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Statistical analysis of blast-induced vibration near an open pit mine

PAULO FILIPE T. LOPES, JOSÉ AURÉLIO M. DA LUZ, TIAGO M. PEREIRA, LEANDRO GERALDO C. SILVEIRA

Abstract: Blast-induced vibration may be harmful to facilities in the vicinity of operating mines, mainly causing structural damage and human discomfort. This study presents an application of multivariate statistics to predict vibration levels regarding their potential to cause structural damage and human discomfort. An extensive seismic monitoring campaign was executed in a large open-pit iron ore mine, near a small village, to gather a dataset for a predictive multivariate analysis. Ten blasting events have produced a dataset of 158 valid measurements. Three classes of vibration peak velocity were adopted from legal standards, which later supported a cluster analysis. Then, it was possible to compare how much these two classification modalities respond to discriminant analysis. The next step was to carry out a principal component analysis (PCA) from the original database, and, comparatively, to plot both the scores concerning the classes derived from the vibration standard and those from the groups obtained from cluster analysis. PCA has considerably explained the data variability, while the three classes from cluster analysis resulted very similar to the corresponding ones from the vibration standards. The results have demonstrated that multivariate statistics may be applied to manage blasting-induced vibration and its deleterious effects with few adjustments and automation.

Key words: rock blasting, vibration, multivariate analysis, cluster analysis, discriminant analysis, principal component analysis.

INTRODUCTION

Rock blasting is a unitary operation of critical importance in hard rock mining and should be designed to combine the best fragmentation (resulting in ideal particle size distribution, with appropriate fragment blockiness and avoiding both over-sized fragments and those fines from over-fracturing) and minimal cost, considering health, industrial hygiene and environmental restrictions (Aler et al. 1996). Among the negative blasting impacts on its surroundings are induced ground vibrations (Hudaverdi et al. 2007, 2011, Ak et al. 2009). The level of vibrations is influenced by two specific groups of parameters. First, the parameters inherent to the rock mass where the waves propagate: its physical properties, such as porosity, mechanical strength, the presence of joint sets, elasticity parameters (Young's modulus, Poisson's modulus, acoustic impedance). Obviously, these parameters are intrinsic to the mined region (NBR 9653:2005, 2005). The other group is concerned with the blasting plan, designed by the engineers, such as charge per delay, distance among blast holes and rows, bench height, drill hole diameter, stemming, delay between holes and rows ignition, sequence, and direction of initiation and subdrilling (Bhandari 1997).

The complexity of the phenomena involved in rock blasting makes the accurate modeling of its features challenging. In line with this statement, various attempts are found in the technical literature, seeking a predictive equation for blast-induced vibration (Fişne et al. 2010). Table I exemplifies this effort, with compiled cases by Kuzu (2008).

As pointed out by Kumar and co-workers (Kumar et al. 2015), researchers generally perform site-specific experimental campaigns, as blast ground vibration is a concern. Seismographs are used in order to provide technical parameters, such as vertical, longitudinal, and transverse peak particle velocities. Their major resultant at a given instant, the so-called peak vector sum (PVS), is considered the main vibration parameter by many authors (Dehghani H & Ataee-Pour 2011). Along this line, Yilma (2016) performed a comparative study of the predictive equations of blast-induced vibrations and has suggested attenuation formulas. As Brazilian mining operation is concerned, Iramina et al. (2018) applied artificial neural network techniques and geomechanics parameters to model blast-induced vibration attenuation. As pointed by those authors, artificial neural network performed better, despite requiring larger datasets.

Database containing blast design parameters and particle velocity or acceleration are usually gathered by researchers, seeking to provide necessary information to support regression analysis that can predict the level of blast-induced vibration (Singh et al. 2008). This approach considers the raw measured blast data to predict ground vibrations.

The nomenclature of the parameters inserted in Table I is as follows: ***v*** — velocity of vibrations [mm/s]; ***k*** — a real multiplicative coefficient from the regression model; ***n*** — a real addictive coefficient from the regression model; ***Q*** — maximum charge of explosives per delay [kg]; ***R*** — radial distance [m]; ***D*** — scaled distance [m/kg² or m/kg^3].

The importance of multivariate techniques applied to mining and geotechnical data has been confirmed by a number of applications in the area. Studies like those from Santos and coworkers (Santos et al. 2019), Sing and coworkers (Singh et al. 2015), Landim (2011), and

Table I. **Regression equations for induced ground vibrations according to many authors (modified from Kuzu 2008).**

