

Aftershock Identification in Deep Underground Mines Using DBSCAN Clustering

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Abstract

Mining-induced seismicity has become a significant concern in deep underground mining, primarily due to the increasing depths of extraction and the complex stress conditions. Significant seismic events are often followed by aftershock sequences that pose significant risks to worker safety and mine infrastructure, highlighting the importance of reliable aftershock identification and exclusion zone determination for re-entry protocols. The goal is to enhance the accuracy of aftershock identification resulting from underground mining activities and minimize noise in microseismic catalogs, thereby supporting mine safety. This study applies the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm to a synthetic microseismic catalog of 1471 events with moment magnitudes ranging from -1.6 Mw to 2.5 Mw. After magnitude of completeness (M_c) filtering, DBSCAN was used to spatially cluster aftershocks, effectively distinguishing them from background seismicity and noise. Results show that large sequences, such as the moment magnitude event 2.5 Mw with 1,471 aftershocks, were reduced to 1,015 clustered events. The clustered events show a more precise spatial concentration than the original distribution, which makes it simpler to tell which aftershocks are related to the mainshock and which are not. Before clustering, the catalog had 1,471 aftershocks for each mainshock with a maximum magnitude of 2.5 Mw. After clustering, 1,015 aftershocks were correctly identified as part of the sequence cluster.

Keywords *Seismicity, aftershock, DB-SCAN*

INTRODUCTION

Mining-induced seismicity has become a critical issue in deep underground mining operations, particularly as extraction depths continue to increase and stress conditions become more complex (Heal et al., 2006; Hidayat et al., 2022, 2024; Hudyma et al., 2017). At greater depths, the in-situ stress field approaches or exceeds the strength of the rock mass, leading to a higher probability of stress-driven seismic instabilities. Seismic events may be directly triggered by stress redistribution associated with mining activities such as blasting, caving, and hydrofracturing, or indirectly by slip along pre-existing faults and fractures that have been critically stressed (Cuello & Newcombe, 2018; Ghosh & Sivakumar, 2018). Unlike shallow mining environments where seismic activity is generally low in magnitude, deep-level mining introduces larger stress concentrations and significant rock mass deformation, increasing the frequency and size of induced seismic events. These events often manifest as either microseismic swarms or distinct mainshock-aftershock sequences. The latter are of particular concern because significant seismic events are frequently followed by a cascade of aftershocks that can persist for hours to days, redistributing stress and sometimes generating secondary rockbursts or collapse hazards (Hudyma et al., 2017; Peng & Zhao, 2009; Zhao et al., 2017).

The risks posed by these aftershock sequences extend beyond immediate structural damage. They can interrupt production schedules, damage expensive underground infrastructure, such as haulage drifts and shafts, and, most critically, jeopardize the safety of workers operating within the confined spaces of the mine. In many mining jurisdictions, reentry to active mining areas following

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a significant seismic event is strictly controlled through the implementation of reentry protocols, which require accurate assessment of both the temporal decay of aftershocks and the spatial extent of seismic hazards. The development of reliable methods for identifying aftershock clusters and quantifying exclusion zones is therefore essential for maintaining safe and sustainable deep underground mining operations. To mitigate these risks, reentry protocols have been developed in many seismically active mining operations. These protocols restrict access to affected zones for a prescribed duration until aftershock activity decays to acceptable levels of seismic hazard (Vallejos & Estay, 2018). A robust reentry protocol requires two critical parameters: the exclusion zone radius (R), which defines the spatial extent of the restricted area around the mainshock source, and the reentry time (T_{mc}), which specifies the minimum safe waiting period before personnel can re-enter the area. The accuracy of these parameters directly determines the balance between maintaining operational efficiency and ensuring worker safety.

