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MINING METHOD SELECTION BASED ON HIERARCHICAL CLUSTERING AND CORRESPONDENCE ANALYSIS

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Abstract: Selecting an optimal mining method is a complex and critical decision in underground mining, influenced by multiple geological, technical, and economic parameters. This study introduces a novel framework that combines Hierarchical Clustering (HC) and Correspondence Analysis (CA) to enhance the selection process by evaluating the consistency and similarity among outcomes from both first-pass methods (UBC and Nicholas) and several multi-criteria decision-making (MCDM) techniques (including AHP, EDAS, PROMETHEE II, AHP-PROMETHEE, TOPSIS, and VIKOR). The proposed HC-CA approach identifies consistent conflicts among the considered mining methods and quantifies the agreement among the initial assumptions of the adopted selection procedures. A case study of a Pb-Zn deposit demonstrates that the framework can effectively detect consistent and co-occurring (i.e., conflicting) solutions, such as Cut-and-Fill Stoping, Shrinkage Stoping, and Sublevel Stoping. The results show that the adopted design criteria align more closely with the UBC selection method, compared to the Nicholas selection procedure for the considered deposit. Additionally, applying the HC-CA approach to the input matrices prior to applying the MCDM methods can yield different results, compared to subjecting the MCDM output scores to the proposed framework. This integrative approach extends traditional selection procedures and links them with commonly used MCDM methodologies and unsupervised machine learning methods by enabling flexible strategy development, with the inclusion of considering mixed-mining-method scenarios tailored to the deposit. Additionally, the approach offers improved decision support in early project stages by visualizing affinities among different assumptions and hence potentially mitigating biases during the following design stage.

Keywords: *underground mining, selection procedure, decision bias, clustering, dimensionality reduction*

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1. INTRODUCTION

When opening a new mine or developing a new section of an existing one, a difficult and responsible task is the choice of a suitable mining method. In general, methodologies for selecting a mining method can be divided into three main groups: qualitative methods, numerical methods and decision-making methods. In the case of qualitative methods, the choice of a mining method is based on a descriptive assessment of the physical-mechanical characteristics of the working environment (Boshkov and Wright 1973; Hartman 1987). Numerical methods use utility scores, that reflect the capabilities of each mining method with respect to the physical-mechanical characteristics and the geometry of the ore deposit (Nicholas 1981; Millet-Tait et al. 1995). In decision-making methods, quantifiable measures and categorical features for a given ore deposit can be used, which can include mining-geological, mining-technical and economic factors of the exploitation of the ore deposit (Bogdanovic et al. 2012). Regarding this class of methods, there are numerous papers on the topic of mining method selection (MMS), however several authors have extensively researched this field, many of which have successfully used multi-criteria decision-making (MCDM) methods in the context of MMS (Mijalkovski et al. 2012a; 2012b; 2021a; 2021b; 2021c; 2022a; 2022b; 2022c; 2023a; 2023b; 2023c; Balusa and Gorai 2018; 2019a; 2019b; Bakhtavar et al. 2009a; 2009b; Ataei et al. 2008a; 2008b; Alpay and Yavuz 2007; 2009).

Apart from these three classical approaches used for solving the MMS problem, the emerging application of supervised and unsupervised machine learning models in the field of mining engineering has led us to believe that certain well-established selection procedures can be re-evaluated. Moreover, this new paradigm has provided ways of establishing an improved understanding of different rules-of-thumb and has led to the adoption of novel approaches to decision-making in traditional mining engineering problems, e.g., underground MMS (Abdelrasoul et al. 2022), surface MMS (Gomaa et al. 2021), slope design (Ragam et al. 2024), stope design (Mortazavi and Osserbay 2021), etc. Thus, this paper aims to explore novel ways of integrating unsupervised machine learning for decision-support in relation to the underground MMS process.

