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Prediction of Ground Vibration due to Blasting Activities of Coal Open Pit Mine Near Village Residents Using Multivariate Logarithmic Regression

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Abstract. Blasting activities are among the most important in mining and can have a negative impact on the environment and surrounding communities, causing disruption and even damaging nearby buildings and infrastructure. If the community protests and demonstrates, mining operations may be shut down, which would be very detrimental to the company. Studies are needed on effective planning to reduce the negative impacts. Ground vibrations measured by Peak Particle Velocity (PPV) are subject to thresholds set by each region's standards; in this research area, the maximum threshold is 3 mm/s to avoid damage to nearby buildings or settlements. The important variables are the explosive charge per delay and the distance, along with other blasting geometry variables such as spacing, burden, stemming, powder factor, and number of blast holes. Several previous researchers have used methods to predict PPV, with detonation parameters as the independent variables. This research uses general empirical methods and multivariate logarithmic regression (MLR). Prediction using MLR is better than general empirical methods; with R2 = 0.925, RMSE = 0.247, MAE = 0.548, MAPE = 0.218, and VAF = 96.66%, indicating near-perfect prediction. The MLR model produces a reference maximum explosive charge per delay of 59.09 kg.

Keywords: ground vibrations, blasting, peak particle velocity, multivariate logarithmic regression.

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1. Introduction

In mining and civil engineering, drilling and blasting are among the most widely used excavation support methods. Blasting is used to break up hard rock in mining, excavation, tunnel construction, road construction, or dam construction [1]. Blasting is planned by designing and specifying blasting parameters to determine the number of explosives and the desired results. A small portion of the energy (20-30%) released during blasting is used to break down and move the rock mass. In contrast, the remaining energy is dissipated into the soil and air, referred to as 'unwanted' or 'waste' energy [2]. This waste energy enters the ground as ground vibrations (wave and heat energy) and noise, and the air as air pressure and fly rock (Figure 1). Sometimes, ground vibrations exceed permitted limits, causing damage to natural and man-made structures and endangering humans [2].

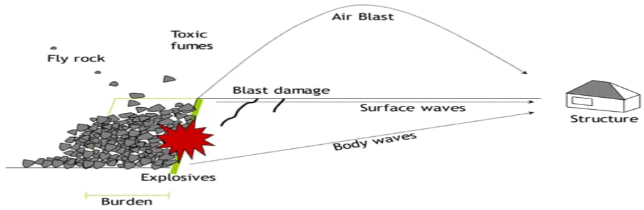


Figure 1. Illustration of the impact of blasting on building structures

Blasting activities are among the most important in mining and can have a negative impact on the environment and surrounding communities, causing disruption and even damaging nearby buildings and infrastructure. Sometimes people complain and demonstrate, disrupting mining operations and causing significant damage to the company. This also occurred in this research area, where the cessation of mining operations following community demonstrations led to losses. The loss of operational cessation resulted in the loss of potential coal production opportunities. Given these substantial losses, a research study was very important to investigate the impact of blasting. By doing so, the impact can be reduced, particularly ground vibrations, which disrupted residential infrastructure.

Ground vibrations resulting from the explosion are caused by a combination of body waves (primary & secondary) and surface waves (Rayleigh), collectively called seismic waves, propagating through the ground. Waves have their respective longitudinal (radial), transverse, and vertical velocities, which are components of the peak particle velocity (PPV). The maximum value between these velocities is known as PPV. PPV values vary with the monitoring distance from the source, explosives, and rock mass characteristics. Currently, the model created by the United States Bureau of Mines (USBM) is used to predict ground vibrations [1]. Generally, the impact of ground vibrations from blasting is assessed using PPV. PPV provides a quantitative value of the intensity of ground vibrations due to the explosion of each blasting process, which can be shown in the following relationship:

$$PPV = k\left[\frac{D}{\sqrt{Q}}\right]^{b} \tag{1}$$

The term, $\left[\frac{D}{\sqrt{Q}}\right]$ In (1), the term Scaled Distance (SD) is used [1]. Where D (m) is the observation distance from the blasting location to the measurement point, Q (kg) is the maximum explosive charge per delay, k and b are site-specific constants, determined by regression analysis. Where PPV is an independent variable parameter, depending on independent variable parameters such as the physical properties of different rock masses or their heterogeneity, geological conditions, blasting design, discontinuity, wave propagation properties, and the distance from the firing point to the measurement point [2-3] PPV is an important factor in identifying, monitoring, and controlling hazards and structural and safety damage caused by ground vibrations from blasting [4].