Researchers	Empirical models	Researchers	Empirical models
Duvall & Petkof (1959)	$v = k(R/Q^{1/2})^{-b}$	Kahriman (2004)	$v = 0.34D^{-1.79}$
Langefors & Kihlstrom (1978)	$v = k(Q/R^{2/3})^{b/2}$	Kahriman et al. (2006)	$v = 0.561D^{-1.432}$
Arnbraseys & Hendron (1968)	$v = k(R/Q^{1/3})^{-b}$	Rai & Singh (2004)	$v = kR^{-b}(Q_{max})e^{-b}$
Nicholls et al. (1970)	$v = 0.36D^{-1.63}$	Nicholson (2005)	$v = 0.438D^{-1.52}$
BIS (1973) [IS 6922]	$v = k(Q^{2/3}/R)^{1.25}$	Rai et al. (2005)	$Q_{ma}x = k(vD^2)^b$
Siskind et al. (1980)	$v = 0.828D^{-1.32}$	Ozer (2008) (sandstone)	$v = 0.257D^{-1.03}$
Ghosh & Daemen (1983)	$v = k(R/Q^{1/2})^{-b}e^{-\alpha R}$	Ozer (2008) (shale)	$v = 6.31D^{-1.9}$
Ghosh & Daemen (1983)	$v = k(R/Q^{1/3})^{-b}e^{-\alpha}R$	Ozer (2008) (limestone)	$v = 3.02D^{-1.69}$
Roy (1991)	$v = n + k(R/Q^{1/2})^{-1}$	Ak et al. (2009)	$v = 1.367D^{-1.59}$
Roy (1991)	$v = n + k(R/Q^{1/3})^{-1}$	Badal (2010)	$v = 0.29D^{-1.296}$
CMRI (1993)	$v = n + k(R/Q^{1/2})^{-1}$	Mesec et al. (2010)	$v = 0.508D^{-1.37}$
Kahriman (2002)	$v = 1.91D^{-1.13}$		

Vezhapparambu and colleagues (Vezhapparambu et al. 2018) can be cited, just to name a few. This research is inserted in this context and aimed at studying ground vibration parameters using multivariate statistical analysis.

Karadogan et al. (2014) made an interesting survey on legal norms concerning the limits of blast-induced vibrations in several countries, in order to guide their own technical study with a view to proposing similar standards for the Turkish mining sector. Nevertheless, for the present study, a combination of Brazilian legal vibration standard NBR 9653:2005 (Brazil 2005) stating vibration limit of 15.0 mm/s (for structure damage application), and the Australian one (Australia 2014) was adopted (vibration limit of 2.0 mm/s, for human comfort), since the latter is one of the few standards that adopts the human comfort as the criterion, in order to achieve a result that can embrace both structure damage and human comfort (Duvall & Fogelson 1962, Erten et al. 2009). From the adoption of these limits concerning the peak velocity of the particles under vibration, a multivariate statistical analysis was carried out to evaluate the discriminating power of some classic techniques of multivariate analysis of empirical data. The idea was to analyze the pertinence of future development of automated algorithms for predicting (and quantifying) the impacts resulting from blasting operations in the vicinity of the mine.

MATERIALS AND METHODS

The field investigations were performed at a large open pit iron mine located in the so-called Iron Quadrangle (Brazil) mineral province. The target mine is located near to a small village (Figure 1). The acquiring method was fully described by Silveira (2017) and Navarro Torres et al. (2018). A total of 20 seismographs

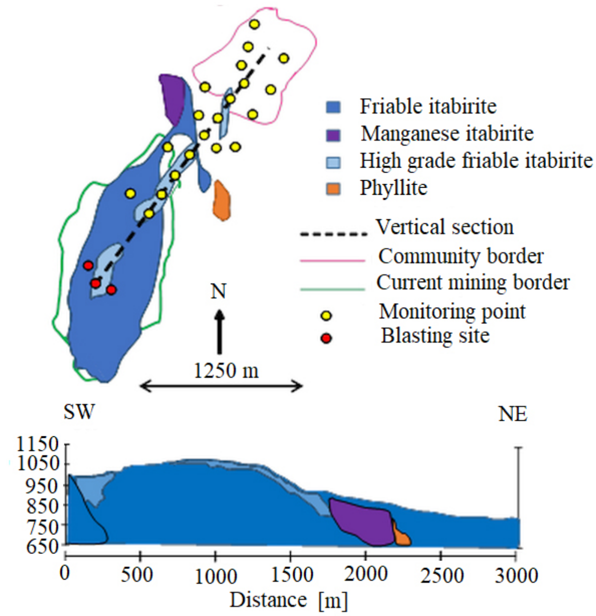

Figure 1. Representation of the region studied.

(from Geosonics®, model SSU 3000 EZ+) were employed, in a campaign of 10 blast events, which has resulted in a large dataset of 158 valid measurements. 42 observations could not activate the trigger level of 0.5 mm/s. This trigger value was adopted because it was the least sensible practical limit for field survey in order to avoid recording events as car traffic or even pedestrians walking. The distance (D) between the vibration source and the monitored point was calculated by allocating UTM coordinates obtained by a Garmin GPS (model Map).

A combination of Brazilian legal vibration standard and the Australian corresponding one was adopted, since the latter is one of the few standards that adopts the human comfort as the criterion, in order to achieve a result that can embrace both structure damage and human comfort (Table II).

Due these criteria, it was created three different classes of vibration level: 15 **<** ***PVS***, 2 < PVS < 15 and ***PVS*** **<** 2. These classes were also used for qualitative grouping of observations (***k*** = 3).

The statistical analysis was initially performed at an exploratory level using *Jamovi*, a free and open statistical software package (The Jamovi Project 2019).

The cluster analysis of data was performed using *Minitab® Version 19.2* (a proprietary system for statistical computation), which are widely used by statisticians. Cluster analysis of one dataset classifies the data into groups so that those within the same cluster share greater proximity of properties, when compared to data from the other groups (ultimately Euclidean distances between points belonging to a definite cluster are smaller than the distances between points of distinct clusters). Under this line of action, k-means clustering was employed. This clustering algorithm is used for partitioning a data set into a set of ***k*** pre-specified clusters. Using, intentionally, ***k*** = 3, two types of categories are obtained: those three ranges derived from vibration standards, and the three groups from cluster analysis. Then, it was possible to compare how much these two classification modalities respond to a discriminant analysis.

