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Design of Cut-Out Distance for Underground Coal Gallery Using Time-Dependent Constitutive Model

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Abstract

The stability of underground coal galleries is critically influenced by time-dependent deformation behavior of surrounding rock masses, particularly in deep mining environments where long-term stress redistribution can lead to delayed failure. In continuous miner-based mining systems, determining an appropriate cut-out distance is essential to ensure productivity and safety, especially for weak rock mass. This study proposes a novel numerical–statistical framework for the optimal design of cut-out distance (COD) in room-and-pillar coal mining using continuous miners. A time-dependent viscoelastic-viscoplastic constitutive model was implemented in FLAC3D to simulate roof deformation across varying geo-mining conditions, including gallery widths (5 & 6 m), depths (100 to 400 m), and COD values (4 to 12 m). The Coal Roof Index (CRI), a composite geotechnical classification parameter, was incorporated to evaluate roof integrity. Results from the numerical simulations were used to develop two empirical models, COD_1 for depths ≤ 200 m and COD_2 for depths > 200 m, via multivariate nonlinear regression. The models demonstrated high predictive accuracy, with R^2 values of 0.95 and 0.90, respectively. The results reveal a strong correlation between the cut-out distance and various influencing parameters, i.e., width, depth, and CRI classification. Statistical validation through t-tests and ANOVA confirms the significance and reliability of the proposed model. Both proposed models have been validated by two field cases of the Indian coal mine. Critical CRI thresholds were quantified for safe CODs, offering actionable insights for field implementation. The proposed design approach provides a robust framework for improving the safety and sustainability of underground coal mine development, particularly under weak roof conditions.

1. Introduction

Room-and-pillar mining continues to be a predominant method of coal extraction in India, with approximately 160 active mines contributing around 35 million tonnes of coal annually. However, the depletion of shallow coal seams, compounded by environmental challenges and difficulties in land acquisition, is gradually limiting the feasibility of surface mining. Consequently, a strategic shift toward underground mining is anticipated in the coming decade.[1] Among underground mining methods, room-and-pillar extraction faces a critical challenge: roof stability. Weak and stratified roof strata often lead to roof collapses in development headings, significantly compromising both safety and operational efficiency.

In mechanized room-and-pillar operations employing continuous miners (CM), determining the optimal cut-out distance (COD), the maximum horizontal advance before installing roof support, is a key design consideration. An overly extended cut-out increases the risk of roof falls, whereas conservative distances may hinder productivity. [2] Literature emphasizes that COD is a pivotal factor for safe and efficient coal production using CM. It directly influences the production cycle, with higher CODs typically resulting in increased coal output. Parameters such as gallery width, mining

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depth, and the mechanical properties of roof rocks are critical in determining suitable COD values.[3], [4].

The Coal Roof Index (CRI), which classifies the quality of the immediate roof rock, provides a practical basis for stratifying roof stability risks.[5] By leveraging numerical modeling tools, particularly FEM, engineers can simulate stress distribution and failure zones to optimize cut-out distance for varying CRI classes. With advances in data analytics, researchers have developed predictive models using machine learning and statistical regression. [6], [7], [8], [9], [10] explored artificial neural networks (ANN), multivariate adaptive regression splines (MARS), and fuzzy inference systems to predict parameters such as the height of the destressed zone (HDZ) and stress concentration factors (SCF). These models, although accurate, are often black-box in nature and not easily interpretable by practitioners.

Multivariate nonlinear regression (MNLR), as used in this study, offers an interpretable, parametric framework for prediction. Its application in COD design is novel, especially when linked with physically meaningful parameters like CRI, depth, and gallery width. The regression models developed in this study demonstrate high predictive accuracy ($R^2 > 0.90$), bridging the gap between numerical modeling and practical field application. A predictive COD model has been developed considering various geometrical characteristics and geo-mining conditions.

A comprehensive parametric investigation was conducted, considering gallery widths of 5.0 m and 6.0 m, five depth levels ranging from 100 m to 500 m, and COD values of 4, 6, 8, 10, and 12 m. The time-dependent elastic-plastic-strain softening constitutive model (TDEPSSCM) was employed to simulate roof deformation across various scenarios. Numerical simulation results for each parameter combination were used to perform multivariate regression analysis, culminating in a predictive COD model. Additionally, critical CRI thresholds were identified to safely permit extended CODs of up to 12 m or more. The developed model provides a valuable tool for field engineers and mining practitioners, facilitating safer and more productive room-and-pillar mining operations using continuous miners. Ultimately, this study contributes to the advancement of geotechnical design in underground coal mining, particularly in optimizing extended cut strategies based on robust analytical and empirical foundations.

2. Cut-out distance (COD)

There is no appropriate study traced that has demonstrated an empirical relationship between COD and affecting variables such as rock quantity parameters, gallery width, and depth of working. An effort has been made in this study to develop a model that would aid in predicting COD for the safe extraction of coal by CM. Alternatively, by setting the threshold limit of the CRI value when driving the roads in coal seams, the model can be used to assess the safe COD of a CM-deployed mine. To maximize a CM face's production capacity and make effective use of the CM, this study is beneficial to mine planners, operators, and working mining professionals. Additionally, it would optimize the support needed when driving the roads in underground coal mines [11].

To develop the empirical relationship between COD and influencing parameters, the elastoplastic material has been considered in this study. FLAC3D (Fast Lagrangian Analysis of Continua in 3D) was employed to simulate roof behavior under varying geo-mining conditions. [12] The input parameters for the parametric study were calibrated to reflect actual field conditions, ensuring model reliability. Based on the outcomes of the numerical simulations, a predictive model for estimating critical roof deformation (COD) corresponding to specific roof strata was developed using multivariate non-linear regression (MNLR). [3] Statistical analysis has been used to validate the predictive model. The safe COD of the CM whenever driving gallery in coal seams can be assessed by employing this model.