Several experts and researchers have developed many PPV prediction models [5-6]. All these models generally depend on only two variables, such as the maximum explosive charge and the distance between the explosion location and the observation point [2]. Some of them use the attenuation coefficient in an exponential order. These different model equations yield different safe PPV values for load per delay. All model equations do not provide the same results at each location, because PPV is also influenced by blasting design, geological and geotechnical conditions, and explosive material parameters [2]. The blasting design in question consists of burden distance, spacing, depth, and blasting sequence. Meanwhile, geological and geotechnical conditions are influenced by natural factors in accordance with the operational objectives of the products produced, such as aggregate mining [7–9], coal [10–12], construction [13,14], and minerals [15–17]. Meanwhile, the explosive parameter is more closely related to the explosive charge that detonates at each delay. Several researchers have studied smaller mine conditions with other parameters held constant except explosive charge and distance from blasting, so that the USBM empirical equation in equation (1) has been widely accepted as a predictor of blasting vibration [11]. However, for larger blasting operations, which vary blasting design parameters based on site conditions and equipment availability, a multivariate analysis approach is needed. This approach involves formulating a hypothesis in which the PPV value of ground vibration is treated as an independent variable, with other parameters such as hole diameter, hole depth, length of explosive charge column, measurement distance, and explosive charge treated as independent variables. The relationship between the dependent and independent variables is examined using multivariate analysis, including multivariate linear, polynomial, and logarithmic regression, which has been studied by several researchers with various model approaches [11].

Various models used in the previous research are the Multivariate Regression Analysis method [2,11], Multiple Linear Regression Analysis [5], Numerical Simulation [6], Artificial Neural Networks (ANN) [8,15,18], Regression Power Analysis (1,3,18) , Time History Analysis [16], Gradient Boosting Regression [9], Relevant Vector Machine [19], Novel Soft Computing Model [10], Brain-Inspired Emotional Neural Network [15], Multivariate Logarithmic Regression [11], Multivariate Adaptive Regression Splines [12], Classification and Regression Tree [12], Support Vector Regression [12], have been used to predict and model ground vibrations caused by explosions. The prediction process includes parameter selection, method use, and prediction of the resulting output. Some researchers examine several top factors, while others consider only two or more. Based on the literature reviewed, there is no single equation that effectively reduces ground vibrations from blasting by modifying the blasting design based on each condition. Therefore, this research takes the research object to be open-pit coal mining in East Kalimantan, Indonesia, with unique geological conditions characterized by hard quartz sandstone with high porosity, and the location and conditions differ from those in previous research.

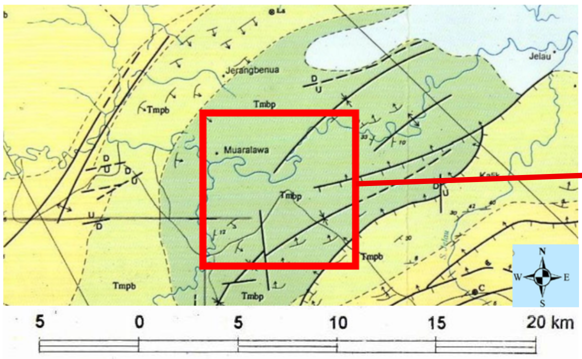
Meanwhile, the method used is the general empirical method of scaled distance theory and Multivariate Logarithmic Regression (MLR), because the empirical model has been tested in previous research, and MLR is one of the more mature and accurate multivariate methods. It does not depend on the data being normally distributed. In addition, the MLR method has advantages for handling non-normally distributed data with non-linear relationships, is robust to outliers, and offers more stable predictions. It also uses a logarithmic transformation to stabilize variance, making the model more reliable.[20]. In this research, the data used were first tested for normality using the Anderson-Darling test, multicollinearity using the variance inflation factor (VIF), and heteroscedasticity using the Breusch-Pagan test, which were not reported in previous research. At the end of the modeling stage, a model evaluation was carried out with the values of Coefficient of Determination (R2), Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Variance Accounted For (VAF) [4,18,19].

2. **Method**

2.1 Description and Geological Conditions of The Research Location

The research area is an open-pit coal mining project in East Kalimantan, Indonesia, located near road infrastructure and residential areas, with the nearest residential area approximately 300 meters away, as shown in Figure 2. This project has received government permission to carry out mining operations in accordance with applicable standards and regulations. Mining business actors strive to operate productively and efficiently. One mining activity is blasting. This blasting activity can affect the environment and surrounding communities. The resulting impacts include ground vibrations, noise, throwing stones, air explosions, and dust, with ground vibrations being the most significant, leading to complaints from residents of surrounding communities.

