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Modelling the relationship between oversize fragments and nature of rock mass for a sublevel caving operation

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ABSTRACT

Rock fragmentation is vital in a sublevel caving operation. The oversize fragments are the most undesired fragmentation category because of their challenges; as such, they require special attention. This study carried out a field test in one of the LKAB's iron ore mines in northern Sweden to analyse the occurrence of oversize fragments. The analysis involved correlation and regression tests and was performed for different types of rock masses. The results showed that an increase in the percentage of solid rock mass caused an increase in the percentage of oversize fragments. The other rock types, including slightly fractured, highly fractured, and rock mass with minor and major cavities, tended to have a reduced percentage of oversize fragments. The results indicate that oversize fragments can be predicted using linear regression or partial least square regression models with R^2 values of 0.78 and 0.73, respectively.

1. Introduction

The sublevel caving (SLC) mining method is typically used in steeply dipping orebodies with a significant vertical dimension.[1] This mining method is very dependent on controlled fracturing of the rock mass, including both the orebody and the waste rock.[1] The ore is drilled in a fan-shaped pattern and blasted to break it down into smaller fragments.[2,3] Once the ore loses its integrity, it flows towards the empty space in the drift during mucking.[4] The waste rock fractures by itself and caves in when the blasted ore is removed from underneath it and the support is gone.[2,3] This flow of broken material is significantly dependent upon rock fragmentation.[5,6]

The blasted rock consists of different fragment sizes. The size of fragmentation is determined by a number of factors, for example, the rock mass characteristics, blast design, and the drilling and blasting operation.[7] The productivity and ore recovery in any SLC operation can be affected by the nature of fragmentation.[8,9] For example, oversize fragments can obstruct the flow of material or cause dangerous hang-ups, leading to safety issues and reduced ore recovery if the hang-ups are not removed.[8] Defining an optimum fragment size for loading operations in SLC can be difficult because of the effect of different factors, such as draw point dimensions or Load-Haul-Dump (LHD) bucket dimensions,[10] but it is possible to define oversize fragments. As per Singh and Narendrual,[11] "any fragment produced from primary blasting, which cannot be adequately handled by the standard loading, hauling and crushing equipment used in an operation can be regarded as oversize fragment". These oversize fragments are commonly observed at drawpoints in caving methods.[12] Manzoor et al.[13] documented the occurrence of oversize fragments (fragments bigger than 1 $\times$ 1 $\times$ 1 m) in more than 20% of LHD buckets loaded from the drawpoint after 70% extraction ratio. Some examples of oversize fragments loaded in LHD buckets are shown in Fig. 1.

The oversize fragments present challenges to the SLC operation. The presence of oversize fragments can significantly interfere with the production cycle in sublevel caving because of the high level of mechanization and increased automation and can create challenges in efficient handling of the ore in subsequent stages.[14] Along with the safety and ore recovery issues mentioned previously, oversize fragments can increase the cost of the downstream processes, including loading, hauling, and crushing the blasted rock.[14]

The productivity and effectiveness of the material loading from drawpoints significantly depends on rock fragmentation in SLC.[7] Oversize fragments can disrupt the loading operation, resulting in unplanned stops and excessive idle time for the LHD machines.[15] These fragments can form interlocking arches and cause blockage of the orepasses.[16] They can damage the orepass walls and generate increased orepass maintenance costs, even if they don't block the orepass.[14] They can get stuck in the chute and disturb the material transportation at the haulage

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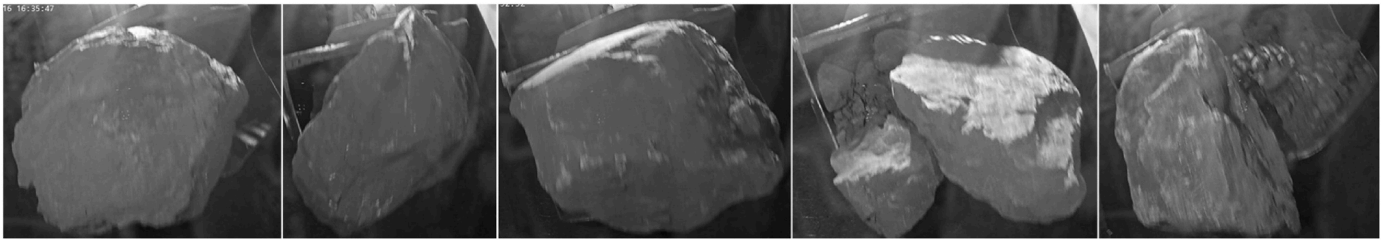

Fig. 1. Oversize fragments in LHD buckets.

