Development of an equation to predict blast induced ground vibrations of open cast lime stone mine by using Multiple Linear Regression (MLR)

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Abstract
This study focuses on predicting ground vibrations generated by blasting activities in open cast limestone mining by integrating blast design parameters with conventional variables. Blasting is a critical operation for the effective removal of overburden and mineral extraction, but it can lead to significant adverse effects, particularly ground vibrations, which pose challenges for both mining and environmental engineers. Conventional methods for estimating these vibrations typically focus on the distance from the blast site and the maximum charge per delay as key independent variables.

Recognizing the substantial impact of blast design on vibration levels, this research employs multiple linear regression analysis to incorporate additional factors such as blast design elements. By developing a more comprehensive predictive model, the study aims to enhance the accuracy of ground vibration forecasts, ultimately contributing to safer and more sustainable mining practices.

Keywords: Blasting, ground vibrations, Multiple linear regression analysis, blast design, open cast mining.

Introduction

During the process of blasting, a little proportion of the energy produced by the explosion was used for the purpose of breaking and dislodging rocks, but the majority of the energy results in negative environmental consequences including ground vibrations, air overpressure, fly rocks and rebound[6,12]. The aforementioned impacts have the potential to compromise the structural stability of tall retaining walls, benches and other architectural structures. Mining engineers have a significant difficulty in devising blast geometry that maximizes the use of explosive energy only for the purpose of rock fragmentation. Therefore, the design of blasts is crucial in mitigating ground vibrations.

One approach to mitigating ground vibrations is through the use of advanced blasting techniques. These techniques involve carefully selecting the type and amount of explosives used as well as optimizing the timing and sequencing of detonations[1,2]. Additionally, engineers can employ specialized blasting materials such as cushioning agents or delay detonators to further minimize ground vibrations and their potential impact on nearby structures. By implementing these measures, mining engineers can strike a balance between efficient rock fragmentation and minimizing the environmental consequences associated with blasting operations. This approach is crucial in areas where mining activities are close to residential or commercial areas.

By carefully selecting the type and amount of explosives, engineers can ensure that the rock is efficiently broken down while minimizing the risk of damage to nearby structures. Furthermore, the use of cushioning agents or delay detonators can help to absorb the shockwaves generated during blasting and reducing the vibrations transmitted to the surrounding environment. Overall, these measures allow mining engineers to carry out their operations in a responsible and sustainable manner.

However, it is crucial from a scientific standpoint to use site-specific control blasting techniques in order to precisely estimate and mitigate the potential damage to structures caused by blasting. At present, the USBM equation is used for the purpose of forecasting the ground vibrations[6]. Generally, the impact of blast induced ground vibrations was assessed in the form of Peak Particle Velocity (PPV). The USBM equation only takes into account two factors, namely distance (D) and maximum charge per delay (MCD). However, other additional elements also exist that exert influence on the ground vibrations caused by blasts[12]. Research has been conducted to forecast ground vibrations generated by blasts, using a combination of controlled and uncontrollable elements through the implementation of soft computing methods.

Various machine learning models including Artificial Neural Networks (ANN)[10,12], Random Forest (RF)[17-19], Support Vector Machines (SVM)[4,7-9,11,14-16] and logistic regression, have been used for the purpose of predicting and modeling ground vibrations caused by blasts. Presently, ground vibrations have emerged as the predominant area of focus in the investigation of blast effect for several machine learning applications. The prediction process encompasses the careful selection of input parameters, the use of a training model and the subsequent prediction of the desired output. The range of input parameters may vary from a minimum of two to a maximum that is determined by the algorithm's robustness and the computational resources at hand.

Various researchers have examined distinct sets of significant parameters in order to forecast ground vibrations

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and have developed diverse artificial neural network (ANN) designs to enhance the precision of these predictions. Certain studies examined a limited number of factors, with some only considering two, while others explored a broader range of characteristics, with as many as 13 being taken into account in order to forecast the ground vibrations resulting from blasts[10]. The development of the equation to forecast the ground vibrations caused by explosions has been hindered by the challenges encountered in data collection. Furthermore, the data available for analysis remains largely unchanged as the overall blast design remains consistent across the entire mining operation.

Identifying the exact contributing components has proven to be a challenging task owing to the intricate nature of the blast phenomena and the multitude of forces at play. However, previous research has examined several aspects that contribute to blast-induced ground vibrations including explosive characteristics, blast design parameters, geological circumstances and rock mass attributes. The primary factors considered in the estimation of blast-induced ground vibrations include the distances between the blast zone and monitoring point, maximum charge per delay, velocity of detonation, blast hole depth, burden, spacing, stemming height, powder factor, rock-quality designation (RQD) and p-wave velocity[12].

