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Detection of Rock Joint Sets using Optimized Fuzzy Clustering by Particle Swarm Algorithm (Case Study: Sungun Copper Mine)

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Abstract

Identifying joint sets is essential in engineering geology for rock mass classification and slope stability analysis in mining. Accurate clustering of joint sets based on dip and dip direction enhances the understanding of rock behavior and ensures stability in mine walls. This study presents a novel clustering approach integrating the Harmony Search (HS) and Particle Swarm Optimization (PSO) algorithms to classify joint sets in the Sungun copper mine. Initially, joint characteristics were classified using the Fuzzy C-Means (FCM) method, with the elbow method selecting a four-class clustering solution. To optimize clustering, FCM was combined with HS and PSO, and joint data were assessed using Davies-Bouldin, Calinski–Harabasz, and Silhouette indices. The results demonstrated that the hybrid FCM-PSO method outperformed alternatives, achieving scores of 0.80, 347.48, and 0.57, respectively, indicating superior clustering performance and stability. In contrast, the FCM-HS method performed worse than FCM alone, ranking third overall. The findings confirm that FCM-PSO effectively classifies joint sets, providing reliable insights into rock mass behavior in the Sungun mine. Considering the features and advantages of the FCM-PSO method, it is concluded that the proposed approach has significant potential for effective joint classification in mining engineering. This improved clustering approach enhances geological analysis, supporting safer and more efficient mining operations.

1. Introduction

The presence of widely distributed structural planes in rock masses (Structural planes in rock masses are natural or induced joints affecting strength, stability, and fluid flow. They are classified by origin, geometry, and mechanics. Key types include bedding planes, joints, faults, shear zones, cleavage, foliation, columnar joints, and folds.) leads to strong joint, heterogeneity, and anisotropy [1]. The inherent randomness and uncertainty of joints greatly affect rock mass deformation, strength, permeability, stress-strain behavior, and failure modes. Recent developments have integrated unmanned aerial vehicles (UAVs) with two-dimensional electrical resistivity tomography (2D ERT) to improve joint characterization. This integration enables accurate determination of properties such as fracturing degree, orientation, and persistence, leading to more precise slope stability assessments. Moreover, correlating 2D ERT resistivity values with Rock Quality Designation (RQD) indices offers a rapid, cost-effective method for evaluating rock mass quality and refining stability assessments [2]. In their natural state, rock masses develop joints that are not randomly distributed but rather form systematic patterns due to geological processes such as tectonic stresses, cooling of igneous rocks, or lithological variations. The distribution patterns of joints in rock masses typically include systematic joint sets, orthogonal networks, or anisotropic clusters, influenced by factors such as stress fields, rock type, and diagenetic history. Grouping joints into systematic sets facilitates the development of representative

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rock mass models by defining parameters such as joint orientation, spacing, and persistence. These parameters are essential for numerical simulations, rock mass classification systems (e.g., RMR and Q-system), and stability assessments in engineering projects[3]. When analyzing joint data, engineers aim to categorize joints into subsets based on similar orientations.

Classifying joints with similar characteristics into the same group is an effective method for statistical analysis of rock joints. To analyze termination distribution, researchers often map joint set orientations onto the Schmidt equal-area projection map. Schmidt [4] proposed a counting approach for classifying joints in rock formations, which is simple and useful. However, the grouping results are influenced by the researcher's experience, introducing some level of subjectivity. Shanley and Mahtab [5] used the objective function to address the subjectivity issue in the artificial grouping of the counting method, further improving its optimization. Mahtab and Yegulalp [6] presented a crucial criterion for classifying the dominance of joints using the counting method. This criterion is based on random tests generated from the Poisson distribution. Chen et al. [7] improved the approach developed by Shanley and Mahtab. However, the density of poles has a significant impact on the counting technique. Furthermore, the sampling variation and the size of the reference circle will impact the classification outcomes [8, 9].

These challenges have driven geologists to seek methods that efficiently classify rock mass joints. The clustering approach, commonly used for initial categorization, effectively addresses this need. Harrison [10] applied the traditional fuzzy C-means clustering method to study rock mass joint grouping based on fuzzy theory. However, due to the spherical nature of joints, represented by dip direction and dip angle, this method has limitations in handling spherical data. Hammah and Curran [11] improved the fuzzy C-means algorithm to efficiently handle data with a spherical structure. Hammah and Curran [12] have extensively studied the selection of distance measures due to their major influence on the fuzzy C-means method's classification results.

However, this approach relies on local search optimization, where the initial clustering center significantly influences the results. Zhou and Maerz [13] conducted a comparative analysis using four prominent grouping techniques: nearest neighbor algorithm, K-means, fuzzy theory, and vector digitizing. Jimenez-Rodriguez and Sitar [14] proposed a spectral clustering method for detecting joints in rock formations. Jimenez-Rodriguez [15] introduced a novel approach combining fuzzy K-means and spectral clustering for classifying rock mass joints. Feng et al. [16] analyzed the best approach for grouping joint orientations, evaluating three methods: standard visual method, fuzzy equivalent clustering, and FCM clustering, highlighting their advantages and drawbacks.