In sequence, a linear discriminant analysis was executed for the legal vibration limits. This technique is a dimensionality reduction tool applied on any homoscedastic dataset. It is an analysis with discriminant functions and is based on replacing original data with a linear combination of measurements that minimizes the variance and maximizes the distance between the means of the classes. Markedly, if standardization is carried out, z-scores are always homocedastic.

In the present case, the next methodological step was to perform a principal component analysis with the original database, and comparatively plot both the scores concerning the classes derived from the vibration standards and scores of the three groups from cluster analysis. The *Jamovi* statistical spreadsheet was used for this step.

Table II. Summary of vibration limits adopted.

Standard	Vibration limit	Application
NBR 9653 (Brazil)	15.0 mm/s	Structure damage
Transport Noise Management (Australia)	2.0 mm/s	Human comfort

Principal component analysis (PCA) is another very useful tool for multivariate data analysis based on reduction of dimensionality by an orthogonal coordinate transformation of a data set, generating a few orthogonal linearly uncorrelated variables called principal components, which capture most of the variability of those original data (Calabrese 2019). Therefore, the basic purpose of PCA is to transform a set of initial variables correlated with each other, into another set of uncorrelated (orthogonal) variables, called main components, which are appropriate linear combinations of the original variables. The components are calculated in descending order of importance, that is, the first main component explains the maximum possible variance of the original data, the second the maximum possible variance not yet explained by the first one, and so on. The last main component will be the one with the least contribution to explain the total variance of the original data. In a principal component analysis, all variables are treated in the same way, that is, there are no dependency relationships between variables, as occurs in regression analysis. The main objectives of this multivariate technique are to reduce the dimensionality of the data and to obtain interpretable combinations of the original variables.

The principal component analysis depends solely on the covariance matrix or the correlation matrix P of the original variables X1; …; Xp. It is

Table III. Descriptive statistics (sample size: 158) showing the Shapiro-Wilk's test for normality.

	D [m]	Lv [mm/s]	Tv [mm/s]	Vv [mm/s]	PVS [mm/s]	Q/delay [kg]
Mean	844.0	3.108	2.327	1.890	3.718	1495
Median	851.5	0.7300	0.7950	0.5100	0.9850	1500
Standard deviation	466.7	8.448	4.218	4.139	9.392	400.0
Minimum	52	0.06000	0.1300	0.06000	0.1900	800
Maximum	1955	65.53	34.04	31.69	74.93	2100
Shapiro-Wilk p	0.0010	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001
25th percentile	474.0	0.3800	0.3800	0.2500	0.5250	1250
50th percentile	851.5	0.7300	0.7950	0.5100	0.9850	1500
75th percentile	1203	2.083	2.030	1.635	2.652	1750

not necessary to assume the normality of the data for the application of the technique, as pointed out by Santos et al. (2019).

RESULTS AND DISCUSSION

Exploratory analysis

Table III presents the descriptive statistics of the variables used to compose the dataset used in this research. It was employed *Jamovi* spreadsheet for this analysis. In Table III and along the text, the symbols stand for the following parameters: ***D*** — distance [m]; ***Lv*** — wave longitudinal velocity [mm/s]; ***Tv*** — wave transverse velocity [mm/s]; ***Vv*** — wave vertical velocity [mm/s]; ***PVS*** — peak vector sum [mm/s]; and ***Q*** — explosive charge per delay [kg]. In turn, the subscript ***_st*** stands for "standardized variable". The descriptive statistics of these data are showed in Table IV. In order to perform an exploratory analysis, a matrix plot of the data was done (Figure 2). This matrix provides a visual idea about the correlation between the variables and sometime called "draftsman's plot".

A careful examination of the matrix plot has allowed inferring that there is some correlation with many of the studied variables. The corresponding boxplot of each measured (raw) variable would not be useful, due to scale discrepancy of variables (which are of very different magnitudes). In view of this, these parameters were standardized (transforming raw data to z-scores) and are shown in Figure 3. Z-scores of a generic variable $\boldsymbol{x_i}$ were obtained by the usual transformation:

$$x_{i\_st} = z_i = \frac{(x_i - \mu_i)}{\sigma_i} \tag{1}$$

It is noteworthy that — at a first approach — some of these velocity measurements could be classified as anomalous, but in fact, they are not outliers (which are actually defined by statistical techniques), since the most discrepant values were those recorded at short distances from the blast faces and they were valid measurements obtained from the field campaign, which will be fully considered in the multivariate analysis.

K-means cluster analysis

In order to compare the legal standard classification adopted (which entails three ranges of vibration level) with the state of art multivariate statistical techniques, a k-means cluster analysis was performed, with three clusters, and standardized variables, as commented in this method explanation (item 2). The result of cluster analysis is displayed in Table V.