2. METHODOLOGY

2.1. INTERPRETING ESTABLISHED MULTI-CRITERIA DECISION-MAKING METHODOLOGIES AS DOMAIN-BASED DIMENSIONALITY REDUCTION TECHNIQUES

Apart from the traditionally used parallel coordinates plot in engineering design, modern decision-support methods often employ unsupervised machine learning techniques – dimensionality reduction, clustering or a suitable combination of both (Bogdanovic et al. 2012; Harding 2016; Nanga et al. 2021; Chen and Geyer 2023; Zangada and

Abdulazeez 2023; Cámara et al. 2023). The purpose of using these methods is to reduce a high-dimensional problem to a less computationally intensive or human-interpretable lower-dimensional representation with minimal information loss. This can involve preserving the total inertia of the point cloud or maintaining the local and global structures that define the relative positions of sample vectors. Although classical multi-criteria decision-making (MCDM) methods do not explicitly aim to preserve spatial structures among solution vectors, they can still be considered a viable means of reducing the multidimensional space of the adopted criteria to a set of easily comparable composite scalar values. In the context of mining engineering, several of the most prominent MCDM procedures used for the selection of a mining method are: TOPSIS, VIKOR, EDAS, PROMETHEE and AHP. Each of the mentioned MCDM procedures aims to reduce the dimensionality of the decision problem from a feature space of the assumed quantitative values to 1D space using scalars or ranks. This provides a general level of understanding of the overall feasibility of employing each mining method under the evaluated conditions, regardless of whether the method is based on distance measures in $\mathbb{R}^n$, a certain level of compromise, or applying averaging or more advanced preference functions. Hence, the above-mentioned MCDM methodologies can be regarded as a domain-specific way of mapping the decision variables to a set of real or discrete values for all considered mining methods. However, the results from these mappings for different MCDM methodologies may not always be coherent with one another, as shown in prior studies (Mijalkovski et al., 2021c). In such cases, the question arises as to whether accurately ordering the solutions is feasible at such an early stage, or whether the notion of ordering is applicable at all, suggesting that considering sets of solutions may be more appropriate. This leads to the discussion of some important issues related to MCDM procedures, as well as first-pass selection methodologies before introducing the proposed framework.

2.2. POTENTIAL SHORTCOMINGS IN THE PROCESS OF MINING METHOD SELECTION

MCDM methods are often used to evaluate mining method alternatives, even with limited or potentially biased data. As these methods can oversimplify the complex interdependencies of geological, technical, and economic factors, this could potentially lead to flawed or ambiguous results. A more accurate assessment and ranking of the methods considered can emerge only at the pre-feasibility stage, where several alternatives are analyzed in detail. Despite using established selection procedures, tied or similar scores can be common. Additionally, if certain criteria are excluded, this may result in sub-optimal decisions due to neglecting future-relevant criteria.

Reaching similar total scores or tied values for different mining methods can be a result of several key reasons. One major reason is related to the ambiguity of the geological and geotechnical conditions of the deposit, which may facilitate the feasible use of more than one mining method. As a result, the selection process is not trivial.

An important reason why some solutions are ambiguous derives from the variability of the geological and geotechnical data, especially in cases when there is substantial variance, or their respective distributions are multimodal. In these cases, the traditionally used central tendency measures (mean and median) may not be sufficient to be used as a single value input for the MMS procedure. The same logic holds for the derivation of overall technical and economic parameters for each mining method in the context of the whole deposit, rather than for certain domains. In such cases, a good alternative would be the separate evaluation of each ore body, or similarly, each geotechnical domain.

Even if we assume that the precision and accuracy problem regarding the score values and their weights is mitigated or representative values for each ore body and geotechnical domain are used as proper input values, the resultant solution can still imply that more than one mining method is feasible. One approach to resolve these conflicts is by applying different selection methodologies for providing additional arguments in support of or against each mining method, i.e. summing or averaging rank values from a set of selection procedures, fuzzy dominance, etc. Indeed, these approaches have been successfully applied in the past to resolve conflicts and to select a single mining method. However, another question can arise – what if the apparent conflict is an indicator that a combination of the conflicting methods would be a feasible solution? Such an untraditional approach for resolving conflicting strategies is similar to the one used in Game theory, where the player can employ mixed strategies, rather than relying on pure ones (assuming the payoffs reflect rational and transitive preferences) (Nash 1951). So far, no traditional MMS procedure provides a framework for yielding a "mixed strategy", i.e. a combination of the considered mining methods (pure strategies). One reason behind this is because there is an inherent ambiguity whether such a combination refers to the transition between the considered methods in time domain (during the life of mine), in spatial domain (for the multitude of ore bodies or the set of geological and geotechnical domains), or in both. Moreover, certain combinations of mining methods may be incompatible, which leads to their careful consideration before accepting them.

