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Application of Electrical Resistivity Tomography for Improved Blast Movement Monitor Locations Planning

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Abstract: Blast-induced rock movement is a highly variable phenomenon which depends on numerous factors. Rock type and its deriving physical and mechanical properties are among such factors, which are crucial to be available prior to planning the locations where each monitor is placed. Hence, Electrical Resistivity Tomography (ERT) was used to acquire additional rock mass data for several benches of an open-pit mining operation. ERT is considered a valuable tool in mine planning. By providing information about the subsurface electrical resistivity distribution, ERT helps in determination of geological structures, composition of the ground and helps assessing potential hazards. A total of 21 profiles were measured, which allowed for relevant data to be obtained regarding each monitor's location. Results from the study showed that blast movement measurements from different rock-type zones do not differ in a statistically significant manner. However, substantial differences were uncovered regarding the mode of movement vectors by using Kernel density estimation (KDE). These results proved that ERT is a fast and reliable support method for establishing different rock mass zones and for location planning of blast movement monitors and blast design optimization prior to drilling.

Keywords: Blast movement, Electrical resistivity tomography (ERT), Kernel density estimation (KDE)

Introduction

Open-pit blasting is a phenomenon that has been extensively studied during the last 50 years. Certain patterns of blast-induced rock movement have been identified, which supplement the fundamental principles of rock blasting and rock fracturing (Zhang, 1994; Gilbride et al., 1995; Gilbride et al., 1996; Thornton et al., 2005; Thornton, 2009a; Thornton, 2009b; Engmann et al., 2013; Eshun and Dzigbordi, 2016). Some researchers, however, base their conclusions purely on practical experience and a small number of observations under certain conditions (Zlatanov et al., 2008). Robust mathematical or statistical methods are rarely employed for proof of concept. Recent breakthroughs in the use of various numerical methods in the field of blast movement have revealed crucial insights that allow a better understanding of the expected outcome of a blast. Machine learning algorithms based on predictors related to the mechanical characteristics of the rock mass, as well as blast design parameters, have achieved highly accurate prediction results (Yu et al., 2019; Yu et al., 2020; Yu et al., 2021a; Yu et al., 2021b). Deterministic models based on mechanical principles have been extensively investigated (Furtney et al., 2009; Tordoir et al., 2010; Furtney et al., 2016; Preece et al., 2015; Preece et al., 2016), but they have only lately emerged as an accurate modelling tool. DNA Blast Group, Itasca and Orica have also provided commercially viable tools which offer physics-based simulations which achieve superb prediction accuracy (https://dnablast.com/?lang=en; https://www.orica.com/Products-Services/Digital-Solutions/orepro-3d; Fu et al., 2023). However, the stochastic element in these approaches is limited to some extent for the sake of time required for computations. Alternatively, statistical modelling has also produced sufficient accuracy for interpreting the probable position of post-blast ore zones, which can be further used to calculate appropriate dig lines (Vasylchuk & Deutsch, 2019; Hmoud & Kumral, 2021; Hmoud & Kumral, 2022). In comparison to prior ways of using Kriging, triangulation, or Inversed distance weighing (Taylor & Firth, 2003), these modern approaches give not only a better estimate of the movement or the anticipated losses and dilution, but also statistics indicating the prediction's uncertainty from the simulation of different scenarios. Moreover, latest studies following this modelling framework have introduced the concept of entropy regarding the lack of information with respect to ore zones (Hmoud & Kumral, 2023).

Nonetheless, all these approaches are still limited to providing a complete understanding of the three-dimensional nature of blast movement and its economic implications. The reason behind this is because they are dependent on distinct sets of assumptions regarding the importance of different input or output features for the model. From a statistical standpoint, the horizontal movement vector provides critical information of great value regarding the magnitude and overall direction of the 3D movement vector. Vertical movement, on the other hand, causes "vertical dilution" and should thus be accounted for as accurately as possible.

Three-dimensional models for grade control and muckpile shape prediction have also emerged as a direct result of the improved accuracy regarding modelling blast movement. Hence, to this date they are considered the industry standard for blast movement modelling. Indeed, deterministic physics-based models appear to be more versatile for modelling 3D movement in different scenarios regarding panel shape, spatial configuration of multiple free faces, buffer presence, explosive and booster types, spatial distribution of rock types, etc. In contrast, statistical models based on physical measurements may not always offer a complete picture of the blasting process, since a significant amount of information is needed. Moreover, some parameters are difficult, if not impossible, to assess in-situ. Therefore, in order to gain meaningful insights in terms of empirical measurements, a design of experiments approach and careful planning is required to gather a meaningful amount of information from a reasonable number of shots. Both approaches, indeed have their pros and cons, however, to this date the physics-based approach has emerged as a better choice for commercial use with the addition of empirical measurements. The stochastic approach primarily serves as a pre-processing tool for gaining additional insights, for model calibration and as a topic for academic research. Nonetheless, the authors of this paper believe that a stochastic approach is more suited to the random nature of a blast and hence its implementation is absolutely necessary. Moreover, this approach can be universally applied to both empirical and artificial (simulated) data. Indeed, there can be some scepticism regarding the amount of bias, as well as the precision and accuracy of physical measurements, based on Blast movement monitors (BMMs) developed by Blast Movement Technologies (BMT) (https://hexagon.com/solutions/mine-blast-movement-monitoring). However, to this date they remain a reliable tool for empirical data acquisition.

Studied Conditions

A two-year-long study was conducted on the "Ada Tepe" gold project, an open pit mine in south-eastern Bulgaria (Kaykov & Terziyski, 2023; Koprev et al., 2022, Terziyski et al., 2021). On 5-metre benches, blasting activities were carried out twice a week. For all shots, vertical drillholes with a diameter of 105 mm were used. The operation employed two types of explosives: ANFO and packaged water gel. Furthermore, two types of drilling patterns were commonly used, depending on the rock hardness: 3x3.5 m for medium-hard rock and 3.2 x 3.7 m for softer rock types. The overall blast panel powder factor ranged between 0.34 and 0.46 kg/m³ over the studied period. After blasting, the average rock size was estimated to be roughly 250 mm. All drill patterns are staggered and initiated in an echelon pattern with a NONEL system, with a 42 ms delay between rows and a 17 ms delay within rows. This results in an initiation sequence in which the shot's isochrones are roughly parallel to the front free face of the explosion. Each blast hole is detonated with a bottom charge of either a 450 g cast boosters or 808 g packaged water gel. Due to the nature of the mined commodity, excavators undertake selective mining in two separate flitches for each bench after blasting. Blast Movement Monitors (BMMs) are employed to track blast movement. In the studied conditions, the number of monitors for a single shot can vary up to 8 monitors per flitch depending on the number of pre-blast ore polygons in each flitch. After the blast, a technician utilises a specialised radio frequency detector to locate each BMM's post-blast location inside the muckpile.