3. Coal Roof Index

Sonu & Jaiswal, (2024) [5] Introduced a geotechnical classification system specifically designed for underground coal mines, which incorporates stand-up time as a key factor. The system evaluates five critical parameters: structural features, weathering characteristics, thickness of roof layers, groundwater conditions, and the uniaxial compressive strength (UCS) of the roof rock. These parameters are assigned ratings, and their product forms the basis of the Coal Roof Index (CRI) classification.

The CRI values range from 0.001 to 1000. The overall CRI is obtained by multiplying the individual parameter ratings.

$$\mathrm{CRI} = \left(\frac{R_{CRI\_1}}{R_{CRI\_2}}\right) \mathrm{X} \left(\frac{R_{CRI\_3}}{RCRI\_4}\right) \mathrm{X}\ R_{CRI\_5} \qquad (1)$$

The ratings assigned to layer thickness, structural features, weatherability, groundwater conditions, and the UCS of the roof strata are denoted as R_{CRI_1}, R_{CRI_2}, R_{CRI_3}, R_{CRI_4}, and R_{CRI_5}, respectively. Table 1 summarizes the statistical analysis of the dataset, which was completed for each of the classes based on the stand-up time and CRI value.

Table 1. Classification of coal roof rock based on CRI values and stand-up time. (modified from [5])

Coal roof description	CRI Value	Stand-up time (days)	
		Average	Standard deviation
Extremely weak	0.001-0.1	0-1	-
Very weak	0.1-2.5	5	7.4
Weak	2.5-7.5	30	21.47
Fair	7.5-25	323	363.5
Strong	25-75	1093	563.7
Very strong	75-400	1278	751.8
Extremely Strong	400-1000	>1825	-

4. Numerical Modelling

In recent years, numerical simulation techniques have become the primary study methods in geotechnical engineering for dealing with complex geo-mining conditions. FDM-based numerical simulation techniques are used to study time-dependent strength deterioration and predict the stand-up time of a gallery.

Numerical methods play a crucial role in modern geotechnical engineering by providing powerful tools for analyzing rock mass stability, optimizing designs, and ensuring safety. Numerical methods often come with powerful visualization tools that allow engineers to visualize stress distributions, displacement fields, failure mechanisms, and other important parameters. This aids in interpreting results and gaining insights into the behaviour of the rock mass. With proper calibration and validation, numerical methods can provide accurate predictions of rock mass behaviour. They can capture nonlinear and time-dependent effects that may be challenging to analyze using analytical methods.

4.1 Model Setup

A three-dimensional coal gallery model is prepared, as shown in Figure 1. There are three basic layers present: roof, coal seam (pillar), and floor. A typical case is demonstrated here. The gallery dimensions are as width 6 m, 30 m in length, and 3.6 m in height. The model was discretized with an element size of 0.4 m × 0.4 m × 0.6 m. During the preparation of the model, the galleries were assigned to different groups to null it to form a pillar. The finite difference method (FLAC3D) is used to simulate the possible combinations mentioned in Table 1. The floor and sides are considered elastic, whereas the roof is considered a time-dependent Hoek-Brown strain-softening material.

4.2 Material Properties and Applied Stress Conditions

Model parameters were selected based on existing literature and adjusted to cover a range of realistic possible behaviors. The model floor was considered an elastic floor, and the pillars and roof were considered viscoelastic-plastic material. [13], [14], [15] The used material properties are tabulated in Table 2.

Table 2. Input Material properties in the numerical model.

Rock mass properties	Young's modulus (Pa)	Poisson ratio	Density (kg/m³)	UCS (MPa)
Floor	5.0E+9	0.25	2.5E+3	20
Pillars	5.0E+9	0.25	2.5E+3	20
Roof	5.0E+9	0.25	2.5E+3	20

The model incorporates roller boundary conditions along the X and Y directions, while the base in the Z direction is completely fixed. A vertical load, calculated as the product of depth and 0.025 MPa, is applied to the top surface to simulate overburden pressure. The developed constitutive model is embedded within the simulation framework, with material parameters obtained through a back-analysis approach. Further sections provide a detailed explanation of the simulation workflow and the process used to calibrate the material properties. [16]

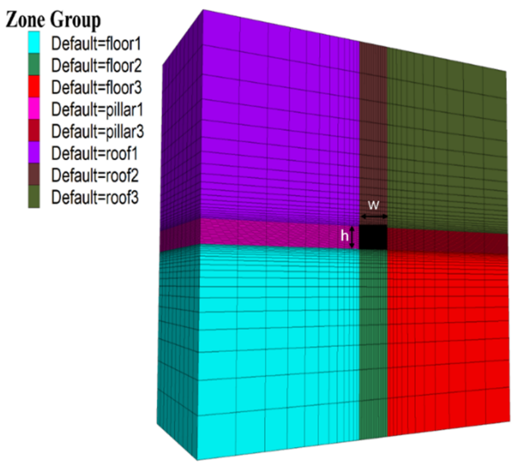

Figure 1. A three-dimensional numerical model for a gallery

Where 'w' represents gallery width and 'h' represents gallery height.

Several researchers have explored methods for properly initializing pre-mining stress under complex conditions. [17]. In this study, the vertical and horizontal in situ stresses, as well as the stress gradient with depth, were estimated using equations (2) and (3) provided by Sheorey (1986) [18]. This approach has been previously used by other studies with successful outcomes for Indian geo-mining conditions. [19], [20], [21], [22], [23]

$$\sigma_v = \gamma H \quad \text{(in MPa)} \tag{2}$$

$$\sigma_h = 2.4 + 0.01H \quad \text{(in MPa)} \tag{3}$$

In this context, σ_v represents the vertical stress, σ_h denotes the horizontal stress, γ is the unit weight of the rock, and H refers to the depth of the gallery. The rock's unit weight is 0.025 MPa/m.

4.3. Simulation Methodology

Generally, coal is cut by CM in a heading and then shifted to another face. The roof bolts are installed after a shift or sometimes after a day. So, there is a time lag between the cutting of coal and the installation of bolts. This time lag has been incorporated as 7 days in the time-dependent numerical model. Seven days has been considered an extra precautionary period due to moisture, humidity, chemical weathering, etc., influencing the rate of strength reduction. The various optimum CRI values are considered in this parametric simulation, including different gallery widths, depths, and COD values. In the simulation, CODs of 4, 6, 8, 10, and 12 meters were evaluated for gallery widths of 5 m and 6 m. Various gallery depths are also modelled as 100, 200, 300, 400 m. The optimum CRI values have been assessed for each combination of variable parameters. The critical CRI value has been proposed for the maximum safe extraction of the underground gallery. The proposed time-dependent constitutive model has simulated each combination.

