Eng Int Syst (2023) 6: 483–494

Engineering
Intelligent Systems

Reverse Engineering Based on Point Cloud Recognition 3D Digital Analysis of Rock Fragmentation

Yang Yang [a] **and Laishan Chang** [b*]

School of Mining Engineering, University of Science and Technology Liaoning, AnShan 114000, LiaoNing, China

Blasting fragmentation in mines and mountains reduces rock handling and transportation overheads. With the development of cloud technologies and their application in mining, the reverse engineering paradigm is applied to identify the minor structure in the fragmentation process. The classification of the particle identification/structure is performed by deconstructing the actual blasting process. This article introduces a three-dimensional analysis using Reverse Engineering (3DA-RE) paradigm for identifying the overhead resulting from the blasting of rock during mining operations. By means of this analysis, the proposed method identifies the cost overloading factor in the blasting process. The fundamental features such as structure detection, fragmentation level, and cost handling, are analyzed in a 3D manner. The different dimensions are established using the cloud analytics of various previous mining actions.

Keywords: blasting fragmentation; cloud data analytics; knowledge learning; reverse engineering

1. INTRODUCTION

In mining, rock fragmentation is a process whereby rock is blasted using explosives. Rock fragmentation by means of blasting is one of the essential tasks to perform in mining as it loosens the rocks to be excavated, and improves the overall performance and efficiency of mining operations [1]. The main aim of the blasting process is to remove fragmented rocks present in the mining field. The blast-induced rock fragmentation require accurate location and calculation of explosives [2]. The rock fragmentation distribution (RFD) method is mainly used in mining. RFD establishes specific criteria before the explosion process [3]. The blasting operations, techniques, and steps of RFD were calculated to reduce the degree of damage caused by rock blasting in the mine. RFD also identifies parameters and variables to provide the best information for evaluation criteria [4]. Calculating the quantity of explosive required is a complicated task when blasting. RFD understands the relationship between rocks and explosives, which provides necessary data to calculate the overall quantity of explosives [5].

Cloud computing is very widely used for various functions and in different fields, and is very effective in mining operations and data analysis. Cloud computing is also used for rock blasting, reducing the level of false data analysis. Via data analysis, cloud computing identifies the necessary information required for rock fragmentation [6, 7]. The cloud-based fragmentation method is used in data analysis to detect fragmented data and produce data for another process [8]. Parameters, variables, patterns, and data scales are required for the blasting of rocks (fragmentation). A cloud-based

*Corresponding author: [a]Email: yangyang1aq@163.com, [b]Email: yangyang202209@126.com

method is used here for rock blasting, reducing the amount of time required for identification and computation [9]. The locally convex connected patches (LCCP) algorithm based on cloud is commonly used in data analysis for rock fragmentation. LCCP uses filtering techniques to detect fragments and solve optimization problems [10]. A convolutional neural network (CNN) algorithm using cloud computing is used for rock fragmentation by blasting. CNN achieves high accuracy in fragment detection that improves effectiveness and reliability of the data analysis [11].

Error mitigation is a process that reduces the error rate in operations, and is crucial when fragmenting rocks since the blasting process requires accurate information [12]. Error mitigation improves the overall performance and efficiency of rock fragmentation, and is achieved by means of the reverse engineering technique. First, reverse engineering determines the relationship among variables via reasoning methods that ascertain key factors and values [13]. Reverse engineering tools are primarily used in rock fragmentation to reduce error levels in mining and analysis systems [14]. Reverse engineering tools identify patterns and fragment parts that provide optimal data for blast-induced rock fragmentation. The reverse engineering technique detects fragmented rocks, improving error mitigation and accuracy. Models based on fragmentation maximize the performance and robustness of blasting operations [15, 16].

2. RELATED WORKS

Han et al. [17] introduced the combined finite-discrete element method (FDEM) for fragmentation using contour blasting. The main aim of the proposed method is to reduce the complexity level of blasting fragmentation. FDEM is used primarily in tunneling that has more in-situ stress. FDEM reduces fractures under tunnels that provide appropriate services to customers. The proposed FDEM improves overall rock heterogeneity, decreasing the fracture of rocks during tunneling.

Bamford et al. [18] proposed a deep learning approach for rock fragmentation analysis systems. A deep neural network (DNN) algorithm is used here to predict characteristics and functions for fragmentation. DNN reduces the time required for prediction, thereby improving the performance of the analysis system. The proposed DNN approach maximizes prediction and detection accuracy.

Gou et al. [19] developed a discrete element (DEM) model for particle fragmentation. DEM analyses the energy that is required to perform fragmentation. Particle size distribution (PSD) is identified here, providing the necessary information to DEM. The proposed model reduces friction levels among particles, maximizing the reliability of fragmentation.

Tao et al. [20] designed an integrated analytical modeling-based, blast-induced rock fragmentation method. The analytical model first identifies patterns and dimensions of rocks, thereby producing optimal data for fragmentation. Then it determines the behaviors of rocks before fragmentation. The proposed method reduces in the time required for identification and prediction. Compared with other methods, their proposed method achieves high performance and effectiveness in terms of rock fragmentation.

Ozer et al. [21] proposed an analytical-based blasting approach for bored pile excavation. Airy stress function to predict the exact stress level of rock at rest. Airy stress functions are used here to predict rocks' exact stress levels during recessThe diameter of holes, pressure, and strength of rocks are required to calculate the amount of explosives required for blasting. This approach improves the efficiency and performance of rock fragmentation. The blasting process reduces cost and increases the speed of fragmentation.

Zhang et al. [22] proposed an entropy weighted matter-element extension model to evaluate the effectiveness of charge blasting. The entropy weighting method is used here to detect the matter-element index of rocks. The proposed model reduces both the cost and time required for evaluation. The proposed model increases the quality of roadways by improving prediction accuracy.

Vokhmin et al. [23] introduced a new method for underground blasting fragmentation prediction. First, drilling and blasting pattern parameters are identified to provide optimal data for further processes. The proposed method is mainly used for oversized or undersized fragmentation. The cost of computation is reduced, which improves the efficiency of blasting. Experimental results show that the proposed method achieves high accuracy in prediction for rock fragmentation.

Zhang et al. [24] developed a rock size distribution (RSD) prediction model for mine bench blasting based on the ant colony optimization (ACO) method. The boosted regression tree (BRT) algorithm is also used to detect action information related to RSD. BRT reduces delay time in predicting variables and parameters of RSD and reduces optimization problems during prediction. The proposed ACO method improves the accuracy of RSD prediction, increasing the efficiency and performance of bench blasting.

Miao et al. [25] proposed a muck-pile model for predicting rock fragmentation size. First, the proposed model analyzes the quality, parameters, and patterns of rocks, thereby providing optimal information for prediction. The support vector machine (SVM) regression model analyzes the necessary data for prediction. Compared with other models, the proposed model achieves high accuracy in terms of size distribution prediction, improving the feasibility and significance level of fragmentation.

Ding et al. [26] proposed new size-distribution characteristics and fragments-prediction methods for open-pit mines. The main aim of the proposed method is to predict the fragments of rocks before the mining begins. Blasting parameters are identified in order to produce appropriate data for prediction and detection. Size and fragment distribution predictions are crucial to all mining operations. The proposed method improves the coal rate and reduces the level of dust pollution in open-pit mining.

