Evaluation of Ground Vibrations through Peak Particle Velocity in Blue Metal Quarry

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Abstract:
Rock blasting although is a versatile and cost-effective technique often generates significant adverse effects. The present study focuses on the assessment of ground vibrations induced by blasting, which are a major concern for both mine operators and nearby residents. A total of twenty full-scale field trial blasts were conducted in a limestone quarry in a Blue Metal Quarry in India, and the resulting ground vibrations were recorded. To predict peak particle velocity (PPV), both multivariate linear regression (MLR) and artificial neural network (ANN) models were employed, using parameters such as the distance between the blast site and the monitoring station, charge per delay, and scaled distance as inputs. Furthermore, the recorded vibration levels were evaluated against the threshold limits prescribed by the Director General of Mines Safety (DGMS), India. Frequency analysis of the recorded data indicated that the dominant frequencies predominantly ranged between 10 and 40 Hz. Although the measured PPV values were found to be within permissible limits, there remains a potential risk of structural disturbances in nearby buildings, particularly when relatively high PPV values occur at lower frequency ranges.

Keywords: Blasting, ground vibration, Blue dust , peak particle velocity, threshold levels.

1. Introduction

Accurately anticipating blast-induced ground vibrations is still difficult despite significant progress. Prediction reliability is nevertheless impacted by the inherent unpredictability of geological circumstances, uncertainty in the distribution of explosive energy, and constraints on empirical constants. Control blasting techniques methods help control the blast's strength and reduce damage to buildings or structures around the quarry that don't belong to the owner [3]. The numerical and empirical equations are commonly helps to find the safe blasting range limits and safe limit is important environmentally controlled mining activities [4-5. To guarantee safe and regulated mining operations, blast-induced ground vibration has been extensively researched. Using artificial neural networks [6] created prediction models for ground vibration and shown that the primary determinants of PPV are charge weight per delay and distance. According to [7] investigation into the effects of blasting vibrations on the environment, if blasting parameters are not optimised, high PPV may result in structural damage. Research conducted by Monjezi [8] demonstrated that empirical equations can effectively estimate vibration levels in quarry blasting. Regression and artificial intelligence models were further applied by S. R. Dindarloo [9] to improve prediction accuracy. Recent research also focuses on machine learning and numerical modeling to reduce vibration effects [10]–[12]. These studies confirm that proper blast design, reduced charge weight, and increased distance significantly decrease PPV values and help maintain vibration within permissible limits.

In blue metal mining, we measure PPV (Peak Particle Velocity) to check how much vibration the ground gets from the blasting point. When we blast rocks, it sends shockwaves through the ground. These shockwaves can shake buildings, roads, and other structures nearby. If the vibrations are too strong, they can cause damage. Make sure the vibrations do not damage nearby structures [1]. The PPV depending on the different parameters and including strata conditions [2]. In mining and quarrying operations, especially blue metal quarries, blasting is the most popular and cost-effective method for rock excavation. However, it causes a number of environmental effects, including fly rock, air overpressure, and ground vibrations. Of these, ground vibration is thought to be the most dangerous because it can result in both structure damage and discomfort for people [14] [15]. Peak Particle Velocity (PPV), which is thought to be the most dependable and widely recognized metric, is frequently used to characterize blast-induced ground vibration [16] [17]. According [20] the primary cause of ground vibrations during blasting is the explosive energy released, some of which is used for rock fragmentation and the remainder of which travels through the ground as seismic waves. Each of these waves primary (P-waves), secondary (S-waves), and surface waves contributes to the overall motion of the particles. According to recent studies, PPV is crucial for determining slope stability and structural safety and is strongly related to dynamic stress in rock masses [21]. Geological circumstances, blast design parameters, and distance-related characteristics are some of the elements that determine the magnitude of PPV[17] [22]. Scaled distance connections are based on charge per delay and distance, which continue to be the most important of them.