The field observations indicate that additional support is necessary when vertical displacement reaches approximately 10 mm. According to Ghosh and Ghosh (1992) [24], the critical roof convergence for failure is typically between 12 and 24 mm. The lifespan of failed cases was evaluated by monitoring vertical displacement in the immediate roof, which was found to reach up to 20 mm.

The cutting sequences were designed to replicate the real-time operational procedures implemented within the mine. The first advancement cut was made for a 2 m length and supported with 4 bolts in a row to avoid the reflection effect. The bolts were installed 0.75 m away from both sides and with 1.5 m spacing in a row. The bolt properties used in the numerical model are tabulated in Table 3. Two rows of bolts supported and cut the next advancement as considered COD value, i.e., 4 m, 6 m, 8 m, 10 m, 12 m. The roof displacement has been analyzed for various permutations and combinations. The floor and sides of the gallery were considered elastic, and the roof was considered an elastoplastic material. For each combination, the optimum CRI values were assessed where vertical displacement reaches 20 mm.

Table 3. Bolt properties used in the numerical model

Roof bolt properties				Grout Properties	
Cross-sectional area, A (m^2)	Young's modulus, E (Pa)	Tensile yield strength (N)	Poisson Ratio	Bond stiffness, kbond (N/m/m)	Bond cohesive strength, sbond (N/m)
5×10^{-4}	1×10^{11}	2.25×10^{50}	0.25	1.75×10^{50}	5.12×10^{12}

4.4. Time-dependent constitutive model

Sonu (2024) [13] Proposed the peak strength parameter function in terms of CRI classification by considering 35 Indian coal mine cases. The peak strength parameter was proposed based on the best-fit curve of observed plastic strain and recorded standup time. Different combinations of strength parameters were simulated, and plastic strain values were calculated. A best-fit curve was generated based on the results of the back analysis. The proposed strength parameters equations (Eq. 4 and 5) can be written in the form of rock mass strength as follows:

$$m_{rm} = 1.633 \text{ x } \mathrm{CRI}^{0.1013} \quad (4)$$

$$s_{rm} = 0.0096 \text{ x } \mathrm{CRI}^{0.3507} \quad (5)$$

$$a = 0.5 \text{ to } 0.7 \qquad \text{(limit 0.5 to 1.0)} \quad (6)$$

Research findings consistently show that the strength of coal roof strata degrades over time, necessitating a time-sensitive constitutive model to accurately simulate stress-strain responses. In conventional strain-softening models, material strength typically diminishes as plastic strain accumulates. Some researchers [17], [21], [25], [26] Apply a linear decrease, while others [27], [28] an exponential pattern. To better represent this, the Hoek–Brown failure model was adapted to include time-dependent weakening. The Hoek-Brown constitutive model [29] was considered and modified to implement the time-dependent strain-softening behaviour. This Hoek-Brown constitutive model was widely used in underground excavation design, as expressed in equation 7.

$$\sigma_1 = \sigma_3 + \sigma_c \left(m \frac{\sigma_3}{\sigma_c} + s \right)^a \quad (7)$$

In this context, m, s, and a represent the strength parameters of the rock mass, while $\sigma1$ and $\sigma3$ are the maximum and minimum principal stresses, respectively. σc denotes the uniaxial compressive strength, and a is a constant. At peak strength, the rock mass strength parameters are represented by m_{rm} and s_{rm}.. Post-failure, the strength decreases exponentially, entering the residual phase [30], [31], [32] To capture this behavior, rock mass strength parameters decrease over time with plastic strain. At t = 0, equations 8, 9, and 10 are used to determine the peak strength parameters (m_{rm} and s_{rm}), while for t > 0, a non-linear exponential function (equations 9 and 10) is applied to compute the time-dependent strength parameters (m_{rmt} and s_{rmt}).

$$\beta = 0.986 \; X \; e^{-0.014 \; X \; t} \quad (8)$$

$$m_{rmt} = (0.2 + 0.8 \text{ x } \beta) \text{ x } m_{rm} \quad (9)$$

$$s_{rmt} = s_{rm}(1 + 0.046\beta)^{-1.1227} \quad (10)$$

Where 't' is the life of the gallery and 'β' is the constant that defines the strength reduction parameter. All external factors, such as humidity, moisture, chemical weathering, etc., affect the rate of strength deterioration over time.

5. Results and Discussions

This section presents the results of the numerical simulations and the subsequent statistical analyses performed to develop and validate a predictive model for cut-out distance (COD) in underground coal galleries. The analysis explores the relationship between critical geo-mechanical parameters, including gallery width, depth, and Coal Roof Index (CRI), and the roof deformation behavior, which directly influences the determination of a safe and productive COD. To investigate these relationships, a comprehensive parametric study was conducted using FLAC3D simulations. The numerical models incorporated a time-dependent viscoelastic-viscoplastic constitutive behavior for the coal roof strata, calibrated with field-observed deformation thresholds and geological parameters. The simulations evaluated the vertical displacement response for various combinations of gallery widths (5 m and 6 m), mining depths (100 to 400 m), and cut-out distances (4 to 12 m), across a range of CRI values. Table 4 presents the descriptive statistics of the optimal CRI values derived from the numerical modeling results.

5.1 Assessment of critical CRI for various cut-out distances

A multivariate nonlinear regression (MNLR) approach was applied to develop an empirical relationship between COD and the influencing parameters. The simulation results (Table 4) show a distinct increase in CRI requirement with increasing gallery depth and cut-out distance. Notably, at greater depths and larger COD values, the critical CRI value necessary to maintain safe roof conditions increases exponentially, indicating a nonlinear interaction between these parameters.