The Kutai Basin is one of the largest and most complex sedimentary basins in Indonesia. The Kutai Basin developed from the Paleogene to the Neogene because of the interaction of regional tectonic processes, including extensional and compressional phases, in East Kalimantan. Stratigraphically, the research area lies within the Middle Miocene to Late Miocene Balikpapan Formation (Tmbp) and is an important part of the Neogene sedimentary fill in the Kutai Basin, as shown in Figure 3. Hydrocarbon deposits in the Lower Kutai Basin are found in sandstone deposited within the delta complex, which becomes younger and thicker towards the east [21]. The lithological character is interbedded with quartz sandstone and shale with coal inserts [22]. The physical characteristics of this quartz sandstone are high porosity and relative hardness. According to Liu et al. [23], the differences in mineral content and pore structure significantly influence the propagation speed of seismic waves. Based on the lithology of quartz sandstone with high porosity and relatively hard texture, this is a special characteristic at the research location that differs from other locations, and it is a consideration factor in blasting operations. Geologically, this region is influenced by a system of folds and faults formed by post-depositional regional tectonic deformation. These structures generally trend southwest–northeast to west–east and are the result of the compression phase that occurred after the Miocene [22]



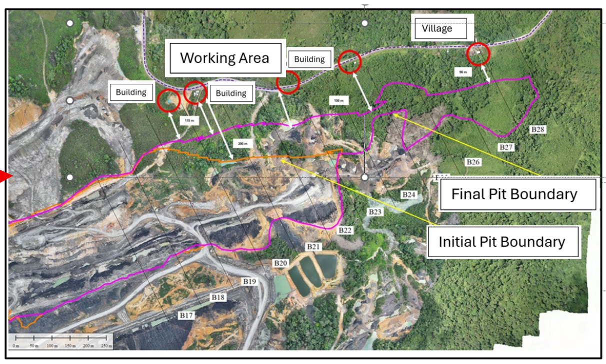


Figure 2a. Location of research area with rock formations on the geology sheet, modification [20]
Figure 2b—Location of the research area close to infrastructure and settlements.

2.2 Blasting Activities

Blasting activity begins with drilling using a 200-inch-diameter drilling machine. The hole resulting from this drilling will be filled with explosives. The number of explosives to be filled is determined by the plan to produce rock dispersion, based on the needs of the digging tools used. After drilling, the sounding drill hole is checked to ensure its depth and quality meet the standards. After that, the explosive material is filled, namely priming (booster & in-hole delay), followed by charging, in which the hole is filled with ANFO material according to the amount planned on the loading sheet. The next process is to tie up the connection between the holes with surface delay up to the initiation point, then check before blasting.

2.3 Methodology

The methodology used in this research can be divided into several stages:

1. Determination and selection of input and output variable data
2. Data collection and testing
3. Development of equation models using conventional empirical models and multivariate logarithmic analysis.
4. Validate the equation model from the predicted and actual output results.
5. Recommendations for filling explosives according to the PPV prediction formula and specified threshold values.

Determination and selection of blasting parameters as input and output variables: The blasting parameters used in this research are burden, spacing, stemming, hole depth, explosive filling, powder factor, and total hole, which are input variables. Burden is the shortest straight line distance between the nearest blast hole and the free surface in the direction where the rock will be thrown. Spacing is the distance between blast holes in a line parallel to the free face. Stemming length is the length of the top of the blast hole, which is not filled with explosives but is filled with aggregate material to cover the blast hole. Hole depth is the depth of the drill hole, which is measured from the surface of the blast hole to the bottom of the blast hole. The explosive charge is the amount of explosive charge, in kg, inserted into the explosion hole. Powder factor is the ratio of the weight of the explosive charge to the volume of material produced by the explosion, in units of Kg/Bank Cubic Meter (BCM). Total holes are the number of blast holes drilled per blast. An illustration of the blasting geometry is shown in Figure 3. Meanwhile, the output variable is the PPV value, which is directly measured using a Micromate instanten seismograph.

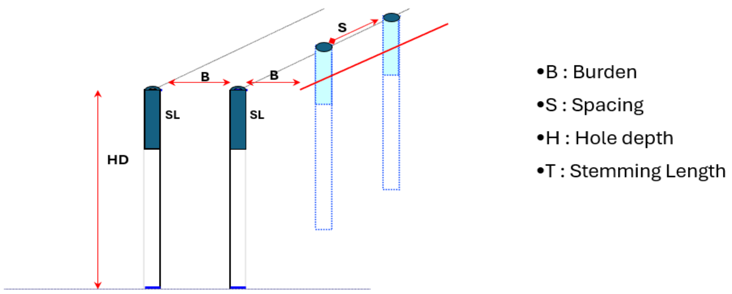


Figure 3. General blasting geometry and parameters.

