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Prediction of Blast-Induced Ground Vibration Using Principal Component Analysis–Based Classification and Logarithmic Regression Technique

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Abstract

Ground vibration is one of the major hazards produced by rock-blasting operation. The accurate prediction of vibration is necessary for designing controlled blasting parameters. The existing vibration predictors consider maximum explosive charge weight per delay and distance as the parameters responsible for ground vibration. These predictors are based on the assumption that the geometrical parameters of the blast will be constant for a site. However, the mining sites with bigger production targets have varying geometrical parameters to suit the excavator utility. Accordingly, the other blast design parameters will also have an impact on ground vibration intensity. A principal component analysis is a dimension reduction technique. This technique along with multivariate logarithmic regression has been used in this paper to predict the ground vibration. The technique has classified the blast design parameters into four principal components. The regression with the scores from these principal components has been carried out. The evaluation of the model performance of predictors along with the existing empirical predictors has been carried out using R^2 and RMSE values. The evaluation suggests that the predictor with logarithmic regression followed by principal component analysis gives better performance with respect to the existing empirical predictors.

Keywords Rock blasting · Ground vibration · Peak particle velocity · Principal component · Data classification · Regression

1 Introduction

Drilling- and blasting-based rock excavation technique is dominantly used in mining and civil construction excavations. This technique comes with many safety and environmental hazards. The major hazards due to blasting are ground vibration, flyrock, air overpressure, noise, dust, etc. The minimization of these hazards is necessary from both safety and productivity perspectives. The higher magnitude of blast-induced hazard can cause improper utilization of explosive energy. It has been reported by various researchers that the maximum utility of explosive energy for rock breakage is in the range of 20–30%. The remaining energy gets devastated in the form of different hazards [6, 8, 29, 36].

The ground vibration from blasting is a major environmental hazard, which may cause stability threats to the nearby structures and nuisance to the habitants. The intensity of ground vibration at a location is measured by peak particle velocity (PPV) and associated frequency. PPV has impacts on controllable blast design parameters and some uncontrollable parameters. The rock mass parameters, geological parameters, presence of discontinuities, etc. are considered uncontrollable parameters influencing PPV. Researchers around the globe have made attempts using different techniques to assess the impact of these controllable and uncontrollable parameters on PPV. The empirical predictor models such as USBM predictors [11], Ambraseys and Hendron [3] model, Langefors and Kihlstrom [27]

Highlights
- PCA is a useful data classification technique and can be used for ground vibration prediction.
- PCA with logarithmic regression gives a more accurate prediction than existing empirical predictors.
- The principal component comprising MCPD, distance, and column length of explosive charge has maximum influence on PPV.

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model, Ghosh and Daemen [12] model, Pal Roy [35] model, etc. have been developed over the years. The empirical models determine site constants for the experimental blast faces. These site constants are specific to the site and are dependent on the vibration propagating media. Himanshu et al. [20] developed a multivariate empirical predictor for a coal mining site. The predictor consisted of other parameters such as hole diameter, number of blast holes, total explosive charge, and distance. Roy et al. [38] have investigated the impact of the total explosive charge on PPV. The scaled distance up to which there is a dependency of total explosive charge on PPV has been given in this study. Khandelwal and Singh [24] considered hole geometry including its diameter and depth along with burden, spacing, bench height, stemming length, total charge, powder factor, etc. as the parameters influencing PPV. Ainalis et al. [2] also considered free face, confinement, coupling of explosive, decking, and charge length as the parameters influencing PPV.

Various researchers have used statistical algorithms such as neural network, genetic algorithms, colony optimisation algorithm, random decision tree, particle swarm optimisation, and support vector machine for the assessment of parameters influencing PPV [1, 13, 17, 25, 31, 41, 42, 44, 46]. These statistical algorithms predict PPV on the basis of analysis of data for the trial blasts conducted at the site. The summary of statistical algorithms used for the prediction of PPV and air overpressure (AOp) is given in Table 1. Rezaeineshat et al. [37] predicted PPV using artificial neural network. The authors found that 'maximum explosive charge weight per delay (MCPD)' and 'distance of the blast face from vibration monitoring point (D)' are most influencing parameters and burden, spacing, and rock quality designation are least influencing parameter for PPV. Nguyen et al. [34] using different machine learning algorithms found that the elevation between blast site and vibration monitoring station is another important parameter influencing PPV along with charging parameters and distance. Additionally, researchers have also used the numerical simulation–based approach for prediction of PPV and damages from the blasting operation [2, 18, 19, 21, 26, 28].