Qin et al. [17] enhanced the clustering center algorithm and developed a fuzzy C-means (FCM) clustering approach using rough sets for advantage grouping analysis. They found that both K-means and FCM are dynamic clustering algorithms, better suited for dominant rock mass joint grouping due to their reduced sensitivity to outliers. However, both methods require an initial clustering center, which significantly affects the results. These methods detect local optimal, often resulting in suboptimal groupings, and also require prior determination of the number of joints, making noise point detection challenging [18].

To address this problem, numerous researchers have consistently conducted investigations and proposed possible solutions to determine the optimal initial clustering center [19, 20, 21, 22]. The researchers conducted valuable work on cluster joints and their orientation-related characteristics. Recently, some researchers have used cutting-edge methods like soft computing and metaheuristic algorithms to solve problems in the field of mining engineering that involve figuring out the mechanical and hydraulic properties of rock masses [23, 24, 25, 26]. Mikaeil et al. [27] demonstrated that integrating metaheuristic algorithms with fuzzy clustering techniques can serve as a powerful tool for optimizing stone-cutting processes. Song et al. [28] and Xu et al. [29] analyzed cluster joints based on orientation, trace length, aperture, and surface morphology. They employed the artificial bee colony algorithm and the mutative scale chaos optimization technique for clustering. Cui et al. [19] and Li et al. [20] applied genetic, ant colony, and other heuristic algorithms to enhance FCM clustering stability by optimizing initial clustering centers and achieving global convergence. Additionally, Song et al. [22] utilized quantum particle swarm optimization to refine the properties of filling materials in cluster joints.

Zarean and Pourmirzaei [30] demonstrated that the Particle Swarm Optimization (PSO) algorithm exhibits a high capability in solving complex and nonlinear problems in geotechnical engineering. Mousavi et al. [31] employed the PSO and ICA metaheuristic algorithms to optimize the costs of

designing reinforced precast concrete elements. These algorithms are efficient due to their strong search capabilities in both exploration and exploitation phases. Sharifi et al. [32] demonstrated that combining the Genetic Algorithm (GA) with Particle Swarm Optimization (PSO) can be an effective approach for solving complex inverse problems. Rezaei and Asadizadeh [33] successfully predicted the uniaxial compressive strength (UCS) of rocks by integrating the Adaptive Neuro-Fuzzy Inference System (ANFIS) with the Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). Esmaeilzadeh and Shahriar [34] introduced an advanced fuzzy clustering approach (DEF3) using evolutionary differential-based optimization to classify joints at the Rudbar tunnel dam in Lorestan. The method demonstrated strong performance based on Davies-Bouldin, Calinski–Harabasz, and Silhouette evaluation criteria. Saeidi et al. [35] developed various predictive models and utilized ANFIS-FCM, ANN, and nonlinear regression to estimate the rock mass drillability index, leveraging similar hybrid approaches for joint characterization. Lotfi Godarzi et al. [36] demonstrated that the Particle Swarm Optimization (PSO) algorithm and metaheuristic methods perform better in solving complex mining planning problems. Nikakhtar et al. [37] demonstrated that the combination of Genetic Algorithm (GA) and Particle Swarm Optimization (PSO) can be referenced for solving complex geotechnical problems. Hu et al. [38] optimized an SVM-based rock mass classification model using PSO, GA, and GWO. Their findings indicated that the GWO-SVC model achieved superior performance during training, advocating for AI-driven evaluation over traditional methods. Nabavi et al. [39] demonstrated that using an optimized XGBoost model, enhanced with the Grey Wolf Optimizer (GWO) and Particle Swarm Optimization (PSO), achieved superior performance in predicting the Back-break phenomenon in blasting operations at the Chadormalu mine. Ruan et al. [40] developed the K-means-PSO method, integrating hybrid particle swarm optimization with game theory to assess rock mass quality. Their results showed strong alignment between K-means-PSO clustering and conventional basic quality classification (BQ), confirming its accuracy and reliability. Ruan et al. [41] introduced a DBSCAN-based approach for identifying dominant rock mass joint partitions. Comparative analysis with fuzzy C-means clustering revealed that DBSCAN achieved higher accuracy by effectively removing outliers, leading to more precise results. Wang et al. [42] developed an integrated machine learning approach for predicting rock mass characteristics. By combining fuzzy C-means clustering, support vector regression, and random forest, they achieved improved predictive accuracy, highlighting the effectiveness of fuzzy clustering in enhancing machine learning forecasts. Yong et al. [43] enhanced the K-means method for rock joint grouping using the Neutrosophic Genetic Algorithm (NGA), demonstrating improved utility and efficiency through optimized clustering centers. Lu et al. [44] proposed a semi-automated method integrating FCM-PSO for joint detection. Using a modified AlexNet CNN for classification and a hierarchical density-based clustering approach, they achieved high accuracy and improved joint identification. Based on a comprehensive review of the literature, a critical gap identified in existing studies is the inadequate treatment of directional data derived from joint measurements during the clustering process. Specifically, the handling of directional data should differ fundamentally from that of conventional scalar or numerical data, due to its vectorial nature and distribution on a spherical domain. This study addresses this gap by explicitly incorporating the directional characteristics of joint orientation data into the proposed clustering framework. By doing so, the algorithm ensures a more accurate and reliable representation of joint sets, thereby significantly enhancing the robustness and geomechanical relevance of the clustering outcomes.