Zhou et al. [27] introduced new particle size distribution prediction models, namely genetic algorithm (GA) for adaptive neuro-fuzzy inference systems (ANFIS). GA is used here to predict parameters and size distribution patterns so as to produce feasible prediction information. GA-ANFIS reduces the root mean square error (RMSE) in computation which

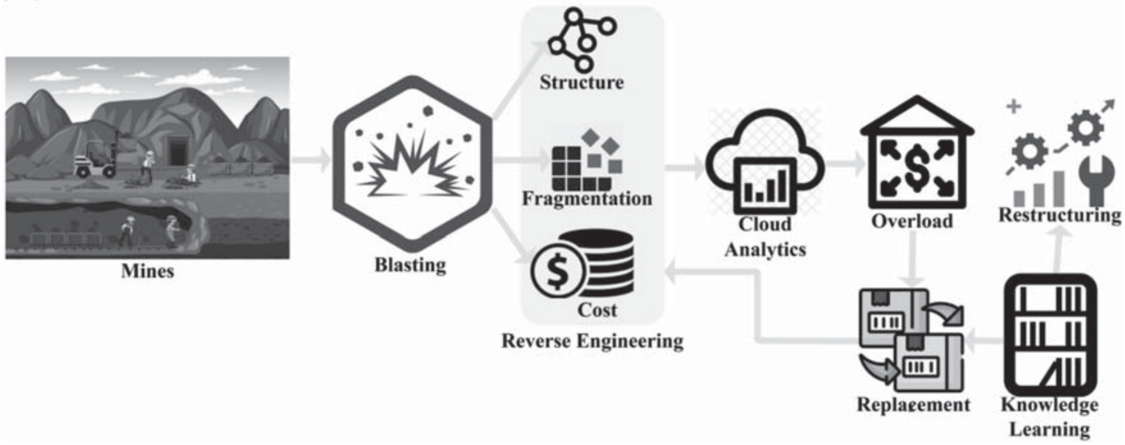

Figure 1 3D analysis method using reverse engineering (3DA-RE) paradigm.

maximizes the effectiveness of prediction. The proposed GA-ANFIS improves the overall prediction accuracy, thereby increasing a mining system's potential and efficiency.

Zhang et al. [28] designed bunch-holes blasting for rock fragmentation. The proposed method first identifies the relationships of rocks and fragments in order to calculate the amount of explosive required. The proposed method reduces critical delay intervals during the mining process. The parameters, patterns, fragments, and sizes of rocks are detected before fragmentation. Bunch-hole blasting maximizes performance and quality of blasting fragmentation by reducing cost and energy consumption rate.

Chen et al. [29] introduced a new evaluation method for pyramid-cut blasting using data for fragmentation behavior. The behavior of fragments is calculated based on uniaxial compression in rocks. The proposed evaluation method provides optimal data for further blasting fragmentation. The proposed method improves accuracy in evaluating pyramid cut blasting, which improves the efficiency and robustness of mining operations.

3. THREE-DIMENSIONAL ANALYSIS USING REVERSE ENGINEERING (3DA-RE) PARADIGM

By utilizing the microscopic composition of the three-dimensional structure of explosions, the rock fragmentation caused by mountainous areas and mines was analyzed. The proposed 3DA-RE model was used as an input for the deconstruction process based on structural description, fragment level research, and cost prediction. 3DA-RE not only affects the blasting fragmentation and leveling of mining geotechnical treatment, but also improves the safety of miners. Therefore, the calculation of 3DA-RE is of great significance in today's scenarios. This method is shown in Figure 1.

Three-dimensional blasting fragmentation analysis is used to identify the overhead incurred by mining operations. This analysis is used to detect the size of blasted rock particles and region segmentation through structures based on the similarity between pixels. The mines and mountain structures are captured in order to analyze the ground truth. The front, middle and back of each muck pile is charged to ensure that the particle size distributions in the structures reflect those in the muck pile. The Reverse Engineering process is then deployed to analyze the networks for particle identification/ structure classification by deconstructing the actual blasting process. Based on the captured structure of the blast muck pile, the cloud analytics and their application in mining are analyzed. Then Reverse Engineering is applied to identify the rock fragments in mines and mountains. This process can locate their position, identify particles and classify the structure according to the original design. Finally, we apply the Reverse Engineering paradigm to measure the rock fragmentation throughout the mining system.

This methodology consists of three challenging steps: (1) structure analysis based on unique patches detection through an entire structure of mines and mountains; (2) the application of a trained Reverse Engineering model to identify the level of rock fragment segmentation; and (3) identification of the cost overloading factor. In this article, the the actual process is deconstructed to reduce the overhead incurred by rock handling and its transportation. Through deconstruction of previous processes, many structures are captured in blast muck piles for detailed rock fragmentation analysis. The structures differ in size and pixels in the rock fragmentation process. The different dimensional structures are processed using cloud analytics for previous mining actions. Cost overloading is identified using knowledge learning for all three dimensions. The overloading process is modified using the structure alteration to reduce the overhead in another process. It ensures affordable and flawless mining services and maximizes the deconstruction process in blast-induced rock fragmentation.

4. REVERSE ENGINEERING IN DECONSTRUCTION PROCESS

This method applies the Reverse Engineering paradigm to detect and analyze segments of rock fragments in blast muck piles. It consists of three steps: first, the regions with possible rock fragments are analyzed using structures; second, the fragmentation levels in blast muck piles are

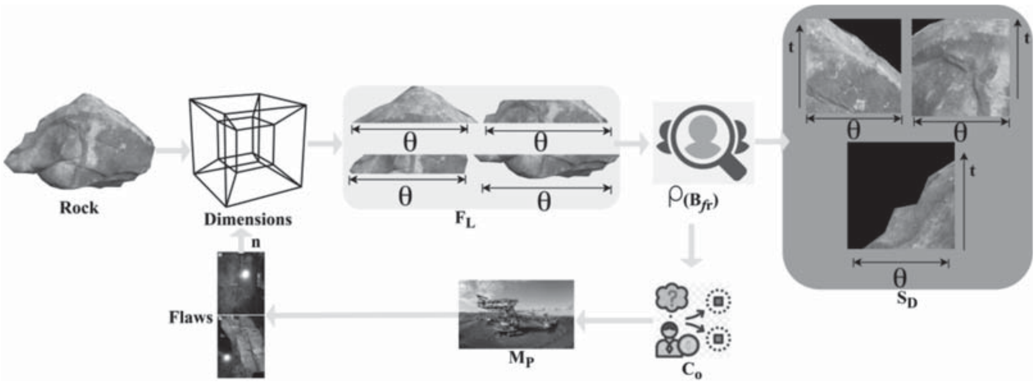

Figure 2 Structure Detection using F_L.

predicted; third, the handling costs are analysed for each region. In the deconstruction process, loading and unloading analyses are concerned with cost handling, which is the paramount consideration in rock fragmentation. Instead of performing the Reverse Engineering process from random blast muck piles, the structure detection (S_D), fragmentation level (F_L)and cost overloading (C_O) regarding three outputs are used to ensure affordable and flawless mining services during the fragmentation process. By means of cloud analytics, the overhead incurred by mining practice M_p in rock fragmentation through 3DA-RE is achieved. Cloud technology is used to identify blast muck piles in mines and mountains. The particle identification and structure classification is performed by deconstructing the actual process based on point cloud recognition. The probability of rock fragmentation in mines and mountains is successfully analyzed at different time intervals t without flaw and is calculated with

$$\rho(B_{fr}) = \frac{\sum_{i\in t} S_D * F_L}{\sum_{j\in n} C_O} \text{flaw}^{-\frac{p_d}{t}} \tag{1}$$

In equation (1), the identification of blast muck piles relies on the particle size and flaw analysis at different time t instances and the actual process used for blasting. Further blasting fragmentation is analyzed without any flaw detection.