Principal component analysis–based classification and logarithmic regression technique has been used in this paper for the prediction of blast-induced ground vibration. The technique consists of representing data in a lower dimensional space. The technique is useful in identifying the linked parameters. The most and least influencing parameters have also been identified using this technique. Researchers, viz., Dehgani and Ataee-Pour [10], Zhongya and Xiaoguang [45], and Shida et al. [39], have used PCA-based and other dimension reduction techniques for the prediction of blast-induced ground vibration.

Table 1 Summary of statistical algorithms for prediction of PPV and AOp

Study	Technique	Input	Output	Total data used	R^2
Amiri et al. [4]	ANN and KNN	Q, D	PPV, AOp	75	0.88 and 0.95
Armaghani et al. [5]	ANFIS, ANN	Q, D	PPV	109	0.97
Azimi et al. [7]	GA-ANN	Q, HD, RD, MRD	PPV	70	0.98
Bayat et al. [9]	FA-ANN	B, S, Q, D	PPV	154	0.938
Hajihassani et al. [14]	ICA-ANN	B, S,Q, D, SL, P, E	PPV	95	0.97
Hajihassani et al. [15]	PSO-based ANN	Hole Depth, Q, B, S, SL, SGD, D, RQD, PF, N	PPV and AOp	88	0.85
Harandizadeh and Armaghani [16]	ANFIS-PNN-GA	Q, PF,D, SL	AOp	62	0.94
Khandelwal and Singh [24]	ANN	Hole Depth, B, S, D, Q, BI,E, Pr, P,Vod	PPV	154	0.98
Khandelwal et al. [23]	ANN	Q, D	PPV	130	0.91
Mokfi et al. [30]	GMDH	SL, PF, B, S, D, Q, Hole Depth,	PPV	102	0.91
Nguyen and Bui [32]	ANNs-RF	Q, D, PF,B,S, SL	AOp	114	0.98
Nguyen et al. [34]	HKM-ANN	B, S, Q, D, PF	PPV	149	0.98
Rezaeineshat et al. [37]	ICA-ANN	B, S, Q, D, RQD	PPV	112	0.90
Taheri et al. [40]	ABC-ANN	Q, D	PPV	89	0.92

ANN, artificial neural network; KNN, K nearest neighbor; ANFIS, adaptive neuro fuzzy inference system; GA-ANN, genetic algorithm-artificial neural network; FA-ANN, firefly algorithm-artificial neural network; ICA-ANN, imperialist competitive algorithm-artificial neural network; PSO, particle swarm optimization; PNN, probabilistic neural network; GMDH, group method of data handling; RF, random forest; HKM, hierarchical k-means clustering; ABC, artificial bee colony; PPV, peak particle velocity; AOp, air over pressure; Q, maximum explosive charge per delay; D, distance of blast face from monitoring point; HD, horizontal distance; RD, radial distance; MRD, modified radial distance; B, burden; S, spacing; SL, stemming length; P, P wave velocity; E, Youngs' modulus of elasticity; SGD, subgrade drilling; RQD, rock quality designation; PF, powder factor; N, number of holes; BI, blastability index; Pr, Poisson's ratio; Vod, velocity of detonation of explosive

1.1 Details of Study Site and Experimental Blasts

The study site was a coal mine located in the Singrauli coalfield, Madhya Pradesh, India. The mine is broadly divided into two parts: the easternmost part is known as Moher sub-basin and the western part is known as Moher main basin. The mining block during the experimental trial was situated in the Moher sub-basin which is a broad basinal structure with uneven undulations on its limbs. An overview of the working benches of the mine is shown in Fig. 1.

Experimental trials were undertaken at different working benches of the mine. The mine consists of shovel and dumper excavators. The benches of the mine have been developed considering the optimum utility of these excavators. Deeper benches of 40–55 m have been developed for the optimum utility of the dragline. Shovel benches were having a height of 20–25 m. The data were recorded for thirty-two experimental blasts. Table 2 summarises the blast design parameters used for shovel benches and dragline benches during trial blasts.