Data collection: This input and output variable data were collected directly at the location as primary data. To collect variable-output data, ground vibrations were measured using the Instantel Micromate Seismograph directly at the site, and the observation distance from the blasting location was recorded. This Micromate Instantel sessimograph instrument consists of one geophone and one microphone (Figure 4a). Microphones are used to measure noise from the blasting location, and geophones are used to measure ground vibrations from the blasting location. Measurements are carried out at a safe distance from the blasting location, either from the house or the nearest infrastructure being studied. Measurements can be made from any direction toward the blasting location, if activities outside the blasting area do not interfere with the geophone or microphone data recording. To avoid external influences and ensure accurate recording of ground vibration levels from explosions, the instrument was set up and calibrated before data collection.

Furthermore, using the Micromate Instantel Seismograph tool, data processing can be carried out with Blastware software, which produces event reports and graphs. One of the measurement results is presented as an event report processed with Blastware software (Figure 4b). The results of data collection from 105 blasting activities, including blasting parameters and ground vibration measurements, are shown in Table 1.

Data testing:

Normality Test: This test assesses whether the data follows a normal distribution before further analysis. The Anderson-Darling test is used because it provides better, more consistent results than other tests [24]. This test can be carried out using any software tools, including Microsoft Excel, provided that the data are normally distributed and the p-value is > 0.05.

Multicollinearity Test: This test assesses whether the data to be processed exhibit correlation among independent variables. A correlation matrix will be produced from Microsoft Excel calculations. If the correlation between two independent variables is > 0.8, it indicates multicollinearity; if it is < 0.8, it indicates no multicollinearity. If the tolerance and VIF values in the table indicate tolerance < 0.1 and VIF > 10, then multicollinearity has occurred. If the tolerance value is >0.1 and the VIF is <10, then multicollinearity is unlikely. [25,26].

Table 1. Descriptive Statistical Data on Blasting Parameters for the Research Area

Variable	Unit	Symbol	Description	Mean	Min	Max	Standard Dev
Hole Depth	m	HD	input	7.51	4.45	11.83	1.48
Total Hole	hole	TH	input	64.50	23	151	30.88
Spacing	m	S	input	7.21	6	9	0.37
Burden	m	B	input	6.04	5	8.5	0.62
Stemming Length	m	SL	input	3.28	3	5	0.48
Powder Factor	Kg/BCM	PF	input	0.22	0.13	0.32	0.04
Distance	m	D	input	595.86	225	1000	198.37
Charge Per Delay	kg	Q	input	173.06	24.75	959.62	148.15
PPV	mm/s	PPV	output	3.69	0.28	13.24	2.28

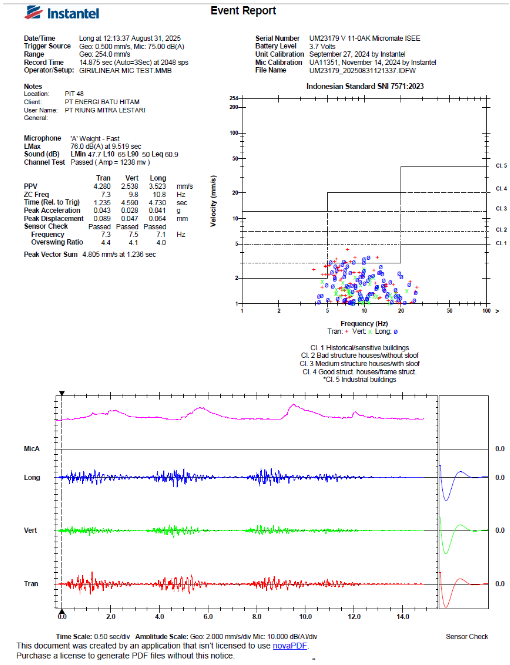


Figure 4a. Instantel Blastmate Seismograph. **4b.** Ground Vibration Event Report from Blastware.

Heteroscedasticity Test: This test uses the Glejser test to determine whether the residual variance remains constant across observations [27,28], which can be calculated in Microsoft Excel. The decision criteria for this test depend on the level of significance obtained: a p-value greater than 0.05 indicates no heteroscedasticity, whereas a p-value below 0.05 indicates heteroscedasticity in the model.

Correlation Test: This test is used to calculate the strength of the relationship between the independent and dependent variables, as indicated by the correlation coefficient. This strong correlation will later serve as the basis for regression analysis. The following is the classification of correlation coefficients and their interpretation [29] (Table 2)

Table 2. Correlation Coefficient & Interpretation

Correlation Coefficient	Interpretation
0.00 - 0.10	Negligible correlation
0.10 - 0.39	Weak correlation
0.40 -0.69	Moderate correlation
0.70 - 0.89	Strong correlation
0.90 - 1.00	Very strong correlation

Model development:

Generalized empirical model equations: Several empirical model equations have been developed to predict PPV using Scaled Distance calculations based on only two variables: the explosive charge per delay and the measurement distance from the blast location, as shown in equation (1).

