fusing the weights of evaluation indices under the constraint of the cloud-atomization condition ( $H_e < E_n/3$ ). Compared with the 0/1 hard assignment used in conventional fuzzy comprehensive evaluation, the cloud model provides continuous transitional memberships and simultaneously accounts for the fuzziness and randomness of evaluation indices, which better matches the actual evaluation of deep heterogeneous rock masses.

When rockburst proneness is severe or rockburst failures have already taken place, borehole pressure relief serves as an effective measure to mitigate such geohazards [29-31], as it reshapes the original stress field of surrounding rock and releases accumulated elastic strain energy [32-34]. Nevertheless, rock mass heterogeneity constitutes a major triggering factor for rockburst incidents [35-37]. Numerous scholars have carried out in-depth investigations into borehole pressure relief technologies. Zang et al. [38] revealed that enlarging borehole diameter and reaming length as well as shortening hole spacing can reduce rock peak strength and elastic modulus, raise the proportion of dissipated strain energy, and accordingly produce superior pressure relief performance. Cui et al. [39] proved that large-diameter relief boreholes can substantially cut down the peak stress and strain energy of surrounding rock, with borehole diameter acting as the dominant control parameter. Jiang et al. [40] put forward an asymmetric borehole pressure relief scheme that arranges relief holes close to deep stress concentration zones, and field practices verified that this technology can sustain long-term roadway stability. At present, borehole pressure relief methods have been widely popularized in coal mine engineering [41-44]. Targeting the severe large deformation of deep roadways in Dong'an Coal Mine, Chen et al. [45] developed a collaborative support strategy integrating high-strength shallow bolting

and deep large-diameter borehole pressure relief, which actively transfers the peak stress zone away from the roadway periphery. Numerically, Liang et al. [46] and Yin et al. [47] employed PFC2D to study the pressure relief effect of boreholes with different diameters, while the bonded-particle model and its micro-parameter calibration have been systematically established in the PFC literature [48-50]. To sum up, current research on rock strength prediction, rockburst proneness evaluation and borehole pressure relief has achieved fruitful results.

However, three prominent deficiencies remain: existing strength prediction models are unsuitable for deep heterogeneous rock masses; conventional rockburst evaluation methods fail to consider the uncertainty caused by discrete rock strength; and borehole pressure relief theories and technologies are rarely studied for heterogeneous rock masses in deep metal mines. These gaps severely restrict the safe mining of deep metal mines represented by Sanshandao Gold Mine.

To fill the aforementioned research gaps, this study combines theoretical analysis and laboratory tests. Firstly, a physically constrained power-law rock strength prediction model based on P-wave velocity and density is established and validated to solve the problem of peak load determination for loading-unloading tests on deep heterogeneous rock masses. Secondly, a rockburst proneness evaluation model coupling the normal cloud model with game-theory combination weighting is constructed, in which rock mass heterogeneity is incorporated into the weighting, cloud parameters and uncertainty intervals. Finally, theoretical calculation and field tests of borehole pressure relief are implemented according to the evaluation results. The proposed technical framework integrates strength prediction, rockburst proneness evaluation and pressure relief control as a complete system, providing theoretical support and engineering guidance for rockburst prevention in deep heterogeneous rock masses.

## 2. Rock strength prediction model based on non-destructive parameters

### 2.1. Determination of basic rock mechanical parameters

Rock specimens were collected from the Sanshandao Gold Mine, Shandong Province, China. A total of 30 uniaxial compression specimens ( $\varnothing 50 \text{ mm} \times 100 \text{ mm}$ ) were used to calibrate and validate the strength prediction model, and five additional specimens were reserved as an independent application set for the loading-unloading tests. In addition, specimens of  $\varnothing 50 \text{ mm} \times 25 \text{ mm}$  were prepared for Brazilian disc splitting tests. The measured physical and mechanical parameters are summarized in Supplementary Tables S1 and S2. The testing equipment and rock specimens are shown in Supplementary Fig. S1.

All tests were performed on a YUMT1000 machine at 0.1 mm/min. Density and P-wave velocity were measured before testing, and the loading-unloading scheme was designed individually from the predicted strength of each specimen (Supplementary Fig. S2).

### 2.2. Physical basis for strength prediction using density and P-wave velocity

For brittle heterogeneous rock, the uniaxial compressive strength is governed mainly by the rock stiffness. Based on the dynamic elastic modulus, a physically constrained power-law model is proposed to predict the uniaxial compressive strength  $S$  from density  $\rho$  and P-wave velocity  $v_p$  as expressed in equation (1):

$$E_d = \rho v_p^2 \frac{(1+\mu)(1-2\mu)}{(1-\mu)} \quad (1)$$

where  $E$  is the dynamic elastic modulus,  $\mu$  Poisson's ratio, and the P-wave velocity relates to the elastic parameters by equation (2):

$$E_d = C(\mu) \cdot \rho v_p^2 \quad (2)$$

and  $C(\mu)$  is a coefficient dependent on  $\mu$ ; substituting yields

$$S = A(\rho v_p^2)^b \quad (3)$$

The exponent  $b$  is not fixed a priori but inferred from data, reproducing the non-linear strength–stiffness relationship of heterogeneous rock.

### 2.3. Model calibration based on 30 specimens

Taking logarithms of both sides of equation (3) gives equation (4):

$$\ln S = \ln A + b \ln(\rho v_p^2) \quad (4)$$

The parameters  $A$  and  $b$  were determined by least-squares regression in the logarithmic domain ( $\rho$  in kg/m<sup>3</sup>,  $v_p$  in m/s,  $S$  in MPa) through equation (5):

$$S = 2.60 \times 10^{-6} (\rho v_p^2)^{0.697} \quad (5)$$

Calibrated on the measured data of the 30 specimens, the model achieves  $R^2 = 0.958$ , RMSE = 3.41 MPa and MAE = 2.62 MPa on the original scale. The 95% confidence intervals of the parameters are  $A \in [6.80 \times 10^{-7}, 9.92 \times 10^{-6}]$  and  $b \in [0.643, 0.751]$ . Notably, the confidence interval of  $b$  excludes both 0.5 and 1, which statistically confirms that the strength–stiffness relationship is a genuine non-linear power law rather than an idealized square-root or linear proportionality. The fitted curve together with its 95% prediction band is shown in Figure 1.