1.2 Prediction of Ground Vibration Using Empirical Models

Different empirical predictors have been proposed over the years for the prediction of PPV. The most popular predictor among these is the US Bureau of Mines (USBM) predictor equation proposed by Duvall and Petkof [11]. The predictor relates PPV with square root scaled distance. Ambraseys and Hendron [3] proposed a cube root scaled distance-based predictor. Pal Roy [35] included a joint parameter as a dominant parameter along with maximum charge weight per delay (MCPD) and distance. The performance of some of the empirical model has been assessed in this study using the data collected at the experimental sites. The empirical models used for comparison are shown in Table 3.

Fig. 1 Overview of the working benches of the study site

Table 2 Summary of blast design parameters used in Shovel and Dragline benches during trial blasts

Blast design parameters	Shovel benches	Dragline benches
Hole diameter (mm)	150, 159, and 259	311
Numbers of blast holes	07–249	96–250
Burden (m)	5–8	10
Spacing (m)	4–10	13
Hole depth (m)	6–28	46–57
Average explosive charge per hole (kg)	75–1300	3860–4571
Maximum explosive weight per delay (kg)	75–1300	3860–17,460
Total explosive charge in a firing round (kg)	3000–123,393	405,270–980,330
Explosive type	Site mixed emulsion (SME) and ammonium nitrate fuel oil (ANFO)	Site mixed emulsion (SME) and ammonium nitrate fuel oil (ANFO)
Initiation system	Detonating fuse (DF) with cord relay and NONEL	Detonating fuse (DF) with cord relay

Table 3 Empirical models for prediction of PPV

No	Researchers	Empirical models
1	Duvall and Petkof [11]	$PPV = K\left(D/Q^{1/2}\right)^{-b}$
2	Langefors and Kihlstrom [27]	$PPV = K\left(Q/D^{2/3}\right)^{b/2}$
3	Ambraseys and Hendron [3]	$PPV = K\left(D/Q^{1/3}\right)^{-b}$
4	Ghosh and Daemen [12]	$PPV = K\left(D/Q^{1/2}\right)^{-b} e^{-\alpha R}$

where *PPV* is peak particle velocity of ground vibration; *D*, distance of blast face from vibration monitoring point; *Q*, maximum explosive charge per delay; *K*, *b*, and *α*, site constants

The recorded PPV data along with blast design parameters were grouped together. The statistical analysis was carried out to compute site constants under different empirical models. The regression plots to establish the USBM predictor, Langefors and Kihlstrom predictor, and Ambraseys and Hendron predictor are shown in Fig. 2. Site constants for Ghosh and Daemen predictor have been evaluated using multivariate statistical analysis. The summary of empirical models for the study site is shown in Table 4.

1.3 Methodology for Classification of Parameters Using Principal Component Analysis.

Principle component analysis (PCA) is a dimension reduction technique. This technique is mainly used for representing data in the lower dimension space. Data in lower dimensional space reduces the complexity of the model. At first, the parameters to be classified are identified for this purpose. The data are normalised before analysis. A matrix is formed using the data set of these parameters. Suppose there are 'm' parameters to be classified with a total of 'n' data set. Then a matrix 'A' of n × m will be formed. In the next step, covariance matrix 'C' of the matrix 'A' is computed as – $C = A^T A$. Here, A^T represents the transpose of matrix 'A'. Matrix 'C' will be the symmetric matrix of m × m. In the next step, the eigenvalues corresponding to this covariance matrix are computed using the relation shown in Eq. 1.

$$|C - \lambda I| = 0 \tag{1}$$

where '*I*' is the identity matrix.

$\lambda = \lambda_1, \lambda_2, \lambda_3, \lambda_m$.

$\lambda_1, \lambda_2, \lambda_3$ represents Eigen values.

Eigenvectors corresponding to each eigenvalues are calculated as per Eq. 2. These eigenvectors are known as principal components (PCs). Each component is compared with the respective eigenvalues to assess the variance of data in that component. The plot of PCs with the respective eigenvalue is known as the scree plot. Variance of the principal components is evaluated as per Eq. 3. The principal component corresponding to λ_1 will have the highest variance of data as compared to other PCs.

$$[C - \lambda I][X] = [0] \tag{2}$$

where [0] is m × 1 null matrix.