Finally, a fundamental shortcoming of the above-mentioned selection procedures and MCDM methods is that although they achieve dimensionality reduction based on domain knowledge, they do not provide a quantifiable measure for information loss.

2.3. EXPANDING THE PROCESS FOR INITIAL MINING METHOD SELECTION BASED ON HIERARCHICAL CLUSTERING (HC) AND CORRESPONDENCE ANALYSIS (CA)

Hence, in this paper we aim to introduce a new formal approach to the MMS process, which addresses the issues related to the ambiguity of MCDM solutions order and the lack of measure for information loss. An unsupervised machine learning approach was applied, based on the joint application of clustering and dimensionality reduction with few arbitrary assumptions. By analyzing the correspondence between the resulting solutions from each selection methodology, one can take into consideration different sets of similarly rated mining methods (pairs, triplets, etc.), which can initially be interpreted as conflicts. These conflicts can be resolved either during the first-pass approach or during the sequential design stages of the project, when additional data of their overall performance can lead to their easier distinguishment. The level of conflict between two solutions can be established via an arbitrary distance measure between the two mining methods in the vector space of an arbitrary set of input features or selection criteria. Traditionally, differences between total score values from each MMS procedure (first-pass and MCDM) are unintentionally regarded as distance measures, as they are essentially scalar values. However, additional distance measures (Cosine, Kendall and Spearman) can be considered for analysis based on the initial input matrix of first-pass or MCDM methods (prior to the MCDM estimation process), or a matrix based on all composite MCDM scores (after their implementation). In the case of first-pass methods such as the UBC and Nicholas selection procedures, the input matrix can consist of the score reference matrix for the geological and geotechnical conditions for the considered mining methods. Alternatively, in the case of MCDM procedures, the input matrices consist of the values of the criteria considered for the decision-making process (ore losses, ore dilution, OHS conditions, environmental considerations, etc.). As discussed, after the implementation of all adopted MCDM methods, a matrix, consisting of all derived scores for each mining method, can also be subjected to HC. The choice of whether each MCDM composite score should be regarded as an independent distance measure or jointly with the other ones is to some extent arbitrary. If the former approach is applied, however, only the Euclidean (which coincides with the Manhattan distance) can be successfully applied for the individual scalar MCDM scores. Hence, this paper adopts the latter approach (using the overall results matrix of composite MCDM scores) so as to utilize additional unconventional distance measures (Cosine, Spearman and Kendall distance). In this case it is crucial to apply normalization prior to subjecting the data to HC.

For the application of additional distance measures, primarily ones which are typically used in HC, can be suitable for the purpose – Euclidean distance, Manhattan distance, Cosine distance, Spearman correlation distance and the Kendall correlation distance. All mentioned distance measures provide different perspectives on the nature of the similarities. In terms of an unsupervised learning problem, these distance measures aim to establish a better understanding of the additional properties which were not initially taken into consideration during the MCDM or initial selection procedure, although they emerge from the same input model. Hence, the employment of these additional distance measures can be considered a necessary extension and a novel way of identifying and resolving conflicting solutions. In addition, HC is complemented by visualization tools using dendrograms or cluster maps (a combination of a heatmap and dendrogram).

As the primary purpose of HC is to identify notable and consistent similarities between the considered mining methods, a higher or lower sensitivity for detecting certain conflicts between the solutions depends on the linkage method between the clusters (Aggarwal 2016). For this case study three linkage methods were chosen for establishing the distances between the considered mining methods and their respective cluster formations in the multidimensional space of the selected criteria – Single linkage, Complete linkage and Average linkage. Undoubtedly, a major aspect of HC is the assumption of a suitable combination between distance measure and linkage method (Aggarwal 2016; Manly and Navarro Alberto 2017). Their choice can indeed be arbitrary, moreover, it can have a significant impact on the detection of potential conflicting solutions. Therefore, in order to simplify matters, a general arbitrary similarity threshold value can be used for achieving better control of the results, regardless of distance measure or linkage method. It serves as a cut-off value for rejecting or accepting conflicts which need to be resolved at the next stage of the project. Depending on the assumed threshold value and the number of times each cluster does not violate it, the number of these occurrences can be considered as an indicator of a conflict worth investigating. This procedure can be repeated for all dendrograms, followed by assigning the total number of each conflict's occurrences to a contingency table, depending on which first-pass or MCDM input matrix was used. Indeed, a Multiple correspondence analysis can also be used, however, in this case study it yielded a small amount of explainability (below 50% of the total inertia) with respect to deriving two or three major components in the analyzed feature space of the categorical values. The reason behind the use of a single CA is that both the assumed distance measures and linkage methods, as well as their contribution to the final number of occurrences for each conflict, are assumed to be equally important. Hence, these two categories were binned for each first-pass and MCDM input matrix, which was considered as the primary categorical variable of interest. Therefore, HC can be considered as a preprocessing