Over 1000 blast monitors were used during the period of the research. For most observations, two monitors are deployed for a single monitoring drillhole. Apart from recalculating the positions of ore polygons after blasting, all of the collected data was used for statistical analyses and predictive modelling. Finally, the gathered data was used to identify the level of influence for different factors in terms of decomposing the blast movement vectors into their respective components.

With the use of a staggered drilling pattern, BMMs are placed on the boundaries of three Voronoi cells, as shown on the left-hand side of Figure 1. This can be considered a good practice for the studied conditions, especially when the local powder factor of the neighboring Voronoi cells is taken into consideration. It is assumed to be the ratio between the amount of explosive and the volume of the Voronoi cells falling into an arbitrary radius from the assumed BMM location. Hence, zones which have an insufficient or an excessive local powder factor should be avoided for better representativity of the blast movement vector.

The echelon firing pattern allows for ensuring a near-parallel movement direction for all zones of the panel, which follows a direction perpendicular to the isochrone, shown on the right-hand side of Figure 1. Therefore, the choice of a BMM location in terms of movement direction has little to no constraints. Of course, BMMs should not be placed near the boundaries of the blast panel as these locations are edge cases and can significantly differ from other locations near the center of the panel. Placing BMMs near auxiliary drillholes is also considered to be non-representative as its supposedly adjacent Voronoi cells do not follow the uniform shape of the pattern and hence can influence the magnitude of movement. Moreover, the isochrones also change their orientation, which would influence the direction of movement. Such zones which can be considered as constraints can be the ones near drillholes 117 and 92 from Figure 1.

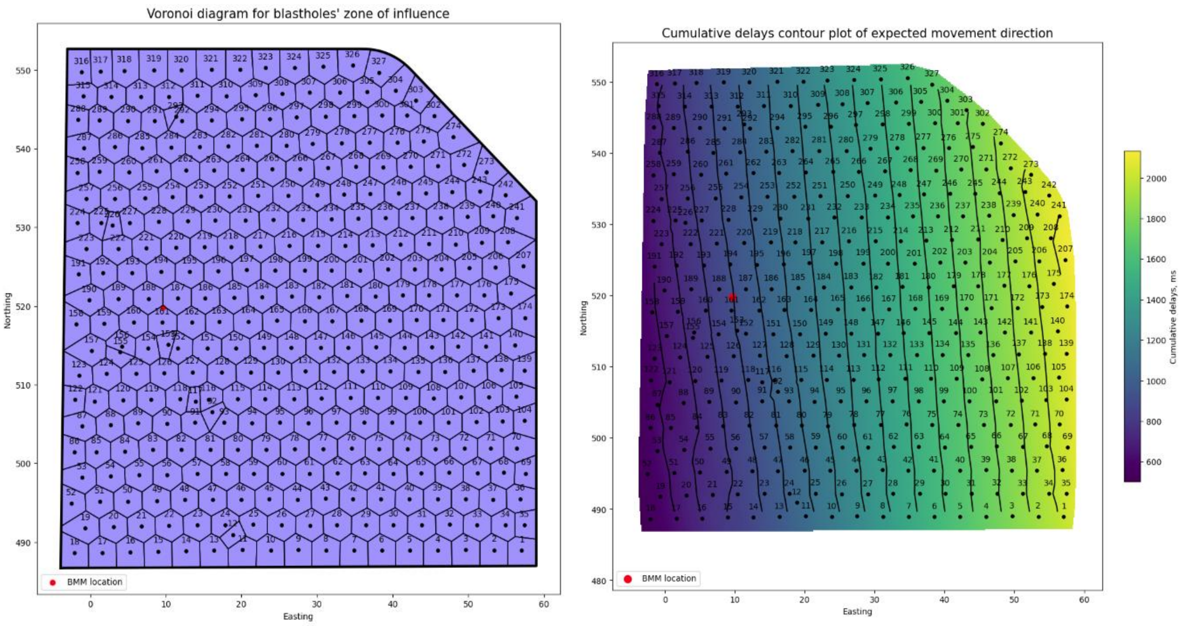

Figure 1. Blast panel conditions influencing the choice of monitoring locations
Left-hand side – Voronoi cells of drillholes' area of effect
Right-hand side – Cumulative delays contour plot

These rules are trivial and are already massively applied in open-pit mines which utilise BMMs. However, little to no information is present (to the authors' knowledge) about how rock mass zones can influence the choice of a BMM's location for the blast panel.

As a result, the purpose of this article is to establish how blast-induced rock movement for both observed flitches can be affected by different rock mass zones. For the purpose Electrical resistivity tomography (ERT) was used as a comprehensive and easy-to-implement method for gathering the necessary data regarding different rock type zones. ERT is considered to be versatile method proving its efficiency in different environments to mining, including acquiring supplementary information regarding the geological composition of blast panels (Grigorova, 2020), quarry's reserves (Grigorova & Koprev, 2019) or for monitoring the saturation level of mine waste facilities (Grigorova, 2023; Tomova & Kisyov, 2023). The total number of used profiles was 21, spanning over a total of 2935 m. The first group of 13 profiles (2 to 14) reached a depth of 25 m, spanning between elevations 445 m and 420 m, while the second group of profiles covered a depth of 15 m, spanning between elevations 470 m and 455 m. Figure 2 represents the studied profiles for the mining operation.

Figure 2. Studied profiles for the mining operation

Upon thorough analysis of the gathered data, it was determined that the electrical resistivity of the rock mass falls within the range of 100 Ωm to 4500 Ωm. The Shavar formation comprises of clay materials, metallic oxides, and sulphide minerals, all of which possess the ability to conduct substantial electrical current through the material itself. Consequently, differentiating between sulphide mineralized rocks and clay materials presented a significant challenge. Following the interpretation process, the researched geoelectrical sections have been classified into four distinct electrical resistivity zones, each characterized by unique lithological features:

- **Zone 1**: This environment is typified by the lowest values of electrical resistivity, ranging from 100 Ωm to 550 Ωm. This zone likely delineates a stratum of Shavar formation sediments, composed of metamorphic clasts and clays.
- **Zone 2:** The zone exhibits relatively higher values of electrical resistivity, ranging from 550 Ωm to 1500 Ωm. Hence, it is assumed that this environment predominantly consists of carbonite breccia and breccia conglomerates.
- **Zone 3:** This zone is marked by nearly the highest electrical resistivity values, ranging between 1200 Ωm to 4000 Ωm. These results show that this environment likely represents siltstones characterized by a high content of quartz or muscovite.
- **Zone 4:** Similarly, featuring high electrical resistivity values, ranging from 2500 Ωm to 4500 Ωm, this zone is attributed to decoupling after blasting in the studied area. Hence, it can be assumed that the zone is a direct consequence of anthropogenic activities.