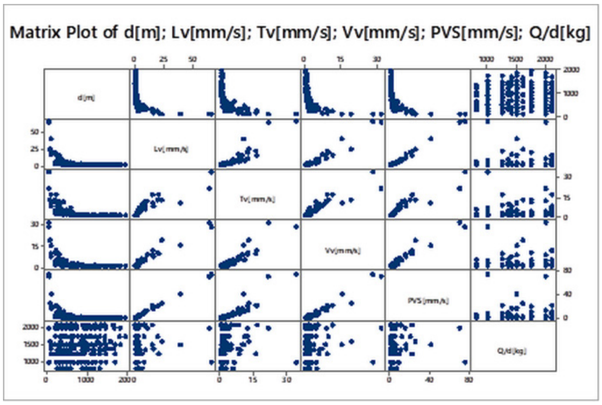

Figure 2. Matrix plot of the dataset (from *Minitab*).

Discriminant analysis

Initially a linear discriminant analysis was carried out for the legal vibration limits, using the standardized data because the original variables were not homoscedastic, as can be verified by the descriptive statistical analysis. Not surprisingly, in a second stage, the quadratic discriminant analysis of the original data proved to be more appropriate due to the lower elimination of measures resulting from excessive apparent correlation (as detected by the algorithm). The groups were: with PVS greater 15 mm/s (9 events), PVS between 2 mm/s and 15 mm/s (40 events), and PVS less than 2 mm/s (109 events). The correct classification proportion concerned legal vibration limits was 151/158 = 95.6 % for the quadratic discriminant function (against 89.2 % for linear function).

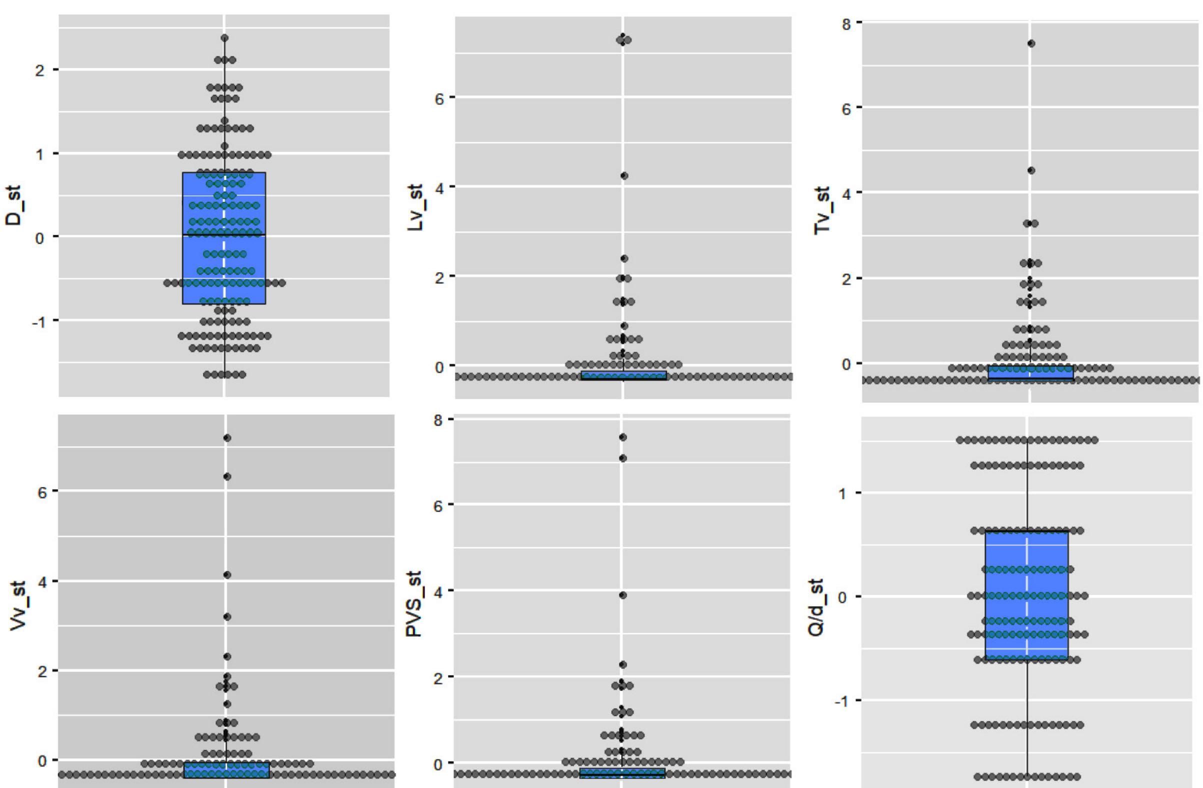

Figure 3. Boxplots of standardized variables (from *Jamovi*).

Table IV. Descriptive statistics for (dimensionless) standardized data (N = 158; mean = 0; variance = 1).

	D_st	Lv_st	Tv_st	Vv_st	PVS_st	Q/d_st
Median	0.016100	-0.28155	-0.36330	-0.33350	-0.29100	0.012700
Minimum	-1.6969	-0.36080	-0.52090	-0.44220	-0.37560	-1.7371
Maximum	2.3804	7.3889	7.5179	7.1998	7.5822	1.5125
Skewness	0.28519	5.7447	4.2095	4.9252	5.7140	-0.048856
Std. error skewness	0.19305	0.19305	0.19305	0.19305	0.19305	0.19305
Shapiro-Wilk p	0.0010	<.0001	<.0001	<.0001	<.0001	<.0001
25th percentile	-0.79270	-0.32300	-0.46170	-0.39630	-0.34000	-0.61230
50th percentile	0.016100	-0.28155	-0.36330	-0.33350	-0.29100	0.012700
75th percentile	0.76815	-0.12145	-0.070500	-0.061625	-0.11345	0.63760

Table V. Final Partition.