[X] is eigenvector of m × 1.

$$\text{Variance of PC1} = \frac{\lambda_1}{\lambda_1 + \lambda_2 + \cdots + \lambda_m} \tag{3}$$

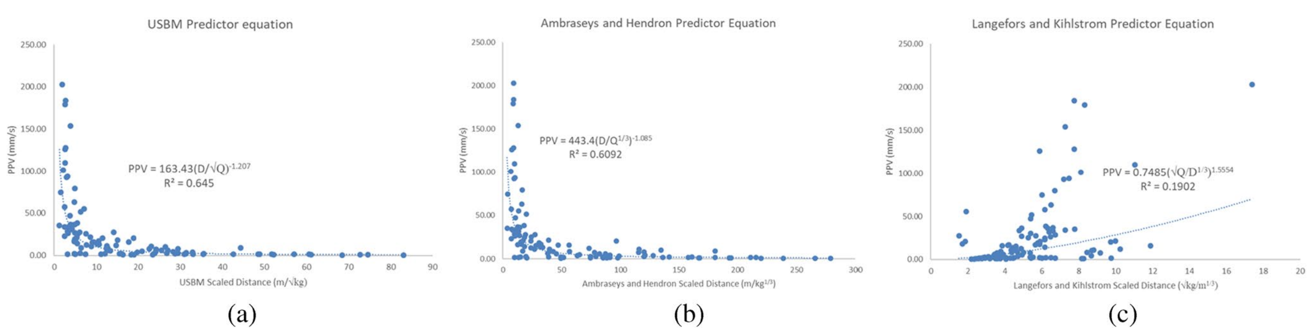

Fig. 2 Regression plots of different empirical ground vibration predictors

Table 4 Empirical models for the study site

No		Empirical models
1	USBM [11]	$PPV = 163.43\left(D/Q^{1/2}\right)^{-1.207}$
2	Langefors and Kihlstrom [27]	$PPV = 0.7485\left(Q/D^{2/3}\right)^{1.5554}$
3	Ambraseys and Hendron [3]	$PPV = 443.4\left(D/Q^{1/3}\right)^{-1.085}$
4	Ghosh and Daemen [12]	$PPV = 184.93\left(D/Q^{1/2}\right)^{-1.31} e^{-0.000133R}$

The data sets are further projected along the corresponding principal component using Eq. 4. The projected data is known as the factor score.

$$[\mathrm{score1}]_{1\times n} = [x_1{}^{T}]_{1\times m}[A^{T}]_{m\times n} \tag{4}$$

This technique of classification and subsequent regression has been used for the prediction of PPV in this study. The purpose of principal component analysis in the study is to classify the parameters influencing PPV in different sets. Eight input blast design parameters influencing PPV have been taken for this purpose. The parameters include hole diameter (Φ), numbers of blast holes (N), burden (B), spacing (S), column length of explosive charge (L), MCPD (Q), total explosive charge in a blasting round (Q_t), and distance of blast face from vibration monitoring point (D). The methodology used in the study is shown in the flow chart in Fig. 3. Initially, the optimum number of principal components is selected based on the scree plot to accommodate the maximum information from the data set. Factor scores are extracted along the selected number of PCs. After that, the regression analysis is performed between the extracted scores and PPV. The correlation coefficient of the regression analysis is determined. The number of PCs is further increased and scores are again extracted if the correlation coefficient is less than 0.9. After achieving a correlation coefficient of more than 0.9, data are classified based on the rotated component matrix. The Kaiser-Varimax rotation is applied to the component matrix of PCs to get a rotated component matrix. The rotation uses a mathematical algorithm that is based on the principle of maximizing the sum of the squares of the loadings. The factor loadings with high and low values are maximised and those of mid-value are minimised under this rotation [43]. Finally, the most dominant parameters along each PC are classified based on the rotated component matrix. This results in the classification of parameters influencing PPV.