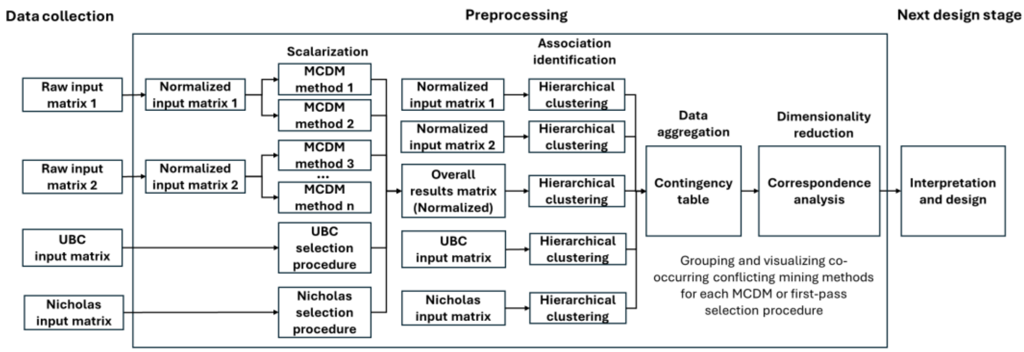

Fig. 1. Assumed methodology, implementing Hierarchical clustering and Correspondence analysis

tool, which aims to detect certain conflicts which were not initially detected but remain consistent regardless of the choice of selection procedure or MCDM method. In cases where clusters of three or more mining methods emerge, their lower rank interactions are also included into the contingency table, following the hierarchy of their agglomeration. Last but not least, the order of mining methods for each cluster is disregarded and hence, each cluster is represented as an unordered collection, i.e., a set. A full representation of the adopted methodology can be seen in Fig. 1.

3. CASE STUDY

For the current case study, a Pb-Zn deposit is taken as an example for demonstrating the proposed framework using data from prior papers (Mijalkovski et al. 2021a; 2021c). The input data for the key geological and geotechnical features were taken from previous papers on the topic, used for estimating the Nicholas and UBC score values (Mijalkovski et al. 2022b; 2022c). The deposit at hand was also previously evaluated using different MCDM approaches – TOPSIS (Mijalkovski et al. 2022a), VIKOR (Mijalkovski et al. 2021b), EDAS (Mijalkovski et al. 2023a), PROMETHEE II (Mijalkovski et al. 2021a), AHP and AHP-PROMETHEE (Mijalkovski et al. 2021c), FUZZY TOPSIS (Mijalkovski et al. 2023c). Although these procedures rely on the same selection criteria (value of mined ore, OHS conditions, coefficient of preparation works, ore recovery, ore dilution, cost per ton of ore, effect of mining, terrain degradation and environmental impact) and similar weights, they have yielded different solution orders, which need to be taken into consideration for the final decision of what mining method is more suitable for the deposit at hand. The pre-feasibility study of the deposit focuses on four primary methods – Cut-and-fill stoping (CFS), Shrinkage stoping (ShS), Sublevel caving (SlC) and Sublevel stoping (SlS).

The similarity threshold value was assumed to be 0.75, which implies that if the distance between two clusters does not exceed 25% of the maximum linkage distance for the evaluated dendrogram, the two clusters are agglomerated. As mentioned above, these clusters of mining methods are regarded as conflicting solutions worthy of further investigation at a later stage of the project to select a single method or their potential combination. Taking into consideration each method's number of occurrences for each combination of considered distance measures and linkage methods leads to the implementation of CA. Hence, the co-occurring conflicting methods, which consistently emerge during this stage of the analysis, are regarded as the ones the design stage should focus on more thoroughly.