The conditions of the study include the use of a Wenner electrode array on the ground surface, where the electrodes were placed with a spacing of 5 m. Data was acquired with an automated multi-electrode resistivity meter Terrameter SAS 1000 and was processed via the RES2DINV computer software. An exemplary profile of the studied rock mass can be seen on Figure 3, which was a part of a previous extensive ERT study (Grigorova, 2020).

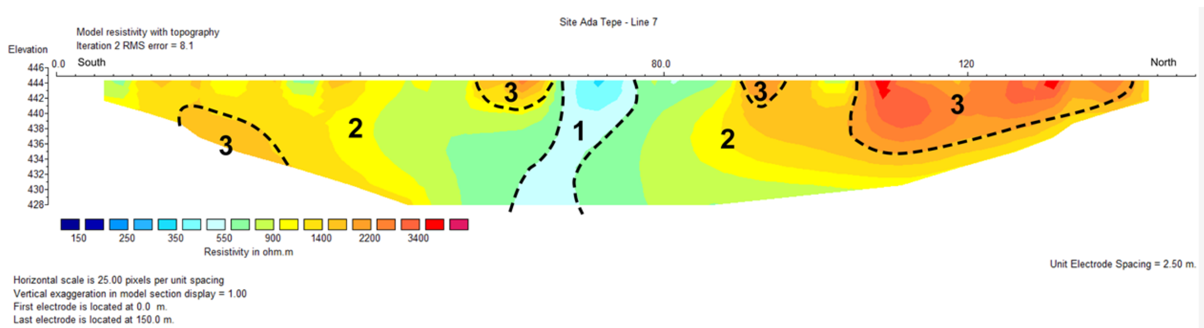

Figure 3. Exemplary ERT profile of the studied rock mass

The covered area by the ERT method allowed for labelling the rock mass zone for a total of 41 blast panels. The obtained data and its relevant interpretations regarding the four rock mass zone classes was used to obtain a sub-sample of the general dataset for those BMMs which were placed in either of the zones. No monitors were placed in Zone 4 and for this reason it was discarded from the analysis. Hence, only zones 1, 2 and 3 were considered as a supplementary categorical variable which was used for further analysis and verifying its influence on the blast movement observations. In order to gain a better understanding of the effect of different rock mass zones, the studied dataset was comprised of observations from shots utilizing only ANFO with a local powder factor value in the interval 0.30-0.40 kg/m³. The reason behind this choice is that the number of observations of shots using a packaged watergel in the cases where ERT data was available were scarce. Hence, they were discarded for this case study. Moreover, the powder factor in the considered range is also representative with the overall powder factor used in most blasts. Hence, these assumed conditions aim to obtain a dataset which closely resembles the conditions of a typical shot. All these conditions used to filter the general dataset led to the use of a sample size of 52 pairs of observations of top and bottom flitch movement. The dataset was further divided into three sub-samples for each rock zone, where 25 pairs of observations were for Rock mass zone 1, 17 for Rock mass zone 2 and only 10 for Rock mass zone 3. Moreover, all observations are based on monitors situated at least 15 m away from the free face and hence they are representative of the blast movement phenomenon for most of the panel, excluding the edge effects.

Methodology

Studied Variables

Each 3D movement vector (M_{3D}) can be decomposed into two main components – the horizontal movement vector (M_H) and the vertical movement vector (M_V). One can also derive the angle of inclination for the 3D movement vector (α_V) and heave effect of the blast, which is calculated as the difference between the elevations of the pre- and post-blast surfaces directly above the monitor. In addition, the azimuth of the movement vector is provided by the report. However, a more rigorous analysis would require the calculation of the ideal angle of horizontal movement relative to the position where the monitor is located, based on the gradient of the cumulative delay field for the blast, as shown via surface plot in Figure 1. As a result, the angle of horizontal deviation can be determined for each monitor as the difference between the ideal direction of horizontal movement and the azimuth of its actual movement. This resulted in the definition of the deviation angle for horizontal movement (α_H). The cumulative delay field and the isochrones for this study were generated from the firing patterns using a Python 3.11 script. Thus, using trigonometric operators, the horizontal movement vector (M_H) is divided into its two components - the horizontal movement in the direction of the free surface (M_{Hff}) and the vector of horizontal deviation towards the first initiated drillhole of the pattern (M_{Hdev}). Both vectors can be estimated via the following equations:

$$M_{H_{ff}} = M_H . \cos\alpha_H \tag{1}$$

$$M_{H_{dev}} = M_H . \sin\alpha_H \tag{2}$$

A visual representation of these variables can be seen on Figure 4.

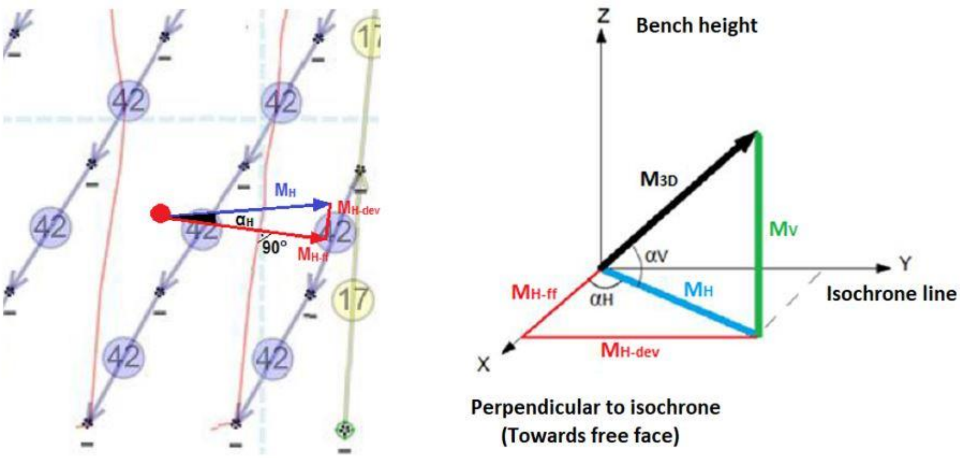

Figure 4. Variables used for the decomposition of 3D blast movement vectors

The components M_{Hff} and M_{Hdev} can assume negative values and they signify the magnitude and direction from the initial position of the BMM. A positive value for the M_{Hff} would indicate perpendicular movement from the isochrone, towards the free face, while a negative value would signify movement opposite the free face. Although these measurements are very rare, such outliers can exist and are interpreted as a potential misinterpretation of the BMM's location. Considering the M_{Hdev} vector component, a positive value signifies movement directed towards the drillhole which was fired first for the echelon pattern, while a negative value indicates the opposite direction. Using both positive and negative values for tracking blast movement can be interpreted as the change of position in the three orthogonal directions from the initial position of the BMM. Therefore, using all three values of M_{Hff} , M_{Hdev} can provide one to estimate the post-blast position of each monitor for an arbitrary location from the blast panel.