In this research, an endeavor was undertaken to formulate an equation by integrating blast design parameters as an input, in addition to the commonly employed inputs, namely D and MCD. In order to address the variation in blast design parameters within the mine, data was gathered from two limestone mines that employed distinct blast designs.

Study Area

Mine 1: The Zuari limestone mine is a mechanized mine. Combination of 7.2 m³ excavators and 60 MT dumpers is used to transport the blasted material. The blast holes are drilled with 2 drill machines of 320 HP for drilling 150mm diameter holes. In addition, dozer, road grader for haul road maintenance and rock breaker to avoid secondary blasting were used at the mine. To suppress the dust, drill machines are provided with water tanks of adequate capacity. The mine is having three working benches advancing in north and west directions with bench height of maximum 10m. The dimension of the pit is 1817m X 924m X 35m (NS-1817m, EW- 9024m, depth-35m). One way traffic system is implemented and the lead distance from 1st bench to crusher hopper is 2.8 km, 2nd bench is 2.50 km and 3rd bench is 2.2 km. A view of mine working is shown in figure 1.

Mine 2: The Bharathi limestone mine is a mechanized mine. Combination of 6.5 m³ excavators and 55 MT dumpers is used to transport the blasted material. The blast holes are drilled with 2 drill machines of 270HP and 380HP for drilling 150mm diameter holes. In addition, dozer, wheel loader, Back hoe, road grader for haul road maintenance and rock breaker to avoid secondary blasting were used at the mine. To suppress the dust, drill machines are provided with water tanks of adequate capacity. The mine is having three working benches advancing in east and west directions with bench height of maximum 8m. A view of mine working is shown in figure 2.

Material and Methods

Instruments details: Blast induced vibrations were monitored by seismographs namely Micromate, Mini Mate, Minimate Blaster and Mini Super graph II. All the seismographs record vibration in three directions i.e. Longitudinal (L), Vertical (V) and Transverse (T). They also record dominant frequency of vibration and compute the peak vector sum of the vibration.

Methodology: The methodology used in this study is as follows:

1. Selection of input and output variables.
2. Data collection and analysis.
3. Development of an equation using multivariate regression analysis.
4. Validation of equation with unseen data.

Fig. 1: A view of Zuari mine working

Fig. 2: A view of Bharathi mine working.

Selection of input and output variables: There are two type of parameters which affect the blast induced ground vibrations i.e. controllable and non-controllable parameters. The non-controllable parameters are those, over which the blasting engineer does not have any control. The local geology, rock characteristics and distances of the structures from blast site are non-controllable parameters. However, the control on the ground vibrations can be established with the help of controllable parameters as follows:

1. Maximum charge per delay. (MCD)
2. Delay Interval and Delay sequence.
3. Direction of blast progression.
4. Blast design.
   a) Burden (B)
   b) Spacing (S)
   c) Hole Length (HL)
   d) Number of holes (NH)
   e) Number of rows (NOR)
   f) Total charge per round.(TC)
   g) Average charge per hole.(ACPH)
   h) Stemming Length (SL)
   i) Charging Length (CL)
5. Bench design
   a) Depth from the surface
   b) Bench height (BH)
   c) Bench inclination
6. Explosives and its parameters.
7. Quality of blasting accessories.
8. Type of face (Free face, Choked face etc.).
9. Confinement.

Among the controllable parameters, only few parameters i.e. B, S, HL, NH, NOR, TC, SL, CL along with commonly used parameters i.e. MCD and distance from blast activity to measuring station (D) are taken into consideration to develop an equation because other parameters are having the uniformity in nature and some of the parameters could not be measured by the mine management. The equation should be useful to mine management to design the blast that will limit the blast induced ground vibrations within the threshold limit value as prescribed by Directorate General of Mines Safety (DGMS), India[5]. The output variable is peak particle velocity (PPV).