For estimating PPV, empirical relationships like the USBM predictor are still frequently employed[16]. However, better forecasting techniques have been developed as a result of their inability to handle site-specific variability. Improved empirical and statistical models for PPV prediction under various geological circumstances, including sedimentary rock environments, have been proposed in recent works [23]. Furthermore, to better characterize PPV distribution in rock masses and simulate blast-induced vibrations, numerical techniques such the finite element method (FEM) have been used [24]. The accuracy of PPV prediction has greatly increased in recent years because to sophisticated computational methods. In mining and quarry settings, machine learning techniques such ensemble models, Gaussian process regression (GPR), and hybrid random forest models have been effectively used[22] [25] [26] .

Fig. 1 Mine Site

These models overcome the drawbacks of conventional regression techniques by incorporating nonlinear connections between blasting parameters and PPV. For instance, GPR-based models have shown excellent statistical performance and high prediction accuracy, and hybrid machine learning approaches further improve reliability by combining many algorithms. Moreover, recent studies have focused on real-field quarry applications, particularly in urban or sensitive environments. For instance, matrix factorization-based models have been developed for predicting PPV in urban quarry blasting, showing improved accuracy using field-monitored data[25][26]. Similarly, research on vibration attenuation in tunnel and subterranean settings emphasizes how crucial it is to comprehend wave propagation properties for precise PPV [26] predictionIn hard rock settings like blue metal quarries, where more energy transfer leads to increased vibrations, the need of PPV becomes very clear. According to recent case studies, poor blast design can result in high PPV levels, which can harm structures and pose environmental risks [28]. Therefore, safe blasting procedures and adherence to legal requirements depend on precise PPV prediction and monitoring.

2. Methodology

Methodologies for PPV forecasting:

Using a technique based on the USBM predictor equation, ground vibrations are identified by measuring PPV to estimate possible damage. PPV is mostly dependent on the maximum charge, the distance between the blast and the measurement location, and the properties of the ground25. The predictor equation developed by USBM (eq. (1)) relates PPV to the maximum charge per delay (CPD) and distance, which is the most widely utilized relationship for its prediction.

$$\text{PPV (mm/s)} = K \times \left(\frac{D}{\sqrt{W}} \right)^{-\beta} \qquad (1)$$

where D is the distance between the blasting and measuring points (m), W the maximum CPD (kg) and $D/\sqrt{W}$ scaled distance (SD; $m/kg^{1/2}$). K and □ are the site constants to be determined by re- gression analysis, and are dependent on ground characteri- stics. The linear relationship between a dependent variable and one or more independent variables can be modelled using MLR analysis 26. It seeks to minimize the sum of squares of the measured and anticipated values and is based on the least-squares approach. In this work, a PPV prediction based on the MLR approach was made.

ANN using multi-layer perceptron: ANN is a form of artificial intelligence that is modeled after the human nervous system. ANN challenges can be solved in a variety of ways, especially when approximating nonlinear behavior without prior understanding of the relationships between system elements27. An artificial neural network (ANN) is a highly integrated computing network made up of fundamental information processing units called neurons or perceptrons. The multi-layer perceptron (MLP) approach is one of the most widely used ANNs, and several researchers have used it to forecast ground vibrations.

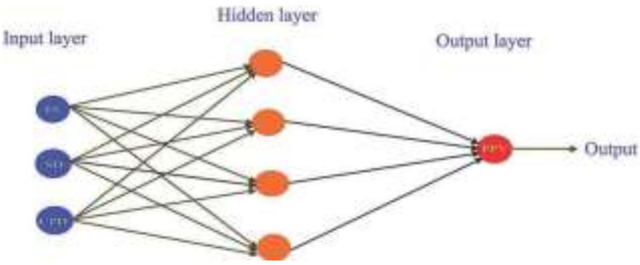

Figure 1. Structure of a three-layer, feed-forward multilayer per- ceptron (MLP) model.

The MLP model's structure to achieve the study's goals is depicted in Figure 1. It is a feed-forward supervised model with the potential for several hidden layers. The MLP layers have many purposes. The output layer is the interface layer on the display side of the network, while the sensory layer (sometimes called the common input layer) is the interface layer on the input side. The term "hidden layers" refers to all intermediate levels.