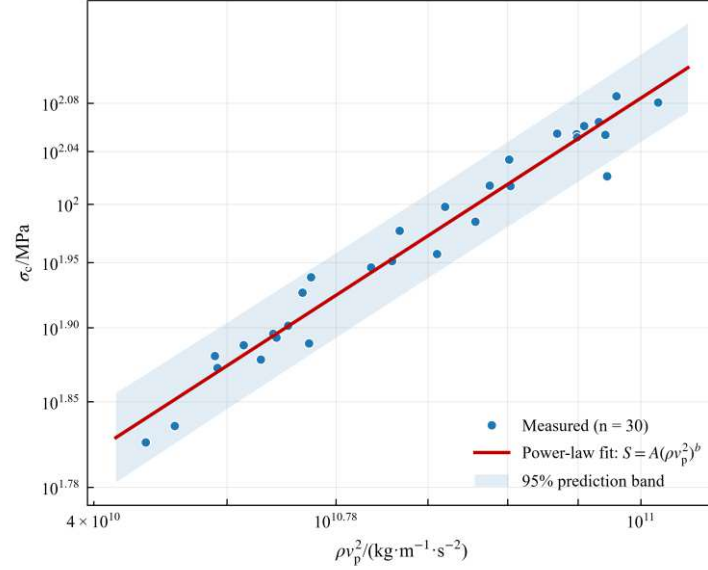


Figure 1 | Power-law fitting curve of uniaxial compressive strength versus the dynamic stiffness index  $\rho v_p^2$  (log–log scale). The shaded band represents the 95% prediction interval.

The calibrated model with high fitting accuracy can be adopted to individually calculate the uniaxial compressive strength of each heterogeneous rock specimen, so as to determine the matched peak load of the loading-unloading tests and avoid test failure caused by the large discrete strength of rock specimens.

## 2.4. Model validation and uncertainty quantification

To verify the generalization ability of the model, leave-one-out cross-validation (LOOCV) and five-fold cross-validation were performed on the 30 calibration specimens, and the prediction performance was compared with the previously used linear model and a Gaussian process regression (GPR) model that provides explicit uncertainty estimates. The results are summarized in Table 1.

Table 1 | Performance comparison of the proposed power-law model with the linear model and the Gaussian process regression model.

| Model                                      | Validation scheme | $R^2$ | RMSE/MPa | MAE/MPa |
|--------------------------------------------|-------------------|-------|----------|---------|
| Power – law $S = A(\rho v_p^2)^b$          | LOOCV             | 0.951 | 3.68     | –       |
| Power – law $S = A(\rho v_p^2)^b$          | 5-fold            | 0.953 | 3.63     | 2.79    |
| Linear $S = a + b \cdot \sqrt{\rho v_p^2}$ | LOOCV             | 0.954 | 3.57     | 2.76    |
| Linear $S = a + b \cdot \sqrt{\rho v_p^2}$ | 5-fold            | 0.955 | 3.54     | 2.74    |
| GPR ( $\rho, v_p$ )                        | LOOCV             | 0.949 | 3.79     | 2.92    |
| GPR ( $\rho, v_p$ )                        | Full fit          | 0.963 | 3.21     | 2.43    |

The LOOCV result of the proposed power-law model is  $R^2 = 0.951$ , RMSE = 3.68 MPa and MAE = 2.81 MPa (Figure 2), and the five-fold cross-validation gives  $R^2 = 0.953$  and RMSE = 3.63 MPa. The prediction accuracy is comparable to that of the linear model (LOOCV  $R^2 = 0.954$ , RMSE = 3.57 MPa), but the power-law form avoids the unjustified square-root exponent assumption and provides a physically interpretable non-linear relation.

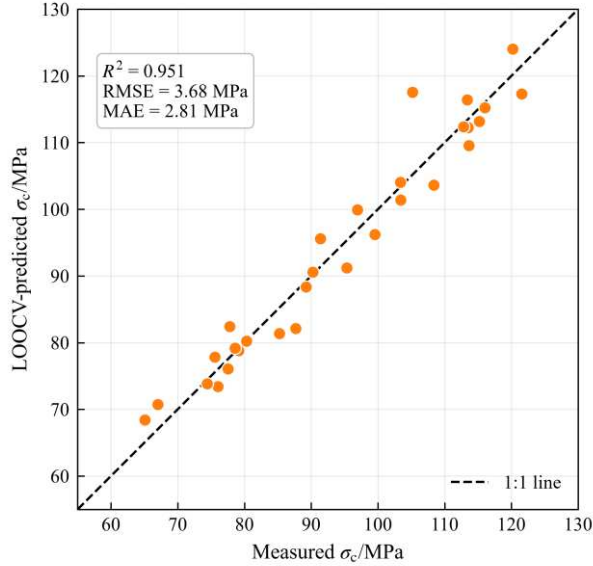


Figure 2 | Leave-one-out cross-validation results of the power-law model: predicted versus measured uniaxial compressive strength (1:1 line as reference).

Residual analysis shows that the residuals are randomly distributed around zero without systematic trends (Supplementary Fig. S3), and the residual histogram is approximately symmetric and concentrated near zero (Supplementary Fig. S3), indicating that the model assumptions are satisfied.

To quantify the prediction uncertainty for application specimens, the Gaussian process regression model with a radial basis function kernel was additionally trained on the 30 calibration specimens. Its mean prediction standard deviation is approximately 3.6 MPa, which yields a 95% prediction interval of about  $\pm 7$  MPa for a single specimen, explicitly reporting the confidence of each predicted strength value.

### 2.5. Application to individualized loading-unloading test design

The calibrated model was applied to the 5 independent specimens reserved for the loading-unloading tests. The predicted uniaxial compressive strength of each specimen and the matched peak load (80% of the predicted strength) are listed in Supplementary Table S3. To demonstrate the engineering value of individualized strength prediction, a comparative analysis was carried out between the proposed scheme and the conventional mean-strength scheme, as shown in Supplementary Fig. S4.

The comparison reveals two critical deficiencies of the mean-strength scheme. First, for the weakest specimen (predicted strength 75.5 MPa), the uniform design stress of 75.6 MPa reaches 100.1% of its strength, so the specimen would be loaded almost to its ultimate capacity and would most likely be damaged before the intended unloading point. Second, for the strongest specimen (predicted strength 104.0 MPa), the uniform design stress only reaches 72.6% of its strength, so the specimen remains in the deep elastic stage with insufficient elastic energy storage, leading to an underestimated elastic strain energy index  $W_{et}$  and an unreliable rockburst proneness assessment. By contrast, the proposed scheme keeps every specimen at a consistent stress level of 80% of its own strength, ensuring that the loading-unloading paths are comparable across specimens and that both test safety and the reliability of the resulting rockburst indices are guaranteed.