Data collection and analysis: To develop an equation to predict the blast-induced ground vibrations of limestone mines, huge data was collected from two lime stone mines i.e. about 81 data sets. Figure 3 shows the vibration recording using seismographs. Some of the data was used for checking the performance of the model in order to check the model accuracy. The data related to PPV and dominant frequency was collected by using micromate, minimate, minimate blaster and mini super graph-II. The input parameters were collected by field visits and measuring the lengths by tape. The data was then normalized by using eq. 1 in order to maintain the performance as good as possible. Normalization transforms these values in the range [0, 1] and make them ready for model development[13]. The blast delay sequence and drill hole schematic diagram are shown in figures 4 and 5. The descriptive statistics of the collected data is shown in figure 6. Further correlation analysis was carried out in order to know the correlation between variables. The results of the correlation analysis are presented in table 2. The PPV is positively correlated with Hole Length (HL), Charge Length (CL), Burden (B), Spacing (S), Stemming Length (SL) and Maximum Charge per delay (MCD) and negatively correlated with no. of holes (NH), number of rows (NOR) and distance from blasting site to monitoring station (D). PPV has strong positive correlation with charge length (CL) and maximum charge per delay (MCD) and strong negative correlation with distance from blasting site to monitoring station (D) and dominant frequency (DF) is positively correlated with number of holes (NH), number of rows (NOR) and is negatively correlated with HL, CL, B, S, SL, MCD, D and PPV. It has strong positive correlation with NH and strong negative correlation with HL, MCD.

$$Xnew = \frac{(X - Xmin)}{(Xmax - Xmin)} \quad (1)$$

Fig. 3: Vibration monitoring

Model development (Multiple Linear Regression): Multiple linear regression is a traditional statistical tool to determine the relationship between dependent and independent variables. The equation of the multiple linear regression analysis is as follows:

$$Y = \beta_0 + \beta_i * X_i + \cdot\cdot\cdot + e \quad (2)$$

where Y is the predicted variable, X_i (i = 1, 2 . . . P) is the predictor, β_0 is called intercept (coordinate at origin), β_i (i = 1, 2. . . P) is the coefficient on the i^{th} predictor and e is the error associated with the predictor. The equation we got after the regression analysis using minitab software is as follows:

$$PPV = -71.4 + 2.32\ NH + 11.18\ NOR - 70.8\ HL + 79.5\ CL - 5.8\ B + 5.45\ S + 74.7\ SL - 0.0289\ TC + 0.292\ MCD - 0.1377\ D \quad (3)$$

The multiple linear regression analysis was carried out with 95% confidence interval. The p-value less than 0.05 is statically significant and rejects the null hypothesis whereas p-value greater than 0.05 is vice versa[3].

Model validation using unseen data: To validate the regression equation, data was gathered from two lime stone mines. A regression analysis was conducted to compare the predicted and actual monitored PPV. The resulting regression graph is depicted in the figure 7. It is evident from the figure 7 that the R^2 value between the predicted and actual data is 0.82, indicating a strong relationship between the two variables.

Results and Discussion

The results presented in table 1 indicate that the factors CL, SL and D exhibit statistical significance and have a notable impact on the PPV. These parameters were found to influence PPV more substantially compared to other factors. In contrast, most of the remaining parameters, with the exception of HL, demonstrated minimal effect on PPV, with HL showing a negligible difference from the significance threshold of 0.05.

Table 1
P-values of input variables

Term	Coef	SE Coef	T-Value	P-Value
Constant	-71.4	90.6	-0.79	0.433
NH	2.32	2.26	1.03	0.309
NOR	11.18	7.19	1.56	0.124
HL	-70.8	37.9	-1.87	**0.066**
CL	79.5	40.1	1.98	**0.051**
B	-5.8	10.8	-0.53	0.597
S	5.45	8.71	0.63	0.533
SL	74.7	35.0	2.13	**0.036**
TC	-0.0289	0.0299	-0.97	0.337
MCD	0.292	0.821	0.36	0.723
D	-0.1377	0.0133	-10.35	**0.000**