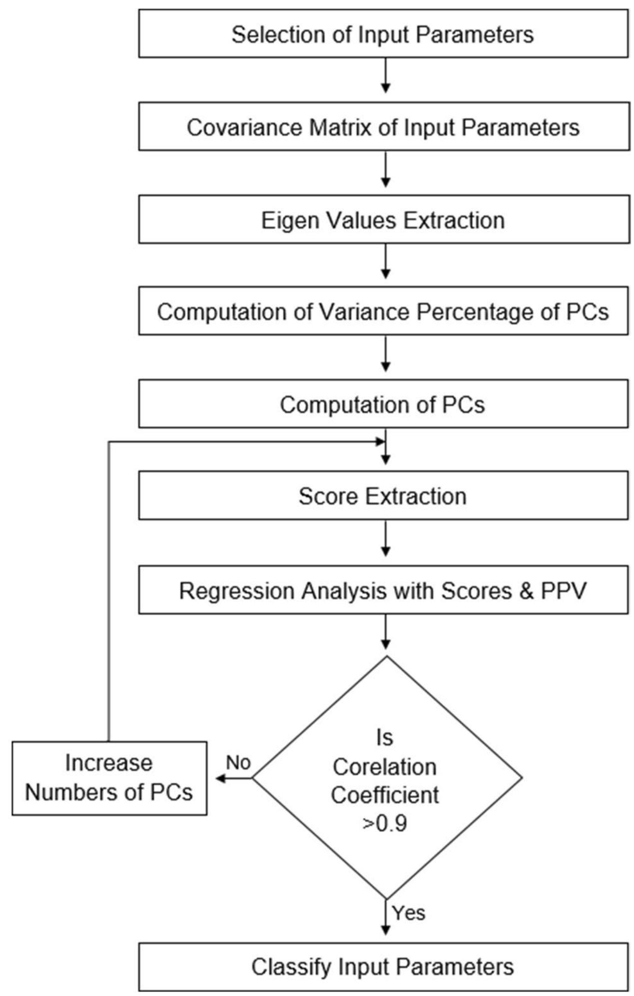

Fig. 3 Flow chart of the methodology for classification and regression using PCA

1.4 Classification of Data Using Principal Component Analysis and Prediction of Ground Vibration.

Initially, the exploratory analysis has been carried out to identify the parameters influencing PPV. The PCA of all the input parameters has been done along with PPV. The result shows the extraction of two PCs with a cumulative variance of more than 80%. The scree plot of PCs is shown in Fig. 4. The parameters have been plotted along the extracted components. The component plot for exploratory analysis is shown in Fig. 5. The plot shows a significant distinction between PPV and other parameters. The distinction between distance and other blast design parameters can also be seen in this plot. It can be drawn from this plot that there is an interrelationship among blast design parameters that affect the magnitude of PPV. The classification of this interdependency is necessary for the accurate prediction of PPV.

The PCA has been carried out among all the input parameters influencing PPV. The scree plot of PCA is shown in Fig. 6. It can be seen in the scree plot that the plot becomes linear after 4th component. Eigenvalue matrix of the components is shown in Table 5. The table shows that the variance of eigenvalues of 1st, 2nd, 3rd, 4th, 5th, 6th, 7th, and 8th components are 72%, 83%, 90%, 95%, 97%, 99%, 99%, and 100% respectively. The first component alone has a very high variance to represent the data. Accordingly, the score for a single PC was extracted and regression analysis was carried out. The regression shows a correlation coefficient of 0.19. So, the score was further extracted with an increasing number of PCs. The regression analysis with two and three scores has correlation coefficients of 0.319 and 0.757 respectively. Four PCs have variance of more than 95%. The scores were extracted for four PCs. The regression analysis with four