In summary, the proposed power-law model, calibrated on 30 heterogeneous specimens and validated by cross-validation with quantified uncertainty, provides a reliable non-destructive approach for predicting the

uniaxial compressive strength of deep heterogeneous rock masses. It supports individualized loading-unloading test design and lays a solid parameter foundation for the rockburst proneness evaluation presented in the following section.

### 3. Rockburst proneness tests and multi-parameter comprehensive evaluation

#### 3.1. Rock strength prediction and loading-unloading tests

Elastic strain energy index  $W_{et}$  and deformation brittleness index  $K_u$  are two core indicators for rockburst proneness assessment, both of which are derived from the stress-strain curves recorded during loading-unloading tests. A total of five groups of loading-unloading tests were designed in this study. Before the mechanical tests, non-destructive physical parameters (density, P-wave velocity, etc.) of all rock specimens were measured. The proposed strength prediction model described in Section 2 was adopted to calculate the theoretical uniaxial compressive strength of each specimen, and the corresponding peak load for loading-unloading tests was further determined.

The predicted strength values and matched test schemes for all specimens are summarized in Supplementary Table S3.

All loading-unloading tests were implemented according to the predicted peak loads, with a constant loading/unloading rate of 150 N/s. Complete stress-strain curves were acquired after each test run (Figure 3).

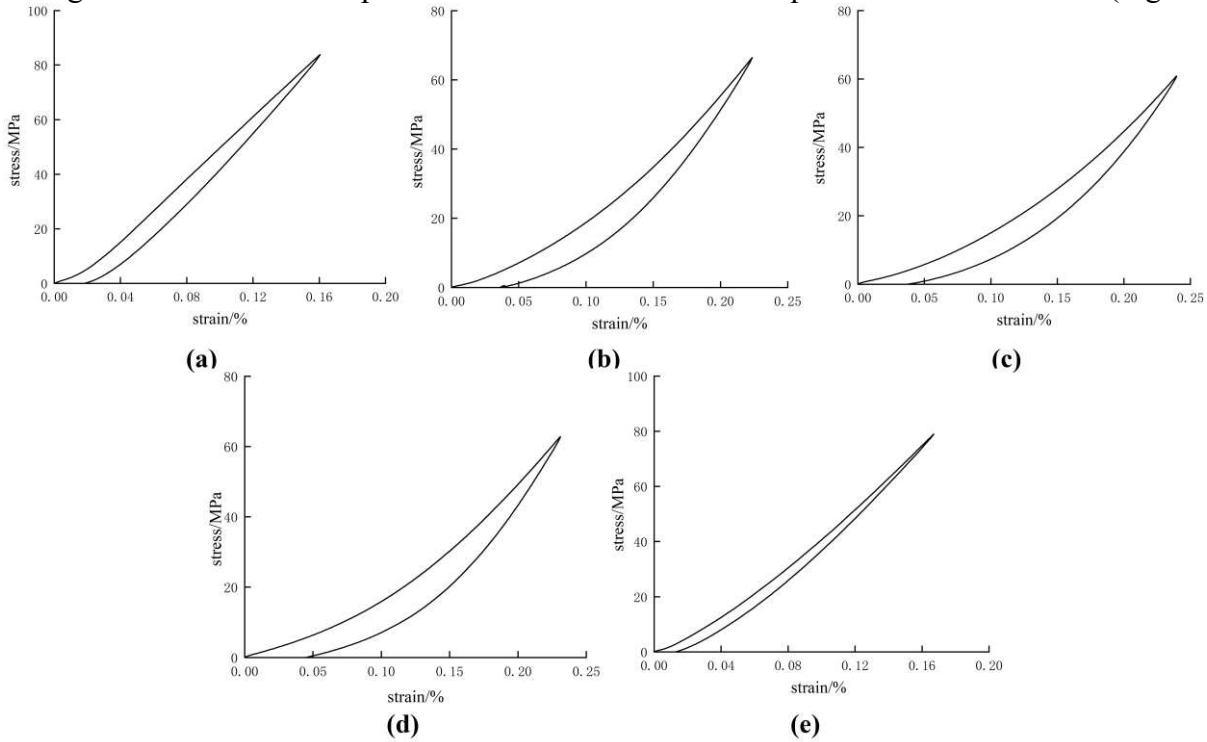


Figure 3 | Loading-unloading stress-strain curves of five groups of rock specimens: (a) Specimen 1; (b) Specimen 2; (c) Specimen 3; (d) Specimen 4; (e) Specimen 5.

A series of laboratory mechanical tests including uniaxial compression and Brazilian disc splitting tests were completed in the loading-unloading tests, through which fundamental mechanical parameters of rock samples such as uniaxial compressive strength were obtained. Nevertheless, rockburst proneness assessment cannot rely merely on laboratory-derived rock mechanical parameters; the in-situ stress condition of the actual engineering site must also be incorporated into the evaluation system. Combined with the measured in-situ stress data of the study area listed in Supplementary Table S4, two critical indicators, the ground stress index ( $S$ ) and tangential stress index ( $T$ ), were quantified. The calculated single-factor rockburst hazard values and corresponding classification results of each indicator are summarized in Supplementary Tables S5 and S6.

#### 3.2. Multi-parameter calculation of rockburst propensity

However, single-index evaluation can only reflect rockburst risk from a single perspective. For the five rock samples in this study, inconsistent hazard grading results appear among different indicators, which cannot objectively characterize the overall rockburst proneness of rock mass. To eliminate the one-sidedness of single-factor judgment, a normal cloud model coupled with game-theory combination weighting is constructed in Section 3.3 for multi-index joint assessment.

### 3.3. Multi-indicator rockburst proneness evaluation of deep heterogeneous rock masses based on the normal cloud model and game-theory combination weighting

Six evaluation indices were adopted: impact energy index  $W_{cf}$ , brittleness coefficient  $B$ , elastic strain energy index  $W_{et}$ , deformation brittleness index  $K_u$ , ground stress index  $S$  and tangential stress index  $T$ , all positive indicators of rockburst severity.  $W_{et}$  and  $K_u$  came from the loading-unloading stress-strain curves, and  $S$  and  $T$  from the measured in-situ stress (Supplementary Tables S4–S6).

#### 3.3.1. Game-theory combination weighting considering rock heterogeneity

##### (1) Objective weights based on the entropy weight method

To extract the objective information contained in the measured data, the entropy weight method is first adopted. Range standardization is performed on the raw measured data to eliminate dimensional differences and value magnitude gaps among distinct indicators as shown in equation (6):

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j)} \quad (6)$$

where  $x_{ij}$  denotes the original test value of the  $j$ -th index for Sample  $i$ ;  $\max(x_j)$  and  $\min(x_j)$  represent the maximum and minimum values of the  $j$ -th index across all samples, respectively; and  $x'_{ij}$  is the standardized value.