In the first case, where the first-pass approaches are considered along with the MCDM procedures, the first two out of four components contribute to explaining 91.90% of the total inertia. Nicholas, UBC and the Overall scores matrix are on opposite sides in the feature space, which is due to their different set of assumptions. Hence Component 1 can be used to distinguish the conflicts obtained by the input matrix of the Nicholas selection process from the other ones. Additionally, it can also be interpreted as the axis separating two fundamentally different approaches – focusing on mass mining methods versus focusing on more environmentally friendly ones. Component 2, on the other hand, distinguished the results obtained by the Overall score matrix (based on MCDM results) from all MCDM input matrices, including the UBC first-pass selection matrix. Hence, both approaches can also lead to fundamentally different conclusions.

Given that the first-pass selection procedure matrices are excluded from the analysis and results deriving only from the MCDM methods are considered instead of the overall result matrix, the first two out of three components in the embedded space contribute to explaining 97.46% of the total inertia. Component 1 in this case corresponds with Component 2 in the left-hand graph, as the order of the points representing the input matrices remains unchanged for this axis in the lower-dimension representation. Figure 2 shows the established representations of all consistent co-occurring mining methods (i.e. conflicts) in the embedded space.

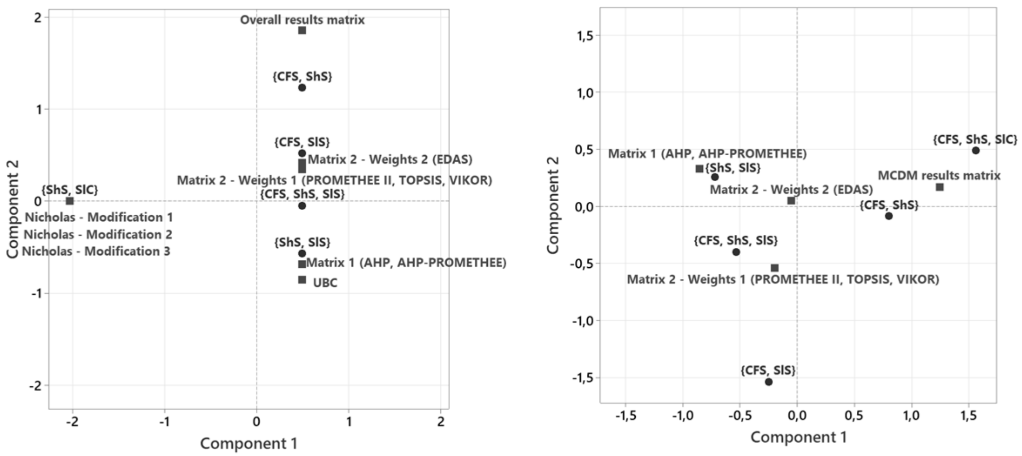

Fig. 2. Correspondence analysis of mining method selection methodologies and their respective co-occurring conflicting mining method solutions.
Left-hand graph – MCDM and first-pass results, Right-hand graph – only MCDM results

Should a different similarity threshold value be adopted, minor changes can be observed in the relative positions of the points in the embedded space. The major difference which occurs is that certain additional clusters would appear or disappear when testing out different threshold values. Hence, the joint use of HC and CA can be reliable as the results are consistent in terms of their interpretation.

Finally, if all points of view are considered – the use of the input matrices prior to and after applying each MCDM method (with or without the first-pass selection methods), the conflict sets which prove to be the most prominent and require to be further analyzed in the sequential design stage are: {CFS, ShS}, {ShS, SlS} and {CFS, ShS, SlS}. Applying the assumed methodology and threshold value has successfully led to the elimination of conflicts with the SlC method in this stage. Additionally, during the next stage of the design process the above-mentioned mining methods need to be thoroughly evaluated so as to provide more accurate evidence for their segregation. In addition, a potential combination of these mining methods may also have to be evaluated for investigating the feasibility of combining them in spatio-temporal domain.