If n denotes the number of possible blasting in mines, the instance of maximizing structure detection $\rho(B_{fr})$ is output in $M_p = 1$ from differing factor and hence the particle size identification and structure detection is computed based on $C_O,\ t \in n$. In fragmentation, flaws can be identified using flaw in t and assists with Reverse Engineering for the instance of B_{fr}. This blasting structure detection and level of fragmentation is computed using equation (2) and is valid for t alone

$$C_O \forall\, t \in n = (1 - p_d)\frac{S_D}{C_O}.M_p.\frac{F_L}{n} i \in t \tag{2}$$

In equation (2), the different intervals of blasting fragmentation in mines can be analyzed through previous process deconstruction in t instance; if the condition $C_O \forall t \in n$ exceeds the actual process, then cost overloading is required. The structure classification in blasting fragmentation maximizes cost; deconstructing the process used for blasting serves as $\{M_p,\ n,\ C_O,\ \rho(B_{fr})\}$ post the fundamental features for all t instances. The output for identifying the small structure in the fragmentation process of B and $F_L \forall j \in n$ is obtained through cloud analytics, analyzed in a 3D manner. The structure detection using fragmentation level is illustrated in Fig. 2.

The mine (rock) dimensions are measured as θ from which individual $\rho(B_{fr})$ is estimated. The S_D is identified as $(t * \theta)$ for $t \in n$) provided C_o is variable. Considering the C_o from the loading/unloading features the M_P is revisited. Therefore the flaws for n across different dimensions are identified. The change in S_D is observed for new θ under F_L (Fig. 2). The different structures are captured for structure detection and fragmentation level in blasting. In the deconstruction process, the different dimensions are handled using previous mining actions relies on M_p and C_O for $\sum_{i\in t} (B_{fr})_i = S_D,\ p_d$ and $\rho(B_{fr})$ based on a different dimension as in equation (1). Let L_d and Un_d denote loading and unloading of mines blasting as in equation (1) in a 3D manner. This refers to the cost overloading factor in any blastings analyzed using the previous deconstruction process. Therefore, the deconstruction process is carried out using D_P

$$D_P = S_D + F_L + C_O \tag{3}$$

5. REVERSE ENGINEERING PROCESS

The Reverse Engineering paradigm helps to detect structure and rock fragments due to fragmentation.Therefore, combining all structures to obtain the original structure to estimate the final cost overload is essential. The issue is addressed in some individual rock fragmentations available in any of the identified blastings. In this study, we modified the overloading process using structure alteration. Identify cost overload factors from a set of exploding deconstructed processes with cloud analysis. The identified overhead in cost handling i for every range of M_P relies on pixel and j. Then, we estimate the general overlap OV_r between each region with:

$$OV_r = M_{Pi} \cap M_{Pj} \forall_{ij} \in flaw \tag{4}$$

The equation (4) is then used to estimate the relative ratio and possible overlap ratio, and the equation (5) is used to analyze each region.

$$R_i = OV_{rij}/M_{Pi} \tag{5}$$

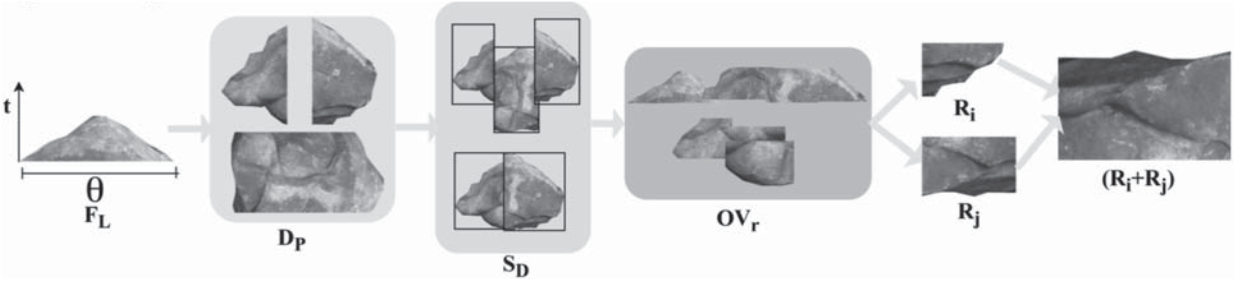

Figure 3 Reverse engineering process for fusion.

such that,

$$R_j = OV_{rij}/M_{Pj} \tag{6}$$

If $R_i \geq \theta$ and $R_j \geq \theta$, two regions are combined into one in order to analyze the same blasting fragmentation. The identification of large fragments, whose structure is larger than the size of a particle, is computed; generally, reverse engineering is used to identify blast muck piles in mines. The reverse engineering process for fusion is depicted in Fig. 3.

In the reconstruction process using reverse engineering (Fig. 3), the flawless regions are identified for OV_r. This OV_r results in flows for the forwarding analysis, provided that R_i and R_j are extracted; this extraction relies on L_d and Un_d observed for which C_o is analyzed. Considering the knowledge update for the new M_p, n dimensions are fused. This fusion process implies S_D (for reconstruction) across $\rho(B_{fr})$. For all the conditions of R_i and R_j, there is probably no loading or unloading of small structure fragments identified beyond another. Therefore, both regions of i and j are included based on cost overload. Moreover, the computations for deconstructing the actual process with a different dimension of θ values and identifying $\theta = 0.5$ are suitable for small structures in blasting.

6. RECONSTRUCTION PROCESS ANALYSIS

In the reverse engineering paradigm, described in the Introduction, the restructuring computation is performed to express the replacement process in blast muck piles, where it estimates the fragment percentage through particle size identification or structure classification. In this article, we are concerned with identifying the small structure of a fragment by means of cloud technology. Fragment size can be measured in a particular region through knowledge learning. However, these identified regions are difficult to visualize for analysis, so fragment sizes are illustrated as the small structure in the fragmentation process, and cost overloads are identified. The proposed model is used for three-dimensional digital analysis of blasting fragmentation that considers the cost of overloading and thus disregards the fragmentation level and structure detection in blasting. The computation of the similarity S between the actual process and the deconstruction process is computed with

$$S = \sqrt{\frac{S_D * F_L}{3OV_r}} \tag{7}$$

Where the structure detection value and fragmentation level in a 3D manner, the maximum cost overloading in blasting fragmentation, C_O is the identification of cost overloads in all three dimensions using knowledge learning, and C_O is outputs in 1. The previous process deconstruction probabilistic factor relies on cost overloading and reverses the construction of structural cloud analytics in further blast fragmentation. The cost overloading factor in blasting fragmentation, the structure altering is performed. In particular, the contrary section analysis, as in equation (1), is performed using knowledge learning to minimize cost overloading in rock fragmentation. The probability of C_O is computed with

$$\rho(C_O) = \frac{\rho(S_D \cap F_L)}{\rho(R_{ij})} \tag{8}$$

where,

$$\rho(S_D) = \frac{\max(C_O) - min(C_O)}{max(C_O)}.\rho(S) \tag{9}$$

From the equation (8) and (9), the estimation of $\rho(C_O)$ relies on a contrary session as in equation (1) and $\rho(S)$ is analyzed at different intervals. For any instance of blasting, if$B_{fr} < C_O$, then flaw occurrence can be identified in blasting fragmentation, which replaced the overloading process using structure alteration. The possible mine blasting regions are continuously monitored and blocked the transportation in that location using knowledge learning and ensuring affordable and flawless mining services, respectively. Instead, the continuous analysis of three dimensions based on C_O for B_{fr} is processed between the structure classification and fragmentation level. The likelihood L in blasting fragmentation analysis $\rho(C_O)$ and $\rho(B_{fr})$ is computed to ensure $B_{fr} < C_O$ as in equation (10)

$$L\rho(B_{fr}|C_O) = \begin{cases} \frac{1}{\sqrt{2\pi i}} \text{ expression } \left[\frac{-(B_{fr})_R}{n^2}\right] \forall i \in n \text{ in } t \\ \frac{1}{\sqrt{2\pi j}} \text{ expression } \left[\frac{-(B_{fr}-flaw)^2{}_R}{2S}\right] \\ \quad \forall\ j \in n \text{ in } t \end{cases} . \tag{10}$$