Multivariate logarithmic regression model equation: One of the main advantages of multivariate regression is its ability to capture the structure of interdependencies among various response variables. Simultaneously modeling response variables can make analysis more efficient and yield more accurate parameter estimates, especially when the response variables are substantively correlated [30]. The MLR method is advantageous for handling non-normally distributed data with non-linear relationships, is robust to outliers, and uses a logarithmic transformation to stabilize variance, making the model more reliable [20]. Logarithmic regression provides the best results for vibration prediction. This aligns with the findings of most researchers. The USBM predictor equation also follows logarithmic regression analysis [11]. Regression analysis has been carried out in several studies [31] especially on blasting activities, considering various blasting parameters and their effects on ground vibrations. The basic equation of multivariate regression is:

$$Y^A = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + \mathrm{E} \tag{2}$$

Where Y^A is the dependent variable, β_0 is the intercept, and β_1, β_2, ... β_n are the coefficients or slopes from each independent variable $X_1, X_2, \ldots X_n$ and error E [17].

Validation of the equation model: *R2, RMSE, VAF, MAE & MAPE:*
To validate the equation model that has been created, you can use R2, RMSE, VAF, MAE, and MAPE analysis with the following formula [27].

$$\mathrm{R}^2 = 1 - \frac{\Sigma\,(y_i - \hat{y}_i)2}{\Sigma\,(y_i - \bar{y}\,)2} \tag{3}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2} \tag{4}$$

$$VAF = \left(1 - \frac{\mathrm{var}(y_i - \hat{y}_i)}{\mathrm{var}(y_i)}\right) \times 100\% \tag{5}$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}_i| \tag{6}$$

$$MAPE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{(y_i - \hat{y}_i)}{y_i}\right| * 100 \tag{7}$$

Where	y_i= Measurable value	, N= Number of Data
	$\hat{y}_i$= Predicted value	*var*= Number of Explosion Holes

The R^2 value is close to 1, indicating that the independent variable accounts for 100% of the variation in the dependent variable (a perfect model). A low RMSE value indicates lower prediction error, indicating better model performance. A VAF value of 100% indicates that the results achieve perfect predictions, and the greater the VAF value, the better the performance of the equation. The smaller the MAE value, the more accurate the model performance, and the smaller the MAPE value, the more accurate the model performance [10,32].

Recommendations for charging per delay: Recommendations for filling explosives can be generated by calculating the proposed PPV prediction formula, with the target PPV set to the safe threshold in accordance with SNI 7571 of 2023 [33] . Where the threshold value does not exceed 3 mm/s in safe conditions without damaging surrounding buildings and infrastructure at 300 m from the blasting location.

3. Results and Discussion

3.1 Data testing

Normality Test: In the normality test, the variables HD, TH, PF, and Q had p-values>0.05, indicating a normal distribution. Meanwhile, the variables S, B, SL, Distance, and PPV had p-values <0.05, indicating non-normal distributions. Therefore, to conduct a regression analysis with these non-normally distributed variables, a logarithmic transformation can be applied to normalize their distribution.

Multicollinearity Test: A multicollinearity test was then conducted using Microsoft Excel. The results showed no multicollinearity, as indicated by a correlation value between the two independent variables of <0.8 (Table 2). Therefore, these variables can be used for further data analysis.

Heteroscedasticity Test: To ensure the residual variance remains constant across observations, a heteroscedasticity test was performed to validate the regression analysis. The results of the heteroscedasticity test were calculated in Microsoft Excel using the Glejser test on the residuals, which were then abstracted and recalculated to obtain probability values. The probability values for all variables in this study were greater than 0.05, indicating the absence of heteroscedasticity (Table 3). With these values, a valid regression analysis can be performed.

Table 2. Multicollinearity Test Results

	HD	*TH*	*S*	*D*	*SL*	*B*	*PF*	*Q*
HD	1							
TH	-0.0065	1						
S	0.2055	0.0938	1					
D	-0.3046	-0.0872	-0.6026	1				
SL	0.2887	0.0417	0.5453	-0.5873	1			
B	0.3215	0.3112	0.5685	-0.6515	0.6046	1		
PF	0.2618	0.2087	0.5662	-0.7160	0.4602	0.6624	1	
Q	0.4924	0.1496	0.6421	-0.7534	0.5698	0.6840	0.7734	1

Table 3. Heteroscedasticity Test Results

Intercept	HD	TH	S	D	SL	B	PF	Q
P-value	0.708	0.057	0.054	0.637	0.657	0.206	0.186	0.156

Correlation Test: Another requirement to ensure a more valid regression analysis is to conduct a correlation test between the dependent and independent variables. The results of the correlation test revealed a very strong correlation between the dependent variable PPV (Q) and strong correlations among D, SL, B, and PF. Meanwhile, HD and TH showed a weak correlation, while S showed a moderate correlation. Therefore, the variables used in the regression test are D, SL, B, PF, and Q.