Recent studies and reviews suggest that optimized clustering methods can be used to identify joint sets in rock masses by determining the optimal initial clustering center in traditional methods, particularly the C-means approach. This study aims to develop a novel clustering method for identifying joint set categories in rock masses. It combines the harmony search (HS) algorithm and particle swarm optimization (PSO) to improve the performance of fuzzy C-means by addressing the limitations of existing methods. The hybrid method was applied to classify joint sets based on common features in the Sungun copper mine, Iran.

2. Materials and Methods

2.1. Geological studied area

The Sungun Copper Mine is a porphyry copper deposit located in Iran, approximately 125 km northeast of Tabriz in the East Azerbaijan province of northwest Iran. The mine is situated in a mountainous area, lying between 461 431 E

longitudes and 381 421 N latitudes, at an elevation of 2000 meters above sea level (Figure 1). In addition to copper, the deposit contains other valuable minerals including molybdenite, gold, and silver. Copper is the primary output of the mine, while molybdenum is considered a by-product. The geological resource of the deposit is estimated to exceed 796 million metric tons (Mt), with a proved reserve of approximately 410 Mt at an average grade of 0.67% Cu. The mine design indicates a maximum open-pit depth of 725 m, extending from an elevation of 2350 m to the final minable level of 1625 m. The operational benches are 12.5 meters in height. Since its opening, the mine has been in operation for about 32 years. The rock mass within the mining area is highly fractured, exhibiting uniform geomechanical properties throughout the site. The Rock Mass Rating (RMR) is approximately 40, indicating a consistent rock quality across the mine.

Figure 1. Location of Sungun copper mine.

The Sungun copper mine, located within the Urmia-Dokhtar magmatic belt, faces significant challenges in rock slope stability due to a combination of geological, topographical, mining-induced, and weathering-related factors. The geological framework consists of porphyritic igneous rocks, including granodiorite and Monzo diorite, highly porous volcaniclastic formations, and hydrothermally altered units with reduced mechanical strength, all of which contribute directly to slope instability. The region's rugged topography, characterized by steep slopes with elevations ranging from 1,625 to 2,700 meters above sea level, and its deeply incised valleys resulting from fluvial erosion and tectonic activity, further intensify gravitational failure potential.

Mining operations exacerbate these challenges by generating airborne particulates and acid gases (e.g., SO_2 and NOx), which accelerate chemical weathering processes, reduce surface rock strength, and increase water permeability along fractures, posing a serious threat to slope stability. Physical weathering mechanisms, including freeze-thaw cycles, chemical weathering through sulfide oxidation-induced acidification, and biological processes such as plant root expansion, simultaneously degrade rock integrity and facilitate the expansion of joints. The high density of faults and joints significantly increases the likelihood of planar, wedge, and toppling failures.

Geotechnical investigations indicate that the uniaxial compressive strength of rocks in the Sungun mining area varies between 50 and 150 MPa. Morphological changes and the presence of groundwater further elevate the probability of slope failures. Joints, particularly the numerous joints in

porphyritic igneous rocks, play a critical role in determining rock mass strength and overall slope stability. These joints can easily interconnect, forming structurally vulnerable zones that enhance permeability and reduce shear strength. Depending on their dip and orientation, joints may initiate planar, wedge, or toppling failures, or contribute to the development of circular failure patterns affecting mine benches and slopes.

Given these challenges, precise identification, classification, and geotechnical assessment of joints are essential for ensuring the long-term stability of rock slopes in the Sungun mining area. A comprehensive management strategy, coupled with continuous monitoring of geotechnical and environmental changes, can mitigate instability risks and enhance the safety of mining operations.

2.2. Methodology

Although up to 10 characteristics of joints can be recorded in the field, only two key attributes dip and dip direction are commonly used to identify joint sets. In this study, data were collected from 19 benches in the Sungun copper mine using a compass clinometer which is a well-established method for structural geological surveys due to its high accuracy and direct field applicability. Unlike remote sensing techniques such as LiDAR or photogrammetry, which require post-processing and complex calibration, the clinometer method enables real-time, high-resolution measurements with minimal instrumental bias. This approach resulted in the collection of 376 joint sets (Figure 2), with each joint characterized by its dip and dip direction. Figure 3 presents the boxplots of the collected data. These boxplots indicate that some outlier values are present in the initial data set, particularly within the dip data. To ensure accurate modeling and prevent deviations, it is necessary to eliminate these outliers from the database. To systematically identify these outliers, the Z-score method was employed, which standardizes data points and flags those exceeding a predefined threshold (typically $|Z| > 3$) as outliers.