MLP employs the back-propagation (BP) learning technique, an iterative process for gradient-based optimization. A multi-layer feed-forward neural network is used for learning by the back-propagation technique. Perceptrons are the units that make up each layer. Each training step's measured properties match the network's inputs. The units that comprise the input layer receive the inputs concurrently. After passing through the input layer, these inputs are weighted and simultaneously supplied to the hidden layer, which is the second layer of perceptrons. One hidden layer unit's outputs can be fed into another hidden layer, and so on. Although only one is actually used, the number of concealed levels is variable. The units that make up the output layer receive the weighted outputs of the final hidden layer as input. These units provide the network's prediction for a particular training. Since none of the weights cycle back to an input unit or to the output unit of a prior layer, the network is feed-forward. Because each unit supplies the input for the subsequent forward layer, it is fully coupled.

Table 1. Safe blasting limits according to Directorate General of Mines Safety (DGMS)

	Dominant excitation frequency (Hz)		
Type of structure	<8	8–25	>25
Building/structures not belonging to the owner			
Domestic houses/structures	5	10	15
Industrial buildings	10	20	25
Sensitive structures/buildings	2	5	10
Buildings belonging to the owner during a limited span of time			
Domestic houses/structures	10	15	25
Industrial buildings	15	25	50

Over the last more than two decades, PPV and frequency have been together used for assessment of damage due to blasting. Table 1 displays the regulation limitations for ground vibration frequency and PPV in accordance with the Indian standard as defined by the DBMS37. It follows that measuring both frequency and PPV is necessary for a comprehensive analysis of blasting vibrations.

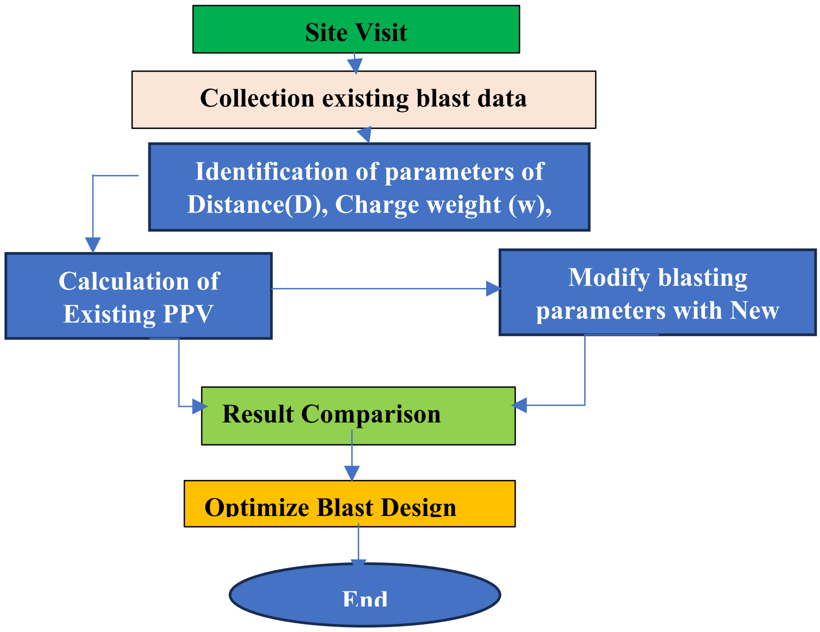

Fig. 2 Methodology Flow chart

The process of real-time trial blasting and the measurement of PPV and frequency are part of the study approach used here. Twenty trial-blasting cycles were conducted and documented in the current investigation (Table 4). The seismographs were positioned at certain distances from the blasting site in order to achieve this. The MLR technique was then used to establish the connection between the input and output parameters for the developing the predictor equation as follows.

$$Y = a + b_1 X_1 + b_2 X_2 + \ldots + b_n X_n , \qquad (3)$$

where Y is predicted value of Y, a the intercept and b is the partial regression coefficient.