Based on the normalized dataset, the information entropy of each index is calculated by equation (7):

$$e_j = -\left(\frac{1}{\ln m}\right) \cdot \sum_l p_{lj} \ln p_{lj}, \quad p_{lj} = \frac{x'_{lj}}{\sum_l x'_{lj}} \quad (7)$$

where  $m$  is the number of samples and  $n$  is the number of indices.

A smaller entropy value indicates more scattered index data and stronger information discrimination capacity, thus assigning a higher weight. The entropy-based objective weight is obtained by equation (8):

$$w_j^e = \frac{1 - e_j}{\sum_j (1 - e_j)} \quad (8)$$

where  $w_j^e$  is the entropy-based objective weight of index  $j$ .

##### (2) Coefficient-of-variation weights for rock heterogeneity

The cloud digital characteristics of the evaluation grades were constructed as follows. For index  $j$ , the coefficient of variation  $CV_j = \sigma_j / \bar{x}_j$  measures the discreteness of the index within the heterogeneous rock mass, and the coefficient-of-variation weight is then defined as equation (9):

$$CV_j = \frac{\sigma_j}{\bar{x}_j} \quad (9)$$

where  $\sigma_j$  and  $\bar{x}_j$  are the standard deviation and mean value of the  $j$ -th index, respectively. A larger CV indicates stronger discreteness of the index within the heterogeneous rock mass, implying that this index carries more information for distinguishing different samples. The coefficient-of-variation weights are then normalized across the six indices, giving equation (10):

$$w_j^{cv} = \frac{CV_j}{\sum_j CV_j} \quad (10)$$

where  $w_j^{cv}$  is the coefficient-of-variation weight of index  $j$ . The entropy and coefficient-of-variation weights are fused by product normalization, giving the objective weight in equation (11):

$$w_j^{obj} = \frac{w_j^e \cdot w_j^{cv}}{\sum_j (w_j^e \cdot w_j^{cv})} \quad (11)$$

where  $w_j^{\text{obj}}$  is the objective weight obtained by the product-normalization fusion of the entropy and CV weights.

### (3) Subjective weights based on the analytic hierarchy process (AHP)

Considering that rockburst is essentially a rapid release of stored elastic strain energy, the energy indices ( $W_{\text{et}}$ ,  $W_{\text{cf}}$ ) are regarded as the most important, followed by the stress indices ( $S$ ,  $T$ ), while the brittleness index  $B$  and the deformation brittleness index  $K_u$  are of relatively lower importance. Based on this priority, the pairwise comparison matrix  $A$  is constructed as equation (12):

$$A = \begin{bmatrix} 1 & 3 & 1 & 2 & 4 & 2 \\ \frac{1}{3} & 1 & \frac{1}{2} & 1 & 3 & 1 \\ 1 & 2 & 1 & 2 & 5 & 3 \\ \frac{1}{2} & 1 & \frac{1}{2} & 1 & 3 & 1 \\ \frac{1}{4} & \frac{1}{3} & \frac{1}{5} & \frac{1}{3} & 1 & \frac{1}{3} \\ \frac{1}{2} & 1 & \frac{1}{3} & 1 & 3 & 1 \end{bmatrix} \quad (12)$$

The subjective weight vector  $w(1)$  is the normalized principal eigenvector of  $A$ . For the constructed matrix,  $\lambda_{\text{max}} = 6.076$ ,  $\text{CI} = 0.015$ ,  $\text{RI} = 1.24$  and  $\text{CR} = 0.012 < 0.1$ , indicating acceptable consistency.

### (4) Game-theory combination weighting

Game-theory combination weighting fused the subjective weights from the analytic hierarchy process with the objective weights from the coefficient of variation (CV) method, in which the CV measures the discreteness (heterogeneity) of each index and thus incorporates rock heterogeneity at the weighting level. The optimal combination coefficients  $\alpha$  and  $\beta$  minimize the deviation between the combined weight and the two basic weights as shown in equation (13):

$$\sum_m \alpha_m w^{(m)} (w^{(l)})^T = w^{(l)} (w^{(l)})^T, \quad l = 1, 2 \quad (13)$$

where  $\alpha^*$  and  $\beta^*$  are the optimal combination coefficients.

After normalization,  $\alpha_1^* = 0.414$  and  $\alpha_2^* = 0.586$ . The combined weight vector is given by equation (14):

$$w^* = \alpha_1 w^{(1)} + \alpha_2 w^{\text{obj}} \quad (14)$$

where  $w_j$  is the combined weight of index  $j$ ,  $w_{j1}$  and  $w_{j2}$  are the subjective and objective weights, and  $\alpha$ ,  $\beta$  are the combination coefficients obtained by minimizing the deviation between the combined weight and the basic weights.

where  $w_{j1}$  is the subjective weight and  $w_{j2}$  is the objective weight obtained by the CV method.

The entropy value, CV, subjective weight, objective weight and combined weight of each index are summarized in Supplementary Table S7 and illustrated in Supplementary Fig. S5. It can be seen that the two energy indices  $W_{\text{cf}}$  and  $W_{\text{et}}$  together account for a combined weight of 0.574 ( $0.318 + 0.256$ ), exceeding half of the total weight, which demonstrates that the energy storage and impact characteristics dominate rockburst occurrence in the test rock mass. In particular, the impact energy index  $W_{\text{cf}}$  obtains the maximum combined weight (0.318), which is attributed to its largest CV (0.633) among the six indices: the pronounced discreteness of  $W_{\text{cf}}$  caused by rock mass heterogeneity grants it the strongest discriminative capacity. The brittleness index  $B$  and the deformation brittleness index  $K_u$  exert relatively weak control effects on rockburst proneness. Such a weighting result quantitatively reflects the heterogeneity of the deep rock mass at the weighting level.