The results indicate that each independent variable is strongly correlated with the immediate roof's deformation. Consequently, an analysis is conducted to determine whether the combined effect of all three variables can effectively predict the COD of the roof during coal seam development using the continuous miner (CM).

Multivariate non-linear regression (MNLR), a statistical technique frequently employed in predictive modeling within mining engineering, has been utilized to develop an empirical model for estimating the safe cut-out distance (COD) under weak roof conditions during coal seam development using a continuous miner (CM). Numerical simulation results have been leveraged to identify and quantify the influence of key parameters, COD, Coal Roof Index (CRI), gallery width, and depth, by establishing best-fit relationships among them.

Table 4. Results of the parametric study for cut-out distance (COD).

Sr. No.	Width (m)	Depth (m)	COD (m)	CRI
1	5	100	4	0.68
2	5	100	6	1.02
3	5	100	8	1.63
4	5	100	10	1.94
5	5	100	12	2.1
6	5	200	4	2.74
7	5	200	6	4.45
8	5	200	8	6
9	5	200	10	6.9
10	5	200	12	7.5
11	5	300	4	10.8
12	5	300	6	16.9
13	5	300	8	21
14	5	300	10	23.2
15	5	300	12	24.3
16	5	400	4	30.7
17	5	400	6	51.8
18	5	400	8	65.3
19	5	400	10	67.6
20	5	400	12	71
21	6	100	4	0.73
22	6	100	6	1.12
23	6	100	8	1.78
24	6	100	10	2.13
25	6	100	12	2.38
26	6	200	4	3.04
27	6	200	6	5.1
28	6	200	8	7
29	6	200	10	7.5
30	6	200	12	8.85
31	6	300	4	12
32	6	300	6	21.3
33	6	300	8	28
34	6	300	10	29.7
35	6	300	12	32
36	6	400	4	37.75
37	6	400	6	58.4
38	6	400	8	87.1
39	6	400	10	89.8
40	6	400	12	95.2

The results indicate a consistent trend where the required CRI for maintaining roof stability increases nonlinearly with both depth and COD. This behavior underscores the critical role of time-dependent weakening mechanisms in weak roof conditions, particularly for extended cut lengths. Roof displacement reached or exceeded the critical threshold (20 mm) for specific CRI-dependent scenarios, signaling potential instability if supports are not adequately planned. Graphical representations (Figure 2) reinforce these observations, highlighting the varying CRI thresholds required to ensure stability across different depths. These findings are instrumental in defining safe operational limits for CM operations under diverse roof conditions.

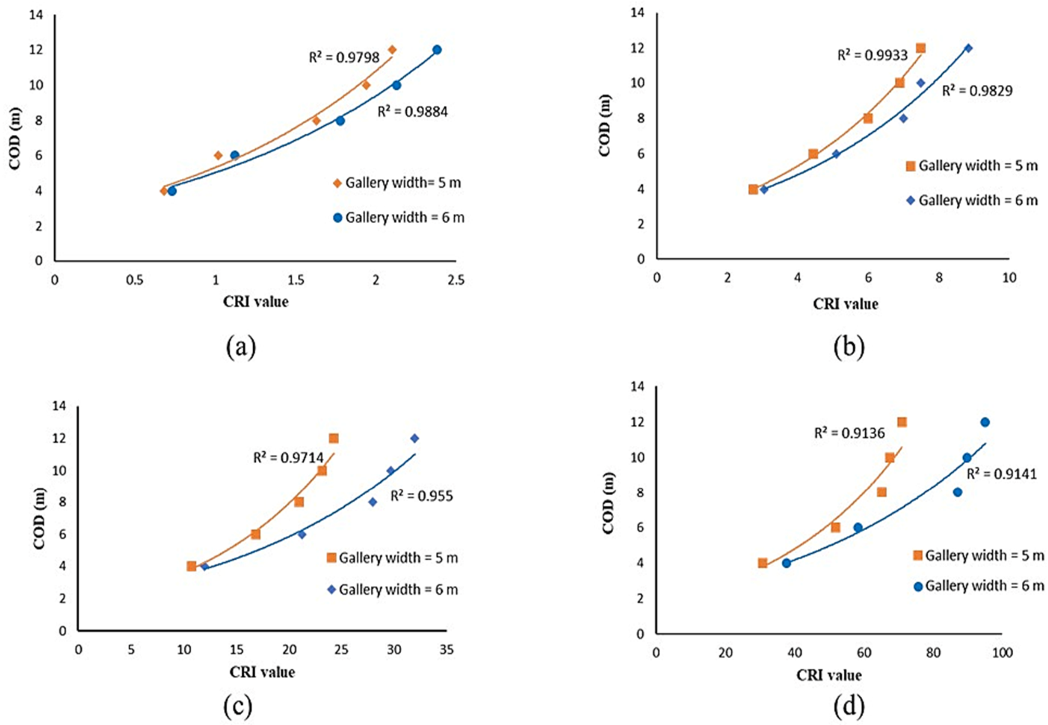

Figure 2. A graphical representation of the CRI value and cut-out distance for various depths of the gallery as: (a) 100 m, (b) 200 m, (c) 300 m, (d) 400 m

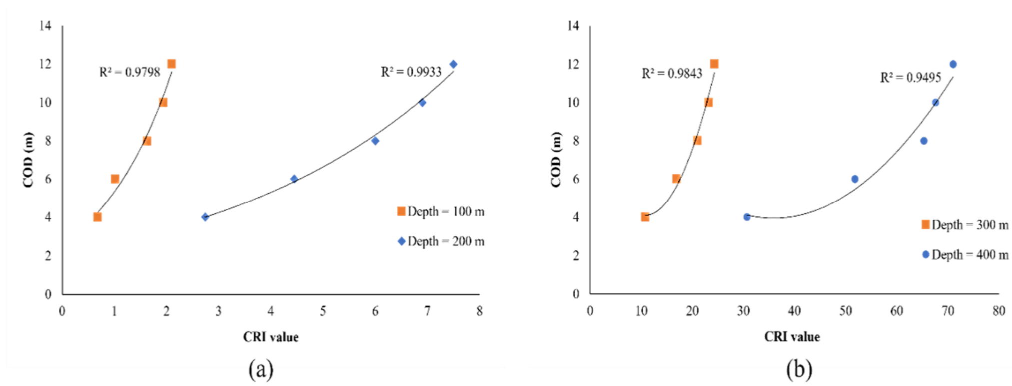

Figure 3. A graphical representation of the CRI value and cut-out distance for a 5 m gallery width.