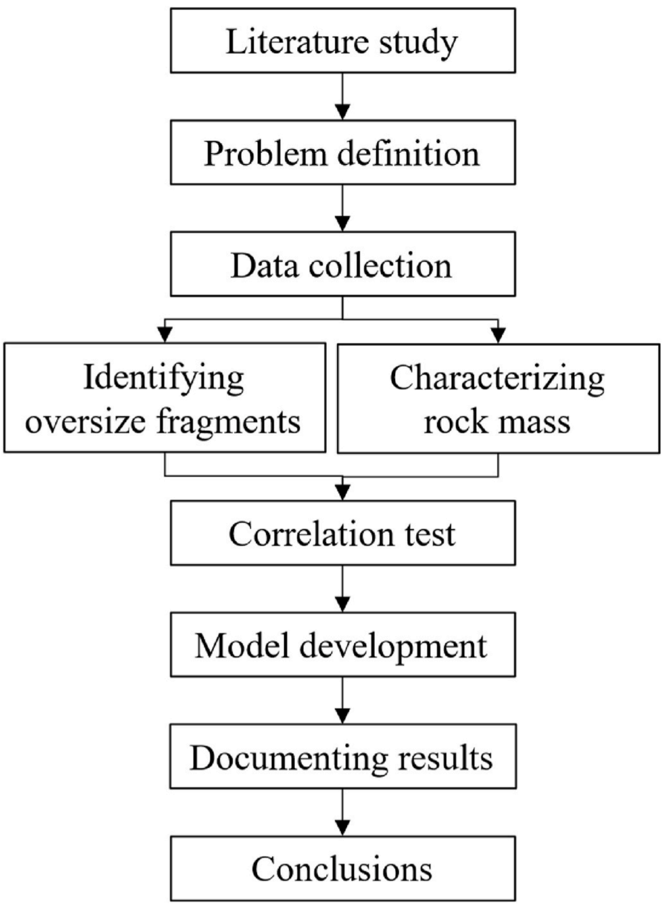

Fig. 2. Research flow.

level.[7] One of the main problems at crushers is caused when oversize fragments form interlocking arches at the top of the crusher and disturb material flow and crusher throughput.[7] They also affect the energy consumption of the crushers, as less energy is consumed if the blasts produce smaller fragments.[17]

Kumar estimated the costs related to oversize handling at different stages of the SLC operation.[14] Paventi et al.[18] found oversize fragmentation could cost 0.5 to 1 M dollars per year for an annual production of 2 Mton from SLC at Stobie mine, Canada, excluding the cost of lost production. Hence it is important to understand and predict oversize fragment generation and find ways to reduce its impact.

Singh and Narendrual[11] listed various sources of oversize fragment generation, including rock mass and blast design related factors in a surface blast. Oversize fragments are normally produced when the blast is designed without accurate insight into the rock mass, and the blasting energy is not sufficient to break the rock.[19] Ghiasi et al.[20] used multiple regression and artificial neural networks to predict the oversize fragment ratio using blast design parameters for surface blasting. Leng et al.[21] documented a new blasting approach combining different diameter blastholes to reduce oversize fragments in an open pit mine. However, there is very little known about oversize generation in sublevel caving as the rock mass description underground is generally not as thorough as it is for surface blasting. The blasting parameters are also different because of the confined nature of blasting,[22] the design of the blast ring,[23] and the specific charge.[24] Therefore, applying similar knowledge or techniques for understanding and predicting oversize fragment generation in sublevel caving as discussed for surface blasting may be misleading.

This paper analyses and models the relationship between oversize fragments and the nature of the rock mass in an SLC mine.

2. Methodology

The study's methodology is visualized in Fig. 2. The study included a literature review, data collection, identification of oversize fragments in LHD buckets, assessment of rock mass quality based on MWD data, correlation tests, and model development based on multiple linear regression as well as partial least square (PLS) regression.

2.1. Test site

The LKAB's Malmberget mine contains 20 ore bodies[25] out of which 13 are currently being mined.[26] Magnetite is the main ore mineral, but hematite is also common in the western part of the mine. Sublevel caving is the mining method used in all ore bodies. Epiroc's Simba WL6C drilling rigs are used to drill long upward boreholes in a fan shape (see Fig. 5), ranging approximately from 20 m to 50 m. After drilling and blasting, LHD machines are used to transport the blasted rock from the drawpoints to the orepasses.