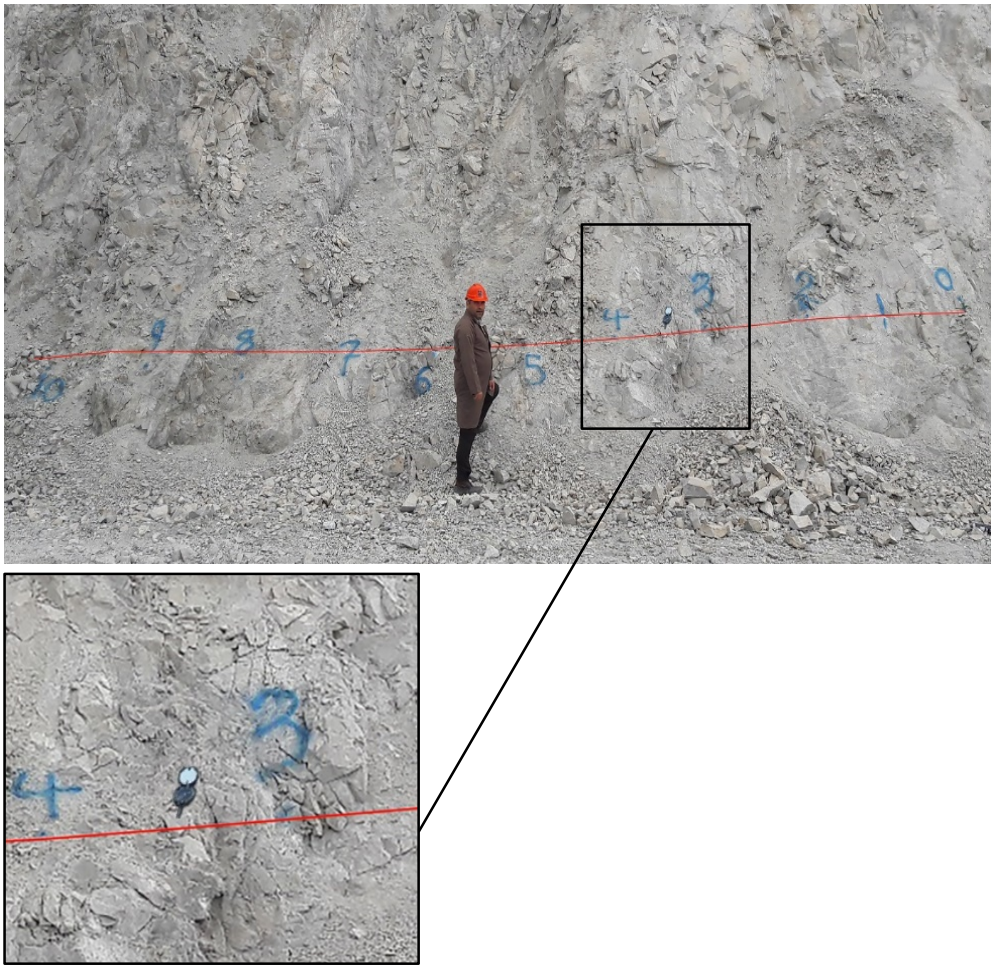


Figure 2. Mapping of the joint surface surveying method with a compass clinometer in Sungun copper mine.

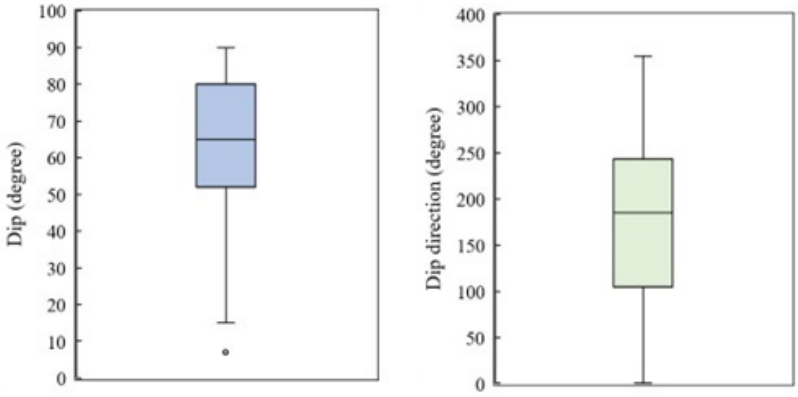


Figure 3. Box plot of the datasets (a) Dip (b) dip direction.