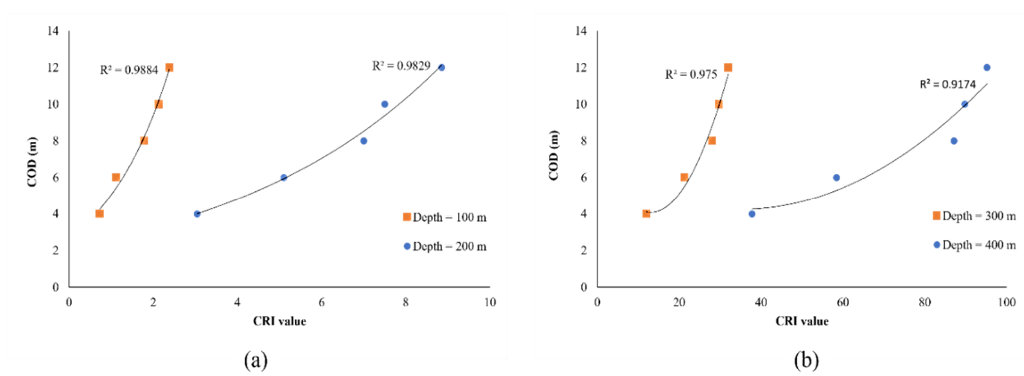

Figure 4. A graphical representation of the CRI value and cut-out distance for a 6 m gallery width.

A regression analysis was conducted to determine the empirical correlation between the dependent variable (COD) and the independent variables, including gallery width, depth, and the CRI of the immediate roof strata. As illustrated in Figures 2-4, each of these independent parameters exhibits a strong correlation with COD. Consequently, the combined influence of these variables was further examined to evaluate their predictive capability for determining safe COD during CM-based development. The results are consistent with the findings of [8] where machine learning models also identified overburden characteristics as key predictors of panel stability. Similarly, Zhang (2018) [33] showed that advanced optimization methods significantly improved design efficiency, which aligns with the improvements seen in our model performance through statistical tuning.

5.2. Development of the predictive model for cut-out distance (COD)

An empirical model for estimating the critical COD of the weak immediate roof during coal seam development using a continuous miner (CM) has been formulated through multivariate non-linear regression (MNLR), a statistical method extensively applied in predictive modeling within mining engineering. Numerical simulation data were employed to establish optimal functional relationships among key parameters influencing roof behavior, including the Coal Roof Index (CRI), gallery width, and depth. Regression analysis facilitated the derivation of a quantitative model linking the dependent variable, COD, to the independent variables—gallery width, depth, and CRI—providing a predictive framework for assessing roof stability under varying geotechnical conditions.

Figure 2-4 illustrates the COD plotted against all input parameters, including CRI, depth, and gallery width. The plot demonstrates the non-linear nature of the curves. The plots show a strong correlation with optimum COD. To quantify and generalize these observations, multivariate non-linear regression (MNLR) was employed to derive empirical expressions that relate CRI, gallery width, and depth to the maximum safe COD. These formulations were segregated into two models, one for shallow galleries (≤ 200 m depth) and another for deeper conditions (> 200 m depth), each demonstrating a strong correlation ($R^2 = 0.95$ and $R^2 = 0.90$, respectively) with observed simulation outcomes. To account for this non-linearity, a generalized non-linear multivariable model is developed by analyzing the variables and exponents in the input parameters as follows:

$$COD\__1 = a \text{ x } (CRI)^b (W)^c \, (H)^d \tag{11}$$

$$COD\__2 = p \text{ x } (CRI)^q (W)^r \, (H)^s \tag{12}$$

$COD\__1$ represents the cut-out distance up to 200 m depth, $COD\__2$ represents the cut-out distance for more than 200 m depth, CRI stands for the Coal Roof Index, W is the width of the galley in m, H is the gallery depth in meters, and a, b, c, d, p, q, r, and s are constants. The coefficients of the proposed model are estimated using multivariate regression techniques. Model accuracy is evaluated by comparing predicted outcomes with the corresponding observed data to assess the predictive reliability of the regression equation.

By solving the statistical analysis, the predictive model for the COD of the unsupported gallery is obtained as:

$$COD\__1 = e^{11.19} \text{ x } (CRI)^{0.94} \text{ x } (W)^{-0.57} \text{ x } (H)^{-1.85} \quad (R^2 = 0.95) \tag{11}$$

$$COD\__2 = e^{25.46} \text{ x } (CRI)^{1.12} \text{ x } (W)^{-1.44} \text{ x } (H)^{-4.27} \quad (R2 = 0.90) \tag{12}$$

The two proposed models facilitate the design of extended cuts under unsupported conditions in weak roof environments. Typically, the boom length of a continuous miner ranges from 12 to 14 meters, which corresponds to the maximum achievable cut length under strong roof conditions characterized by higher Coal Roof Index (CRI) values. However, the formulations presented herein are specifically developed to address scenarios involving weak roof strata, indicated by lower CRI values, where standard support systems may be inadequate.