	Number of observations	Within cluster sum of squares	Average distance from centroid	Maximum distance from centroid
Cluster1	3	41.860	3.612	4.742
Cluster2	131	240.026	1.235	2.309
Cluster3	24	85.866	1.742	4.168

Table VI. Summary of classification from legal vibration limits.

	True Group (before cross validation)			True Group (after cross validation)		
Put into Group	**15 < PVS**	**2 < PVS < 15**	**PVS < 2**	**15 < PVS**	**2 < PVS < 15**	**PVS < 2**
15 < PVS	9	1	0	8	4	0
2 < PVS < 15	0	38	5	1	35	5
PVS < 2	0	1	104	0	1	104
Total N	9	40	109	9	40	109
N correct	9	38	104	8	35	104
Proportion	1.000	0.950	0.954	0.889	0.875	0.954

After a cross validation procedure, in order to compensate for an optimistic apparent error rate of misclassified observations, the correct classification proportion was 147/158 = 93.3 %. Detailed results are presented in Table VI.

The same process was applied for the cluster classification. The correct classifications proportion from cluster analysis was 156/158 = 98.7 %. Groups from cluster analysis were: group 1 (4 events), group 2 (117 events) and group 3 (37 events). Detailed results are presented, as shown in Table VII.

Principal component analysis

In order to reduce the number of dimensions of the dataset, preserving most of the original variability, a principal component analysis (PCA) was executed, as shown in Table VIII and Table IX. As already mentioned, the variables were standardized due to the high scale discrepancy of variables. Once this was done, a correlation matrix must be adopted, instead of a covariance matrix, as one of the PCA premises.

From these three techniques applied to the dataset, it was possible to reach the final

Table VII. Summary of classification from cluster analysis.

	True Group		
Put into Group	**1**	**2**	**3**
1	4	0	0
2	0	115	0
3	0	2	37
Total N	4	117	37
N correct	4	115	37
Proportion	1.000	0.983	1.000

Table VIII. Eigenanalysis of correlation matrix from PCA.

	PC1	PC2	PC3	PC4	PC5
Eigenvalue	3.2191	1.0395	0.6253	0.0923	0.0239
Proportion	0.644	0.208	0.125	0.018	0.005
Cumulative	0.644	0.852	0.977	0.995	1.000

Table IX. Eigenvectors from PCA.

Variable	PC1	PC2	PC3	PC4	PC5
Distance [m]	-0.367	0.302	0.867	-0.134	-0.066
Longitudinal velocity (long_vel) [mm/s]	0.530	0.049	0.324	0.431	0.653
Transverse velocity (trans_vel) [mm/s]	0.537	0.037	0.090	-0.835	0.067
Vertical velocity (vert_vel) [mm/s]	0.543	0.062	0.199	0.313	-0.751
Charge per delay [kg]	0.033	0.949	-0.309	0.033	0.034

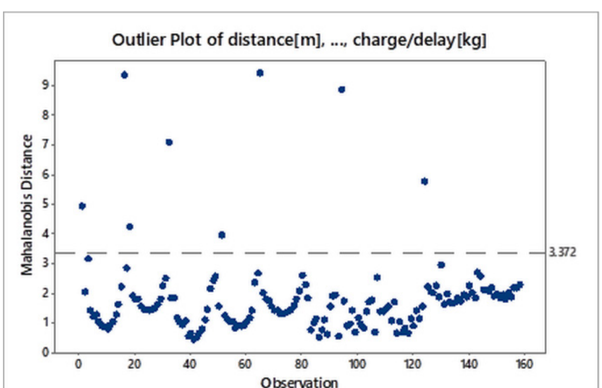

Figure 4. Outlier plot from principal component analysis (PCA).

results of multivariate assessment, as follows. Figure 4 shows the Mahalanobis distance for the observations, where some pseudo-outliers were detected, accordingly with the high variability explained before in the exploratory data analysis.

Figure 5 displays the scree plot of eigenvalues of each component from PCA. Despite of criticism against its use (Yeomans & Golder 1982), the Guttman–Kaiser criterion for selecting the number of components was used because of its widespread employment in technical literature. Following the Guttman–Kaiser criterion, components were retained, which represent 85.2 % of the total variability of data. This cumulative proportion can be safely considered as a good representation of the total variability, plus a system dimension reduction from five to two.

Figure 6 shows a biplot of score from the first two components and the loading of all eigenvectors, in order to present the correlation between the data dispersion and the eigenvectors' growth directions. As the distance increases, all velocities decrease, both ruled mostly by the first component, and the charge per delay grows in a direction ruled by the second component.

Figure 7 was the score plot of the first two components, filtered by the legal vibration limits groups. There is a clear division in three groups, even though they were not defined by statistical techniques.

Figure 7 and Figure 8 show the same chart, but the former has the cluster group filter. The division of scores is clear too, and most important, it was almost identical to the legal vibration limit classification.