As previously discussed, the main groups of factors known to influence blast movement are blast design parameters and rock properties. Numerous writers (Thornton, 2009a; Thornton, 2009b; La Rosa and Thornton, 2011; Poupeau et al., 2019; Yu et al., 2019) have already investigated the impact of these factors on blast movement. D. Thornton (2009a, 2009b) previously explored the difference in flitch movement as well as movement in buffered and free face blasting. Furthermore, Z. Yu et al. (2019, 2020) studied the relationships between the M_{3D}, M_H and M_V variables. The correlations between horizontal movement vectors for several flitches was introduced by Hmoud and Kumral (2021, 2022). However, the relationship between all vector components of both flitches is not thoroughly investigated. Hence, in order to analyse its degree of strength between the vector components for both flitches, a traditional approach was initially used by estimating two non-parametric measures – the Spearman and Kendall correlation coefficients.

Statistical Methods

Conventional descriptive statistics such as mean, median, standard deviation and inter-quartile range (IQR) were obtained. Rock mass type was assumed to be a categorical variable for the purpose of hypothesis testing in order to determine how flitch movement differs in all zones. Due to the non-normal nature of the data, non-parametric tests were performed to investigate blast-induced rock movement under various conditions. As top and bottom flitch movement depend on the same monitoring hole position, all hypothesis tests were performed separately for both flitches. The hypothesis tests which were assumed to be best-suited for this analysis include the Kruskal-Wallis test (Kruskal and Wallis, 1952), Mood's test (Corder and Foreman, 2014) and Levene's test for equality of variances (Levene, 1960). The significance level of the tests is assumed to be 0.05. Should the p-value remain below this threshold, the null hypothesis is to be rejected. Table 1 displays the hypothesis tests that were applied, their purpose, and the stated null hypotheses.

The three considered tests are used for comparing the values of all three vector components. Moreover, if the null hypothesis is rejected in either of the cases, this is an indicator that the central tendency or variance of the investigated movement vector component for at least one rock mass zone is significantly different than the other zones. However, if the null hypothesis is failed to be rejected, this does not indicate that there is no observable difference regarding the variance and central tendency of the vector components' values. On the contrary, the hypothesis should be retained until further evidence suggests otherwise.

Table 1. Applied hypothesis tests

Performed test	Purpose	Null hypothesis (H_0)
Kruskal-Wallis	Investigate the influence of rock mass zone regarding the central tendency (median) for all vector components	All medians are equal
Mood's test	Investigate the influence of rock mass zone regarding the central tendency (median) for all vector components	All population medians are equal
Levene's test	Investigate the influence of rock mass zone regarding the variances for all vector components	All variances are equal

Kernel Density Estimation

As the provided sample sizes can be a limitation for obtaining accurate results from the hypothesis testing regarding some rock mass zones, an alternative analytical tool was also considered. Kernel Density Estimation

(KDE) is a powerful non-parametric method utilized for the estimation of the probability density function (PDF) of a random variable. Unlike conventional parametric approaches, KDE does not presume any specific underlying data distribution. Instead, it utilizes the data itself to generate a smooth estimation of the distribution. This makes it a versatile tool for data analysis and visualization, especially in the cases where limited number of observations are available and an initial estimation regarding the population's distribution is required. At its essence, KDE involves the placement of a smooth, symmetrical function, referred to as a kernel over each data point. The collective contributions from each kernel are then aggregated to produce a continuous estimate of the density function (Gramacki, 2017). The mathematical formulation of this relationship for a given dataset is as follows:

$$\hat{f}(x) = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right) \tag{3}$$

where

$\hat{f}$ – estimated density at point x;
K – kernel function;
h – bandwidth;
x_i – *i*-th observation from the dataset;
n – sample size.

This method provides an estimate of the actual PDF of the data, thereby offering a more precise representation compared to histograms, which may be susceptible to bin widths. Moreover, KDE contributes to establishing intrinsic details of the dataset, which are difficult to be estimated through a parametric approach. Such details can support gathering evidence for the presence of a potential multimodal PDF. Hence, its primary aim is to establish an estimation of the value for a single or multiple modes of the dataset.

The key components of KDE are the kernel function and bandwidth. The **kernel function** denotes a smooth, symmetrical function that integrates to the value of one. Common selections can include the Gaussian (normal) kernel, Epanechnikov kernel, uniform kernel, triangular kernel, etc (Gramacki, 2017). The Gaussian kernel's extensive usage is attributable to its smoothness and mathematical properties. Mathematically, a Gaussian kernel is defined as:

$$K(u) = \frac{1}{\sqrt{2\pi}} e^{-\frac{u^2}{2}} \tag{4}$$

where $u = \frac{x - x_i}{h}$ (5)

For the purpose of this case study a Gaussian kernel was assumed, as it was believed to be better suited to the nature and the scale of the data. The purpose of the Gaussian kernel is to simulate the potential presence of random errors regarding the measurements of each BMM's location.

The bandwidth parameter regulates the width of the kernel function and consequently, the level of smoothing in the density estimation process. A smaller bandwidth results in a more intricate estimate with reduced smoothing, leading to more prominent noise, while a larger bandwidth yields a smoother estimate. The selection of an appropriate bandwidth is pivotal as it optimizes the trade-off between bias and variance. Various methodologies, including cross-validation, Silverman's rule of thumb, and Scott's rule, can aid in identifying an optimal bandwidth for each density function. Another general rule for finding the best bandwidth value is to avoid under- and oversmoothing of the PDF, as the aim is to iteratively alter the signal to noise ratio until meaningful interpretations can be made.

This approach, based on KDE, can be considered very well-suited to the stochastic nature of blast movement, especially in cases where different physical and mechanical rock properties are binned under a single rock mass zone category. Moreover, in these cases multimodality is suspected to be present and therefore, a parametric approach could be insufficient. Hence, KDE would allow for one to establish intrinsic details of the potential PDF of each movement vector component for the sake of improving BMM locations planning.

Results

Descriptive statistics for each rock mass zone are provided in tables 2, 3 and 4 respectively. According to the average and median values, movement occurs with a significantly smaller magnitude than other operations of similar bench heights. This can be attributed primarily to the use of a very low powder factor due to the presence of softer rock formations. The smaller amount of explosive utilised, and as a result the smaller amount of produced gas products leads to the observed results.