Table 4. Input and output parameters for analysis

Blast no.	Distance (m)	Charge per delay (CPD, kg)	Scaled distance (SD, $m/kg^{1/2}$)	PPV (mm/s)	Frequency (Hz)
B1	140	50	19.80	5.2	30
B2	150	50	21.21	5.3	24
B3	160	41.7	24.78	4.8	27
B4	170	44.48	25.49	3.6	47
B5	190	40.3	29.93	3.5	23
B6	200	44.48	29.99	1.9	12
B7	210	47.26	30.55	2.9	34
B8	240	51.4	33.48	1.9	23
B9	250	40.6	39.24	1.9	26
B10	260	50.2	36.70	2.1	64
B11	280	50.2	39.52	1.4	10

B12	290	50.05	40.99	1.6	30
B13	300	43.2	45.64	1.3	57
B14	310	50.2	43.75	1.6	32
B15	320	46.2	47.08	1.4	34
B16	340	50.4	47.89	1.7	12
B17	350	50	49.50	1.5	10
B18	360	43.94	54.31	1.1	24
B19	370	76.39	42.33	1.3	18
B20	400	82.21	44.12	1.4	33.33

To further substantiate the results, ANN (MLP) was used to predict PPV. The MLP module was used to build the neural network model. The MLP neural networks were trained using a back-propagation algorithm to update weights to reduce the error function. Out of 15 trial- blasting datasets, about 70% were used for training and 30% were assigned for testing. In the present ANN module, the training datasets provided the weights for building the model, while the testing datasets identified the errors and prevented overtraining. Further, the PPV and frequency values of all 20 trial blasts were evaluated in light DGMS criteria in order to properly ascertain the damage risk of the nearest buildings and structures.

3. Results and discussion

Table 3 shows the primary descriptive statistics of all the input and output parameters of the study, together with their symbols. The salient results obtained from this study are discussed below.

Table 3. Descriptive statistics of the parameter

Parameter	No. of data	Minimum	Maximum	Mean
Distance	49	140	400	257.69
CPD	49	29.74	82.21	48.61
SD	49	19.79	66.01	37.43
PPV	49	1.10	5.80	2.56
Frequency	49	2.00	64.00	27.63

3.1 Prediction of PPV by the MLR technique

The predictor equation for PPV (output parameter) in terms of input parameters (D_i, CPD and SD) was obtained using the MLR technique. The MLR-based predictor equation is given as follows

PPV = 6.018 – D_i □ 0.020 + CPD □ 0.026 + SD □ 0.012. (5)

It is evident from Figure 6 that the predicted values of PPV using the MLR technique are almost similar to the observe values.

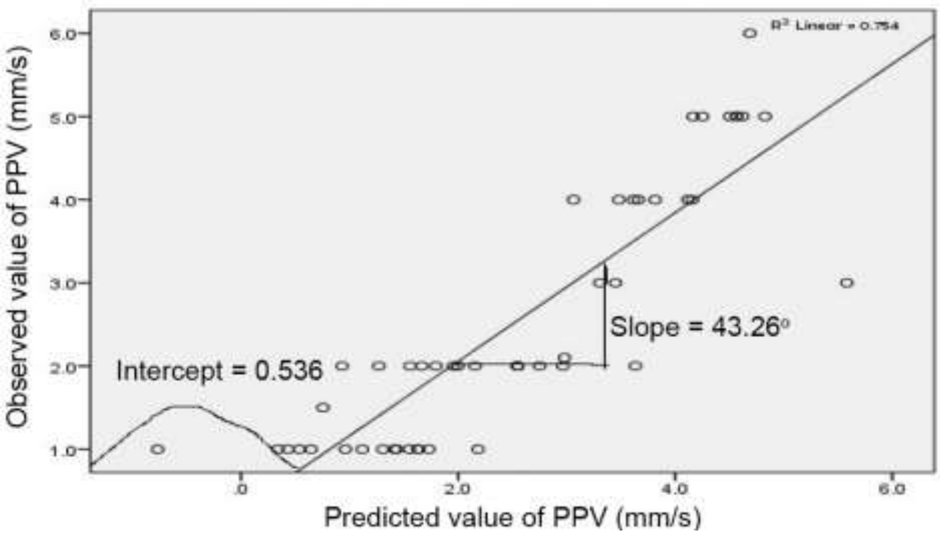

Figure 5. Plot between observed and predicted PPV values using multi-variate linear regression (MLR) technique.