In equation (10), the consideration of cost overloading in a 3D manner for t and $\left[t - \frac{S_D}{n}\right]$ instance, the probability of likelihood is validated for t intervals. Therefore, the occurrence of a flaw in blasting is analyzed through the deconstruction process in any t instances considering the maximizing S_D. Based on the L_h. analysis of $\rho(B_{fr})$ and $\rho(C_O)$. The different dimensions are handled using cloud technologies

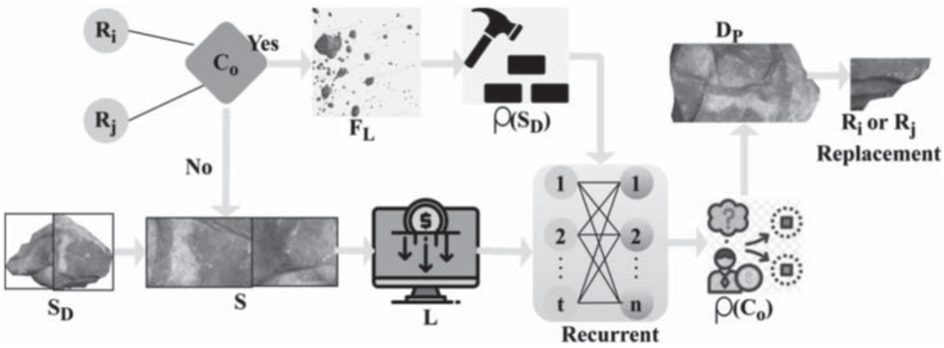

Figure 4 Learning for overload and replacement.

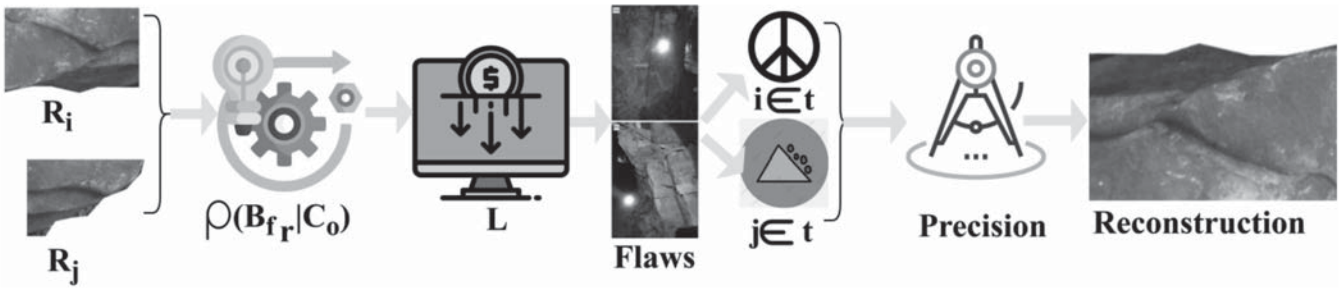

Figure 5 Reconstruction using L.

for performing other mining actions. The overload and replacement using the learning process are illustrated in Fig. 4.

The R_i and R_j replacement pursues the knowledge learning for recurrent training and analysis. Using the C_o occurrence the F_L/L process is differentiated. The mapping performs $(t:n)$ for identifying $\rho(C_o)$ such that D_p is preceded. Depending on M_P, the Un_d is alone estimated for OV_r for identifying R_i or R_j (for replacement) (Fig. 4). In the following cost overloading analysis based $L_h[.]$ computation, the objective is to minimize the cost and flaw $(t - \frac{S_D}{n})$ through the learning process is to perform restructuring as required with the construction of structural cloud analytics relies on $B_{fr} \in C_O$ and $0 < M_P < 1$ and $\rho(B_{fr}) \in \rho(C_O) \neq 0$. To compute the reverse structural cloud analytics based on True Positive (T_P), False Positive (F_P), and False Negative (F_N) analysis is performed for precision and restructure. Precisionis used to calculate the accurately detected blast fragments with all blast fragmentation detected by the method. Restructuring calculates the ratio of accurately detected blast fragments with all ground truth-based blast fragments in mines.

$$\text{Precision} = \frac{T_P}{T_P + F_N} \tag{11}$$

Such that

$$\text{Restructure} = \frac{T_P}{T_P + F_P} \tag{12}$$

The blasting-induced rock fragmentations are performed in all t instances due to their precision and restructure computation in equations (11) & (12). The reconstruction using L factor is shown in Fig. 5.

The replaced R_i and R_j are used for verifying $\rho(B_{fr}|C_o)$ such that L for the succeeding features is observed. Based on the flaw observed, the $i \in t$ and $j \in t$ are used for precision estimation. This is required for addressing the shortcomings of reconstruction. The above process is utilized to maximize the precision for which S is estimated (Fig. 5). Hence, the structure classification and particle identification rely on a deconstruction process other than replacement to help minimize cost overloading, overhead in rock handling, and its transportation in that particular rock fragment region, and maximize the restructuring for the $0 < M_P < 1$ condition in any blasting with different dimensions.

7. PERFORMANCE ANALYSIS

The performance of the proposed method is evaluated using the same data [30] on rock size, sensitivity, and variations observed in different blasting processes. Using the L_d and Un_d processes, the structures are varied between 2 and 26. Also, the time-based analysis is conducted for the purpose of evaluation over 7 hours of M_p. The data is modified for the assessment as shown in Fig. 6.

The time, $F_L$and demand-based data is extracted from the input data for assessment. The physical examination provides rock sizes post the blasting. The demand factor ensures cost management through L_d and Un_d provided F_L is high/low (based on size). Considering the cost of handling the S_D and reconstruction recommendation is illustrated in Fig. 7.

The reconstruction recommendations rely on financial management to reduce L_d and Un_d. Based on θ and t modifications the maximum structural possibilities are analyzed. Post this possibility $\rho(C_o)\ \forall\ t \in n$ is estimated. This estimation results in reconstruction from the consecutive L_d and Un_d processes. Therefore, for the given data representation, the $C_o$for F_L and $\rho(B_{fr})$ is analyzed in the Fig. 8 series.