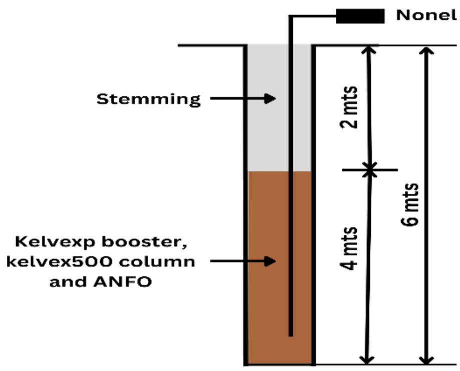

Fig. 4: Schematic diagram of drill hole

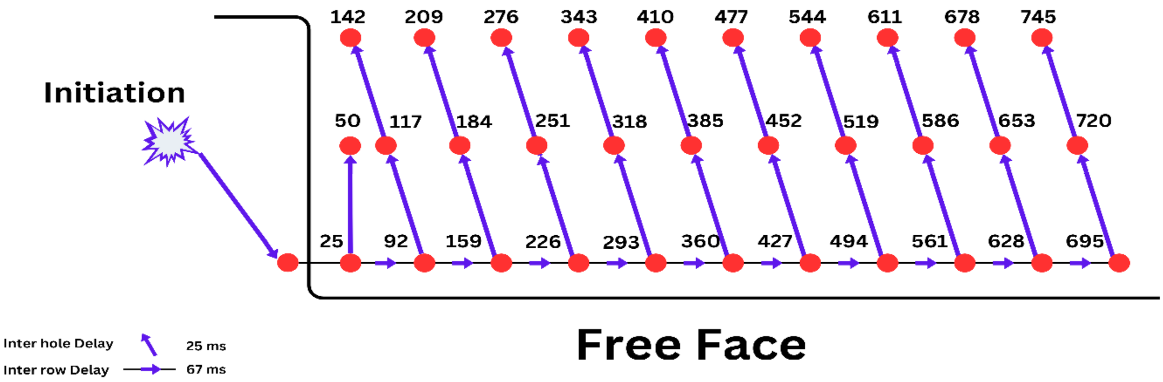

Fig. 5: Delay sequence used in lime stone mine

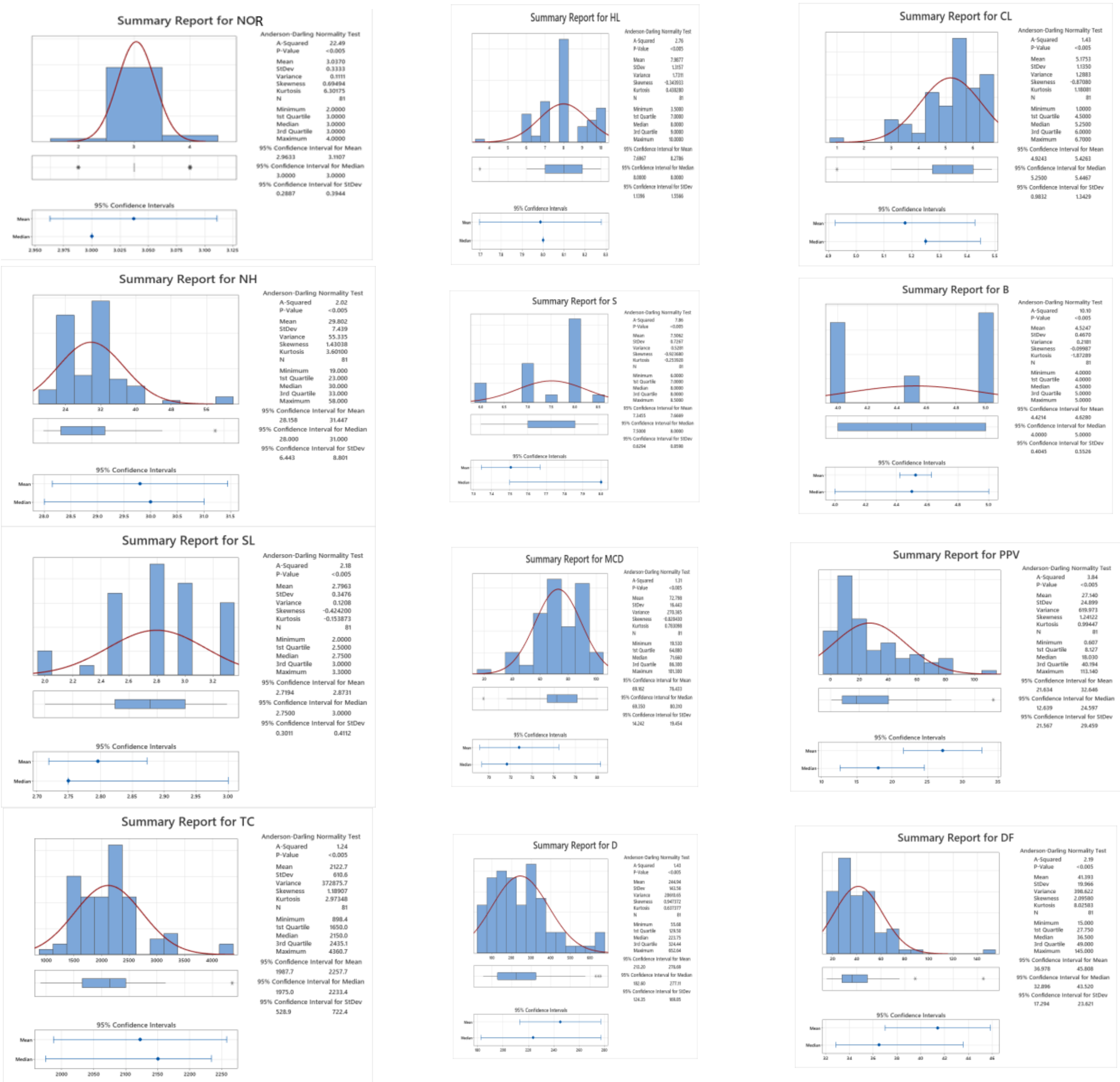

Fig. 6: Descriptive statistics of collected data with 95% confidence intervals

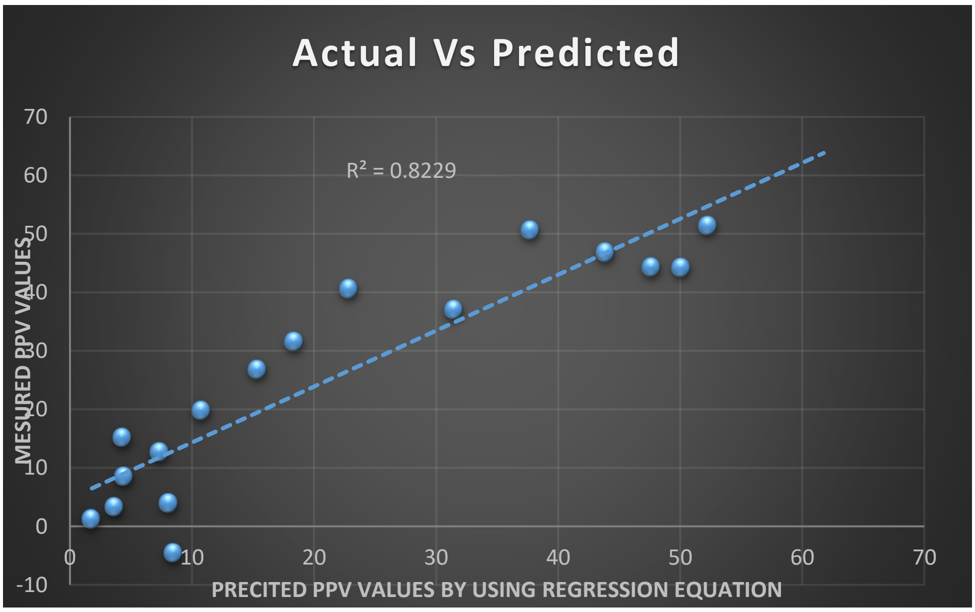

Figure 7: Regression analysis for Actual monitored PPV vs Predicted PPV using regression equation

Table 2
Correlation matrix of collected data

	NH	NOR	HL	CL	B	S	SL	TC	MCD	D	PPV
NOR	0.190										
HL	-0.346	0.172									
CL	-0.337	0.133	0.971								
B	-0.511	0.074	0.682	0.601							
S	-0.532	0.051	0.592	0.531	0.828						
SL	-0.255	0.147	0.642	0.443	0.609	0.519					
TC	0.507	0.311	0.486	0.529	0.153	0.214	0.121				
MCD	-0.389	0.254	0.850	0.866	0.695	0.698	0.426	0.572			
D	0.132	0.149	-0.180	-0.228	-0.101	-0.160	0.053	-0.082	-0.161		
PPV	-0.040	-0.018	0.212	0.232	0.048	0.069	0.064	0.104	0.118	-0.763	
DF	0.191	0.086	-0.431	-0.426	-0.301	-0.359	-0.310	-0.263	-0.431	-0.003	-0.029

Equation 3 has been validated using an independent set of unseen data, achieving a strong coefficient of determination ($R^2 = 0.82$), indicating that the equation provides reliable predictions of PPV. The correlation between the predicted and actual PPV values is strong, confirming the accuracy of the model in forecasting the outcomes of different blast designs. This strong correlation emphasizes the robustness of the equation as a tool for predicting PPV based on various blast parameters.

The use of eq. 3 by mine management offers a practical approach for forecasting PPV values in different blast scenarios. In instances where the predicted PPV exceeds the regulatory limits set by the DGMS circular[5], the equation can guide necessary adjustments to the blast design to ensure compliance with safety standards.

Conclusion

In conclusion, the findings suggest that charge length (CL), stemming length (SL) and distance (D) are the most significant factors affecting PPV, while other parameters, including HL, have a lesser influence. Equation 3 has proven to be a reliable predictive tool for PPV, with a high coefficient of determination ($R^2 = 0.82$) and a strong correlation between predicted and actual values. This demonstrates that eq. 3 can be effectively utilized by mine management to forecast PPV for various blast designs.

When PPV values exceed the limits specified by the DGMS circular[5], eq. 3 can assist in adjusting the blast design to meet the required safety criteria. Overall, the equation provides a valuable tool for optimizing blast designs and ensuring the safety and efficiency of mining operations.

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