5.3. Statistical validation of the proposed formulation

The validity of the developed model was assessed by analyzing the deviation between the observed and predicted values of COD. Figure 5 illustrates the relationship between the predicted cut-out distance (COD) and the actual COD values obtained from numerical simulations for gallery depths up to 200 meters, which corresponds to the application of the $COD\__1$ model. The scatter plot in the figure showcases a near-linear correlation, with data points clustering closely around the 45-degree reference line, indicating a high level of agreement between predicted and observed results. This alignment confirms the model's ability to accurately replicate the outcomes of complex, time-dependent deformation simulations under shallow mining conditions. The high coefficient of determination (R^2 = 0.95) further reinforces the predictive strength of the COD_1 model. It demonstrates that 95% of the variability in COD can be explained by the independent variables, Coal Roof Index (CRI), gallery width, and depth, used in the multivariate non-linear regression. The minimal deviation observed in a few data points reflects the natural variability in geological conditions but does not undermine the model's robustness. The strong linear trend displayed in this figure validates the model's suitability for field application in shallow-depth mining scenarios, where accurate COD estimation is essential for optimizing continuous miner productivity while maintaining roof stability. This figure serves as compelling evidence that the regression-based predictive approach can effectively substitute for computationally intensive numerical simulations, enabling faster and more accessible decision-making for mine planners and geotechnical engineers.

Figure 6 presents a comparative scatter plot of the predicted cut-out distances (COD) against the actual COD values obtained from numerical simulations for gallery depths exceeding 200 meters. This figure corresponds to the performance of the COD_2 model, which was specifically formulated for deeper mining conditions. The plotted points align closely along the ideal 1:1 line, indicating a strong agreement between predicted and observed values. The R^2 value of 0.90, derived from the regression line, underscores the model's high predictive accuracy in deeper strata where geo-mechanical behavior tends to be more complex due to increased overburden pressure and potential time-dependent deformation.

A direct comparison between the COD values derived from the numerical simulation approach (FLAC3D) and the COD value calculated using the Multivariate Non-Linear Regression (MNLR) model has been presented in Figure 7. This side-by-side analysis was conducted for both shallow (COD_1) and deep (COD_2) gallery conditions.

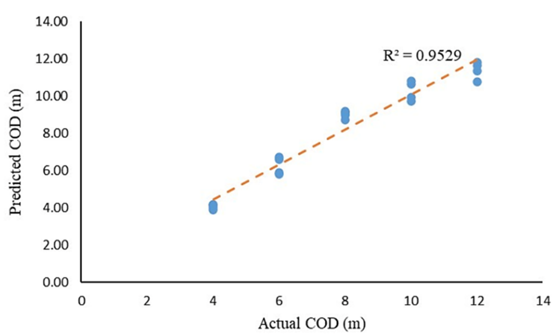

Figure 5. Predictive COD vs. actual COD for the continuous miner up to 200 m depth

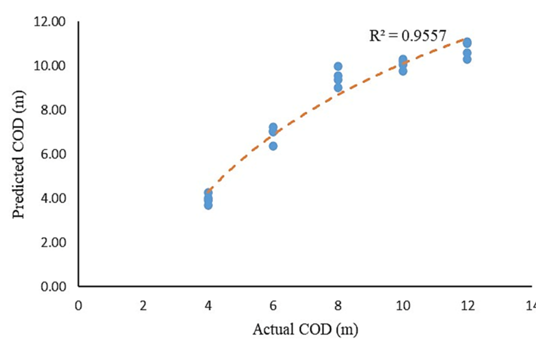

Figure 6. Predictive COD vs. actual COD for the continuous miner at depths greater than 200 m

Figure 7 illustrates that for nearly all combinations of input parameters (gallery width, depth, and CRI), the COD values estimated by the MNLR model closely match the results from the numerical simulations. This demonstrates the capability of the regression-based approach to effectively replicate the outcomes of complex, time-dependent numerical modeling with much simpler mathematical expressions.

The consistency across both models implies that the MNLR formulations can serve as reliable surrogates for detailed numerical simulations, offering a practical tool for field engineers to make quick, informed decisions without compromising on safety or accuracy. The close alignment of these values indicates that the model effectively captures the underlying relationships among the variables.

Figure 8 shows the residual distribution for the predictive models. Residuals are defined as the differences between the observed COD values (from FLAC3D simulations) and the predicted values (from the regression models). Analyzing residuals is critical to assess model validity and underlying assumptions such as linearity, homoscedasticity (constant variance), and normality. Extreme values can occasionally cause incorrect data interpretation, which can then result in incorrect conclusions. Therefore, a thorough analysis of the predicted values and residuals is conducted following the fitting of any regression equation. Finding the residuals can be used to validate the model.

A model is considered valid if the residuals have a constant variance and are normally distributed with a zero mean. [34]. Figure 8 shows a histogram of the residuals for the COD model in the development galleries. It can be seen that the residuals follow a normal distribution, with a constant variance and a mean of zero.

5.4. Statistical Analysis

The T-test and ANOVA (analysis of variance) were the statistical tools used to validate the developed COD model. The T-test and ANOVA provide a strong statistical foundation to evaluate the reliability and accuracy of the developed COD model. These tests help determine whether the differences in predicted versus actual results are statistically significant, ensuring that the model's predictions are not due to random variation. A low p-value (typically < 0.05) from these tests would indicate that the model's predictions are statistically aligned with empirical data.

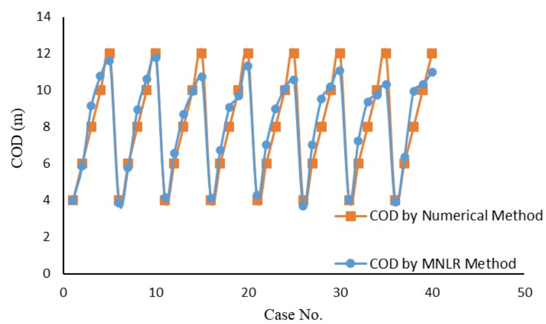

Figure 7. Comparison of the COD by the numerical method and the COD by the MNLR method

5.4.1. The 't' test

When comparing the difference between two means regarding the variation in the data, the t-test is typically employed. The significance of the R values is also ascertained using the t-test. If the variables have a normal distribution that forms a bell-shaped distribution and the observations are collected randomly, the R values are considered significant. If the P value, or the percentage level of significance, is less than 0.05, the data is considered statistically significant. When the CRI was tested using the t-test, it was discovered that each case's P-level, gallery width, and depth concerning COD were all less than 0.05, as shown in Tables 5 and 6. Therefore, it can be concluded that the data for each of the three parameters exhibits statistical significance.