#### 3.3.2. Construction of standard normal clouds of the evaluation indices

The certainty degrees of the evaluation grades were calculated by the forward cloud generator, and the comprehensive certainty was obtained by weighting as expressed in equation (15):

$$E_x = \frac{L+R}{2}, \quad E_n = \frac{R-L}{6} \quad (15)$$

where  $E_x$  represents the most representative value of the grade concept, and  $E_n$  reflects the ambiguity of the grade boundary based on the  $3\sigma$  principle of the normal distribution. For the terminal grades, the no-rockburst

grade  $[0, R_1)$  takes  $Ex = R_1/2$  and  $En = R_1/6$ , whereas the strong-rockburst grade  $[L_4, +\infty)$  mirrors the width of the moderate grade  $w_3 = R_3 - L_3$ , i.e.,  $Ex = L_4 + w_3/2$  and  $En = w_3/6$ . To incorporate rock mass heterogeneity into the cloud characteristics, the hyper-entropy  $H_{ej}$  of each index was calibrated by its coefficient of variation through equation (16):

$$H_{ej} = \min\left(0.1, \frac{CV_j}{3}\right) \cdot E_{nj} \quad (16)$$

which guarantees that  $H_{ej} \leq E_{nj}/3$ , i.e., the cloud-atomization condition is always satisfied, so that the generated clouds remain recognizable. A larger CV (stronger heterogeneity) yields a larger  $H_e$ , indicating stronger randomness of the grade concept and a wider dispersion of the cloud drops. The cloud grading criteria and the digital characteristics of the six indices are listed in Supplementary Table S8, and the standard normal cloud membership curves are illustrated in Supplementary Fig. S6.

### 3.3.3. Comprehensive cloud evaluation of rockburst proneness

Monte Carlo simulations of the forward cloud generator output both the mean comprehensive certainty and its uncertainty interval, quantifying the influence of rock mass discreteness on the evaluation results. The certainty degree of each sample with respect to the evaluation grades is computed by equation (17):

$$\mu_{ijk} = \exp\left[-\frac{(x_{ij} - E_{xjk})^2}{2(E'_{nj})^2}\right], \quad E'_{nj} \sim N(E_{nj}, H_{ej}^2) \quad (17)$$

where  $E'_n$  is a random value of the entropy drawn from a normal distribution  $N(E_n, H_e^2)$ , which endows the membership with the randomness induced by rock heterogeneity. For the terminal grades, the membership saturates to 1 when the value lies beyond the cloud center, i.e.,  $\mu_{ij1} = 1$  if  $x_{ij} \leq E_{xj1}$  and  $\mu_{ij4} = 1$  if  $x_{ij} \geq E_{xj4}$ . The  $6 \times 4$  cloud membership matrix  $R_i$  of each sample can thus be established; taking Sample 1 as an example, expressed in equation (18):

$$R_1 = \begin{bmatrix} 0.000 & 0.000 & 0.000 & 1.000 \\ 0.177 & 0.000 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.001 & 0.074 \\ 0.000 & 0.487 & 0.000 & 0.000 \\ 0.000 & 0.000 & 0.000 & 1.000 \\ 0.000 & 0.000 & 0.000 & 1.000 \end{bmatrix} \quad (18)$$

The comprehensive certainty of the  $i$ -th sample to the  $k$ -th grade is obtained by the weighted average operator using the combined weights as expressed in equation (19):

$$B_{ik} = \sum_j w_j \cdot \mu_{ijk} \quad (19)$$

Considering the randomness of  $H_e$ , Monte Carlo simulations ( $N = 3000$ ) of the forward cloud generator are performed, and both the mean value and the standard deviation of the comprehensive certainty are obtained. The final rockburst grade is determined by the maximum certainty principle. The results of the five samples are summarized in Supplementary Table S9 and illustrated in Figure 4.

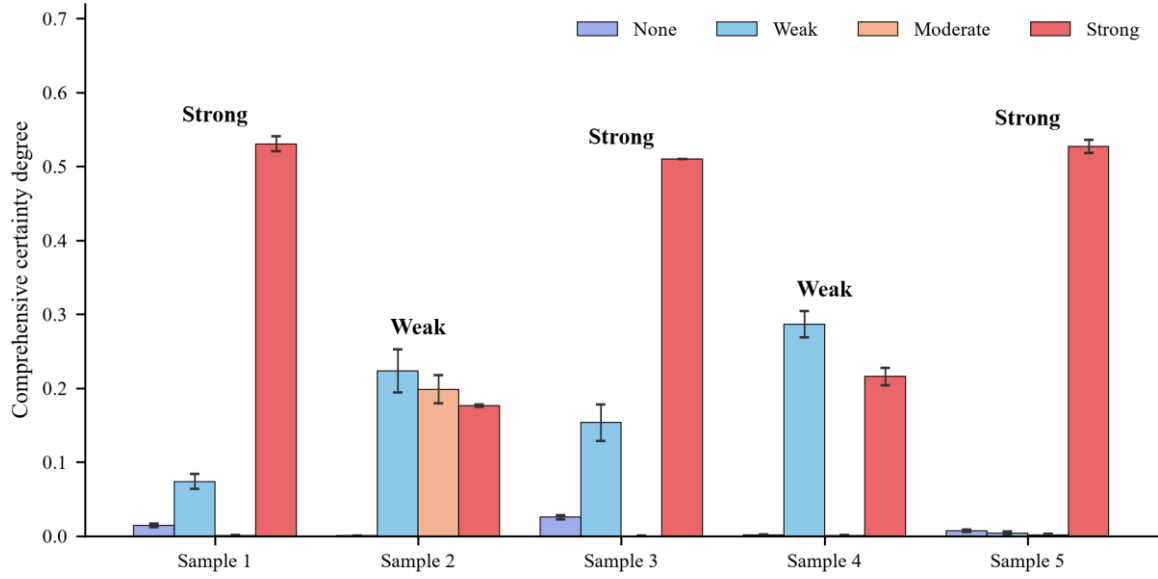


Figure 4 | Comprehensive certainty degrees of the five samples with Monte Carlo uncertainty intervals (mean  $\pm$  SD).

Compared with the conventional 0/1 fuzzy evaluation, the cloud model provides continuous certainty degrees that reveal more information. For instance, the comprehensive certainties of Sample 2 toward the weak, moderate and strong grades are 0.223, 0.198 and 0.176, respectively, which are quite close to each other. This near-tie certainty honestly reflects that Sample 2 is located near the weak-moderate-strong transition (its single indices are graded as two strong, one moderate and three weak), which can hardly be captured by the conventional 0/1 assignment. Similarly, Sample 4 exhibits close certainties toward the weak (0.286) and strong (0.216) grades. Such borderline characteristics precisely demonstrate the advantage of the cloud model in describing the uncertainty caused by rock mass heterogeneity. Meanwhile, the Monte Carlo intervals are relatively narrow for the strong certainty of Samples 1, 3 and 5, whereas the weak certainty of Samples 2 and 4 shows wider intervals, quantitatively reflecting that the evaluation of the transitional samples is more sensitive to rock mass discreteness.