Table 2. Descriptive statistics of blast movement for Rock mass zone 1

Flitch	Vector	Mean	Std. dev	Median	IQR
TOP	M_{Hff}	0.88	0.30	0.80	0.50
	M_{Hdev}	-0.09	0.27	-0.13	0.34
	M_V	0.45	0.15	0.45	0.15
BOT.	M_{Hff}	0.75	0.38	0.70	0.46
	M_{Hdev}	-0.03	0.30	-0.03	0.31
	M_V	0.13	0.18	0.15	0.19

Table 3. Descriptive statistics of blast movement for Rock mass zone 2

Flitch	Vector	Mean	Std. dev	Median	IQR
TOP	M_{Hff}	1.00	0.37	1.01	0.53
	M_{Hdev}	-0.14	0.26	-0.11	0.20
	M_V	0.42	0.25	0.37	0.22
BOT.	M_{Hff}	0.80	0.39	0.73	0.55
	M_{Hdev}	-0.12	0.28	-0.14	0.43
	M_V	0.08	0.25	0.12	0.19

Table 4. Descriptive statistics of blast movement for Rock mass zone 3

Flitch	Vector	Mean	Std. dev	Median	IQR
TOP	M_{Hff}	0.88	0.47	0.95	0.67
	M_{Hdev}	0.11	0.45	0.00	0.53
	M_V	0.50	0.35	0.42	0.27
BOT.	M_{Hff}	0.73	0.48	0.63	0.84
	M_{Hdev}	0.05	0.34	0.08	0.56
	M_V	0.12	0.20	0.05	0.21

Taking the M_{Hff} vector into account, movement for both flitches and all three rock mass zones exhibit a substantial level of variation. The observable difference between the mean and median values for all movement vectors is a direct result of dealing both with slightly positively and negatively skewed PDFs. Hence, this led to the choice of using the forementioned non-parametric hypothesis tests, instead of the traditionally applied ANOVA and Bartlett's test.

Table 5 displays the results of the applied tests and the decision made with respect to the null hypothesis. Results show that for both flitches and all movement vector components there is no statistically significant difference in the observed results. This can be interpreted as the lack of any practically meaningful difference between movement in each of the studied rock mass zones. Indeed, this interpretation has some reason behind it, as one of the key factors directly influencing the magnitude of blast movement is the powder factor and its respective volume of gas products distributed to the amount of rock mass moved.

Table 5. Results from hypothesis testing regarding differences in the movement vector components on both flitches in different rock mass conditions

Studied flitch		TOP			BOTTOM		
Vector		M_{Hff}	M_{Hdev}	M_V	M_{Hff}	M_{Hdev}	M_V
Mood's test	*p* value	0.641	0.364	0.129	0.952	0.211	0.779
	Decision	*Retain H_0*	*Retain H_0*	*Retain H_0*	*Retain H_0*	*Retain H_0*	*Retain H_0*
Kruskal-Wallis test	*p* value	0.368	0.276	0.571	0.849	0.319	0.796
	Decision	*Retain H_0*	*Retain H_0*	*Retain H_0*	*Retain H_0*	*Retain H_0*	*Retain H_0*
Levene's test	*p value*	*0.393*	0.185	0.189	0.324	0.690	0.688
	Decision	*Retain H_0*	*Retain H_0*	*Retain H_0*	*Retain H_0*	*Retain H_0*	*Retain H_0*

However, non-parametric tests as robust as they are for non-normally distributed data, could also be prone to Type II error, i.e. failing to reject the null hypothesis. All three tests can be susceptible to small sample sizes and hence, they can be indeed prone to a Type II error. Therefore, this requires for the use of an alternative approach which could provide a more detailed look into the rationale behind the non-obvious difference in blast movement for different Rock mass zones.

As mentioned above, a good alternative in this case is the use of KDE. Assuming a univariate distribution for each vector component for both flitches yielded the results presented in Figures 5 and 6. The choice of bandwidth in all cases were based primarily on a leave-one-out cross validation with the occasional use of Silverman's rule or a custom choice of value, which provided a balance between under- and oversmoothing. Moreover, the median values are also shown in Figures 5 and 6 with dashed lines for each rock mass zone for the sake of comparison with the estimated mode values.

Indeed, results show that the KDE proves to be suitable for these cases where one aims to establish a mode-based measure of the central tendency for the magnitude of movement in different conditions. Moreover, the difference between the modes of M_{Hff} for the top flitch is substantially different in Rock mass zone 1, compared to the other two zones. Furthermore, this difference is more prominent compared to the one observed for the medians in the three rock mass zones. Another key result is that the variance of the vertical movement component M_V also seems to be different to some extent for Rock mass zone 1, compared to zones 2 and 3. This can be attributed to the predominant presence of clasts in clays for zone 1, which would lead to a substantial decrease in the overall magnitude of movement. Interestingly, the PDF of the horizontal deviation vector M_{Hdev} for Rock mass zone 3 differs from the other ones. This deviation in movement could be a result of the resistance put by harder rock inclusions of quartz compared to the zone of softer breccias. In all cases the deviation vector is predominantly affected by the variance in the delays of the NONEL system, however the movement vector in harder rock formations is slightly more likely to redirect compared to the other cases. A reason behind this phenomenon could be the insufficient local powder factor used for all Voronoi cells located in Rock mass zone 3. However, this aspect of the interpretation requires to be further supported by additional observations, as the observed result can be due to "fatter tails" based on the small sample size of Rock mass zone 3.