The C_o is influenced by F_L and $\rho(B_{fr})$ under different M_p. This is due to the demand and S_D possibilities. Considering

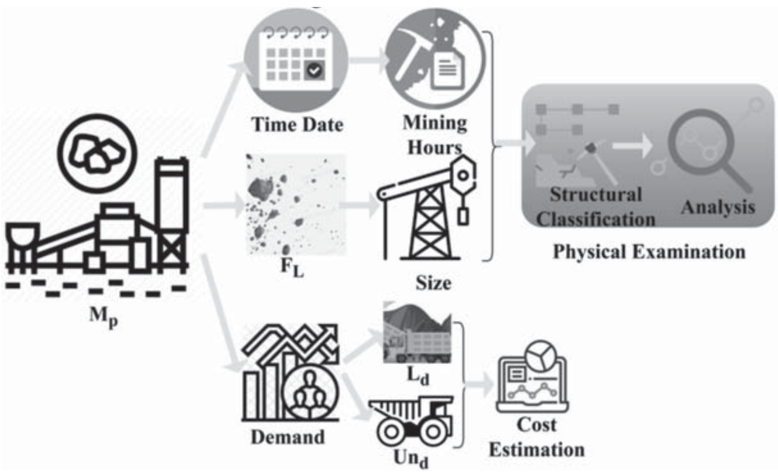

Figure 6 Data representation for assessment.

Figure 7 S_D and Reconstruction Recommendation.

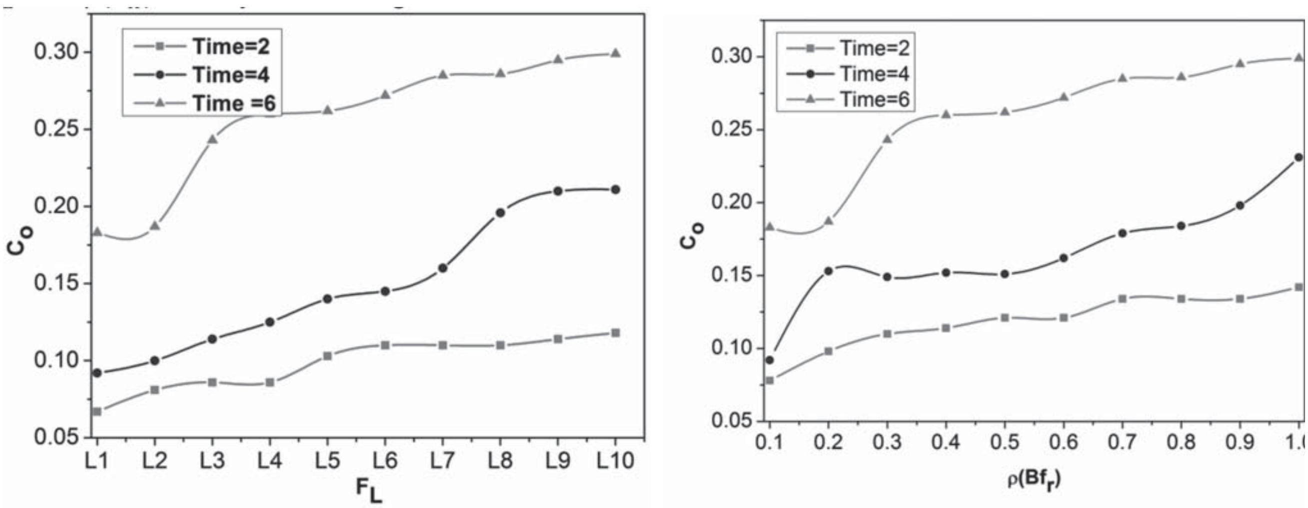

Figure 8 C_o Analysis for F_L and $\rho(B_{fr})$.

the $L_d + Un_d \in \theta * t \in n$ the C_o optimization is performed. In the consecutive processes, the available D_p and its OV_r are identified for a further split. Therefore, R_i and R_j or everyone is deformed for analysis by achieving high $L[\rho(Bf_r|C_o)]$. In this process the $\rho(S_D)$ is neglected as M_p is consecutive with the demand and, therefore C_o is adaptable (Fig. 8).

The analysis of the precision of the restructuring process of $\rho(C_o)$ and $\rho(S_D)$ is shown in Fig. 9.

The precision decreses with the increase of C_o probability compared to S_D. The cost demand increases the S_D for which D_p is pursued; hence, the L_d and Un_d are analyzed. The $\rho(B_{fr})$ is validated for M_p pursuing OV_r detection; the R_i and R_j differentiations rely on S factor. Considering the knowledge update from the previous D_p, the L is validated. Therefore, the precision is retained. In this process, S_D improves the analytics for precision improvement, reducing C_o (Fig. 9). The comparative analysis discussion is presented below for the metrics deconstruction ratio, data analysis, overload identification, cost overhead, and fragmentation ratio. The structures and mining time are varied for different instances. The existing ACO-BRT [24], RFA-DL [18], and DEM-PSD [19] methods are used alongside the proposed 3DA-RE.

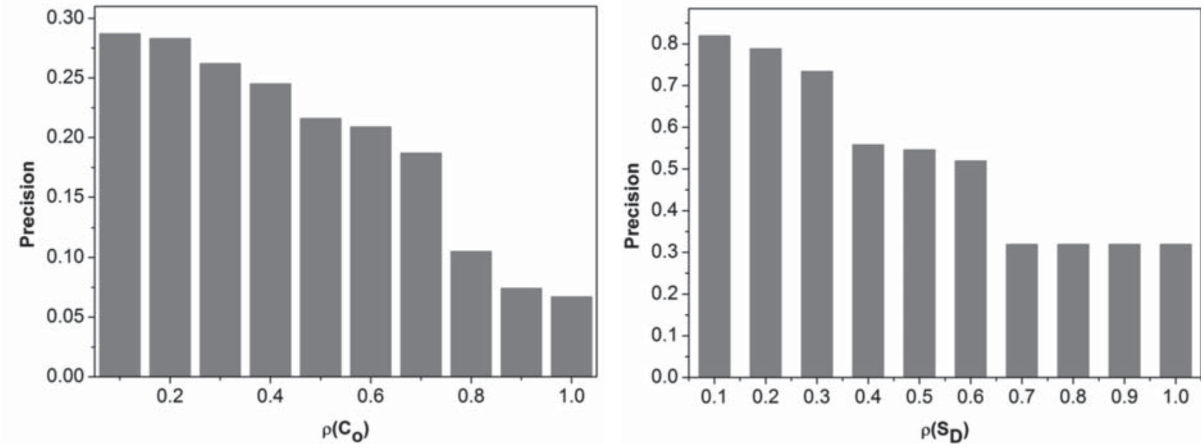

Figure 9 Precision Analysis.

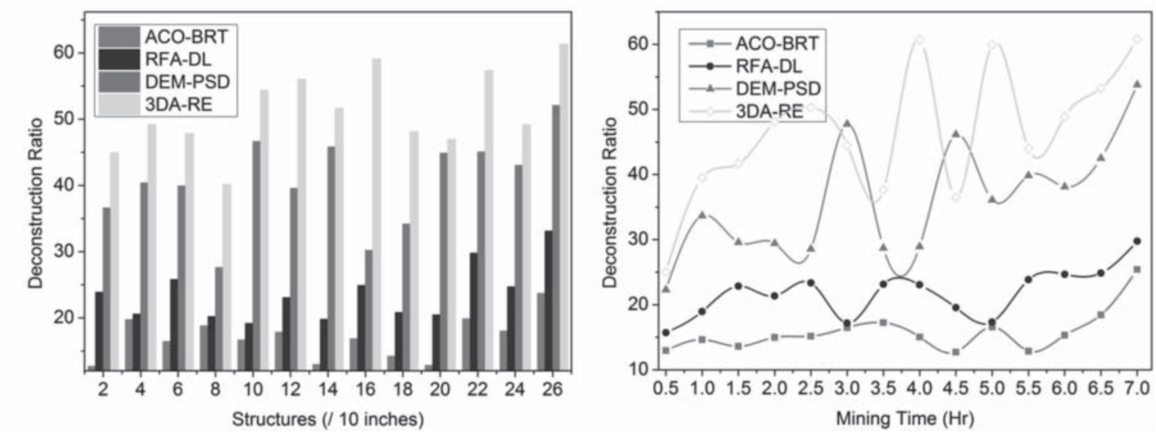

Figure 10 Deconstruction ratio.