Previous studies, such as those conducted by Vallejos and McKinnon (2010) and Vallejos and McKinnon (2008), estimated exclusion zones and reentry times using single-link clustering to identify aftershock sequences and empirical regression models to relate mainshock magnitude to seismic hazard parameters. While these approaches provided valuable first-order insights, they are limited by their sensitivity to noise and their inability to capture the actual density-based structure of aftershock clusters. Single-link methods often overestimate cluster size by chaining loosely related events, while regression models derived from diverse geological settings may not generalize well to specific mining environments. In this study, we propose an improved methodological framework by integrating the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm for aftershock identification. DBSCAN offers significant advantages over traditional clustering techniques because it groups events based on spatial density rather than distance alone, enabling the separation of physically meaningful aftershock clusters from background seismicity and noise (Schubert et al., 2017). By employing DBSCAN on an extensive microseismic catalog from an underground mine in Indonesia, this research aims to refine aftershock identification by enhancing clustering accuracy and mitigating noise effects, utilizing synthetic data as a validation approach.

LITERATURE REVIEW

Density-Based Spatial Clustering of Applications with Noise (DBSCAN) is one of the most widely used density-based clustering algorithms for identifying patterns in spatial and spatio-temporal datasets (Gholizadeh et al., 2021; Hahsler et al., 2019). Unlike partition-based methods such as k -means, which require the number of clusters to be predefined, DBSCAN automatically determines the number of clusters based on the density distribution of data points. This property makes DBSCAN particularly effective for datasets where the number of clusters is unknown or where noise and irregular distributions are present (Arlia & Coppola, 2001; Hahsler et al., 2019; Schubert et al., 2017). The clustering process begins with an arbitrary point in the dataset. If the point is a core point, DBSCAN expands a cluster by recursively including all density-reachable points within its neighborhood. Border points are then attached to the nearest cluster, while noise points remain unclustered. This iterative process continues until all points have been evaluated. From a computational perspective, DBSCAN has a time complexity of $O(N \log N)$ when supported by spatial indexing structures, such as R-trees or KD-trees. However, in the absence of indexing, the complexity can degrade to $O(N^2)$ in the worst case (Kriegel et al., 2011). Despite this, DBSCAN is highly efficient for large datasets and has been successfully applied in geospatial analysis, anomaly detection, and seismological applications. However, DBSCAN also has certain limitations. The algorithm is sensitive to the choice of parameters (eps and $minPts$), and its performance can decline in datasets with variable density. Recent studies have therefore proposed improvements and

variants such as OPTICS and K-DBSCAN to address these limitations (Gholizadeh et al., 2021; Schubert et al., 2017).

Given these characteristics, DBSCAN is particularly well-suited for clustering aftershock sequences in mining-induced seismicity studies, where events are often irregularly distributed, contaminated by noise, and exhibit varying density in space and time. The DBSCAN algorithm begins by selecting a random point from the dataset and checking whether there are other points located within the ϵ radius. If such points exist, they are added to the cluster being formed. The algorithm then examines each newly added point to determine whether additional points lie within its ϵ neighbourhood; if so, those points are also included in the cluster. This process is repeated iteratively until no further points can be added to the cluster. Once the expansion is complete, the algorithm continues the clustering procedure with unclustered points and repeats the process (Arlia & Coppola, 2001; Gholizadeh et al., 2021; Hahsler et al., 2019; Kriegel et al., 2011). In terms of computational efficiency, DBSCAN has a time complexity of $O(N \log N)$, where N is the number of data points. However, if sequential search methods are applied without spatial indexing, the complexity may increase to $O(N^2)$ in the worst case (Kriegel et al., 2011).

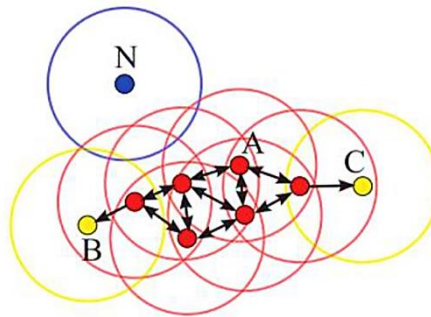


Figure 1. Illustration of the DBSCAN clustering model modified from Schubert et al. (2017)