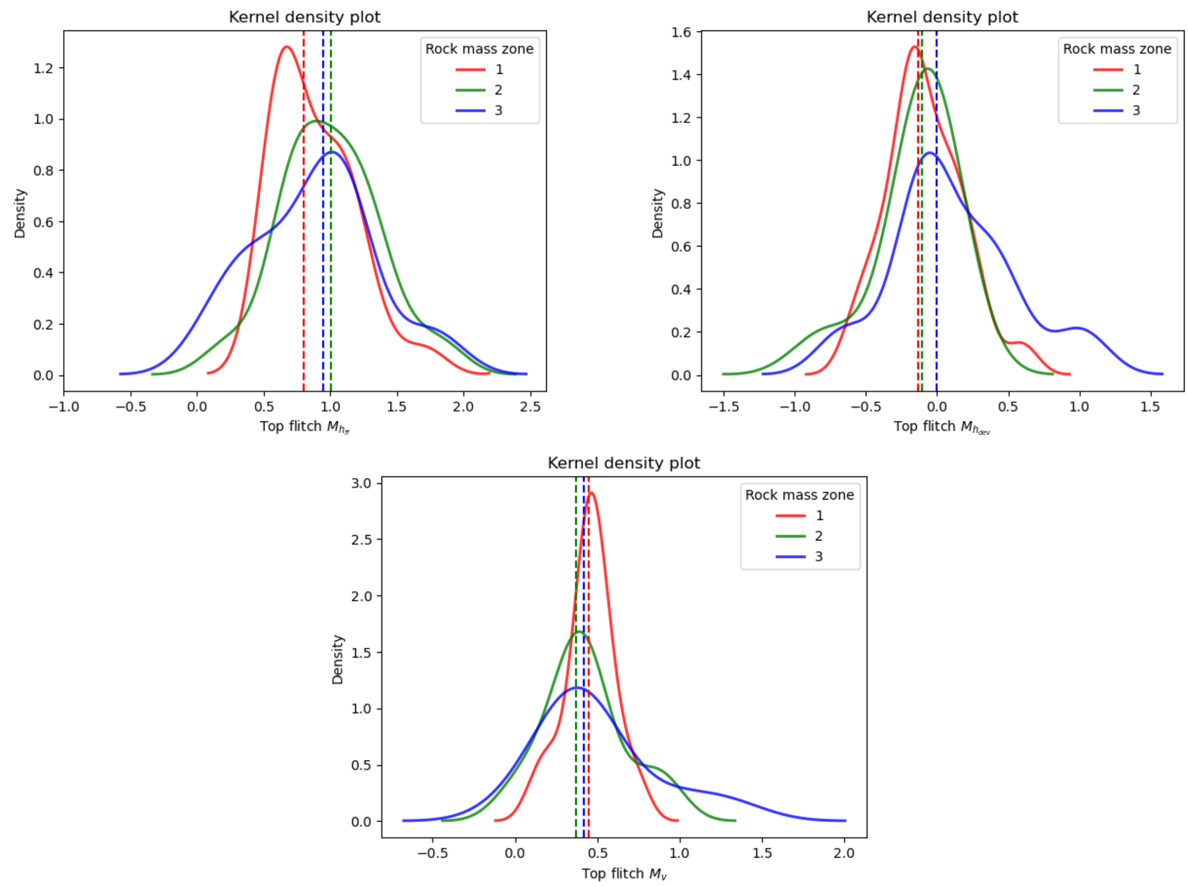

Figure 5. Kernel density plot of blast movement distribution for all three rock mass zones (Top flitch)

An additional insight which was established from the dataset is that there is a substantial difference in the mode value and the PDF of the M_{Hff} vector component for the bottom flitch for Rock mass zone 3, as well (Figure 6). Moreover, there is some evidence suggesting that the observed distribution could be bimodal for Rock mass zone 3. This indicates that an additional factor could be present, but not accounted for in the data associated with the analysed zone. Apart from the discussed key differences, the other movement components for the lower flitch exhibit similarities in their PDFs, which further support the results from the hypothesis tests. As the utilized powder factor and the bench height severely dampen the magnitude of blast movement, it may not be entirely obvious how the use of KDE can be helpful. However, in cases where the difference between the PDF of movement vectors is scaled in magnitude, this can have severe effect on the ore losses, dilution and misclassification.

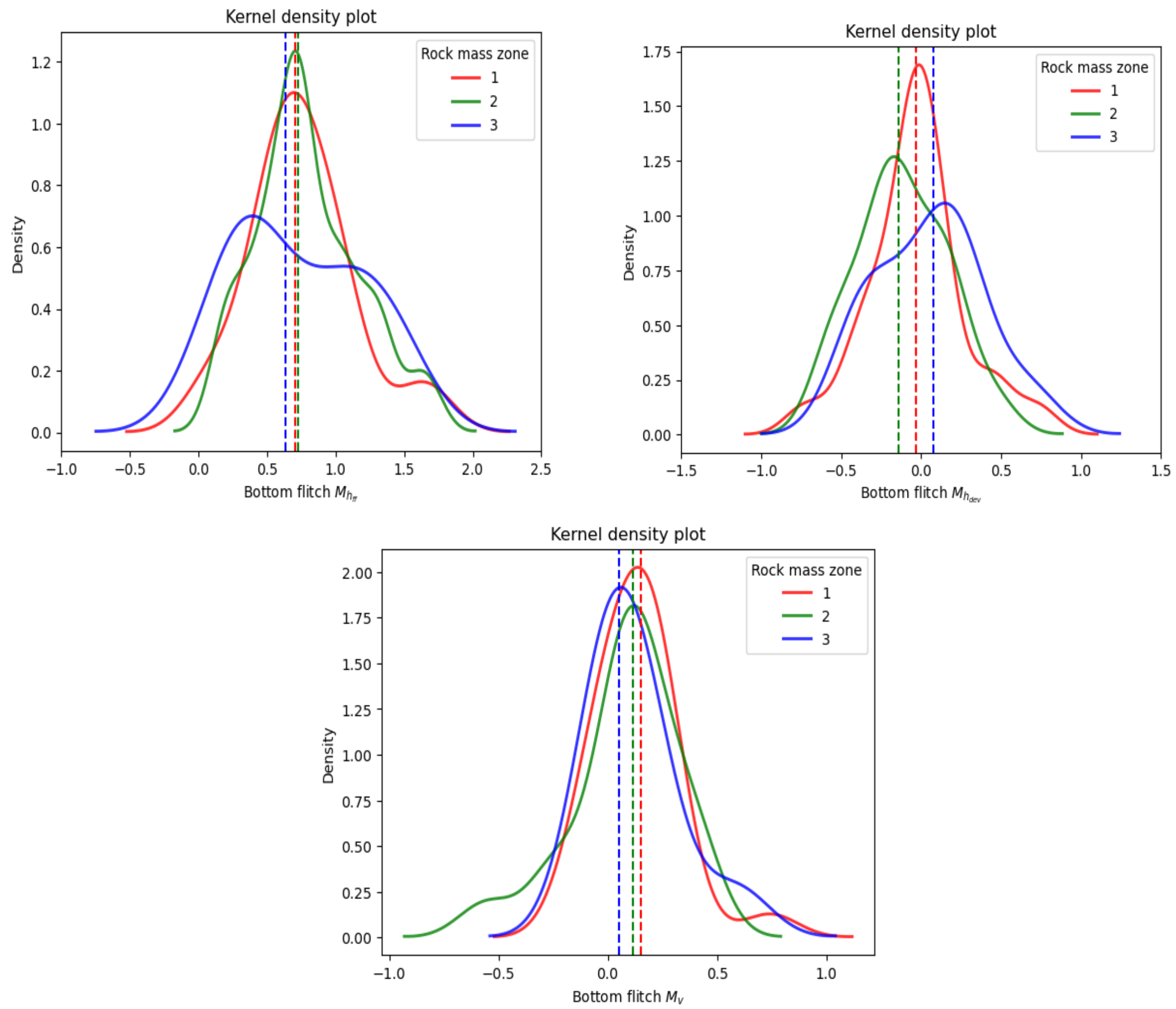

Figure 6. Kernel density plot of blast movement distribution for all three rock mass zones (Bottom flitch)