Table 4. Correlation Test Results

	HD	*TH*	*S*	*D*	*SL*	*B*	*PF*	*Q*
PPV	0.316	0.165	0.686	-0.810	0.701	0.706	0.883	0.932
Interpretation	weak	weak	moderate	strong	strong	strong	strong	very strong

3.2 Model Development

Generalized empirical model equations: In accordance with equation (1), the PPV prediction value can be calculated as follows

$$PV = k\left[\frac{D}{\sqrt{Q}}\right]^b \quad \text{dimana} \quad SD = \frac{D}{\sqrt{Q}} \quad \text{maka} \quad PPV = k[SD]^b \tag{5}$$

Based on the measurement data D and explosive charge per delay, a power regression graph can be created as in Figure 6. Furthermore, based on the graph (Figure 6), the constant values, coefficients, and determination values can be determined (Table 5).

Table 5. Power PPV & SD Regression Results

Constanta dan Coefficient		R^2
K	***m***	
119.6	-0.945	0.9151

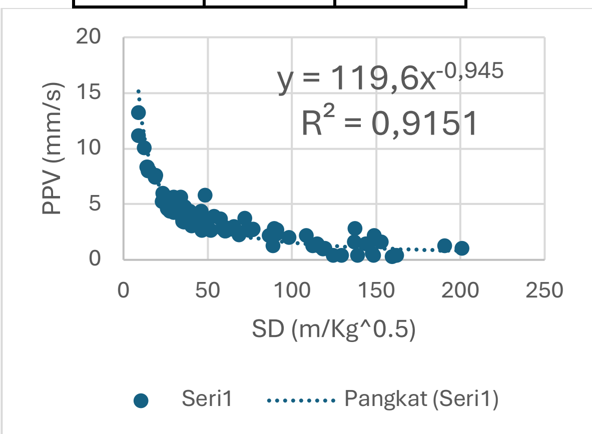


Figure 6. PPV & Scaled Distance Regression Power Graph

Based on Table 5, the PPV prediction equation based on the empirical Scaled Distance equation is as follows:

$$PPV\ Prediction = 119.6\left[\frac{D}{\sqrt{Q}}\right]^{-0{,}945} \tag{8}$$

The complete results of the PPV prediction calculations using the empirical model can be seen in Table 7.

Multivariate logarithmic regression model equation: Next, the model was developed using the second method, namely Multivariate Logarithmic Regression. To predict the PPV using Multivariate Logarithmic Regression, the independent variables are D, SL, B, PF, and Q. Using equation (2), the data from the independent variables are first transformed to a natural log scale and then analyzed using regression, producing constant and coefficient values as in Table 6.

Table 6. Constants and coefficients

Constanta & Coefficients						***R^2***
e	**Q**	**D**	**SL**	**B**	**PF**	
1.674	0.406	-0.388	0.273	-0.123	0.039	0.922

From these values, they can be entered into the following equation:

ln PPV = 1.674 + 0.406 ln Q - 0.388 ln D + 0.273 ln SL – 0.123 ln B + 0.039 ln PF.

Based on the Multivariate Logarithmic Regression approach, the PPV prediction equation can be produced as follows:

$$PPV = e^{1.674}\ \frac{Q^{0.406} SL^{0.273}\ PF^{0.039}}{D^{0.388} B^{0.123}} \tag{9}$$

From the Prediction PPV equation, the prediction PPV can be calculated using the Multivariate Logarithmic Regression (MLR) approach, as shown in Table 7.

Table 7. Prediction Results with the Empirical Model and MLR compared with Actual PPV.

ID Blast	PPV Actual	PPV Prediction by Empiric Model	PPV Prediction by MLR	ID Blast	PPV Actual	PPV Prediction by Empiric Model	PPV Prediction by MLR
1	1.82	1.05	1.700	**54**	0.58	1.06	1.746
2	1.27	0.83	1.452	**55**	0.28	0.99	1.665
3	3.73	2.09	2.896	**56**	2.87	2.45	2.741
4	1.00	0.79	1.384	**57**	3.49	3.74	3.983
5	13.24	15.01	11.123	**58**	2.56	2.47	2.777
6	7.58	7.41	6.015	**59**	2.58	2.49	2.788
7	11.15	15.17	10.059	**60**	3.46	4.14	4.160
8	5.97	6.07	5.303	**61**	2.65	2.86	3.439
9	5.20	6.20	4.990	**62**	4.21	3.86	3.852
10	5.63	5.90	5.427	**63**	4.56	5.41	5.304
11	2.17	1.05	1.783	**64**	3.05	3.60	3.775