Ground vibration data were gathered from blasting activities at a blue metal quarry. For each blast, we recorded key factors including the charge weight per delay, the distance from the blast point, and the stemming height. We calculated the Peak Particle Velocity (PPV) values using a standard empirical equation that connects distance with explosive charge weight. The results obtained were then compared with established blasting parameters, aiming to optimize the blast design and minimize vibrations while staying within permissible safety limit.

3.2 Prediction of PPV by ANN technique

Table 4 provides the ANN model pro- cessing summary. The ANN architecture has three nodes for the input layer, three nodes for the hidden layer and one node for the output layer. Activation function was the hyperbolic tangent and identity function for hidden and output layers respectively. Sum of errors was used as the error function in the said architecture. Figure 7 shows the network diagram to predict PPV.

Table 4. Model processing summary of artificial neural network (ANN)

	N	Percentage
Sample		
Training	33	67.3
Testing	16	32.7
Valid	49	100.0
Excluded	0	
Total	49	

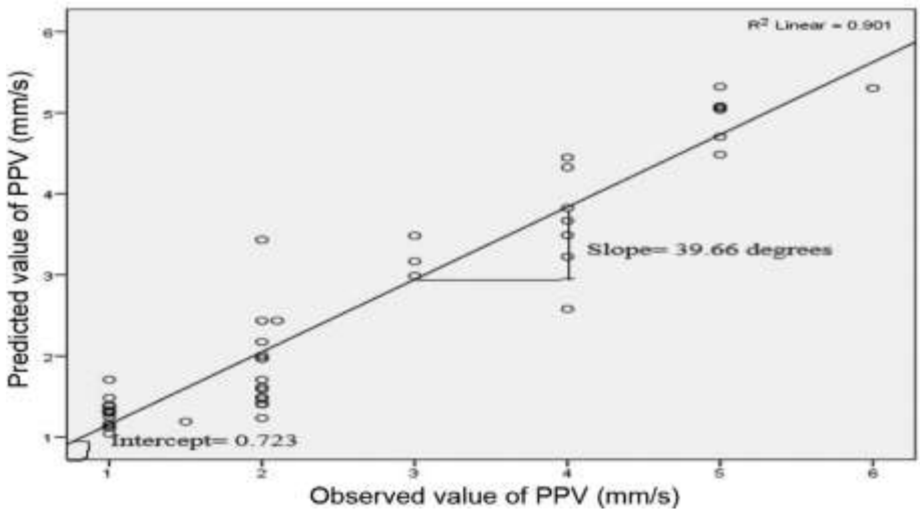

Figure 8. Plot between observed and predicted PPV values using artificial neural network (ANN) technique.

Results of damage risk assessment for the studied blasts

It is evident from Figures 11–14 that the PPV values for the trial blasts place almost all of them (excepting one with low frequency of 2 Hz) under the safe and acceptable category vis-à-vis various damage criteria assessment standards.

Results of frequency analysis

The classification of recorded frequency values from the study mine is shown in Figure 15 as a pie chart , it may be observed that only 2% of the measured frequencies lie in range 1–4 Hz, 10% in the range 4–15 Hz, 82% in the range 15–40 Hz and 10% in the range 4–15 Hz. Therefore, it may be interpreted from an Indian as well as global perspective that the PPV values vis-à-vis dominant frequencies in the study blast are safe. The present methodology and the proposed equation can be used for other sites with similar ground characteristics.

Conclusion

The results of this study lead to following conclusions:

- Although USBM and MLR-based predictor equations have given acceptable results, this study reveals the superiority of ANN-based prediction of PPV in comparison to the MLR technique and USBM predictor equation.
- It is found that the distance of the measuring station from the blasting location and SD together exert a significant impact on the prediction of PPV by MLP- based neural network approach. However, CPD exerts slightly less impact than distance and SD.

Based on the established damage criteria of DGMS, the measured values of ground vibration (PPV) and frequency at the field were below the threshold levels, indicating them to be safe

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