RESEARCH METHOD

Hidayat et al., (2024) conducted a local seismic tomography study in an underground mining environment to map the velocity structure of body waves in the vicinity of the mining zone. The study employed local tomography inversion on seismic data collected from an internal mine seismometer network to identify velocity heterogeneities and structural features that are relevant to rock stability and microseismic wave propagation modeling. Previously, Hidayat et al. (2022) developed synthetic seismic event distributions and evaluated the reliability of seismometer placement in underground mines. By constructing a synthetic event catalog that mimics the magnitude distribution and source locations of microseismic activity in mining settings, this study tested the performance of station placement algorithms and localization techniques. The analysis demonstrated how multiple factors such as tunnel orientation, source depth relative to the measurement surface, and variations in signal amplitude govern location accuracy and precision. The results provide practical guidelines for designing efficient station configurations for monitoring purposes, including the trade-off between the number of stations and spatial coverage, as well as the importance of positioning stations along dominant wave propagation paths to minimize localization uncertainties.

This study employs synthetic data in the form of a microseismic catalog. The dataset was generated over a defined time span with a total of 1471 event. The synthetic data were designed to replicate real seismic conditions, following the spatial distribution of events reported in Hidayat et al. (2024). The most minor magnitude in the synthetic catalog is -1.6 Mw, while the largest is 2.5 Mw. This synthetic catalog serves as the baseline for developing test scenarios that evaluate the performance of the DBSCAN algorithm. The use of synthetic data has two primary objectives: first,

to test the consistency of DBSCAN in detecting aftershocks within the complex environment of underground mines; and second, to assess the sensitivity of DBSCAN parameters, particularly ϵ and MinPts, to variations in spatial and temporal densities. The spatial distribution of aftershocks was modeled using a multivariate normal distribution with radii ranging from 50 to 500 meters around the synthetic mainshock epicenters.

In comparison, depth variations were set within a range of 20 to 100 meters. The temporal distribution followed Omori's law with parameters $c = 0.1$ days and $p = 1.1$, resulting in a clustering of events during the initial days after the mainshock and an exponential decay thereafter. Aftershock magnitudes were generated using the Gutenberg–Richter law with a b -value of approximately 1, constrained to the range -1.6 Mw to 2.5 to maintain consistency with the real catalog. Additionally, several small clusters containing 20 to 50 events were included, with radius of less than 50 meters and occurrence times of less than one hour, to simulate blasting activities within the mine. The first stage of the analysis involved data selection using the Magnitude of Completeness (M_c) to ensure that only seismic events reliably detected by the seismic monitoring system were included.

The M_c value was estimated using the Maximum Curvature (MAXC) method developed by Wiemer and Wyss (2000), which determines M_c by identifying the maximum value of the first derivative of the Frequency–Magnitude Distribution (FMD) curve. For each major event, spatial clustering of aftershocks was performed using the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm. Spatial clustering was applied to ensure that only seismicity groups spatially associated with the mainshock were classified as part of the aftershock sequence. A maximum search radius of 50 meters was adopted to separate clusters, with a minimum threshold of 10 events required to define a valid cluster.

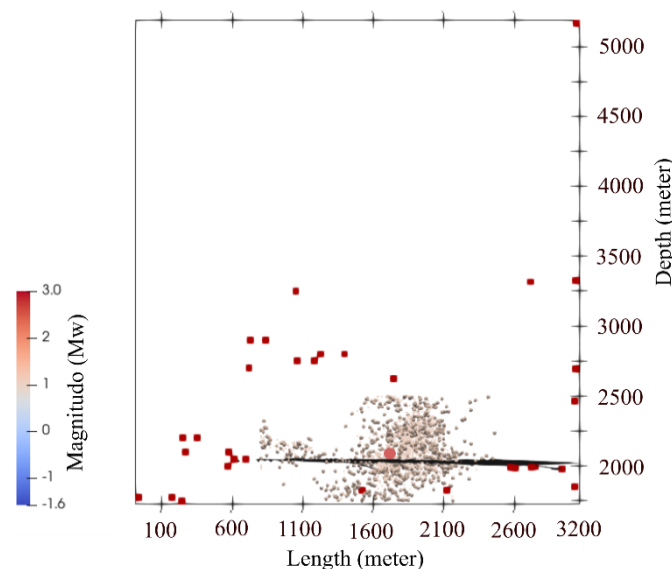


Figure 2. Illustration of The Distribution of Synthetic Earthquake Events, Where Red Circles Represent Events With a Magnitude of 2.5 Mw.