The thickness of overburden as well as the mine design and layouts vary depending upon the orebody and the depth of operation. Mostly, a longitudinal SLC layout is used up to level 780 m below surface and a transverse layout from level 805 m downwards.[6] Production drifts are driven in a way to avoid weak zones as well as the major waste intrusions, and to minimize ore loss. The sublevel interval in the mine varies from 20 to 30 m depending on the size and shape of the orebody whereas the drift spacing is fixed at 22.5 m for all the orebodies.[6] The test was performed in one of the bigger orebodies (Alliansen) in Malmberget mine. The orebody has the highest sublevel interval in the mine i.e. 30 m.[6] The test area had a transverse SLC layout. The mine site used a fixed design of the blast ring in the test area with a borehole diameter of 115 mm and a ring-to-ring distance (burden) of 3.5 m. Data were collected from eight rings (level 1052, drift o4960 and o4990) from a total of 71 holes containing 72562 individual MWD data measurement points. More than 8000 buckets were filmed during the loading operations at these eight rings.

2.2. Data collection

To characterize and understand the nature of the rock mass, the study used MWD data. MWD involves measurement of a number of drilling parameters (depth, time, penetration rate, feed force, rotation

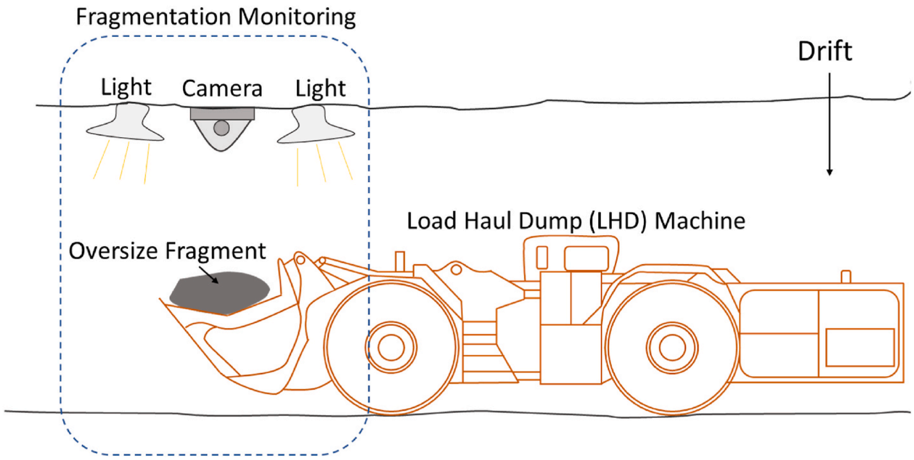

Fig. 3. Monitoring oversize fragments in a production drift using surveillance camera.

pressure etc.) to provide a fingerprint of the penetrated rock mass.[27–29] The technique was previously used in Malmberget mine to characterize rock mass quality and chargeability and was found effective.[30]

The drilling operation in Malmberget is fully automated; drill plans and log files containing MWD data are automatically transferred to and from the drill rigs through a mine-wide Wi-Fi network. All data are stored on a cloud server for further processing. The drill monitoring data for the eight rings were collected from this server.

The transport of blasted rock from the drawpoints to the orepass was recorded using motion detection cameras installed at the entrance of the drifts. A short video was recorded every time an LHD moved underneath the cameras. An illustration of the recording process is shown in Fig. 3.

2.3. Data processing and analysis

2.3.1. Identifying oversize fragments

Malmberget mine defines oversize fragments as rock blocks bigger than 1 × 1 × 1 m.[7,8] These oversize fragments can be the blasted ore or the caved waste rock. The surface dimensions of LHD buckets at Malmberget mine are normally 3 m × 2 m. An observational method like the one reported by Petropoulos,[31] Wimmer et al.,[32] Danielsson et al.,[8] Danielsson et al.,[33] and Manzoor et al.[29,34] was used to identify oversize fragments. More than 8000 recordings were manually explored, and the oversize fragments were counted. As it is not appropriate to compare the absolute boulder count because of its dependence on total blast volume in the ring,[35] the percentages of total boulder count for total number of buckets loaded from a blasted ring were computed and compared. For that purpose, the total number of oversize fragments observed for a certain ring was divided by the total number of buckets loaded from that ring.