8. DECONSTRUCTION RATIO

The computation for structure detection and level of rock fragmentation relies on mine blasting and fundamental features of all three dimensions using knowledge learning as shown in Fig. 10. In this proposed model, deconstructing the actual process achieves high-cost overloading by computing the identification of rock fragmentation level in blasting. In this article, the mine blasting precision and restructuring process at different time intervals prevents rock-handling overhead. The instance of $\frac{\sum_{i\in t} S_D * F_L}{\sum_{j\in n} C_O}$ is performed until a flaw is detected. The flaw is detected based on point cloud recognition for performing the deconstruction process that reduces handling costs. Hence, the blast muck piles analysis from mines and mountains is estimated to maximize the mining services through the previous deconstruction process using knowledge learning in a high deconstruction ratio. The reverse engineer could detect the accurate and reliable explosion recognition of the mine, so as to reduce the expense of over load caused by the structure detection.

9. DATA ANALYSIS

In Figure 11, cloud analysis is used for blasting fragmentation and its application in mining, rock processing and high data analysis.The fundamental factors are analyzed in a 3D manner using knowledge learning to analyze data for the condition C_O, $t \in n$ and achieves restructuring based on point cloud recognition. The data analysis is performed for various previous mining operations with different dimensions. Hence, in mining, the structure classification and particle size validation reverse the construction of cloud analytics. The mine blasting instance is suitable for high data analysis in the deconstruction process and replaces the overloading process. Therefore, identifying overhead-causing mining practices in rock fragmentation through previous deconstruction processes and rock transportation reduces the overload of rock fragments. Thus, the blasting is determined by the mines, and mountains are computed in 3D, preventing high data analysis due to replacement in fragmentation levels.

Overload Identification

This proposed method achieves high overload identification in mine blasting analysis depending on structure detection and fragmentation level at different dimensions computed using knowledge learning (refer to Fig. 12). The flaw and overhead are mitigated for the condition $\sum_{i\in t} (B_{fr})_i = S_D$, p_d, and $\rho(B_{fr})$ is computed using cloud analytics for different previous mining actions. The overloading process is replaced based on structure alteration in order to analyze further rock fragmentation due to various mining services performed through knowledge learning. Reverse engineering is applied

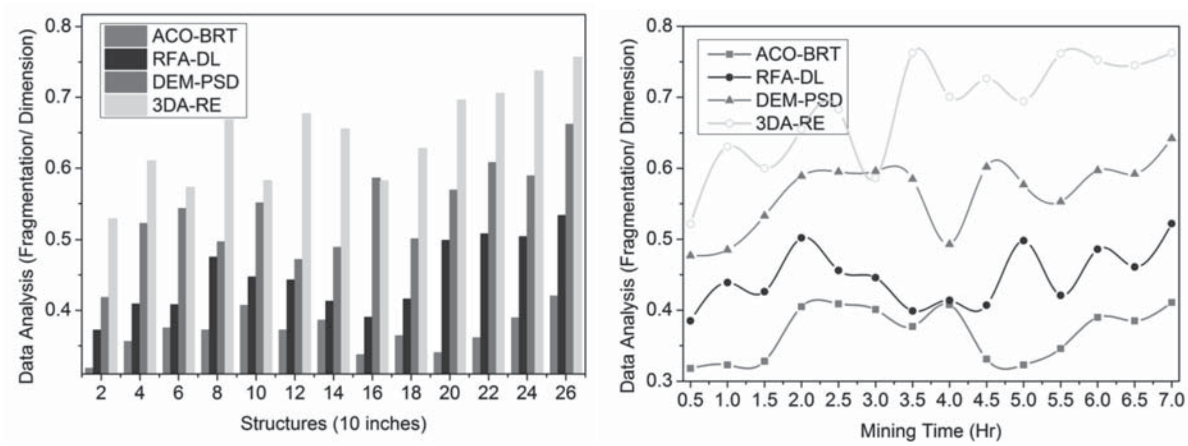

Figure 11 Data analysis.

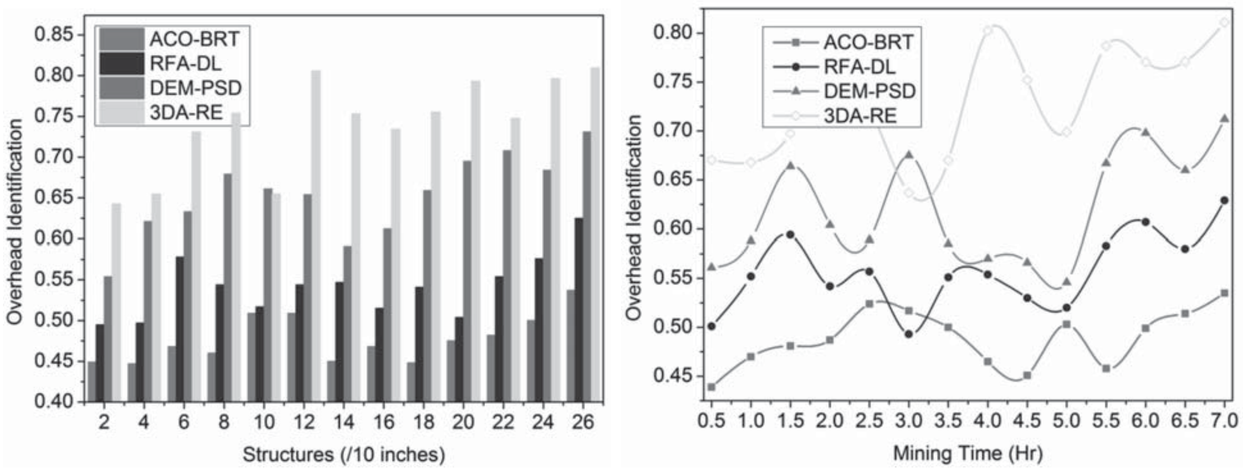

Figure 12 Overhead identification.

to identify cost overloading, and minimizing overhead relies on M_p and C_O estimation. The rock fragmentation in mining poperations is analyzed in three dimensions for restructuring through knowledge learning and deconstruction. The lelve of rock fragmentation is consecutively measured through the previous deconstruction process. Similarly, the structure classification is determined with cloud analytics in order to improve the replacement process depending on other rock-fragmentation metrics. This enables the accurate identification of the overload.

Cost Overhead

The cost overloads are identified in a 3D manner using knowledge learning to reduce the overloading associated with rock handling, and the transportantion of rock fragments. Theprevious process deconstruction causing overhead in mining operations is represented in Fig. 13. In this proposed model, the structure detection, fragmentation level, and cost handling analysis lead to less overhead. Knowledge learning is used for replacing the overloading process using deconstruction at different time intervals, and its loading and unloading verification process is performed through a learning process. The rock fragmentation process relies on small structures in a 3D manner at the different instances for computing L_d and Un_d. Cloud analytics is used for identifying the particle size and structure classification in any blasting operation in order to calculate the cost of overloading. The mine blasting is analyzed according to three dimensions using knowledge learning wherein the previous mining operations are preceded using equations (3), (4), (5), (6), (7), (8), (9), and (10) computations. Reverse engineering depends on three fundamental features for further deconstruction in this proposed method. Therefore, the overhead is less than the other factors associated with rock fragments.