The aftershock distribution is shown by circles shaded from gray to red, indicating increasing magnitudes. The black line represents the haulage illustration, while the red boxes depict the locations of seismometer stations.

FINDINGS AND DISCUSSION

Data catalog selection using the Magnitude of Completeness (M_c) resulted in a new catalog

containing events with magnitudes ranging from -1.6 to 2.5 Mw. After that, aftershock clustering was performed for each significant event with a magnitude greater than or equal to 1.0 and an ES/EP ratio greater than 8.0 using the DBSCAN method, resulting in spatially clustered aftershock sequences. A total of 20 main events were obtained after selecting sequences that contained more than 50 aftershocks within 24 hours following the mainshock. The clustering parameters applied were a maximum search radius of 50 meters and a minimum of 10 samples to form a valid cluster. Figure 3 illustrates a reduction in aftershock activity and a propensity for events to aggregate around the mainshock. The clustered aftershocks for each main event with a maximum magnitude of 2.5 Mw had 1,471 aftershocks before clustering. After clustering, 1,015 aftershocks were included in the sequence cluster.

This clustering result provides valuable insights for recommending that mining operations proceed in a more controlled and safer manner. A comparison of the number of aftershocks in each sequence associated with the main events, both before and after clustering with DBSCAN, is presented below. This comparison highlights the effectiveness of the algorithm in organizing seismic data, allowing for more clear identification of aftershock distribution patterns. Before clustering, all aftershocks were mixed in a single large dataset without separation based on spatial or temporal proximity. After applying DBSCAN, the data were organized into several more representative clusters, allowing the identification of groups of earthquakes with similar characteristics while separating anomalous events or noise. Thus, the comparison provides not only a quantitative overview of the number of earthquakes in each sequence but also demonstrates how the DBSCAN method enhances the clarity of the underlying seismicity structure driving aftershock activity.

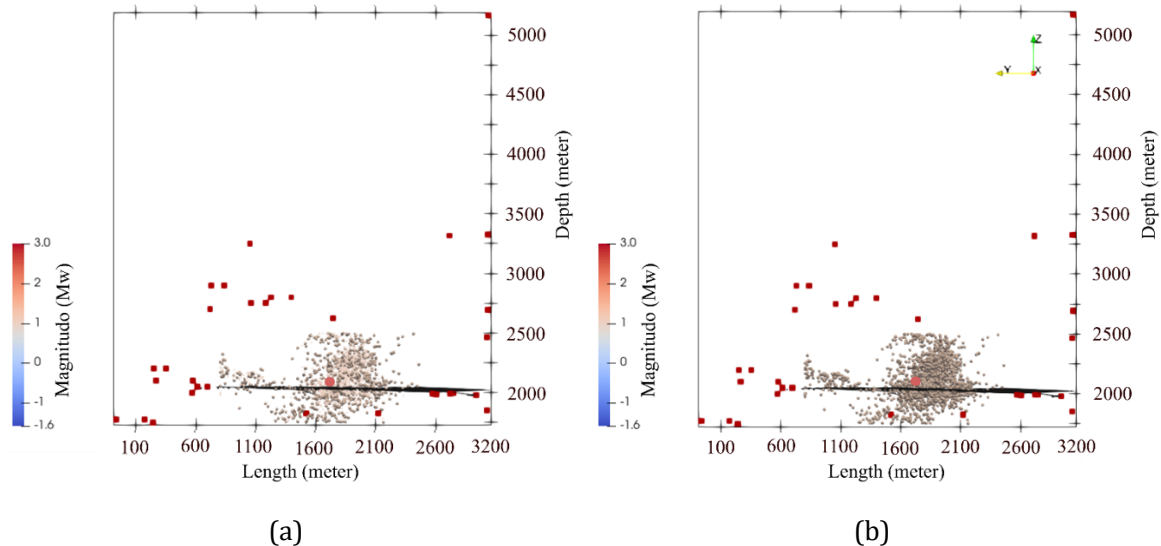


Figure 3. The illustration of Synthetic Earthquake Events Shows Red Circles Representing Earthquakes With a Magnitude of 2.5 Mw.