2.3.2. Characterizing rock mass

During the test, the drilling parameters were recorded during drilling at every 3 cm along the borehole. MWD data commonly include outliers, noise, or faulty values. Outliers are sometimes generated because of machine adjustments during the drilling process but may also include responses to extreme and rarely occurring rock mass conditions. Faulty data can also be recorded during the addition of a new rod to the drill string to drill longer boreholes. Some faulty values, such as negative penetration rates or pressures recoded in thousands of bars which are beyond the machine capacity, are easy to identify and remove. It is important to remove all such values before using the data for rock mass characterization to get a better representation of the rock mass.

To remove noisy or faulty data samples from the MWD data, the study computed the time difference between consecutive recorded samples. For the given sampling interval of 3 cm, the time difference

Table 1
Filter limits for MWD data (Ghosh et al.[30]).

Recorded parameters	Filter limits
Penetration rate (m/min)	≥0.1 and ≤ 4
Percussive pressure (bar)	≥20 and ≤ 200
Feed pressure (bar)	≥35 and ≤ 100
Rotation pressure (bar)	≥25 and ≤ 125

between two recorded samples was usually around 3 s. Longer time intervals between samples indicated irregularities in the drilling process, such as rod changes or other types of stoppages. For the rod addition, the time difference jumped to approximately 50–60 s. Therefore, using the time difference, the samples recorded during the rod addition process were identified and replaced by interpolated values before and after them. After such stoppages, the applied forces will only gradually regain their normal values, and it will take some time before drilling is stable again. This means that several data points surrounding stoppages are not reliable and should be removed from the data. After removing and replacing these samples with interpolated values, the filter limits used by Ghosh et al.[30] (see Table 1) were applied to remove all other abnormal or unrealistic data samples. More details of this filtering procedure can be found in Manzoor et al.[34]

After filtering, the MWD data were used to characterize the rock mass quality into five categories: 'Solid (C1)', 'Slightly fractured (C2)', 'Highly fractured (C3)', 'Minor cavities (C4)', and 'Major cavities (5)'. The details of how to characterize the rock mass in this way can be found in Ghosh et al.[30] A brief description of the procedure is given below:

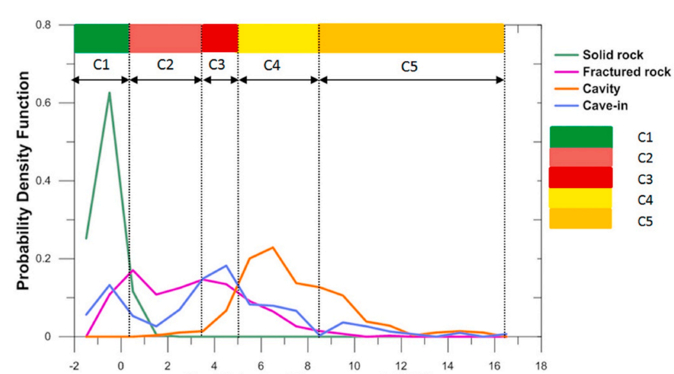

Fig. 4. Rock mass categories based on PCA (Source: Ghosh et al.[30]).

Table 2
Occurrence of different rock types based on MWD data.

Fan	C1	C2	C3	C4	C5
17	89.211	8.507	0.413	0.433	1.436
18	98.464	1.527	0.000	0.009	0.000
19	93.575	6.288	0.088	0.029	0.020
20	89.398	10.051	0.250	0.175	0.125
21	95.251	4.523	0.104	0.017	0.104
22	84.169	13.871	1.080	0.825	0.116
23	89.787	9.138	0.576	0.422	0.077
31	92.608	5.916	1.003	0.452	0.022

2.3.2.1. Calculating rock mass fracturing. A fracturing parameter is calculated using penetration rate and rotation pressure from MWD data as given in Equation (1).

$$Fracturing = \frac{1}{5}\left[0.5 \times \left(\frac{PRV}{\sqrt{\sigma_{PR}^2}}\right) + 0.5 \times \left(\frac{RPV}{\sqrt{\sigma_{RP}^2}}\right)\right] \qquad \text{Equ. 1}$$

where.

PRV = penetration rate variability.

RPV = rotation pressure variability, and

σ = variance of the corresponding parameter.

2.3.2.2. Principal component analysis (PCA). PCA is performed using filtered MWD parameters as well as the fracturing parameter, PRV and RPV. The MWD parameters used in PCA include penetration rate, rotation pressure, feed pressure and percussive pressure. Based on PCA, rock mass is characterized as shown in Fig. 4.

The percentage occurrence of different categories (solid, slightly fractured, highly fractured, minor cavities, major cavities) in each analysed ring based on MWD data is given in Table 2.

Fig. 5 shows the rock mass characterization in graphical user interface of a newly developed charging tool for three of the eight analysed rings.