The Z-Score statistic was utilized to eliminate outliers from the data. The Z-Score, also known as the standard score, is a statistical measure that calculates the extent to which a data point differs from the mean of a dataset, expressed in terms of standard deviations. It is utilized to assess if a specific statistic is within the usual range or an outlier in comparison to the remaining data. The formula (Equation 1) for this evaluation is as stated by Aggarwal et al. [45]:

$$Z=(x-\mu)/\sigma \quad (1)$$

where:

Z- Z-Score,

x – Individual data point,

μ – Mean of the dataset,

σ- Standard deviation of the dataset.

Data points that exceeded three standard deviations from the mean were considered outliers and consequently excluded from the analysis. After eliminating these outliers, a total of 375 joint datasets were retained for this study. Table 1 summarizes the measured parameters.

Table 1. Input parameters and their statistical characteristics.

Joint characteristics	Units	Number of Datasets	Values				
			Maximum	Minimum	Mean	Range	Standard deviation
Dip	Degree	375	90	20	65.13	70	17.82
Dip direction	Degree	375	355	0	177.56	355	91.76

The orientation of joints is a critical factor in geomechanical and structural analyses, particularly in the context of rock mass characterization and slope stability studies. In this study, the equal-angle upper hemisphere projection technique is employed to mathematically evaluate the orientation of joints, which are typically represented as poles in stereographic projections (Figure 4). The spatial orientation of a joint is characterized by two fundamental parameters: Dip direction (α): The azimuthal angle measured clockwise from the north, ranging from 0° to 360°, Dip angle (β): The inclination from the horizontal plane, ranging from 0° to 90° [34]. In a Cartesian coordinate system, the unit normal vector e_i is used to indicate the direction of a joint plane. This vector is essential for accurately determining the spatial orientation and is commonly expressed using direction cosines. The normal vector e_i for a joint is defined as: $e_i = (x_i, y_i, z_i)$, where: x_i, y_i and z_i are the direction cosines corresponding to the x, y, and z axes, respectively [46]. These direction cosines are mathematically formulated as follows:

$$x_i = \cos\alpha \sin\beta$$

$$y_i = \sin\alpha \sin\beta \quad (2)$$

$$z_i = \cos\beta$$

where:

α – Dip direction of the joint,

β – Dip angle of the joint.

These equations describe the spatial components of the unit normal vector, which collectively define the orientation of the joint in three-dimensional space. The resulting vectors are then projected onto an equal-angle upper hemisphere, allowing for precise stereographic representation of the joints.

This study utilizes stereographic plots to visually interpret the orientation data of joints. These plots are instrumental in assessing the geological structure and identifying potential kinematic failure modes. Specifically, Figure 5 illustrates the stereographic projection of joint sets collected from the Sungun copper mine dataset, revealing the distribution and clustering patterns of joint orientations.

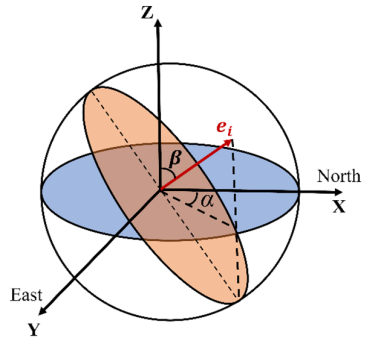
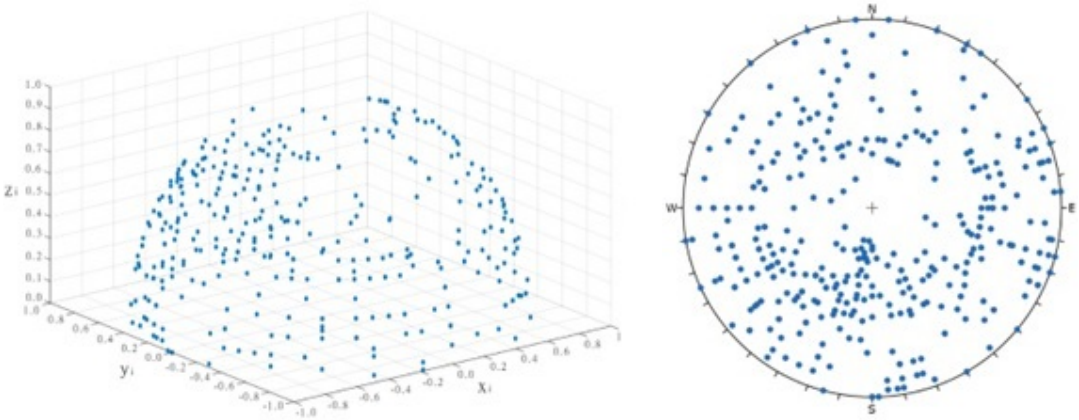


Figure 4. Representation of vector data in spherical space [6].



(a) **(b)**

Figure 5. Scatter of joint datasets (a) Spherical space (b) Two-dimensional space equivalent to the upper hemisphere.