The aftershock distribution is depicted by circles shaded from gray to red, indicating the corresponding magnitudes. The black line represents the haulage illustration, while the red boxes indicate the locations of seismometer stations. It can be observed that the distribution of earthquakes after the mainshock is more concentrated (figure 3b) compared to that shown in Figure 3a.

Figure 3a illustrates the distribution of synthetic seismic events generated by a mainshock with a magnitude of 2.5 Mw. In contrast, Figure 3b shows the distribution of synthetic microseismic events clustered using the DBSCAN algorithm. Compared to the initial distribution, the clustered events exhibit a more compact spatial concentration, effectively delineating aftershocks associated with the mainshock and separating them from unrelated seismic events. Prior to clustering, the catalogue contained 1,471 aftershocks for each mainshock of maximum magnitude 2.5 Mw. Following the clustering process, 1,015 aftershocks were successfully identified as belonging to the sequence cluster, indicating that DBSCAN effectively reduced noise and isolated seismically coherent groups. The application of DBSCAN clustering to the microseismic catalogue demonstrates clear advantages in analyzing aftershock sequences in deep underground mining environments. Traditional approaches, such as single-link clustering, often overestimate cluster sizes by linking loosely related events, leading to inaccurate hazard characterization.

In contrast, DBSCAN utilizes spatial density as the primary clustering criterion, allowing the algorithm to isolate physically meaningful aftershock groups while discarding background seismicity and noise. The results of this study confirm the effectiveness of DBSCAN in reducing catalogue complexity and improving interpretability. These reductions highlight how DBSCAN prevents overestimation of aftershock sequences and provides a more realistic assessment of seismicity directly linked to the mainshock.

Furthermore, the analysis underscores the spatial and temporal variability of aftershock behavior. Some sequences displayed dense clustering within a confined zone, while others were characterized by broader dispersion and fewer retained events after clustering. This variability suggests that aftershock activity is strongly influenced by local geological structures and stress conditions, underscoring the importance of site-specific approaches in mining-induced seismicity studies. Overall, the findings demonstrate that DBSCAN offers a reliable and adaptive framework for identifying aftershock sequences in complex mining environments. Despite demonstrating the effectiveness of DBSCAN in identifying aftershocks, this study has several limitations. First, the analysis relies on a synthetic dataset, which may not fully capture the complexity of actual seismic conditions in deep underground mines. Second, the generalizability of the results from this study to mining-induced seismicity is limited, as geological heterogeneity and stress conditions may differ from those considered in the scenarios. Thirdly, the clustering results are sensitive to the selection of DBSCAN parameters (ϵ and minPts), which means careful calibration is required for operational applications.

CONCLUSIONS

This study employed the DBSCAN algorithm on a microseismic dataset from a deep underground mine in Indonesia to enhance the identification of aftershocks. The main conclusions are as follows: (1) DBSCAN efficiency: The algorithm effectively separates aftershock sequences from background seismicity and noise, reducing catalog overestimation common in conventional clustering methods; (2) Improved clarity of aftershock patterns: DBSCAN organizes seismic events into spatially meaningful groups, enhancing the visibility of aftershock structures and their relation to mainshocks; (3) Site-specific insights: The variability of clustering results across different mainshocks emphasizes the importance of tailoring aftershock analysis to local geological and stress conditions; (4) Contribution to seismic hazard management: By providing a more accurate representation of aftershock sequences, DBSCAN supports safer and more reliable assessment of mining-induced seismic hazards. In conclusion, DBSCAN represents a robust methodological improvement for aftershock clustering in mining seismology, offering both practical and scientific benefits for deep underground mining operations.

LIMITATIONS & FURTHER RESEARCH

The variability of clustering results across different mainshocks emphasizes the importance of tailoring aftershock analysis to local geological and stress conditions. For future research, integrating temporal parameters could capture the evolution of aftershocks over time. Parameter optimization using adaptive or machine learning approaches would improve DBSCAN performance under varying geological conditions. Comparative studies with algorithms like OPTICS or K-DBSCAN can benchmark effectiveness. Finally, translating clustering results into operational guidelines and exclusion zones will enhance worker safety and mine productivity.

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