The lines in the figure represent the boreholes, and the discs around them show the degree of rock fracturing. The sections of the boreholes between the discs show the solid rock mass while yellow, blue, black, and red discs represent the rock mass with slight fracturing, high fracturing, minor cavities, and major cavities respectively. As Fig. 4 shows, the rock mass categories do not represent the exact values but cover a range based on PCA, the diameter of the discs in Fig. 5 indicates where the calculated value for a specific rock type lie in the range. Bigger the size of the disc, closer to the upper end of that category range the value lies.

The ring in Fig. 5a shows good quality rock with very few disturbances in the rock mass. The ring in Fig. 5b shows a very disturbed rock mass with extensive fracturing and cavities in the upper part of the ring. The ring in Fig. 5c represents an intermediate case with some pronounced fracture zones crossing the ring.

Finally, the percentage of each category (solid, slightly fractured, highly fractured, minor cavities, major cavities) in each ring was calculated and used in the correlation analysis below.

2.3.3. Correlation test

The study was interested in predicting the occurrence of oversize fragments using MWD data. It is important to look at the correlation coefficients because higher correlation coefficients can result in better predictions with fewer errors.[36] In this study, to calculate the correlation coefficients, the nature of the rock mass based on MWD data was used as an explanatory variable (X) and the occurrence of oversize fragments was a response variable (Y). A correlation test was performed for the following null and alternate hypotheses.

Null hypothesis: There is no correlation between the nature of the rock mass and oversize fragment generation, i.e., $R = 0$.

Alternate hypothesis: There is a non-zero correlation between the nature of the rock mass and oversize fragment generation, i.e., $R \neq 0$.

It is important to remember that R only quantifies the strength of a correlation. It does not say anything about the statistical significance of the correlation. To determine whether the measured strength of relationship was statistically significant, p-values were also calculated. The p-value represents the probability of occurring a strength as extreme as the measured strength if the null hypothesis was true.[37] Using a significance level of 5%, the null hypothesis was rejected if the p-value was less than 0.05, as this meant the measured R value was statistically significant. The study tested the Pearson and Spearman correlation to measures if the correlation between variables is strictly linear or not. The Pearson correlation method produced higher coefficients, indicating a stronger linear than non-linear relationship between the nature of rock mass and oversize fragment generation. Finally, the coefficients of determination (R^2) were measured to find out the captured variance by the linear regression models.

2.4. Model development

If the relationship between the explanatory variables (nature of rock

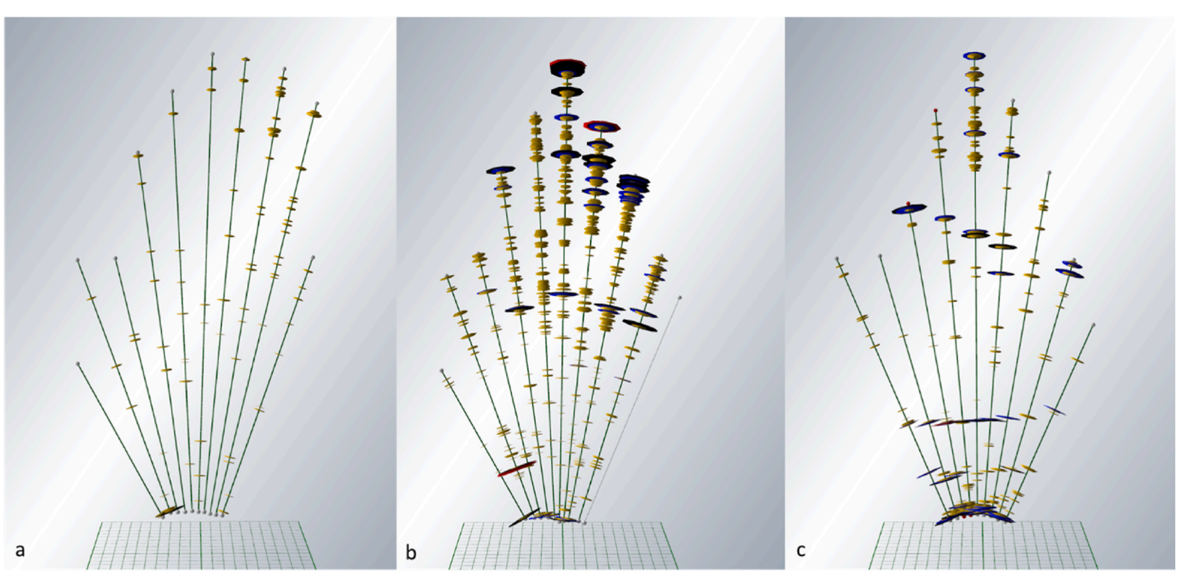

Fig. 5. Fractures and inhomogeneities in drilled rings based on filtered MWD data. (Courtesy of AFRY, Sweden).