4. DISCUSSION AND FUTURE WORK

As shown, the proposed HC-CA framework to some extent resembles the complementary Geometrical Analysis for Interactive Aid (GAIA) for PROMETHEE (Bogdanovic et al. 2012). This is due to successfully reducing the dimensionality of the problem with negligible information loss, as GAIA is based on PCA in the context of criteria and the features of design alternatives. While GAIA serves to identify the level of conflict or agreement between criteria, as well as clusters of similar alternatives in the embedded space, the HC-CA approach addresses all conflicts in the original high dimensional space before applying dimensionality reduction. Moreover, the HC-CA approach explores the level of coherence between the results obtained from different MCDM and first-pass selection approaches for the sake of generalization and better decision support. Additionally, subjecting the input matrices to the proposed framework prior to and after using different MCDM methods is also compared in terms of the similarity of the yielded results.

A notable drawback, however, of using this framework is that the ability to identify potential conflicts is based primarily on hyperparameters (an arbitrary set of distance measures, linkage methods and accepted threshold value), rather than strict domain expertise. As this approach aims to aid the engineer at an early stage of the project, there is a possibility for some conflicts to be falsely discarded. Hence, this requires further investigation. However, similar to other problems based on unsupervised machine learning, one can easily find the most practically meaningful results through a trial-and-error process. Therefore, this allows for testing out different threshold values and pairs of distance measures and linkage methods, as well as input matrices of different MCDM approaches. Regardless, the proposed modelling framework can be utilized for an arbitrary set of MMS procedures and an arbitrary set of suitable mining method alternatives. However, in cases where several hundreds or thousands of features are used, the HC-CA approach would lose its power due to the "curse of dimensionality". As the approach estimates distances between different alternatives in the original feature space, in such cases their values would no longer provide practical meaning. In these extreme cases, dimensionality reduction would be required, prior to clustering and applying CA.

Another drawback of the proposed modeling framework is that it is entirely dependent on the accuracy of the values provided by the matrices from the first-pass approaches, as well as the input scores and weights in different MCDM procedures. Hence, as flexible as this framework may be, it is also prone to subjectivity, similar to other decision-making methods. Last but not least, given that the proposed framework suggests that a mining method should be excluded from the set of consistently co-occurring conflicting mining methods, it does not provide an answer whether it is inherently more efficient or profitable than the other ones. Rather, it is expected that its overall performance would be significantly different from the conflicting ones. Regardless, this paper demonstrates a way to establish similarities between the results of the assumed selection methodologies when the order of solutions based on rank is ambiguous. In addition, the HC-CA approach can be further used to determine whether certain first-pass or MCDM methodologies are biased towards a certain set of solutions or if they reach the same conclusions independently.

In terms of future work, the proposed unsupervised machine learning framework could be extended to a supervised one. This would allow for reconciling the reliability of each first-pass or MCDM approach with respect to the solutions obtained in the later stages of the mining project. Moreover, additional performance measures (e.g., accuracy, precision, recall and specificity) of different first-pass selection approaches and MCDM procedures can be established to gain a better understanding of their capability with respect to different types of deposits.

5. CONCLUSION

This study proposes a novel methodological framework that integrates Hierarchical Clustering (HC) and Correspondence Analysis (CA) to support early-stage underground mining method selection. While traditional multi-criteria decision-making (MCDM) techniques such as AHP, PROMETHEE, TOPSIS, and VIKOR offer scalarization-based ranking of alternatives, the proposed HC-CA framework further utilizes these outputs through the lens of unsupervised machine learning. By treating each MCDM procedure as a form of domain-specific dimensionality reduction, the framework enables the systematic exploration of the structural relationships among mining method alternatives, capturing consistent patterns across different assumptions, expressed through multiple input matrices and MCDM results.

Applied to a platy-tabular Pb-Zn deposit, the HC-CA approach aided in identifying several mining methods as consistently conflicting with one another, most notably Cut-and-Fill Stoping (CFS), Shrinkage Stoping (ShS), and Sublevel Stoping (SlS). Moreover, the proposed framework demonstrated the stronger alignment of the UBC first-pass method with the assumptions used for the MCDM inputs and their results, in contrast to the Nicholas approach. These findings underline the framework's potential to support more nuanced and interpretable decision-making, especially in contexts where traditional and MCMD selection methods yield ambiguous outcomes.

Future research should assess the framework's generalizability across various deposit types, testing its capability in different geological and operational contexts via a supervised machine learning approach, where results from subsequent design stages can be evaluated against each other.

To conclude, the HC-CA framework complements MCDM-based methodologies by providing a flexible tool for better-informed decision-making in complex underground mining conditions.

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