The parameters that determine the intensity and occurrence of the vibrations are vast and very heterogeneous, becoming extremally hard to predict and interpret without good statistical

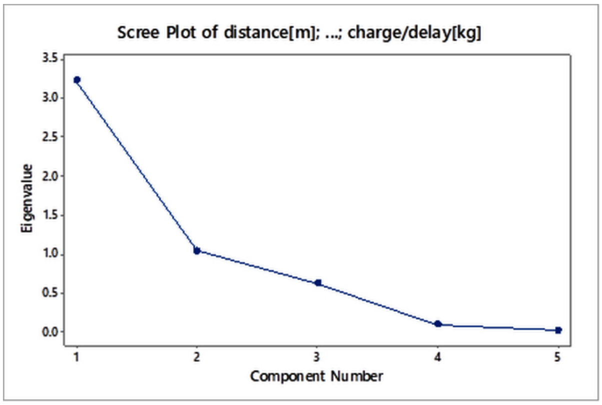

Figure 5. Scree plot from principal component analysis (PCA).

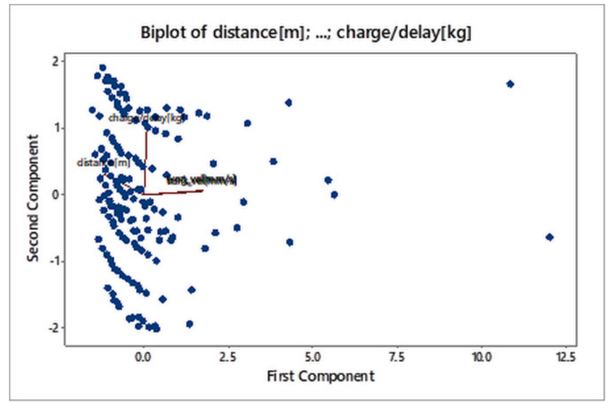

Figure 6. Biplot chart from principal component analysis (PCA).

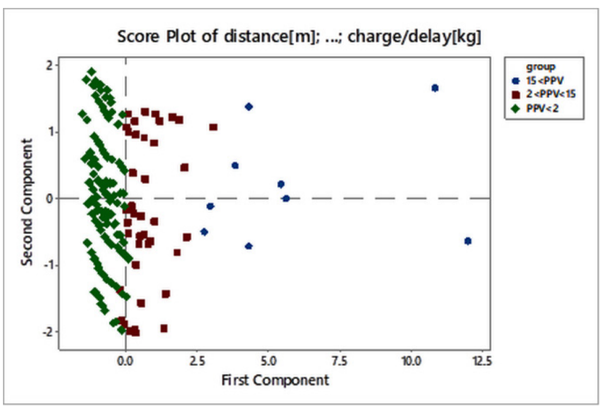

Figure 7. Score plot from principal component analysis (PCA) with legal vibration limits groups.

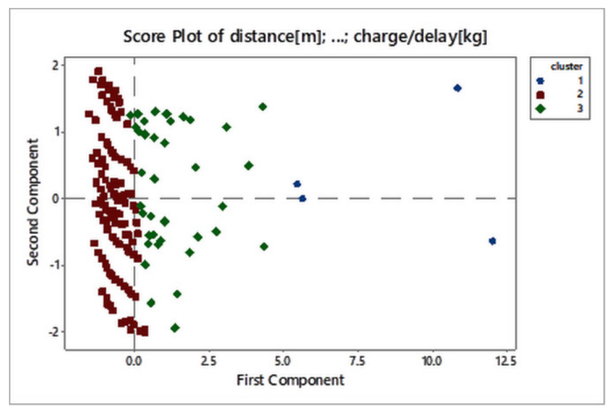

Figure 8. Score plot from principal component analysis (PCA) with cluster groups.

tools. In this mine-village context, depending on the regulation, the extrapolation of imposed limits can cause production stoppages, fines and affect the geotechnical structures such as slopes, stockpiles, waste piles and dams.

Once applied these statistical methods to the rock blasting data and to the mechanical properties of the rock mass, it was obtained a prediction model for the vibration intensity and its occurrence. Adding value through an anticipated and planned decision-making, reduction of production stoppage, and mitigation of eventual impacts on the geotechnical structures.

CONCLUSIONS

The impact of mining operations on communities located in its surroundings (which often arise from population settlement after the beginning of the mineral exploitation) has been the subject of many controversies among stakeholders and, consequently, studies aiming to alleviate this type of problem have been carried out. In this context, the adoption of computerized systems for the optimization of procedures, aiming at a lower impact due to blast vibrations, is extremely welcome.

The application of combined cluster, discriminant and principal component analysis allowed classifying this complex dataset under study, on a statistical basis, without losing the real application based on legal standards. In line with these results, one could think of those specialist systems and those based on artificial intelligence, just to mention two common techniques. In any case, these results of multivariate statistics may be important instruments for their implementation in the field, creating, for example, automatic systems for detecting occasional violations of preset limits of ground vibration.

Therefore, it will be possible to automate this type of analysis for forecasting of blast-induced vibration with respect to its harmful effects, once the k-means cluster analysis reaches an almost identical result compared to the legal vibration limit classes. One could implement, for instance, an algorithm incorporating statistical analysis and regression models into a decision tree, excluding the subjectivities inherent to the human factor. This methodological approach may be widely applied in the research area of induced ground vibrations from rock blasting.

Acknowledgments

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REFERENCES

AK H, IPHAR M, YAVUZ M & KONUK A. 2009. Evaluation of ground vibration effect of blasting operations in a magnesite mine. Soil Dyn Earth Eng 29(4): 669-676.