As blast movement is a complex spatial phenomenon, which is based on multiple dependent variables, it was necessary to extend the univariate PDFs into a higher dimension based on their inter-flitch relationship. The obtained correlation matrices for the three studied rock mass zones are provided below (Figure 7). As the results show, movement vectors on either flitch correlate to a higher degree with their respective vector components on the other flitch. Hence, the dependency of the considered vector components is important for analysing blast movement and should be taken into consideration. Moreover, the established correlation matrices provide an estimate of the differences between the movement component vectors, which are essential for the application of advanced stochastic models, e.g. Monte Carlo or Copula-based simulations.

Therefore, pairing the observations for M_{Hff}, M_{Hdev} and M_V for both flitches can lead to an additional perspective in terms of the joint distribution of each vector component's value based on an arbitrary location of the blast panel. Thus, KDE can also be applied in the case of providing a rough estimation of the bivariate PDF for the top and bottom flitch vector components

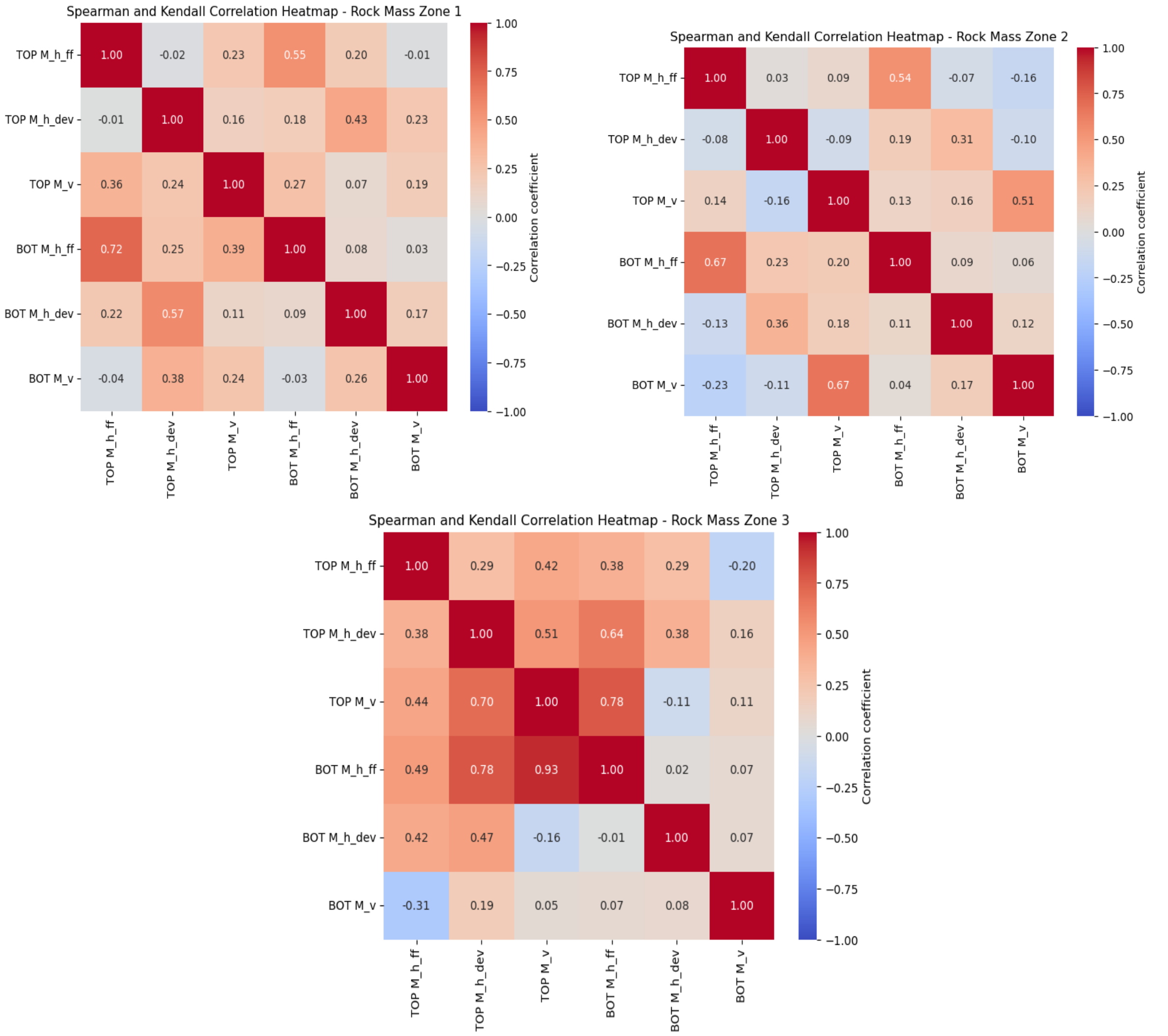

Figure 7. Correlation matrices for all three rock mass zones.
Lower left triangular matrix – Spearman correlation coefficient
Upper right triangular matrix – Kendall correlation coefficient

Figure 8 represents the bivariate PDF for all three movement vector components. The “x”-marks for each distribution are the locations of the median values for each movement vector for both flitches. Once more, KDE has provided a key insight for the central tendency of the joint distribution of the movement vectors for an arbitrary monitoring location. Indeed, the mode and median values can differ significantly, as seen for the M_{Hff} and M_V components in Figure 8. Moreover, the KDE has provided a comprehensive way of establishing several important aspects of the analysis at the same time – the presence or absence of a monotonic relationship between the top and bottom flitch vector components, the strength of this relationship, the inherent variance for the movement vectors in each rock mass zone and the central tendency of their values. Indeed, the estimated bivariate PDFs are not robust, but they provide a more detailed overview of the joint distribution of vector components. This way the difference in terms of variance and central tendency is more evident and hence the shapes of the bivariate distributions contribute to the explanation why the assumed hypothesis tests are not sensitive enough to detect these intrinsic differences.

Therefore, the differences between all movement components for the three rock mass zones are primarily outside the central tendency. Hence, certain movement value ranges are more likely to be observed for each rock mass zone. Furthermore, based on the bivariate PDF for each of the vector components and the established correlation matrices, it can be pointed out that the correlation between the components of Rock mass zones 1 and 2 is observed to be higher than the variance of Rock mass zone 3. These results further support the hypothesized interpretation about the effect of the insufficient local powder factor in significantly harder rock mass zones.