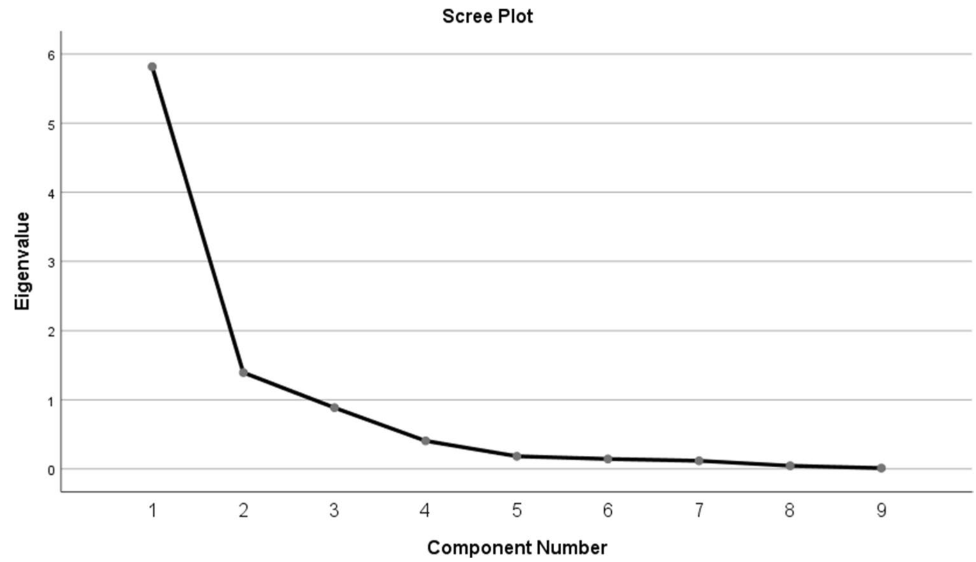

Fig. 4 Scree plot of PCA with blast design parameters and PPV

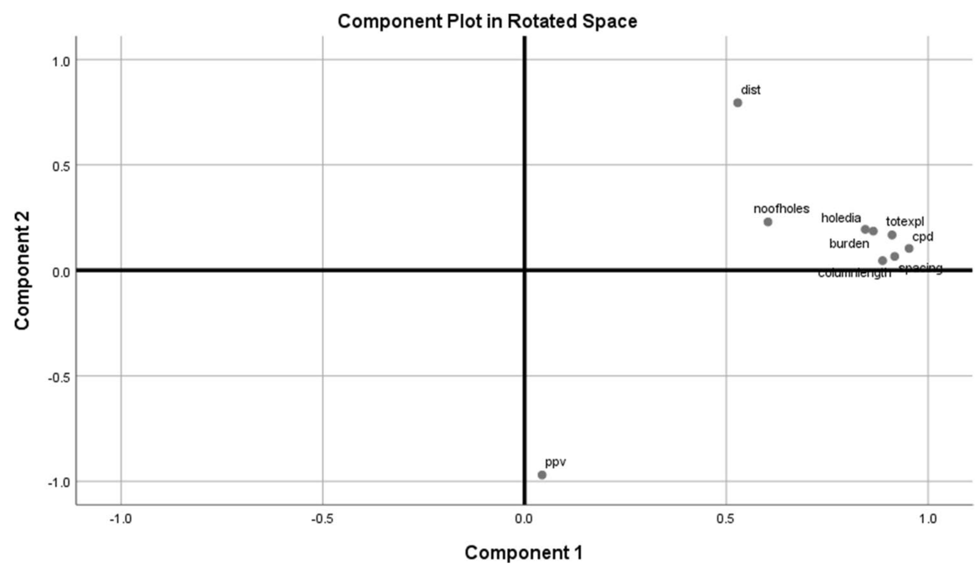

Fig. 5 Component plot for exploratory analysis

extracted scores and PPV shows a correlation coefficient of 0.931. Hence, the classification of data along four PCs has been accepted.

The rotated component matrix with four PCs is shown in Table 6. The comparison of component scores of each parameter shows that PC1 contains Φ, B, and S parameters. The parameters of PC1 can be termed geometrical parameters. PC2 contains L and Q parameters. PC3 contains N and Q_t parameters. The parameters of PC2 and PC3 can be termed charging parameters. PC4 contains D as the dominant parameter. The scores along all the four PCs have been extracted. The logarithmic regression analysis has been carried out between extracted scores and PPV. The relationship between PCs and PPV has been established based on the regression output. The relationship is shown in Eq. 5.

$$PPV = 7.36\frac{PC1^{0.022}PC2^{0.072}}{PC3^{0.005}PC4^{0.532}} \tag{5}$$

The study of powers of PCs in this equation reveals that the dependency of PPV on PCs is in order of PC4 > PC2 > PC1 > PC3. The higher dependency of PPV on PC4 (i.e. distance) and PC2 (i.e. MCPD and column length of the explosive charge) is in the same line with the conclusions of other researchers who considered Q and D as the most dominant parameters influencing PPV. Holmberg and Persson (1978) have also considered Column length of explosive charge as a dominant factor influencing PPV. The predicted magnitude of PPV was determined using Eq. 5. The comparison between the measured and predicted values of PPV is shown in Fig. 7.