ALER J, DU MOUZA J & ARNOULD M. 1996. Evaluation of blast fragmentation efficiency and its prediction by multivariate analysis procedures. Int J Rock Mech Min 33(7): 96-189.

ARNBRASEYS NR & HENDRON AJ. 1968. Dynamic behavior of rock masses. In: STAGG K & WILEY J (Eds). Rock mech Eng. London: Wiley, p. 203-207.

AUSTRALIA. 2014. Transport Noise Management. Code of Practice. Volume 2. Construction Noise and Vibration. Brisbane: Department of Transport and Main Roads (State of Queensland), p. 25-27.

BADAL KK. 2010. Blast vibration studies in surface mines Rourkela. Department of Mining Engineering, National Institute of Technology of Rourkela. B Tech thesis.

BHANDARI S. 1997. Engineering Rock blasting operations. Rotterdam: A. A. Balkema, 375 p.

BIS - BUREAU OF INDIAN STANDARDS. 1973. IS 6922. Criteria for safety and design of structures subject to underground blast. New Delhi: Bureau of Indian Standards (BIS).

BRAZIL NBR 9653. 2005. Guia para avaliação dos efeitos provocados pelo uso de explosivos nas minerações em áreas urbanas — Procedimento. Rio de Janeiro: Associação Brasileira de Normas Técnicas (ABNT), 8 p.

CALABRESE B. 2019. Data Reduction. In: Ranganathan S, Gribskov M, Nakai K & Schönbach C (Eds) Ency Bioinfo Comp Biol Amsterdam: Elsevier 1: 480-485.

CMRI - CENTRAL MINING RESEARCH INSTITUTE. 1993. Vibration standards. Dhanbad: CMRI.

DEHGHANI H & ATAEE-POUR M. 2011. Development of a model to predict peak particle velocity in a blasting operation. Int J Rock Mech Min Sci 48(1): 48: 51-58.

DUVALL WI & PETKOF B. 1959. Spherical propagation of explosion generated strain pulses in rock. Washington: U.S. Department of the Interior, Bureau of Mines.

DUVALL WI & FOGELSON DE. 1962. Review of criteria for estimating damage to residences from blasting vibration. Report no. 5968. Washington: United States Bureau of Mines, 19 p.

ERTEN O, KONAK G, KIZIL MS, ONUR AH & KARAKUS D. 2009. Analysis of quarry-blast induced ground vibrations to mitigate their adverse effects on nearby structures. Int J Min Miner 1(4): 313-326.

FIŞNE A, KUZU C & HUDAVERDI T. 2010. Prediction of environmental impacts of quarry blasting operation using fuzzy logic. Environ Monit Assess 174(1-4): 461-470.

GHOSH A & DAEMEN JK. 1983. A simple new blast vibration predictor. Proceedings of the 24th U.S. Symposium of Rock Mechanics, Texas, USA, p. 151-161.

HUDAVERDI T, KULATILAKE PHSW & KUZU C. 2011. Prediction of blast fragmentation using multivariate analysis procedures. Int J Numer Anal Methods Geomech 35(12): 1318-1333.

HUDAVERDI T, KUZU C & FIŞNE A. 2007. Analysis of blast induced vibrations in aggregate mining. In: Proceedings of the 36th international congress and exposition on noise control engineering. Istanbul. Paper no. 463: 28-31.

IRAMINA WS, SANSONE EC, WICHERS M, WAHYUDI S, DE ESTON SM, SHIMADA H & SASAOKA T. 2018. Comparing blast-induced ground vibration models using ANN and empirical geomechanical relationships. REM Int Eng Journal 71(1): 89-95. Jan/Mar. http://dx.doi.org/10.1590/0370-44672017710097.

KAHRIMAN A. 2002. Analysis of ground vibrations caused by bench blasting at Can Open-pit Lignite Mine in Turkey. Environ Geol 41: 653-661.

KAHRIMAN A. 2004. Analysis of parameters of ground vibration produced from bench blasting at a limestone quarry. Soil Dyn Earthq Eng 24(11): 887-892.

KAHRIMAN AU, OZER U, AKSOY M, KARADOGAN A & TUNCER G. 2006. Environmental impacts of bench blasting at Hisarcik Boron open pit mine in Turkey. Environ Geol 50 (7): 1015-1023.

KARADOGAN A, KAHRIMAN A & OZER U. 2014. A new damage criteria norm for blast-induced ground vibrations in Turkey. Arab J Geosci 7: 1617-1626. https://doi.org/10.1007/s12517-013-0830-8.

KUMAR R, CHOUDHURY D & BHARGAVA K. 2016. Determination of blast-induced ground vibration equations for rocks using mechanical and geological properties. J Rock Mech Geotech Eng 8(3): 341-349. Available online 12 March 2016. http://dx.doi.org/10.1016/j.jrmge.2015.10.009.

KUZU C. 2008. The importance of site-specific characters in prediction models for blast-induced ground vibrations. Soil Dyn Earthq Eng 25(5): 405-414.

LANDIM PMB. 2011. Análise estatística de dados geológicos multivariados. São Paulo: Oficina de Textos, 208 p.

LANGEFORS U & KIHLSTROM B. 1978. The modern technique of rock blasting. New York: J Wiley, 438 p.