12	2.81	1.14	1.868	**65**	2.84	2.54	3.070
13	7.41	7.56	6.626	**66**	2.34	1.69	2.231
14	10.07	11.05	8.927	**67**	0.39	1.05	1.702
15	4.33	4.09	4.210	**68**	2.72	1.68	2.176
16	4.81	4.29	4.406	**69**	4.76	4.01	4.151
17	2.19	1.42	2.107	**70**	3.69	3.65	3.730
18	4.36	3.72	3.842	**71**	4.87	5.03	5.063
19	4.24	4.53	4.335	**72**	1.24	1.72	2.366
20	4.58	4.97	4.745	**73**	5.64	4.83	4.920
21	3.93	3.33	3.514	**74**	1.23	1.37	2.019
22	3.92	3.60	3.841	**75**	3.41	3.13	3.681
23	1.58	1.14	1.708	**76**	3.65	2.58	3.042
24	7.97	9.53	7.682	**77**	0.42	1.25	1.997
25	2.64	2.02	2.464	**78**	0.38	1.20	1.921
26	2.23	1.70	2.197	**79**	4.93	4.31	4.351
27	2.74	2.35	2.804	**80**	1.45	1.09	1.666
28	4.34	3.20	3.552	**81**	5.63	5.68	5.792
29	8.33	9.96	7.980	**82**	2.81	2.04	2.532
30	2.76	1.96	2.373	**83**	4.36	5.20	5.045
31	3.65	3.21	3.548	**84**	5.78	3.05	3.914
32	2.34	1.68	2.176	**85**	2.19	1.76	2.303
33	0.39	0.97	1.634	**86**	4.36	4.13	4.947
34	2.72	1.97	2.502	**87**	4.24	4.83	5.000
35	4.76	5.03	5.063	**88**	4.58	5.53	5.338
36	3.69	4.14	4.111	**89**	3.93	3.50	3.768
37	4.87	4.74	4.831	**90**	3.92	2.77	3.231
38	1.00	1.29	1.946	**91**	1.58	1.03	1.691
39	5.64	4.26	4.782	**92**	7.97	9.12	7.463
40	1.24	1.33	1.956	**93**	2.64	3.16	3.716
41	3.41	4.06	4.093	**94**	2.23	2.19	2.646
42	3.65	4.13	4.143	**95**	2.74	2.49	2.788
43	0.42	1.12	1.796	**96**	4.34	5.02	5.306
44	0.38	0.97	1.593	**97**	8.33	9.69	7.613
45	4.93	4.69	4.913	**98**	2.76	2.48	2.894
46	1.45	1.34	2.132	**99**	3.65	4.05	4.155
47	5.63	5.61	5.347	**100**	3.21	3.60	3.775
48	2.81	1.70	2.298	**101**	2.95	2.96	3.785
49	4.36	4.01	4.030	**102**	4.23	3.86	3.852
50	5.78	6.02	5.902	**103**	4.96	5.38	5.332
51	1.98	1.56	2.192	**104**	3.25	3.60	3.775
52	3.98	4.20	4.233	**105**	2.96	2.28	2.919
53	0.98	1.31	2.037				

3.3 Validation of the equation model

R2, RMSE, VAF, MAE, and MAPE. In accordance with equations (3) and (4), validation can be carried out on the empirical model and the MLR model (Table 8).

Table 8. Validation of the PPV Prediction Formula

Validation Formula	R2	RMSE	VAF	MAE	MAPE
PPV Prediction by Empirical Model	0.915	0.346	85.33%	0.620	0.291
PPV Prediction by MLR	0.925	0.247	96.66%	0.548	0.218

Based on the values shown in Table 8, PPV Prediction by MLR is relatively better than PPV Prediction by the Empirical Model, which has a value of R2 = 0.925, RMSE 0.247, VAF 96.66%, MAE 0.548, and MAPE 0.218, indicating low error prediction with good model performance, and showing results that are close to perfect prediction. A comparison of model evaluation with other researchers' can be seen in Table 9.