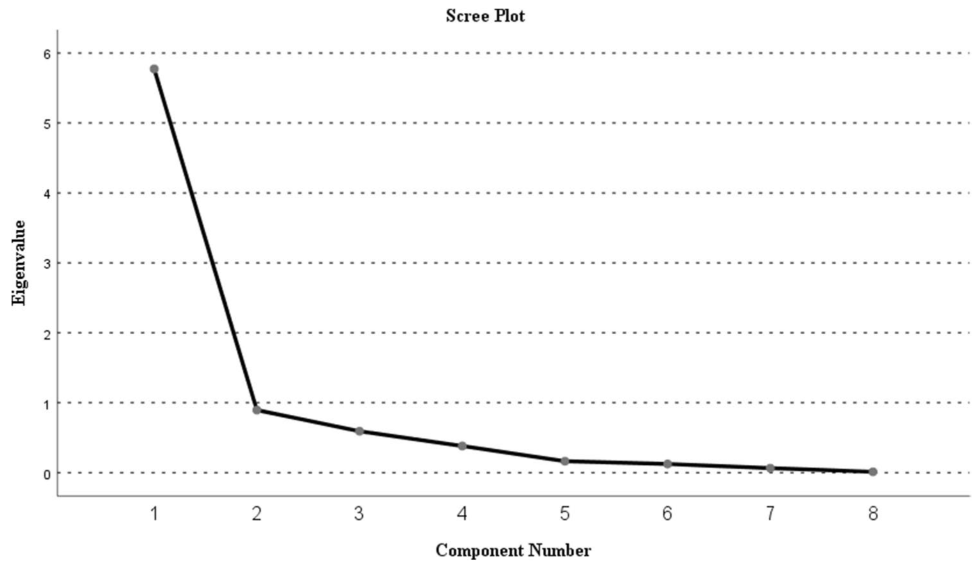

Fig. 6 Scree plot of PCA for input parameters

1.5 Evaluation of Models' Performance.

The performance of empirical predictors and PPV prediction using PCs has been evaluated. The evaluation has been done by computing R^2 and root mean square error (RMSE) values. The computation of RMSE has been done on the basis of the relation shown in Eq. 6

$$\mathrm{RMSE} = \sqrt{\left(\frac{1}{n}\sum_{j=1}^{n}(\mathrm{Predicted}PPV - \mathrm{MeasuredPPV})^2\right)} \tag{6}$$

The computed values of R^2 and RMSE for different predictors are shown in Table 7. The analysis of the computed values reveals that USBM and Ghosh and Daemen predictors are the best empirical predictors. The prediction comprising of regression analysis followed by PCA shows better R^2 values than all the empirical predictors. RMSE value for PPV prediction using this method is also significantly low. Hence, predictions using this classification and regression technique are more accurate.

Table 5 Eigenvalues of PCs for PCA of input parameters influencing PPV

Principal component	Eigenvalues		
	Total	**% of variance**	**Cumulative %**
1	5.774	72.169	72.169
2	0.894	11.179	83.348
3	0.591	7.390	90.738
4	0.380	4.755	95.494
5	0.163	2.034	97.527
6	0.123	1.541	99.068
7	0.064	0.794	99.863
8	0.011	0.137	100.000

2 Conclusions

The accurate prediction of blast-induced ground vibration is the main challenge in designing controlled blasting parameters for rock excavation. The identification of the impact of different parameters on vibration intensity is also important. The regression analysis followed by principal component analysis–based data classification can be a useful tool to identify the parameters and predict PPV. This paper has used this technique for the classification of eight input parameters influencing PPV. The dimension reduction of parameters has been carried out for this purpose using PCA. The appropriate numbers of principal components have been initially selected by assessment of the