Table 3
VIF values for the explanatory variables.

Variables	C1	C2	C3	C4	C5
VIFs	183318	135567	1882	591	2376

mass) and the response variable (oversize fragments) is linear, multiple linear regression may be used for model development. However, if the explanatory variables demonstrate very high dependence and inter-correlation, with a high level of multicollinearity, linear regression is not recommended because it can cause misinformation in the model. To deal with this problem, the redundant variables that do not provide information to the model because of their dependence on other variables should be removed from the model, or other methods that can inherently deal with multicollinearity, such as partial least square (PLS) regression, may be used. In this case, the model was developed using both methods i.e., linear and PLS regression, to ensure the best possible results.

Multiple linear regression is a statistical technique to model the relationship between a response variable and multiple explanatory variables; it is a well-established and widely used statistical tool for prediction and inference making.[38] The general formulation of the multiple linear regression model used in this study is given by Equation (2).

$$Y = \beta_0 + \beta_1 C_1 + \beta_2 C_2 + \beta_3 C_3 + \beta_4 C_4 + \beta_5 C_5 \qquad \text{Equ. 2}$$

where Y is the response variable, i.e., the percentage occurrence of oversize fragments,

β_0, β_1, β_2, β_3, β_4, and β_5 are regression coefficients, and C represents the rock mass category, so that.

C_1 = percentage of solid rock mass.
C_2 = percentage of slightly fractured rock mass.
C_3 = percentage of highly fractured rock mass.
C_4 = percentage of rock mass with minor cavities.
C_5 = percentage of rock mass with major cavities.

The strength of the correlation between the explanatory variables was determined using the variable inflation factor (VIF) (see Table 3), a common statistical tool for testing multicollinearity.

The VIF values greater than 10 show high correlation among the variables,[39] which in this case, is true for all the explanatory variables as given in Table 3. One way of dealing with this issue is by dropping the less informative variables from the model as same information is provided by the other variables. As the percentage of solid rock mass was the dominant explanatory variable (ranging from 84% to 98.5% for individual rings), VIF was calculated by dropping all other variables one by one. VIF tests showed the multicollinearity existed until all the variables were dropped except the solid rock mass. This means the solid rock mass alone provided enough information to the model; the other variables did not provide any further information. Therefore, Equation (2) was reduced to Equation (3).

$$Y = \beta_0 + \beta_1 C_1 \qquad \text{Equ. 3}$$

PLS regression generalizes and combines features from principal component analysis and multiple linear regression.[40] In this study, PLS regression models were developed for different components to select the optimum number of components capturing most of the data variability. PLS components are linear combinations of the explanatory variables that maximize their covariance with the response variables. R^2X cum and R^2Y cum were calculated for the models with different PLS components. The R^2X cum measures the cumulative fraction of the variation of the X variables (rock type based on MWD) explained for any selected PLS components. R^2Y cum (R^2), also known as a coefficient of determination, describes the amount of variability in the Y variable (oversize fragments) captured by the given model. Dogruoz et al.[41] reported R^2 values as low as 0.41 showing strong correlations between explanatory and response variables in a rock engineering application.

Table 4
Results of pearson correlation test.

Parameters	Solid Rock	Slightly Fractured	Highly Fractured	Minor Cavities	Major Cavities
R	0.88	−0.87	−0.62	−0.74	−0.25
R^2	0.78	0.76	0.39	0.55	0.06
p-value	0.004	0.005	0.100	0.036	0.554