2.3. Optimal number of clusters

Determining the optimal number of clusters is a fundamental step in data clustering, as it directly influences the accuracy and reliability of the clustering results. In this work, the elbow method was employed to identify the most suitable number of clusters. The elbow method is a widely recognized approach for selecting the optimal number of clusters by analyzing the percentage of variance explained in relation to the number of clusters. This method suggests choosing the number of clusters where adding another cluster does not lead to a significant improvement in data modeling. By plotting the percentage of variance explained against the number of clusters, the initial clusters were observed to capture a substantial amount of variance, indicating a significant contribution to information representation. However, beyond a certain point, the additional variance explained by each new cluster diminished considerably, forming an "elbow" shape on the graph. Identifying the elbow point [47], however, is often challenging due to its subjective interpretation and lack of a precise mathematical definition. Adolfsson et al. [48] proposed an approach to quantify the variance percentage using the F test (Equation 3), which evaluates the ratio of between-group variance to the overall variance as follows:

$$F = \frac{\sum_{i=1}^{K}(n_i(\overline{Y_i} - \overline{Y}))/(K-1)}{\sum_{i=1}^{K}\sum_{j=1}^{n_i}((\overline{Y_{ij}} - \overline{Y_i}))/(N-K)} \quad (3)$$

where:

i – Index of data within each group,

$\bar{Y}i$ – Mean of the data in the i^{th} group,

$\bar{Y}$ – Overall mean of the dataset,

K – number of clusters,

Yij – j^{th} data point within the i^{th} group,

N – Total number of data points.

If the between-group variance is substantially larger than the within-group variance, the F-value becomes significantly high, indicating a well-

separated clustering structure. This method effectively quantifies the optimal cluster number by balancing explained variance and model complexity.

2.4. Fuzzy clustering

The Fuzzy C-Means (FCM) clustering technique is a widely recognized and commonly utilized approach for fuzzy clustering across diverse fields. Initially introduced by Bezdek et al. [49] in 1984 within their doctoral dissertation, FCM has since gained extensive application in data analysis due to its flexibility and effectiveness in handling uncertainty in cluster assignments. FCM is a data clustering algorithm designed to partition a dataset into c clusters, assigning each data point a specific membership grade for each cluster. The primary objective of FCM is to classify a set of n data objects into c distinct clusters, thereby maximizing intra-cluster similarity while minimizing inter-cluster similarity. The dataset is represented as a matrix A, defined as: A: {a_1, a_2, ..., a_n}, where each data point a_i comprises m features, expressed as:

a_i: {a^1_i, a^2_i, ..., a^m_i}. The objective function of FCM, which guides the clustering process by minimizing intra-cluster distance and maximizing inter-cluster separation, is formulated as follows:

$$j(u,v) = \sum_{k=1}^{n}\sum_{i=1}^{c}(v_{ik})^2(d_{ik}^2) \quad (4)$$

where:

u – membership matrix indicating the membership values of each pattern vector for each cluster,

v – cluster center matrix, containing the coordinates of the cluster centroids,

v_{ik} – membership value of the k^{th} pattern vector to the i^{th} cluster,

d_{ik}^2 – Squared Euclidean distance between the pattern vector a_k and the i^{th} cluster center C_i .

It is important to note that the membership grades must satisfy the unity constraint, ensuring that the sum of membership values for each data point across all clusters equals 1. The Euclidean distance between the k^{th} pattern vector and the i^{th} cluster center is calculated using the following equation:

$$d_{ik}^2 = (a_k - C_i)^T(a_k - C_i) \quad (5)$$

where:

a_k – feature vector of the k^{th} data point,

C_i – feature vector of the i^{th} cluster center,

$(a_k - C_i)^T$ – transpose of the difference between the data point and the cluster center,

$(a_k - C_i)$ – The difference between the two vectors.

By minimizing the objective function (Equation 4), the FCM algorithm iteratively updates the membership values and cluster centroids, thus enhancing the clustering accuracy and robustness of the model. The FCM technique's ability to assign partial membership allows for a more flexible grouping of data points, effectively capturing overlapping clusters in complex datasets.

The Fuzzy C-Means (FCM) algorithm iteratively updates the cluster centers and membership matrix to achieve optimal clustering results. This iterative process continues until the improvement in the objective function becomes less than a predefined threshold (ε). The cluster centers are computed using the following equation:

$$C_i = \frac{\sum_{k=1}^{n}(v_{ik})^2.ak}{\sum_{k=1}^{n}(v_{ik})^2} \quad (6)$$

where:

C_i– i^{th} cluster center,

v_{ik} – membership value of the k^{th} data point for the i^{th} cluster,

ak – k^{th} data point,

n – Total number of data points.

The updated membership matrix is calculated using the following equation:

$$v_{ik}^{(r+1)} = \left[\sum_{j=1}^{c}\left(\frac{d_{ik}^r}{d_{jk}^r}\right)^2\right]^{-1} \quad (7)$$

where:

$v_{ik}^{(r+1)}$ – updated membership value of the k^{th} data point for the i^{th} cluster at iteration r+1,

d_{ik} – euclidean distance between the k^{th} data point and the i^{th} cluster center,

c – total number of clusters,

r – current iteration step.