Fragmentation Rate

In Fig. 14, the blasting fragmentation is identified with cloud analytics in order to reduce the cost overloading in mining operations by placing the small structure in that process at different time intervals. The deconstruction process minimizes overhead in rock handling in other instances. Cloud analytics is used for structure detection, and the fragmentation level from the previous mining operation is replaced using the structure-altering method to identify possible blasting sites in a region. This is done through knowledge learning. The rock fragmentation rate is computed with the last process deconstruction for the instance of $\rho(C_O)$ and $\rho(B_{fr})$ analysis in blasting fragmentation. This overhead is addressed and rectified using the reverse engineering paradigm to achieve a high deconstruction process with different dimensions, preventing cost overloading. Therefore,

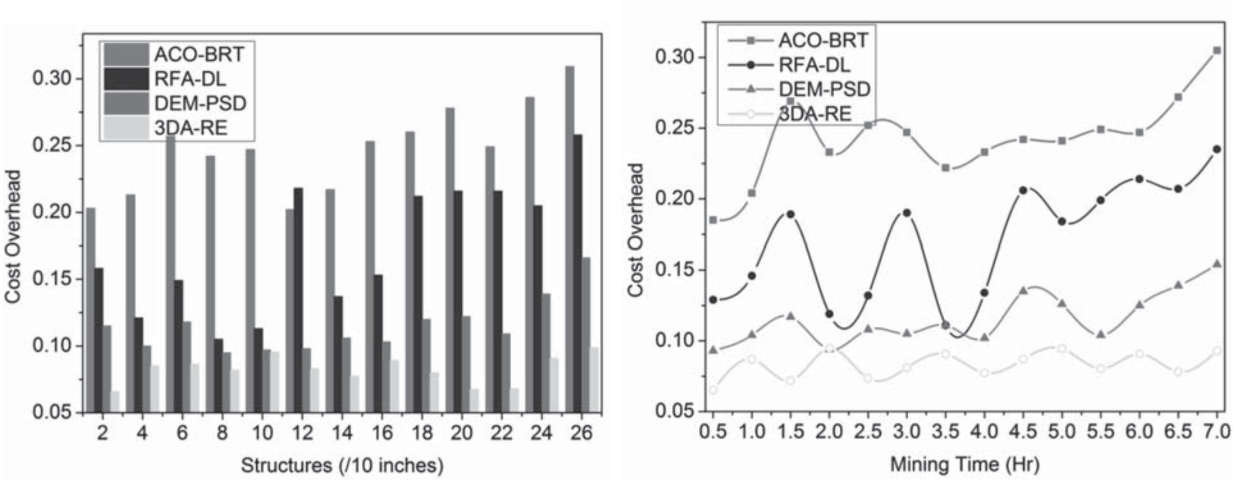

Figure 13 Cost overhead.

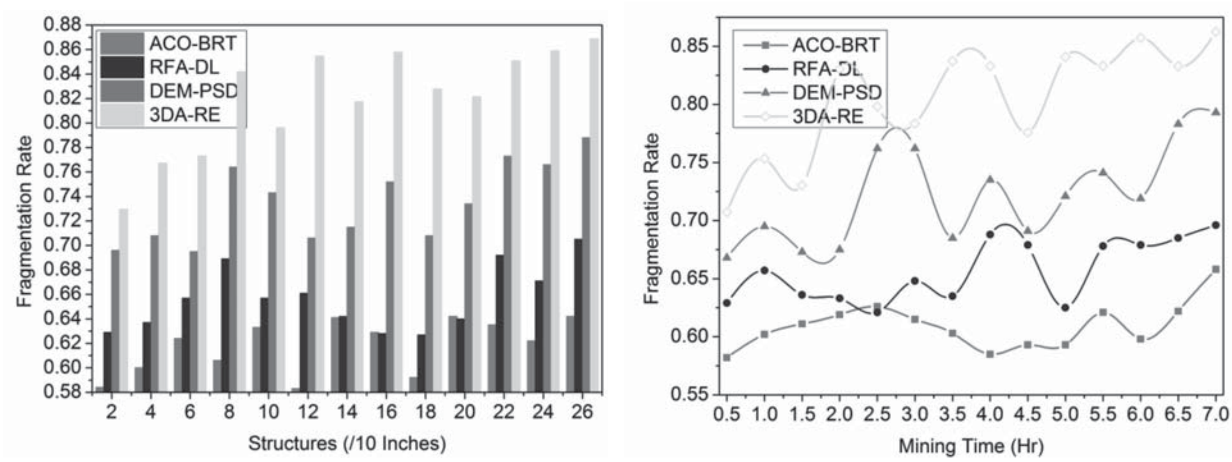

Figure 14 Fragmentation rate.

Table 1 Summary of structures.

Metrics	ACO-BRT	RFA-DL	DEM-PSD	3DA-RE
Deconstruction Ratio	23.67	33.11	52.09	61.293
Data Analysis (Fragmentation/ Dimension)	0.42	0.533	0.662	0.7565
Overhead Identification	0.537	0.625	0.731	0.8094
Cost Overhead	0.309	0.258	0.166	0.0986
Fragmentation Rate	0.642	0.705	0.788	0.8687

Table 2 Summary of mining times.

Metrics	ACO-BRT	RFA-DL	DEM-PSD	3DA-RE
Deconstruction Ratio	25.41	29.75	53.79	60.814
Data Analysis (Fragmentation/ Dimension)	0.411	0.522	0.642	0.7624
Overhead Identification	0.535	0.629	0.712	0.8108
Cost Overhead	0.305	0.235	0.154	0.0929
Fragmentation Rate	0.658	0.696	0.793	0.8625

further rock fragmentation and rock handling in mine blasting sites are represented. In mines, blasting can achieve a high breakage rate. The overhead is identified in the fragmentation process, preventing high-cost overloading and rock handling due to structure altering for further operations in blast muck piles. In Tables 1 and 2, the above discussion is summarized.

The proposed method improves the deconstruction ratio, data analysis, overhead identification, and fragmentation rate by 12.5%, 10.91%, 8.92%, and 15.7%, respectively. The cost overhead is decreased by 7.29%.

The proposed method improves the deconstruction ratio, data analysis, overhead identification, and fragmentation rate by 12.25%, 11.87%, 9.27%, and 14.68%, respectively. The cost overhead is decreased by 6.92%.

10. CONCLUDING REMARKS

This article introduced a three-dimensional analysis using the reverse engineering paradigm that takes into account the blasting demands and the associated cost. The proposed method identifies the loading and unloading (handling) costs for different levels of rock fragmentation. The deconstruction and structure-detection processes are revisited by estimating the levels using individual probabilities. Cloud data analysis identifies overloads in fragmentation, structural analysis, and blasting. The identified overlapping instances are verified using similarity and likelihood features for improving the reconstruction feature. Therefore, the precision of the data analysis is improved, maximizing the deconstruction. This deconstruction process is aided by learning from the probability analysis of the various structures. The recurrent process is utilized for consecutive mining and fragmentation to identify overloading. Under the different systems, 2DA-RE improves the deconstruction ratio, data analysis, overhead identification, and fragmentation rate by 12.5%, 10.91%, 8.92%, and 15.7%, respectively. There is a 7.29% decrease in overhead cost.