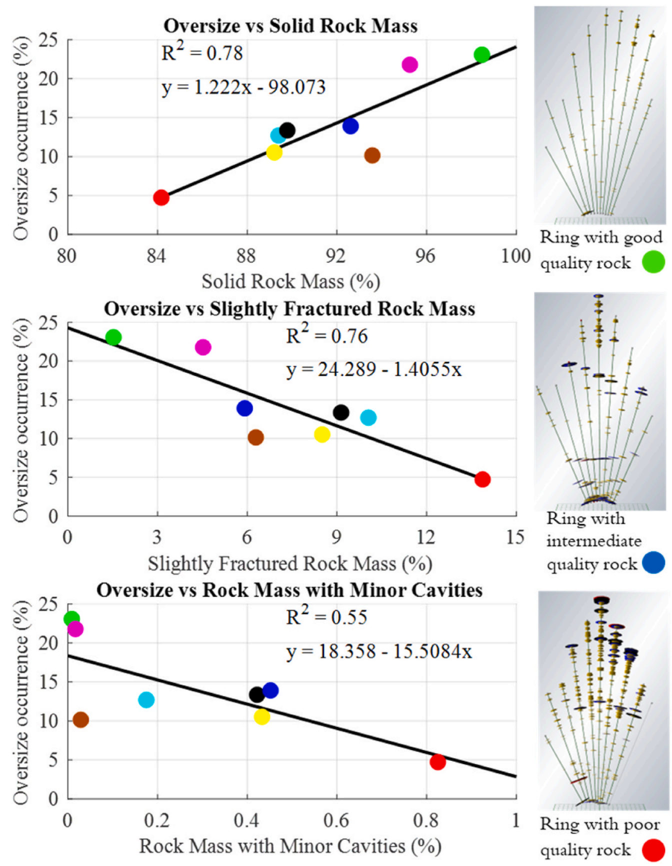

Fig. 6. Scatter plots and linear regression lines for oversize fragments (Y) and rock types (X).

3. Results and discussion

Table 4 presents the R, R^2, and p-values for the Pearson correlation test. The correlation coefficients suggest a positive correlation between oversize fragments and solid rock mass, and a negative correlation between oversize fragments and other rock types. Therefore, with an increase in the percentage of solid rock mass, there will be a subsequent increase in the occurrence of oversize fragments. As the rock mass becomes more fractured and has cavity issues, the intact block size before blasting will be reduced, leading to less boulder generation. The solid and slightly fractured rock masses both have strong correlations with the occurrence of oversize fragments as per their R values.

The p-values for solid rock, slightly fractured rock, and rock mass with minor cavities less than 0.05 show that the R values for these categories are highly unlikely if the null hypothesis were true which leads to the rejection of null hypothesis for these categories. Hence, there is a statistically significant correlation between these variables and the oversize fragments. Meanwhile, the correlation between oversize fragments and highly fractured rock and rock mass with major cavities is not significant, with a significance level of 0.05 as the p-values are greater than 0.05. The R^2 values also show that the models for solid and slightly fractured rock mass capture higher variability (0.78 and 0.76) in

Table 5
Linear regression model for predicting oversize fragments.

Equation	R^2	Adjusted R^2	P-value
$Y = -98.07 + 1.22C_1$	0.78	0.74	0.0038

Table 6
PLS regression summary for an increasing number of components.

Components	% Variance	R^2
1	69.83	0.73
2	81.56	0.77
3	99.32	0.78
4	100.00	0.79

response variables than the models for highly fractured (0.39), minor cavities (0.55), or major cavities (0.06).

The oversize fragments were modelled as a function of the rock types which had statistically significant correlation as shown in Table 4 i.e., solid, slightly fractured, and minor cavities (see Fig. 6). The figure also shows the R^2 values and linear regression equations for different relationships. The percentage of rock mass obtained from MWD data is plotted on the x-axis, and the percentage of occurrence of oversize fragments is plotted on the y-axis. The colours in the figure represent different rings to show the behaviour based on the nature of the rock mass. For example, the ring with good quality rock mass is illustrated as green points, and the ring with broken rock is shown as red points. The ring with intermediate quality rock mass is blue. The nomenclature of good, intermediate, and poor rock quality is based on the overall appearance of these rings in Figs. 5 and 6.

Fig. 6 shows that the linear regression model for the solid rock mass captures the maximum data variability, with an R^2 of 0.78. Moreover, as stated in section 2.4, the linear regression model which does not have the problem of multicollinearity and captures maximum information given by Equation (3) involves only solid rock mass. The linear regression model for predicting oversize fragments using solid rock mass is given in Table 5.

In the table's equation, Y represents the percentage of oversize fragments from a blasted ring, and C_1 represents the percentage of solid rock mass in that ring based on MWD data. R^2 shows that the model captures 78% of the variability of the response variable. The p-value of the regression model suggests the information brought by this explanatory variable is statistically significant, at a significance level of 5%.