Table 9 Results and Validation of PPV Prediction Model

Reference	Best Models	Project	No. of Datasets	Input Parameter	Performance Indices
Hossain et al [1]	Empirical	Granit	46	D, Q, SD	$R^2 = 0.271$
Kumar et al [2]	MVRA	Coal	32	Q, D, S, B, HD	$R^2 = 0.9142$
Nateghi [3]	Empirical	Construction	52	Q, D, SD	$R^2 = 0.809$
Khandelwal & Singh [4]	ANN	Coal	174	HD, B, S, Q, D, BI	$R^2 = 0.986$; MAE = 0.196
Ravikumar et al [5]	MLR	Limestone	125	CL, SL, D, HD	$R^2 = 0.82$
Bulushi et al [8]	Empirical	Limestone	20	HD, B, S, Q, D	$R^2 = 0.83$
Fulawka et al [19]	Empirical	Copper Ore	57	HD, SL, Q, TH	$R^2 = 0.8175$
Himanshu et al [17]	MLR	Coal	111	HD, TH, D, CL, B, S, Q	$R^2 = 0.836$
Hosseini et al [27]	LSTM	Lead Zinc	162	B, S, SD, Q	$R^2 = 0.9951$
Nguyen et al [32]	SVR	Limestone	125	Q, D, S, B	$R^2 = 0.940$, MAE 0.530; RMSE = 0.843
Tran et al [33]	BR	Quarry	300	Q, D, SL, PF, B, S	$R^2 = 0.916$, MAE = 0.229, RMSE = 0.276, VAF = 89.981,
Fissha et al (34]	RVM	Quarry	200	D, Q, SD	$R^2 = 0.9175$, MAE = 13.46, MAPE = 0.3055, RMSE = 18.54, VAF = 67.99
This study	MLR	Coal	105	Q, D, SL, PF, B, S, HD, TH, SD	$R^2 = 0.924$, MAE = 0.74; MAPE = 0.33; RMSE = 0.305, VAF = 93.72

Table 9 shows that this research differs from other research in that it was conducted on a coal project with a better MLR model and more complete model equation validation (R2, MAE, MAPE, RMSE, and VAF) as well as specific parameter inputs (Q, D, SL, PF, B, S, HD, TH, SD).

3.4 Recommendations for charging per delay

Based on the PPV prediction formulation with a better MLR approach, it is possible to plan recommendations for explosive fillings based on expected PPV results that do not exceed the PPV threshold for buildings or infrastructure, which is a maximum of 3 mm/s. With the maximum PPV value of 3 mm / s, it can be entered into equation (6) which is modified to determine the maximum explosive filling per delay (Q) with a specified distance (D) of 300 m, and blasting parameters according to the blasting plan, namely Burden (B), Stemming Length (SL), Powder Factor (PF) and the value of e which is a natural number (2.71828) according to equation (10).

$$Q = \sqrt[0.406]{\frac{PPV \;\; D^{0.388} B^{0.123}}{e^{1.674} \; SL^{0.273} PF^{0.039}}} \tag{10}$$

Where D is distance, B is Burden, SL is Stemming Length, PF is Powder Factor, and e is a natural number (2.71828).

If we assume the blasting parameters for B are 8 m, PF 0.20 kg/BCM, SL 3 m, and PPV 3 mm/s, then the maximum explosive charge per delay is 59.09 kg (Table 9).

Table 9. Calculation Results of Maximum Charging per Delay.

PPV	SL	B	D	Q	PF
m/s	m	m	m	kg	kg/BCM
3	3	8	300	59.09	0.20

4. **Conclusion**

Ground vibrations due to blasting, as measured by the PPV, are driven by several key variables. They are explosive charges per delay, measurement distance, burden, stemming length, and powder factor. To anticipate resident complaints about ground vibration disturbances, blasting parameter planning is required to keep the PPV below 3 mm/s [35]. Based on research data, PPV values can be predicted using general empirical models and multivariate logarithmic regression. The predicted PPV values closest to the perfect model are obtained using the equation from the multivariate logarithmic regression analysis. This is also strengthened by the validation of good and valid model equations from the values of R2 = 0.925, MAE = 0.548, MAPE = 0.218, RMSE = 0.247, and VAF = 96.66%. From the PPV prediction calculation that has been set with a threshold of 3 mm/s, the maximum value of the blasting material charge per delay that is allowed is a maximum of 59.09 kg for the assumption of SL = 3 m, B = 8 m, D = 300 m, and PF = 0.20 kg/BCM. Thus, the model can be applied to areas with the same characteristics and blasting parameters. The hope is that the results of this research can serve as a reference for safe blasting planning and have sustainable aspects in terms of environmental and social impacts, so that there will be no more operational stops due to community complaints and demonstrations. Several other parameters need to be considered in a similar study, including the location of the blast initiation point, the direction of the blast face, and the size of the delay. Other factors caused by blasting also need to be studied, namely the impacts of fly rock and air blast, which affect safety and comfort for both local workers and residents of the surrounding community.

Declaration of AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used TRINKA in a limited manner to assist in clarifying and refining the language of the writing, and only to check grammar and spelling. After using this tool/service, the author(s) reviewed and edited the content as needed and took full responsibility for the publication's content.

Declaration of Competing Interests

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.

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