Table 6 Rotated component matrix[a] with four PCs

	Component			
	1	**2**	**3**	**4**
Hole dia	.863	.246	.265	.270
No. of holes	.148	.155	.958	.166
Column length	.342	.880	.205	.180
Burden	.757	.476	.143	.259
Spacing	.717	.589	.181	.152
Totexpl	.378	.556	.696	.223
Cpd	.478	.723	.355	.258
Dist	.293	.219	.228	.901

Extraction method: principal component analysis

Rotation method: Varimax with Kaiser normalisation[a]

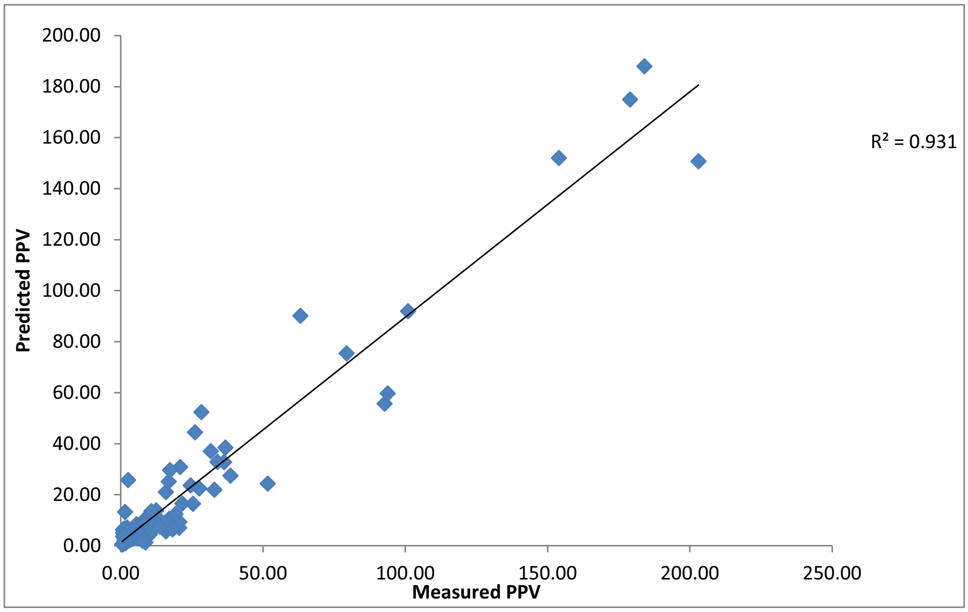

Fig. 7 Comparison between measured and predicted values of PPV using PCA

Table 7 Computed R^2 and RMSE values for different PPV predictors

PPV prediction model	R^2	RMSE
USBM	0.645	32.08
Ambraseys and Hendron	0.60	34.51
Langefors and Kihlstrom	0.19	39.67
Ghosh and Daemen	0.648	32.06
Regression analysis followed by PCA	0.93	11.11

variance of data in different principal components. The original data has been projected along the required number of principal components to extract the factor score. The regression analysis has been done by taking the factor scores of PCs as input and PPV as output. The regression with four PCs gives a correlation coefficient of more than 0.9. Accordingly, the data has been classified into four PCs. The comparison of component scores of each parameter shows that PC1 contains geometrical parameters such as hole diameter, burden, and spacing. PC2 contains MCPD and column length of the explosive charge. PC3 contains number of blast holes and total explosive charge in a blasting round. PC4 contains the distance of the blasting face from the monitoring point. The relationship between these PCs and PPV has been established using logarithmic regression analysis. The comparison of coefficients of PCs reveals that the dependency of PPV on PCs are in order of PC4 > PC2 > PC1 > PC3. The performance of the vibration prediction model using regression analysis followed by PCA has been compared with the existing empirical predictors. This prediction technique gives better predictions than the existing empirical predictors. Hence, the prediction technique can be used for a more accurate prediction of PPV at a rock excavation site having large variations in blast design parameters. The technique used in the paper may be applied for the prediction of ground vibration for sites similar to the study site. The technique can also be used in the future for the assessment of the impact of other input parameters such as rock mass properties and joint conditions on PPV.

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Declarations

Conflict of 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.

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