PLS regression was performed for an increasing number of components (up to four) to determine the percentage of variance in the explanatory variables explained by each component and to select the optimal number of components for the model. The components are linear combinations of the explanatory variables that that try to maximize the observed variability in the explanatory variables. It is important to note that the model is developed using the primary variables, but components construct different combinations of those primary variables capturing different variance. With increasing number of components, more complex combinations are constructed that increase the captured variance in the data. However, an optimal number of components should be selected for model development to avoid any loss of information as well as over-fitting the model. Table 6 shows the percent variance explained (R^2X) for different components and R^2 (R^2Y) values for the corresponding variables.

As the table indicates, the variance explained when increasing the number of components increased up to the third component. However, cross-validation showed that the first component captured the maximum variance and was optimal for model development. Selecting more components would over-model the dataset and introduce errors instead of increasing prediction capabilities. Therefore, a model with the first component was selected to predict oversize fragment occurrence using the five rock mass categories (see Equation (4)).

$$Y = -12.81 + 0.353C_1 - 0.406C_2 - 2.619C_3 - 4.480C_4 - 0.892C_5 \quad \text{Equ.4}$$

Where Y represents the percentage of oversize fragments and C represents the rock mass categories. The PLS regression model with the first component had an R^2 value of 0.73, as shown in Table 6. It captured a little less variation in the response variable, i.e., oversize fragments, than the linear regression model in Table 5. A visual illustration of the comparison of the models is given in Fig. 7.

As shown in Fig. 7, a linear regression model considering only solid rock mass performed as well as a multivariate model generated using PLS regression and all rock types. The maximum variation captured by the linear regression model was 78%, and the PLS regression model captured 73%. The solid rock mass had a strong positive correlation; this means that with an increasing percentage of solid rock mass, there is an increase in percentage occurrence of oversize fragments. This may be due to the increased percentage of solid competent blocks of the rock mass which can produce bigger rock pieces after blasting.

4. Conclusions

This study explored the relationship between the nature of rock mass based on MWD data and oversize fragments after blasting in a sublevel caving operation. As shown in the results of the correlation and regression analysis, solid and slightly fractured rock masses tend to have more influence on oversize fragment generation than highly fractured rock mass or rock mass with minor or major cavities. The greater

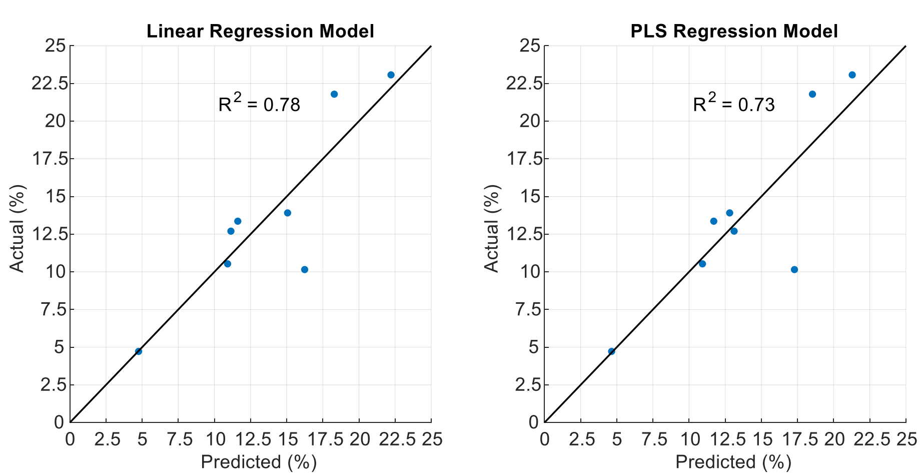

Fig. 7. Comparison of actual and predicted oversize fragment occurrence.

influence of solid and slightly fractured rock mass can be attributed to the more frequent occurrence of these rock mass types in the dataset; in fact, they comprise almost 99% of the total rock mass.

The study reached the following conclusions:

- An increasing percentage of solid rock mass leads to an increase in percentage occurrence of oversize fragments, while an increasing percentage of other rock types leads to a decrease.
- The occurrence of oversize fragments can be predicted using a linear regression model involving only solid rock mass with an R^2 of 0.78 or a PLS regression model involving all rock types with an R^2 of 0.73.
- For this study, multiple linear regression was able to predict oversize fragments because of the linear relationship between the variables. Also, the solid rock mass was in abundance that didn't require any other rock type to influence the model. However, PLS regression can be a better choice if the relationship is not strictly linear, and the model is not influenced by only single rock type.

The results look quite promising and suggest MWD data can be used to predict oversize fragments for a sublevel caving operation. This forecast can help mine planning engineers devise special handling procedures for these fragments. This is important, as they can seriously affect productivity and the success of any sublevel caving operation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors do not have permission to share data.

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