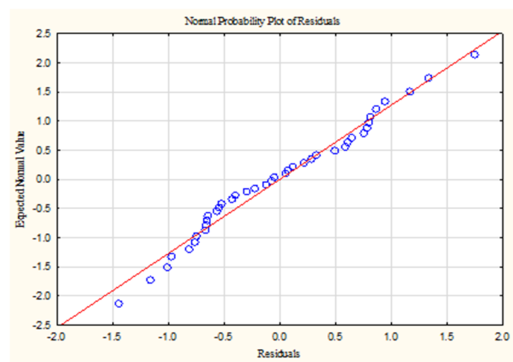

Figure 8. Residual plots for predicted COD and observed COD

Table 5. The t-test for the CRI-based $COD_{\_1}$ model

Parameter	t value	P level
COD vs CRI	22.2620	0.000000
COD vs width	-3.0421	0.007765
COD vs depth	-19.1383	0.000000

Table 6. The t-test for the CRI-based $COD_{\_2}$ model

Parameter	t value	P level
COD vs CRI	13.5273	0.000000
COD vs width	-4.5158	0.000352
COD vs depth	-11.5773	0.000000

5.4.2. ANOVA analysis

A statistical method for evaluating variables with two or more categories is ANOVA. Typically, it is employed to evaluate the possible variation in a dependent variable at the scale level via a nominal-level variable. The ANOVA method, commonly known as Fisher analysis, was created in 1918 by Ronald Fisher. By using this method, the limitations of the t and z tests, which only allow the nominal level variable to have two categories, are eliminated. Since there were 20 cases and three input parameters were used for the $COD_{\_1}$ model, the degree of freedom was 3. For F (3, 16), 0.005 should be the statistically significant value at a 5% significance level, and the R^2 value obtained is 0.95, which shows a strong correlation. At a 5% significance level, the observed value of F (3, 16) was 165.19, as shown in Table 7. As stated by Cardinal (2006) [35] the observed value ought to exceed the critical value. Thus, statistical significance was determined based on ANOVA analysis of the data.

Table 7. ANOVA test for proposed COD_1 formulation.

Parameter	Sum of squares	Df	Mean square	F value	P value	R^2 value
Regression	2.916239	3	0.972080	165.1982	0.000000	0.95
Residual	0.094149	16	0.005884			
Total	3.010388					

Since there were 20 cases and three input parameters were used for the COD_2 model, the degree of freedom was 3. For F (3, 16), 0.015 should be the statistically significant value at a 5% significance level, and the R^2 value obtained is 0.90, which shows a strong correlation. At a 5% significance level, the observed value of F (3, 16) was 60.99, as shown in Table 8. As stated by Cardinal (2006) [35], the observed value ought to exceed the critical value. Thus, statistical significance was determined based on ANOVA analysis of the data.

Table 8. ANOVA test for proposed COD_2 formulation.

Parameter	Sum of squares	Df	Mean square	F value	P value	R^2 value
Regression	2.768331	3	0.922777	60.99568	0.000000	0.90
Residual	0.242057	16	0.015129			
Total	3.010388					

6. Validation From Field Cases:

As per the author's knowledge, very limited research has been conducted on the optimum estimation of cut-out distance for underground coal mines. Mandal (2018) [3]the study suggests the optimum cut-out distances (COD) for the Sheetaldhara-Kurja mine and Shanthikhani underground coal mines, considering field-measured convergence data. The study utilized a combination of elasto-plastic numerical modeling and multivariate nonlinear regression to develop a predictive model of roof convergence as a function of key parameters—gallery width, rock mass rating (RMR), and COD. The model was validated using monitoring data from several mines, including Sheetaldhara-Kurja and Shanthikhani, confirming the safe implementation of 12 m and 6 m CODs, respectively, under their site-specific geotechnical conditions. The detailed geo-mining parameters of this case study have been tabulated in Table 9. The safe COD for both cases has been calculated by the proposed models. The current study also suggests the optimum COD is 6.44 m for the Shantikhani mine and 11.99 m for the Sheetaldhara Kurja mine, which is very close to the earlier proposed safe COD by Mandal et al. (2018). These field cases support the reliability of the predictive COD model for designing site-specific continuous miner-based room-and-pillar mining operations.

Table 9. Geo-mining parameters of two Indian coal mines [3]

Name of Mine	Shantikhani Mine	Sheetaldhara Kurja Mine
Seam thickness	5.0 - 8.7 m	1.8 - 2.5m
Nature of the immediate roof	Coal	Shale and sandstone
Working height	3.4	2.5
Width	4.5	4.8
Depth	240	150
Actual COD	6	12
CRI	5.81	4.68
Predicted COD	6.44	11.99

6. Conclusions

This study introduces a novel framework for the quantitative design of cut-out distances (COD) in underground coal galleries by incorporating a time-dependent elastic-plastic-strain softening constitutive model (TDEPSSCM) into a three-dimensional numerical simulation tool (FLAC3D). The cut-out distance (COD) is a critical parameter for optimal and safe production from Room and Pillar extraction using mechanized methods, such as Continuous Miners (CM) operations. The major influencing parameters of COD include rock characteristics, gallery width, and working depth. A comprehensive parametric investigation was conducted across varying gallery widths (5 m and 6 m), depths (100–400 m), and cut-out distances (4–12 m). The simulation results were used to develop two predictive models, COD_1 for shallow workings (≤ 200 m) and COD_2 for deeper workings (> 200 m), through multivariate non-linear regression (MNLR). Both models exhibited strong predictive performance, with coefficients of determination (R^2) of 0.95 and 0.90, respectively, confirming the models' robustness.

Importantly, the study quantifies critical Coal Roof Index (CRI) thresholds required to ensure roof stability for specific COD scenarios. These thresholds provide explicit design guidance, enabling optimized advancement lengths while maintaining geo-mechanical safety. The statistical validation, including residual analysis, t-tests, and ANOVA analysis, demonstrates that the proposed models are statistically sound and generalizable across a range of geo-mining conditions. The proposed COD models have been validated by considering two Indian coal mines.