Hence, ERT can prove to be a valuable method for gathering additional data required for improving the results from blasting. This effect is expected to hold true and be magnified in cases where higher bench heights are involved, as well as a higher level of the powder factor. Moreover, even in cases where advanced statistical models are not initially planned to be developed, the initial assumption of each component's PDF shape can prove to be useful when assessing how different points from the ore-waste boundary are expected to behave based on their location in either of the established rock mass zones. Hence, this information is crucial for BMM location planning in order to preserve a maximum level of representativity with respect to the location of the ore-waste contact zones. Last but not least, intrinsic knowledge of the PDF of each vector component, their potential multimodality and their continued updating can be used for uncovering factors which were initially not accounted for and can improve the results regardless of the applied modelling framework (e.g. multivariate Monte Carlo or Copula-based simulations, advanced machine learning models used as surrogate models based on physics simulations, etc.).

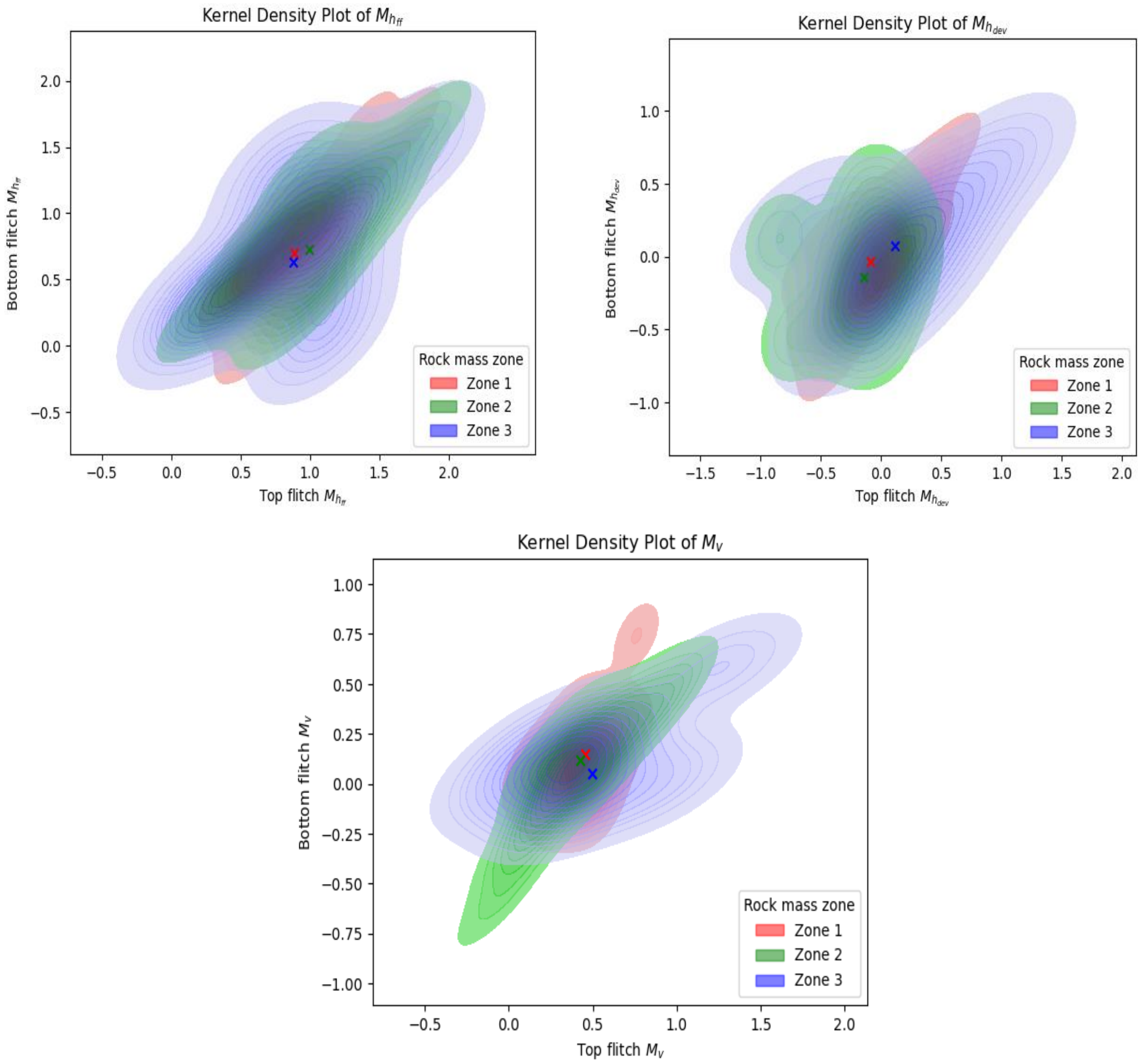

Figure 8. Bivariate distribution of blast movement vectors' components for all three rock types based on KDE

Conclusion

Based on the obtained results from the applied statistical and data mining methods, we conclude that the use of ERT can be beneficial for gaining additional insights regarding the behaviour of blast movement in different environments. Although the applied hypothesis tests fail to detect the presence of notable differences regarding the variance and the median-based central tendency for the blast movement vectors, KDE proves to be a viable instrument for detecting intrinsic details. Indeed, the failure to reject the null hypotheses is due to a high density of observations for all three rock mass zones in the same intervals for both flitches, considering each movement vector component. However, there are more notable differences between the established modes of the movement vectors compared to the observed difference between their median variables. This is evident mainly for the horizontal movement component directed towards the free face (M_{Hff}).

Furthermore, it was established that a multivariate approach can indeed lead to the detection of certain differences regarding the realization of the 3D movement vector components for both flitches, considering a monitoring drill hole. The joint PDF of the occurring vectors in their respective feature space indeed proves to be crucial and a more powerful tool which complements the use of well-established hypothesis tests. As it was presented for the case study, some notable differences can be observed for the mode values when dealing with the univariate PDF for each vector component in the studied rock mass conditions. However, the difference in their PDFs is more easily observable when the bivariate distribution of each vector component for both flitches is considered. Moreover, by observing the bivariate distribution, one can easily identify the strength of relationship between the top and bottom flitch vectors' components, their variance, as well as the presence of multiple modes for the distribution. Therefore, ERT with a combination of using KDE and hypothesis tests can be used continuously for supplementing one's understanding of blast movement under the influence of different rock mass zones, regardless of the lack of details in terms of their composition.

Scientific Ethics Declaration

The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the authors.

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