The cloud model coupled with game-theory combination weighting provides a more reliable multi-index evaluation for heterogeneous rock masses. Six evaluation indices reflecting energy storage, brittleness and in-situ stress characteristics were integrated, and rock mass heterogeneity was incorporated at the weighting, cloud-parameter and result levels.

#### 3.3.4. Regional rockburst risk assessment

The discrete evaluation results of individual samples arise from the prominent heterogeneity of deep rock masses. To obtain a regional risk assessment, the sample grades were statistically integrated:

$$S = \sum_k P_k C_k \quad (20)$$

The regional rockburst risk score was calculated by equation (20), where  $P_k$  is the proportion of samples classified as rockburst grade  $k$  (scores 1–4 for none, weak, moderate and strong) and  $C_k$  is the assigned score of grade  $k$ . Three of the five samples were strong and two weak, giving a regional score of 3.2 (moderate-to-strong risk zone).

To further quantify the heterogeneity of the deep rock mass at the site scale, the uniaxial compressive strengths of the 30 groups of rock specimens (Supplementary Table S1) exhibit a mean value of 94.45 MPa with a coefficient of variation of 0.18, confirming the pronounced strength discreteness of the heterogeneous rock mass. It is exactly this site-scale heterogeneity that necessitates the heterogeneity-corrected weighting and the Monte Carlo cloud evaluation adopted in this study. Such divergence in the evaluation results (three strong and two weak) fully reflects the significant control effect of rock mass heterogeneity on rockburst proneness.

## 4. Study on the pressure relief effect of borehole technology in roadways with moderate-to-strong rockburst proneness

Based on the rockburst proneness evaluation above, which showed that the ground stress index  $S$  and the tangential stress index  $T$  of all rock specimens far exceeded the critical value of strong rockburst risk, prominent stress concentration was identified in the surrounding rock. The outstandingly high stress parameters reveal that high geostress is the primary inducement for potential rockburst failure. To alleviate concentrated stress and reduce rockburst hazards, PFC2D numerical simulations and field industrial tests on borehole pressure relief technology were carried out.

### 4.1. PFC2D numerical simulation of pressure relief boreholes

#### 4.1.1. Model establishment and parameter calibration

A plane-strain PFC2D 6.0 model ( $2.3 \text{ m} \times 2.3 \text{ m}$ , 27,289 particles with radii 0.006–0.009 m) was established with a central borehole (boundary-to-center distance  $5.75D$  for the maximum diameter; Kirsch perturbation  $< 1\%$ ). Four servo walls applied 40 MPa hydrostatic confining pressure matching the deep in-situ stress. The parallel-bond model was adopted with elastic moduli of 20 GPa, stiffness ratio  $k_n/k_s = 2.5$ , tensile strength 25 MPa, cohesion 50 MPa and friction angle  $30^\circ$ . The established PFC2D models for the four borehole diameters are shown in Supplementary Fig. S7.

To reproduce rock heterogeneity, a Weibull random field (shape parameter  $W_k = 6.0$ , normalized to  $CV \approx 19.5\%$ ) was applied to the tensile strength and cohesion of each parallel bond, matching the mean  $CV$  of  $\sigma_t$  ( $\approx 18\%$ ) and  $E$  ( $\approx 21\%$ ) measured on the 30 specimens. A Mohr–Coulomb weakening criterion (tensile failure when  $\sigma > \sigma_t = 10.5 \text{ MPa}$ ; shear failure when  $\tau > c - \sigma \cdot \tan \varphi$ ,  $c = 15.8 \text{ MPa}$ ,  $\varphi = 53^\circ$ ) was applied to bonds in the disturbed zone ( $r < 0.9 \text{ m}$ ). Four borehole diameters (0.05, 0.10, 0.15 and 0.20 m) were excavated and compared with a no-hole baseline.

#### 4.1.2. Stress field and plastic-zone distribution

After excavation, the four diameters show distinct stress redistribution. The 0.05 m hole retains a high wall stress of 14.75 MPa (baseline 21.04 MPa), with a stress-release coefficient  $\eta_s$  of only 0.299, indicating insufficient relief. The 0.10 m hole reduces the wall stress to 2.39 MPa ( $\eta_s = 0.886$ ), with the high-stress region transferring deeper and forming a "shallow relief, deep bearing" stress arch. The 0.15 m and 0.20 m holes reduce the wall stress to 1.95 MPa and 0.74 MPa respectively ( $\eta_s = 0.907$  and  $0.965$ ), with the wall stress approaching zero, indicating over-relief and loss of bearing capacity (Figure 5).

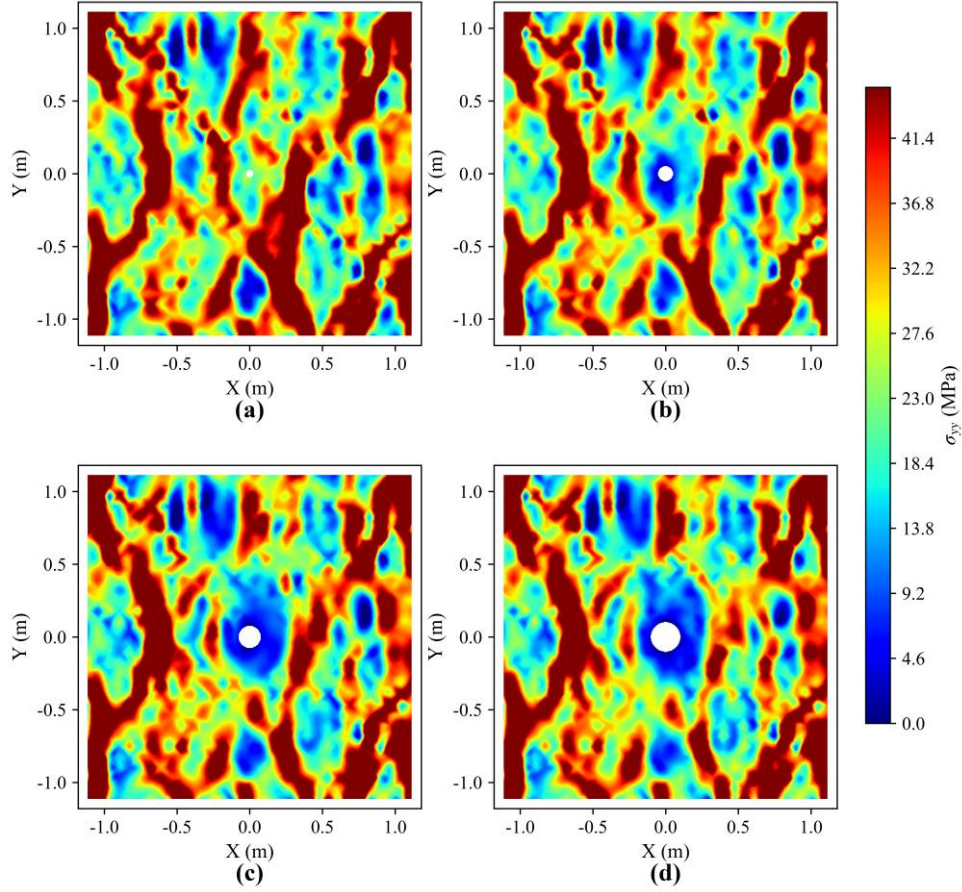


Figure 5 | PFC2D stress field ( $\sigma_{yy}$ ) distribution after excavation for the four borehole diameters: (a)  $D = 0.05$  m; (b)  $D = 0.10$  m; (c)  $D = 0.15$  m; (d)  $D = 0.20$  m.