REFERENCES

1. I. Vennes, H. Mitri, D. R. Chinnasane, M.Yao, Large-scale destress blasting for seismicity control in hard rock mines: a case study. International Journal of Mining Science and Technology, 30(2) (2020), 141–149.
2. P. Yang, Q. Lei, J. Xiang, J. P. Latham, C. Pain, Numerical simulation of blasting in confined fractured rocks using an immersed-body fluid-solid interaction model. Tunnelling and Underground Space Technology, 98(2020), 103352.
3. T. Li, M. Chen, D. Wei, W. Lu, P. Yan, Disturbance Effect of Blasting Stress Wave on Crack of Rock Mass in Water-Coupled Blasting. KSCE Journal of Civil Engineering, 26(6) (2022), 2939–2951.
4. X. Ma, G. Yang, J. Zuo, Y. Wang, Y. Jin, Q. Li, Study on Failure Characteristics of Stemming Structure on Iron Ore Under Blasting Load. Rock Mechanics and Rock Engineering, (2022),1–21.
5. P. Guo, K. Ye, Z. Tao, H. Liang, Y. Yuan, Experimental study on key parameters of bidirectional cumulative tensile blasting with coal-containing composite roof. KSCE Journal of Civil Engineering, 25(5) (2021), 1718–1731.
6. Y. Wang, W. Tu, H. Li, Fragmentation calculation method for blast muck piles in open-pit copper mines based on three-dimensional laser point cloud data. International Journal of Applied Earth Observation and Geoinformation, 100(2021), 102338.
7. H. Y. Grisaro, Effect of combined blast and fragmentation load on the dynamic response of reinforced concrete structures. Engineering Structures, 248(2021), 113244.
8. Z. X. Zhang, D. F. Hou, Z. Guo, Z. He, Q. Zhang, Experimental study of surface constraint effect on rock fragmentation by blasting. International Journal of Rock Mechanics and Mining Sciences, 128(2020), 104278.
9. N. V. Bhagade, V. M. S. R. Murthy, Controlling backbreak and enhancing fragmentation in dragline bench blasting—a geo-engineering approach. Arabian Journal of Geosciences, 13(7) (2020), 1–20.
10. M. A. Núñez-Andrés, N. Lantada Zarzosa, J. Martínez-Llario, Spatial data infrastructure (SDI) for inventory rockfalls with fragmentation information. Natural Hazards, (2022), 1–24.
11. J. A. Gili, R. Ruiz-Carulla, G. Matas, J. Moya, A. Prades, J. Corominas, O. Mavrouli, Rockfalls: Analysis of the block fragmentation through field experiments. Landslides, 19(5) (2022), 1009–1029.
12. L. Y. Chi, C. Wang, Z. X. Zhang, X. Xu, J. Yang, Experimental Investigation of Decoupled Charge Effect on Rock Fragmentation by Blasting. Rock Mechanics and Rock Engineering, (2022), 1–16.
13. C. Pan, X. L. Xie, X. Li, K. Liu, P. F. Gao, L. G. Tian, Numerical investigation of effect of eccentric decoupled charge structure on blasting-induced rock damage. Journal of Central South University, 29(2) (2022), 663–679.
14. X. Li, K. Liu, J. Yang, R. Song, Numerical study on blast-induced fragmentation in deep rock mass. International Journal of Impact Engineering, (2022), 104367.
15. H. Zhang, T. Li, Y. Du, Q. Zhu, X. Zhang, Theoretical and numerical investigation of deep-hole cut blasting based on cavity cutting and fragment throwing. Tunnelling and Underground Space Technology, 111(2021), 103854.
16. Z. Yu, X. Z. Shi, Z. X. Zhang, Y. G. Gou, X. H. Miao, I. Kalipi, Numerical Investigation of Blast-Induced Rock Movement Characteristics in Open-Pit Bench Blasting Using Bonded-Particle Method. Rock Mechanics and Rock Engineering, (2022), 1–21.
17. H. Han, D. Fukuda, H. Liu, E. F. Salmi, E. Sellers, T. Liu, A. Chan, Combined finite-discrete element modelling of rock fracture and fragmentation induced by contour blasting during tunnelling with high horizontal in-situ stress. International Journal of Rock Mechanics and Mining Sciences, 127(2020), 104214.
18. T. Bamford, K. Esmaeili, A. P. Schoellig, A deep learning approach for rock fragmentation analysis. International Journal of Rock Mechanics and Mining Sciences, 145(2021), 104839.
19. D. Gou, Y. Li, X. An, R. Yang, DEM modelling of particle fragmentation during compaction of particles. Powder Technology, 398(2022), 117073.
20. J. Tao, X. G. Yang, H. T. Li, J. W. Zhou, S. C. Qi, G. D. Lu, Numerical investigation of blast-induced rock fragmentation. Computers and Geotechnics, 128(2020), 103846.
21. U. Ozer, A. Karadogan, U. K. Sahinoglu, M. C. Ozyurt, Z. Sertabipoglu, M. K. Günay, C. B. Zaif, An analytical and applied blasting approach to facilitate rock-socketed bored pile excavation. Arabian Journal of Geosciences, 13(12) (2020), 1–11.
22. H. Zhang, X. Zhang, H. Yu, J. Li, H. Zhou, D. Li, Comprehensive evaluation of shaped charge blasting effect of rock roadway based on entropy-weighted matter-element extension model. Arabian Journal of Geosciences, 14(8) (2021), 1–12.
23. S. A. Vokhmin, A. A. Kytmanov, G. P. Erlykov, E. V. Shevnina, G. S. Kurchin, A. K. Kirsanov, Prediction and Actual Oversized/Undersized Fragmentation in Underground Blasting. Journal of Mining Science, 57(2) (2021), 210–219.
24. S. Zhang, X. N. Bui, N. T. Trung, H. Nguyen, H. B. Bui, Prediction of rock size distribution in mine bench blasting using a novel ant colony optimization-based boosted regression tree technique. Natural Resources Research, 29(2) (2020), 867–886.
25. Y. Miao, Y. Zhang, D. Wu, K. Li, X. Yan, J. Lin, Rock fragmentation size distribution prediction and blasting parameter optimization based on the muck-pile model. Mining, Metallurgy & Exploration, 38(2) (2021), 1071–1080.

26. X. Ding, W. Zhou, X. Lu, M. Li, E. Manda, X. Shi, C. Qi, Distribution characteristics of fragments size and optimization of blasting parameters under blasting impact load in open-pit mine. IEEE Access, 7(2019), 137501–137516.
27. J. Zhou, C. Li, C. A. Arslan, M. Hasanipanah, H. Bakhshandeh Amnieh, Performance evaluation of hybrid FFA-ANFIS and GA-ANFIS models to predict particle size distribution of a muck-pile after blasting. Engineering with computers, 37(1) (2021), 265–274.
28. S. Zhang, X. Qiu, X. Shi, X. Huo, Y. Liu, Influence of detonator delay scatter on rock fragmentation by bunch-holes blasting. Geomechanics and Geophysics for Geo-Energy and Geo-Resources, 8(5) (2022), 1–21.
29. S. Y. Chen, L. Y. Yang, A. Y. Yang, C. Huang, H. Z. Xie, Damage evolution and fragmentation behavior of pyramid cut blasting under uniaxial compression. Journal of Mountain Science, 19(5) (2022), 1475–1486.
30. M. Jamei, M. Hasanipanah, M. Karbasi, I. Ahmadianfar, S. Taherifar, Prediction of flyrock induced by mine blasting using a novel kernel-based extreme learning machine. Journal of Rock Mechanics and Geotechnical Engineering, 13(6) (2021), 1438–1451.