The proposed model has the ability to provide field engineers and mine planners with a reliable, computation-efficient decision-making tool. The predictive equations eliminate the need for iterative numerical modeling in routine operations, thus improving both productivity and safety in continuous miner-based room-and-pillar mining systems. Future research could extend this research to incorporate probabilistic risk assessment or appropriate support design strategies in various mining conditions.

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Competing Interests

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Appendix

"Coal Roof Rock Class Categorization for proposed *CRI* classification

"Based on stand-up times, the proposed CRI classification range has been divided into seven classes: extremely poor (less than one week), very poor (less than one month), poor [one to three months], fair [three to seven months], good [seven to twenty months or less than 1.5 years), and very good [> twenty months or less than 5 years), and extremely good (> five years). The extremely weak and extremely strong class coal roof rock are very rarely observed in the field. The selected data has not fallen in these two classes, so it is not shown in Figure The class system and the stand-up time range are displayed in Figure Black dotted lines represent the upper and lower bounds of the scattered data for each of the 44 cases, while dark orange lines represent the average value."

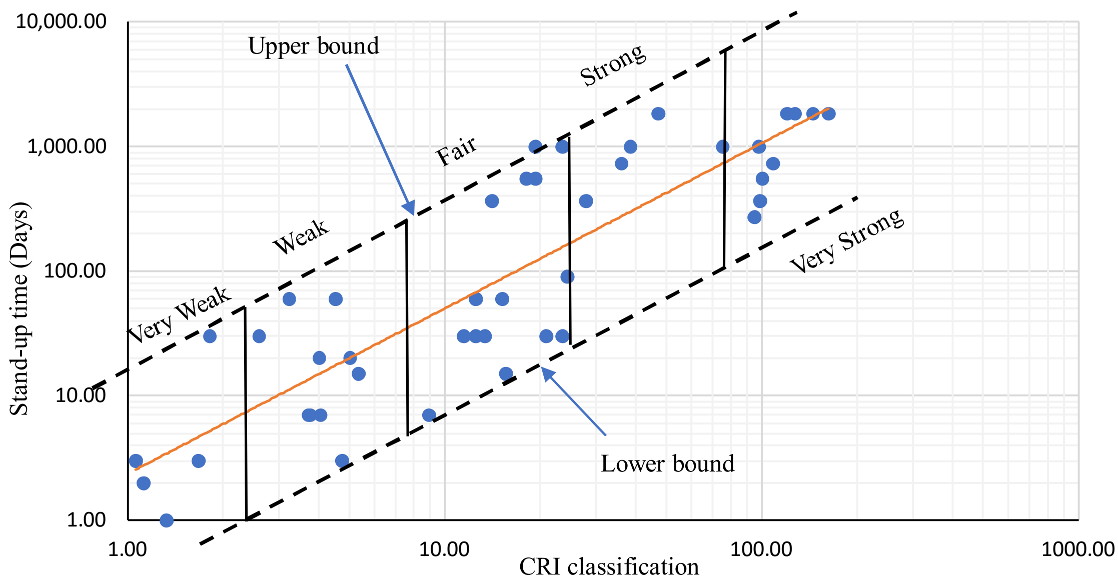

Figure A. CRI classification"

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طراحی فاصله برش برای گالری زغال‌سنگ زیرزمینی با استفاده از مدل ساختاری وابسته به زمان

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کلمات کلیدی

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چکیده

پایداری گالری‌های زغال‌سنگ زیرزمینی به شدت تحت تأثیر رفتار تغییر شکل وابسته به زمان توده‌های سنگ اطراف، به ویژه در محیط‌های معدنکاری عمیق که توزیع مجدد تنش طولانی‌مدت می‌تواند منجر به شکست تأخیری شود، قرار دارد. در سیستم‌های معدنکاری پیوسته مبتنی بر معدنچی، تعیین فاصله برش مناسب برای اطمینان از بهره‌وری و ایمنی، به ویژه برای توده سنگ ضعیف، ضروری است. این مطالعه یک چارچوب عددی-آماری جدید برای طراحی بهینه فاصله برش (COD) در معدنکاری زغال‌سنگ اتاق و ستون با استفاده از معدنچیان پیوسته ارائه می‌دهد. یک مدل ساختاری ویسکوالاستیک-ویسکوپلاستیک وابسته به زمان در FLAC3D برای شبیه‌سازی تغییر شکل سقف در شرایط مختلف معدنکاری زمین، از جمله عرض گالری (۵ و ۶ متر)، عمق (۱۰۰ تا ۴۰۰ متر) و مقادیر COD (۴ تا ۱۲ متر) پیاده‌سازی شد. شاخص سقف زغال‌سنگ (CRI)، یک پارامتر طبقه‌بندی ژئوتکنیکی مرکب، برای ارزیابی یکپارچگی سقف گنجانده شد. نتایج حاصل از شبیه‌سازی‌های عددی برای توسعه دو مدل تجربی، COD1 برای عمق $\leq$ ۲۰۰ متر و COD2 برای عمق > ۲۰۰ متر، از طریق رگرسیون غیرخطی چند متغیره استفاده شد. این مدل‌ها دقت پیش‌بینی بالایی را با مقادیر R^2 به ترتیب ۰.۹۵ و ۰.۹۰ نشان دادند. نتایج، همبستگی قوی بین فاصله برش و پارامترهای مختلف تأثیرگذار، یعنی عرض، عمق و طبقه‌بندی CRI را نشان می‌دهد. اعتبارسنجی آماری از طریق آزمون‌های t و ANOVA، اهمیت و قابلیت اطمینان مدل پیشنهادی را تأیید می‌کند. هر دو مدل پیشنهادی توسط دو مورد میدانی از معدن زغال سنگ هند اعتبارسنجی شده‌اند. آستانه‌های بحرانی CRI برای CODهای ایمن تعیین شدند که بینش‌های عملی برای اجرای میدانی ارائه می‌دهد. رویکرد طراحی پیشنهادی، چارچوبی قوی برای بهبود ایمنی و پایداری توسعه معادن زغال سنگ زیرزمینی، به ویژه در شرایط سقف ضعیف، فراهم می‌کند.

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