The plastic-zone radius  $r_p$  is determined by an incremental-count method: cracks are counted in 0.10 m radial bands within the Mohr–Coulomb disturbed zone ( $r < 0.9$  m), baseline counts are subtracted, and  $r_p$  is the outer edge of the farthest band whose incremental count continuously exceeds 30 cracks/band. Connectivity between adjacent boreholes is defined by  $r_p \geq 0.5$  m (half the 1.0 m spacing). The results are: 0.05 m  $r_p = 0.20$  m (not connected); 0.10 m  $r_p = 0.50$  m (critically connected, exactly half the spacing); 0.15 m  $r_p = 0.60$  m (connected); 0.20 m  $r_p = 1.00$  m (extensively connected, approaching the model boundary). Tensile cracks dominate ( $\sim 95\%$ ), with shear cracks concentrated on both sides of the hole wall (Supplementary Fig. S8).

#### 4.1.3. Pressure relief and surrounding-rock stability efficiency index (PRSEI)

The Pressure Relief and Surrounding-rock Stability Efficiency Index (PRSEI) quantifies the trade-off between stress relief and rock-mass integrity:  $PRSEI = \eta_s \cdot (1 - D_n)$ , where  $\eta_s = (\sigma_0 - \sigma_w)/\sigma_0$  is the stress-release coefficient ( $\sigma_0 = 21.04$  MPa far-field wall stress,  $\sigma_w$  post-excavation wall stress) and  $D_n = (N_c - N_{c,0})/(N_{c,max} - N_{c,0})$  the normalized damage degree ( $N_{c,0} = 5,933$  baseline cracks).

The calculated PRSEI values are 0.283 (0.05 m), 0.466 (0.10 m), 0.173 (0.15 m) and 0.000 (0.20 m), exhibiting a clear unimodal distribution (Figure 6). With the hole diameter increasing,  $\eta_s$  continues to rise (0.886 for 0.10 m, 0.907 and 0.965 for 0.15 m and 0.20 m), whereas  $D_n$  increases even more sharply (0.475, 0.809 and 1.000), causing PRSEI to decline after the peak; the 0.10 m hole therefore attains the maximum PRSEI where stress release is sufficient and damage remains moderate. This unimodal behavior quantitatively captures the trade-off between insufficient relief at small diameters and rock-mass failure at large diameters, providing a computable criterion for borehole optimization.

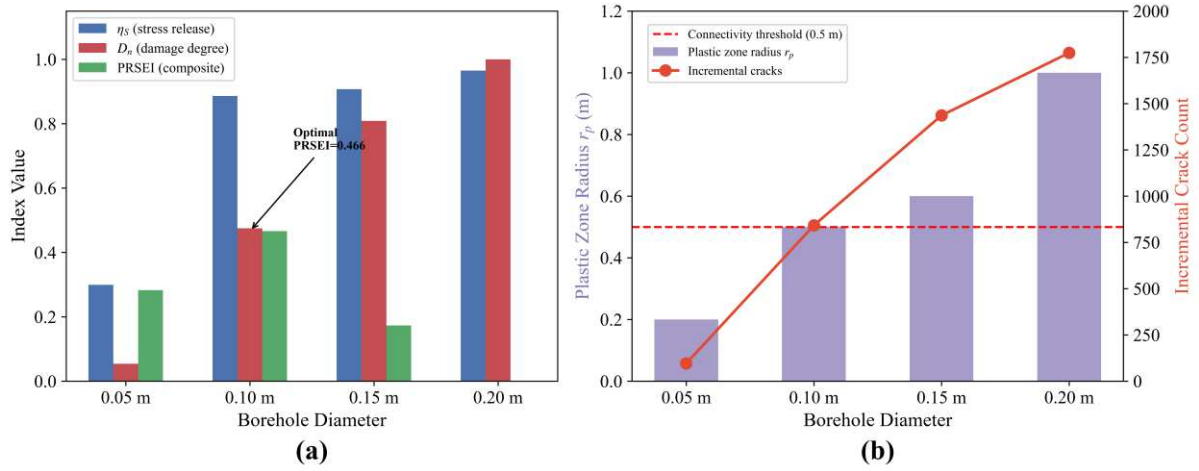


Figure 6 | Comprehensive comparison of the pressure-relief efficiency indices for the four borehole diameters: (a)  $\eta_s$ ,  $D_n$  and PRSEI; (b) plastic-zone radius and incremental crack count.

#### 4.1.4. Borehole optimization and field verification

Combining the stress field, plastic-zone and PRSEI analyses above, the 0.10 m diameter was identified as the optimum: its plastic-zone radius of 0.50 m reaches exactly half the borehole spacing, so that adjacent relief zones are critically connected without compromising rock integrity, and its incremental damage is moderate (+842 cracks, only 47% of that of the 0.20 m hole). This conclusion is fully consistent with the 0.10 m borehole diameter (1.0 m  $\times$  1.0 m spacing) adopted in the field, verifying the rationality of the field scheme.

The PFC2D simulations reveal a clear gradient in the pressure relief effect with increasing borehole diameter: the 0.05 m borehole provides insufficient relief with a non-connected plastic zone, the 0.10 m borehole achieves critical plastic-zone connectivity with moderate damage, and the 0.15 m and 0.20 m boreholes cause extensive connectivity and over-relief. Based on the proposed PRSEI ( $PRSEI = \eta_s \cdot (1 - D_n)$ ), the 0.10 m borehole attains the maximum value of 0.466 and is identified as the optimal scheme.