The iterative process in the FCM algorithm involves two primary steps: Calculation of cluster centers using Equation (6). Updating the membership matrix using Equation (7).

These two steps are repeated iteratively until the following convergence criterion is satisfied:

$$\|J^{r+1} - J^r\| \leq \varepsilon \quad (8)$$

where:

J^r – objective function value at iteration r,

ε – Predefined threshold indicating the convergence tolerance.

The variable "r" denotes each iteration step. Once the change in the objective function is less than ε, the FCM algorithm is considered converged, and the final cluster centers and membership matrix are obtained.

2.5. Particle swarm optimization (PSO) algorithm

The Particle Swarm Optimization (PSO) algorithm is an optimization technique inspired by the collective behavior of bird flocks. Introduced by Kennedy and Eberhart [50] in 1995, PSO is a stochastic population-based optimization method. This algorithm emulates the social behavior observed in bird flocks, where individuals interact to find optimal paths for searching or migrating. In PSO, a swarm of particles represents potential solutions for the optimization problem [51]. Each particle moves within the search space, guided by its individual experience and the collective intelligence gained from particles exhibiting better performance within the swarm. The procedural steps of the PSO algorithm are as follows [52]:

1. Initialization: Particles are randomly distributed throughout the search space, each with a random position and velocity. Initial fitness values are assigned to particles based on the objective function evaluation.
2. Particle Movement: The velocity of each particle is adjusted according to: Its current velocity, its distance from its personal best solution, and Its distance from the global best solution discovered by any particle in the swarm. Each particle updates its position using the newly calculated velocity.
3. Evaluation and Update: The fitness of each particle's new position is evaluated using the objective function. If a better solution is found: The particle updates its personal best position and fitness. If this solution is better than any previous global solution, the global best position and fitness are also updated.
4. Termination: The steps of movement and update are repeated until a termination condition is met, such as: Reaching the maximum number of iterations, or achieving a desired fitness value. Figure 6 shows the flowchart of the PSO algorithm.

The selection of PSO parameters was guided by previous empirical studies and sensitivity analyses conducted in similar geotechnical clustering applications. An inertia weight (w) of 1.0 was adopted to maintain a suitable balance between global exploration and local exploitation. The inertia Weight Dsamping Ratio (WDR) was set to 0.99 to gradually reduce the inertia weight over iterations, thereby promoting convergence. The maximum number of iterations (Maxit) was fixed at 1000, and the swarm size (PS) was set to 50, based on preliminary trials aimed at ensuring both convergence stability and computational efficiency.

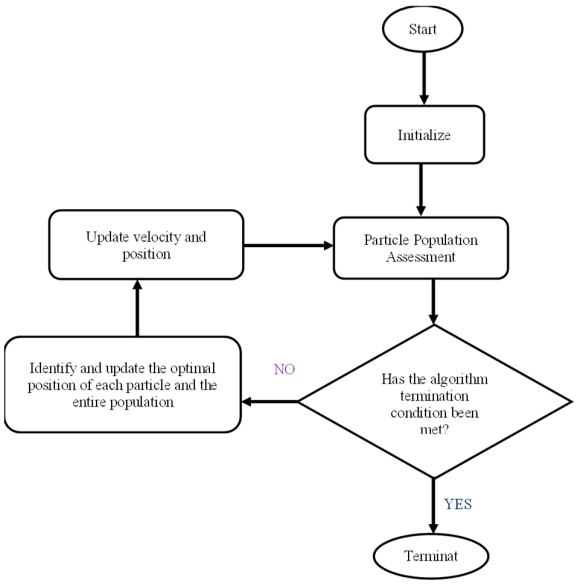


Figure 6. Flowchart of PSO algorithm.

2.6. Harmony Search (HS) algorithm

The Harmony Search (HS) algorithm is a metaheuristic optimization method initially proposed by Geem et al. [53]. This algorithm is particularly effective for managing uncertain and complex systems. It demonstrates remarkable computational efficiency when dealing with both linear and nonlinear datasets. The HS algorithm is inspired by the musical improvisation process used by musicians to compose new melodies. Specifically, it mimics the way a composer creates a new song by blending different musical notes and pieces. During this process, the composer: Selects the most suitable notes and segments to form a melody, considers their limited memory to recall and combine musical elements effectively [54]. The steps of the HS algorithm are as follows:

1. Initialization of Harmony Memory (HM): Harmony Memory (HM) is initialized by randomly generating multiple solutions based on

the problem's constraints. For an n-dimensional problem described by Equation (9), the Harmony Memory Size (HMS) is defined as follows [55]:

$$HM = \begin{bmatrix} x_1^1 & x_2^1 & \dots & x_n^1 \\ x_1^2 & x_2^2 & \dots & x_n^2 \\ . & . & . & . \\ x_1^{HMS} & x_2^{HMS} & \dots & x_n^{HMS} \end{bmatrix} \quad (9)$$

where:

x_j^i – denotes the value of the j^{th} decision variable for the i^{th} solution.