MESEC J, KOVAČ I & SOLDO B. 2010. Estimation of particle velocity based on blast event measurements at different rock units. Soil Dyn Earthq Eng 30(10): 1004-1009.

NAVARRO TORRES VF, SILVEIRA LGC, LOPES PFT & LIMA HM. 2018. Assessing and controlling of bench blasting-induced vibrations to minimize impacts to a neighboring community. J Clean Prod 187: 514-524.

NICHOLLS HR, JOHNSON CF & DUVALL WI. 1970. Blasting vibrations and their effects on structures (Bulletin 656). Washington: U.S. Department of the Interior, Bureau of Mines.

NICHOLSON RF. 2005. Determination of blast vibrations using peak particle velocity at Bengal Quarry, in St Ann, Jamaica Lulea: Department of Civil and Environmental Engineering, Division of Rock Engineering, Lulea University of Technology. Master dissertation, 72 p. (Unpublished).

OZER U. 2008. Environmental impacts of ground vibration induced by blasting at different rock units on the Kadikoy–Kartal metro tunnel. J Eng Geol 100(1-2): 82-90.

RAI R, SHRIVASTVA BK & SINGH TN. 2005. Prediction of maximum safe charge per delay in surface mining. Transactions of the Institution of Mining and Metallurgy, Section A: Min Technol 114(4): 227-231.

RAI R & SINGH TN. 2004. A new predictor for ground vibration prediction and its comparison with other predictors. Indian J Eng Mater Sci 11: 178-184.

ROY PP. 1991. Vibration control in an opencast mine based on improved blast vibration predictors. Int J Min Sci Technol 12(2): 157-165.

SANTOS AEM, LANA MS, CABRAL IE, PEREIRA TM, NAGHADEHI MZ, SILVA DFS & SANTOS TB. 2019. Evaluation of Rock Slope Stability Conditions Through Discriminant Analysis. Geotech Geol Eng 37: 775-802.

SILVEIRA LGC. 2017. Controle de vibrações e pressão acústica no desmonte de rochas com explosivos: estudo de caso em uma mina do Quadrilátero Ferrífero (M. Sc. dissertation). Ouro Preto: PPGEM -UFOP, 138 p. (Unpublished).

SINGH TN, DONTHA LK & BHARDWAJ V. 2008. Study into blast vibration and frequency using ANFIS and MVRA. Min Technol 117(3): 116-121.

SINGH PK, ROY MP, PASWAN RK, DUBEY RK & DREBENSTEDT C. 2015. Blast vibration effects in an underground mine caused by open-pit mining. Int J Rock Mech Min Sci 80: 79-88. doi: 10.1016/j.ijrmms.2015.09.009.

SISKIND DE, STAGG MS, KOPP JW & DOWDING CH. 1980. Structure response and damage produced by ground vibration from surface mine blasting. Washington: U.S. Department of the Interior, Bureau of Mines.

THE JAMOVI PROJECT. 2019. Jamovi. (Version 1.0) [Computer Software]. 2019. Retrieved from https://www.jamovi.org. (access: November 12th, 2019).

VEZHAPPARAMBU VS, EIDSVIK J & ELLEFMO SL. 2018. Rock Classification Using Multivariate Analysis of Measurement

While Drilling Data: Towards a Better Sampling Strategy. Minerals 8: 384. (doi:10.3390/min8090384).

YEOMANS K & GOLDER P. 1982. The Guttman-Kaiser Criterion as a Predictor of the Number of Common Factors. J R Stat Soc Series D (The Statistician) 31(3): 221-229.

YILMA O. 2016. The comparison of most widely used ground vibration predictor equations and suggestions for the new attenuation formulas. Environ Earth Sci 75: 269. https://doi.org/10.1007/s12665-015-5011-5.

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PAULO FILIPE T. LOPES[1]
https://orcid.org/0000-0001-7320-3093

JOSÉ AURÉLIO M. DA LUZ[2]
https://orcid.org/0000-0002-7952-2439

TIAGO M. PEREIRA[3]
https://orcid.org/0000-0003-2564-5895

LEANDRO GERALDO C. SILVEIRA[4]
https://orcid.org/0000-0002-8848-8789

[1]Beyond Mining Tecnologia e Projetos Ltda, Rua Francisco Feio, 70, Apto 401, Gutierrez, 30441-161 Belo Horizonte, MG, Brazil

[2]Universidade Federal de Ouro Preto, Escola de Minas, Departamento de Engenharia de Minas, Campus Universitário, s/n, Bauxita, 35400-000 Ouro Preto, MG, Brazil

[3]Universidade Federal de Ouro Preto, Instituto de Ciêncas Exatas e Biológicas, Departamento de Estatística, Campus Universitário, s/n, Bauxita, 35400-000 Ouro Preto, MG, Brazil

[4]Vale S. A. Fazenda da Mutuca, s/n, Área Rural, 34019-899 Nova Lima, MG, Brazil

Correspondence to: **José Aurélio Medeiros da Luz**
E-mail: jaurelio@ufop.edu.br

Author contributions

All authors contributed to the development of the manuscript. Paulo Filipe Trindade Lopes: methodology, validation, statistical analysis, investigation, and writing — original draft. José Aurélio Medeiros da Luz: conceptualization, formal analysis, and writing — original draft, review and editing, supervision. Tiago Martins Pereira: statistical analysis. Leandro Geraldo Canaan Silveira: methodology, validation, and review.