#### 4.2. Field industrial test and effect analysis

Based on the simulation results and drilling capacity, 100 mm diameter boreholes with 1 m  $\times$  1 m spacing were adopted in the test roadway. Vibrating wire stress meters were pre-installed on five resin anchor bolts, and the axial force was recorded before and after pressure relief drilling. The drilling construction site and borehole layout are shown in Supplementary Fig. S9, and the resin bolts equipped with vibrating wire dynamometers are shown in Supplementary Fig. S10.

After completing all pressure relief boreholes, the axial force of five resin anchor bolts was monitored continuously for 7 consecutive days, and the statistical monitoring data are listed in Table 2. The measured results show that the axial force of each anchor bolt decreased monotonically and gradually over time, with the daily decrement diminishing day by day. On the 7th day after the pressure relief construction, the axial force of all anchor bolts remained at 83.23%–86.97% of the value measured before drilling, without any rebound. The time-varying curves of the anchor bolt axial force are drawn in Supplementary Fig. S11.

Table 2 | The change of bolt axial force before and after pressure relief

| Time                        | Axial force of resin bolt/kN |      |      |      |      |
|-----------------------------|------------------------------|------|------|------|------|
|                             | 1                            | 2    | 3    | 4    | 5    |
| Before pressure relief      | 7.32                         | 8.91 | 5.67 | 9.24 | 6.83 |
| 1 day after pressure relief | 7.09                         | 8.64 | 5.5  | 8.96 | 6.62 |
| 2 day after pressure relief | 6.89                         | 8.40 | 5.35 | 8.71 | 6.43 |
| 3 day after pressure relief | 6.72                         | 8.19 | 5.22 | 8.49 | 6.27 |
| 4 day after pressure relief | 6.57                         | 8.01 | 5.10 | 8.30 | 6.13 |
| 5 day after pressure relief | 6.43                         | 7.84 | 4.99 | 8.12 | 6.00 |
| 6 day after pressure relief | 6.31                         | 7.69 | 4.9  | 7.97 | 5.89 |

|                                |        |        |        |        |        |
|--------------------------------|--------|--------|--------|--------|--------|
| 7 day after pressure relief    | 6.22   | 7.47   | 4.88   | 7.69   | 5.94   |
| After / before pressure relief | 84.97% | 83.84% | 86.07% | 83.23% | 86.97% |

It should be noted that the 7-day cumulative reduction of the bolt axial force (13%–17%) is considerably smaller than the wall-stress drop predicted by the numerical model ( $\eta_s = 0.886$  for the 0.10 m hole). This difference is physically reasonable for the following reasons: first, the bolt–rock composite system has a high overall stiffness, and the bolt axial force responds to the strain (deformation) of the surrounding rock rather than directly to the local stress; second, the stress release first reshapes the displacement field around the boreholes, whereas the monitored bolts are installed in the rock between boreholes at a certain distance from the hole wall; third, the 7-day monitoring window is short and the decay is still ongoing with a gradually decelerating rate. Nevertheless, the sustained, monotonic decline without rebound corroborates the stress-transfer trend induced by borehole pressure relief. The excavation of relief holes creates deformation space for deep surrounding rock masses and releases a considerable part of the elastic strain energy accumulated under high geostress, which mitigates the severe stress concentration reflected by the ground stress index  $S$  and the tangential stress index  $T$  in Chapter 3 and weakens the potential rockburst hazard of the roadway surrounding rock.

The field monitoring data show a sustained and monotonic decline of the anchor bolt axial force without rebound after borehole pressure relief, corroborating the numerically simulated stress-transfer trend obtained from the PFC2D analysis. Borehole pressure relief is therefore confirmed as an effective disaster prevention method for roadways with moderate-to-strong rockburst proneness in deep heterogeneous metal mines, and the recommended 0.10 m borehole diameter is verified in the field application.

## 5. Conclusions

This study systematically investigated rockburst proneness assessment and borehole pressure relief technology for deep heterogeneous rock masses through theoretical derivation, laboratory tests, numerical simulation and field monitoring. The major conclusions are as follows:

(1) A physically constrained power-law strength prediction model based on the dynamic stiffness index  $\rho v_p^2$  was established by revealing the internal correlation between the dynamic elastic modulus and rock stiffness. Calibrated on 30 heterogeneous specimens from the Sanshandao mining area, the model achieved  $R^2 = 0.958$  (RMSE = 3.41 MPa, MAE = 2.62 MPa), and leave-one-out cross-validation confirmed its generalization ability ( $R^2 = 0.951$ ). The model provides a reliable non-destructive approach for individually determining the peak load of loading-unloading tests on heterogeneous rock samples.

(2) Based on the predicted strengths, a series of loading-unloading tests was completed, and six evaluation indices reflecting energy storage, brittleness and in-situ stress characteristics were calculated. A normal cloud model coupled with game-theory combination weighting was established, incorporating rock mass heterogeneity at the weighting, cloud-parameter and result levels. The regional rockburst risk score of the Sanshandao deep rock mass was 3.2, corresponding to a moderate-to-strong rockburst proneness zone.

(3) PFC2D numerical simulations with a Weibull random strength field calibrated against the heterogeneity characteristics of 30 rock specimens were performed for boreholes with four diameters (0.05, 0.10, 0.15 and 0.20 m). The 0.10 m borehole was identified as the optimum, achieving the maximum PRSEI of 0.466 with a plastic-zone radius of 0.50 m (critically connected, exactly half the borehole spacing), which balances stress relief and rock-mass integrity.

(4) Field industrial tests verified the optimized scheme: 100 mm diameter relief boreholes (1.0 m  $\times$  1.0 m spacing) were installed, and the axial forces of five resin anchor bolts decreased monotonically to 83.23%–86.97% of the pre-drilling values within 7 days without rebound. Borehole pressure relief is therefore confirmed as an effective disaster prevention measure for roadways with moderate-to-strong rockburst proneness in deep heterogeneous metal mines.

Several limitations should be acknowledged. The strength prediction model and the evaluation framework were calibrated on specimens and in-situ stress data from a single mining area, and their generalization to other deep heterogeneous rock masses requires further validation. The plane-strain PFC2D model simplifies the three-dimensional stress state, and the Weibull random field only approximates the actual meso-scale heterogeneity. In addition, the field monitoring period of seven days may not fully capture the long-term pressure

relief effect, and longer-term monitoring of bolt axial force and borehole deformation is recommended in future work. Nevertheless, the proposed framework provides a quantitative basis for rockburst evaluation and pressure-relief optimization in deep heterogeneous rock masses, and the field-verified 0.10 m borehole scheme offers practical guidance for similar deep metal mines.

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#### **Additional Information**

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