HMS is the total number of harmonies (solutions) stored in memory.

2. Creating a new harmony from the HM: A new harmony (solution) is generated by considering the existing solutions stored in the Harmony Memory (HM). This is done by either random selection, memory consideration, or pitch adjustment to explore the search space effectively.

3. Updating the Harmony Memory (HM): The new solution is evaluated using the objective function. If this new solution performs better than the worst solution currently in the HM, it replaces that solution, ensuring that the HM always retains the best harmonies.

4. Termination Condition: Steps 2 and 3 are repeated until the termination conditions are met. These conditions are typically based on achieving a desired level of accuracy or reaching a maximum number of iterations. Figure 7 illustrates the flowchart of the HS algorithm.

The control parameters of the Harmony Search (HS) algorithm were carefully selected to ensure an effective balance between exploration and exploitation. The Harmony Memory Considering Rate (HMCR) was set to 0.2, encouraging the reuse of high-quality solutions from memory. To introduce moderate variability and enhance search diversity, the Pitch Adjusting Rate (PAR) was assigned a value of 0.1. The maximum number of iterations (Maxit) was fixed at 1000, while the harmony memory size (HMS) was set to 50, based on preliminary testing aimed at optimizing algorithmic performance and convergence behavior.

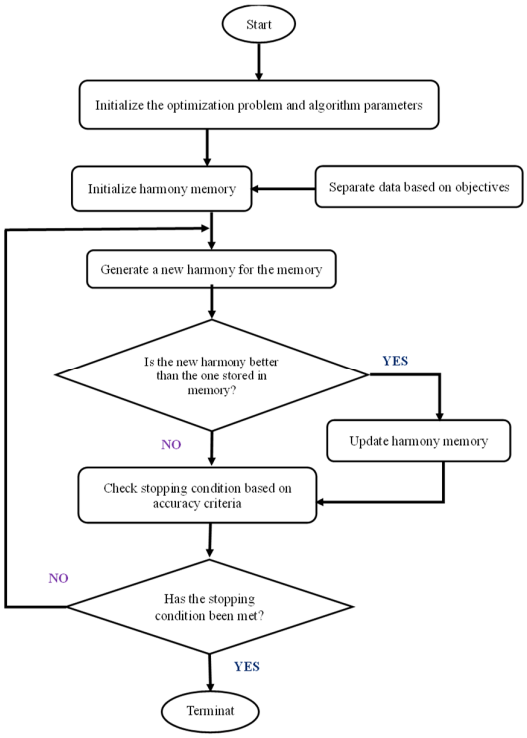


Figure 7. Flowchart of HS algorithm.

2.7. Proposed hybrid clustering algorithm (FCM-PSO)

The selection of the FCM-PSO hybrid model is motivated by its ability to combine the adaptive search capability of PSO with the fuzzy clustering flexibility of FCM. Unlike traditional hybrid models such as HS-K-means or PSO-K-means, which often rely on hard boundaries and are sensitive to initial centroids, the FCM-PSO framework effectively handles overlapping joint sets and converges more reliably in the presence of noise and joint variability. Furthermore, PSO's population-based optimization offers a faster and more stable convergence compared to evolutionary algorithms like HS, making it more suitable for geomechanical data with complex structures. The following steps outline the proposed FCM-PSO algorithm:

1. Initialization: Define the number of clusters, particle population, and algorithm parameters.

2. Data Preprocessing: Normalize the joint orientation dataset to ensure unbiased distance calculations.

3. FCM Execution: Apply FCM to obtain initial fuzzy membership values and cluster centers.

4. PSO Optimization: Initialize particles representing candidate cluster centers. Evaluate the fitness of each particle based on a clustering validity index.

5. Position and Velocity Update: Update particle velocities and positions based on personal and global best solutions.
6. Convergence Check: Iterate the PSO process until convergence criteria are met (e.g., maximum iterations or minimal change in fitness).
7. Final Clustering: Assign data points to clusters based on optimized fuzzy membership values.
8. Evaluation: Validate clustering results using indices such as Davies-Bouldin, Calinski-Harabasz, and Silhouette scores.

2.8. Cluster criteria evaluation

Evaluating the performance of clustering methods is essential to ensure the effectiveness, accuracy, and precision of the applied techniques. This study employs three well-established metrics for this purpose: Calinski–Harabasz Index (CHI), Davies-Bouldin Index (DBI), and the Silhouette Score. These indices provide comprehensive insights into the clustering structure, enabling a robust comparison of different methods. The Calinski–Harabasz Index (CHI) is a widely recognized metric that measures the compactness and separation of clusters. It assesses the ratio of between-cluster variance to within-cluster variance, providing an indication of how well clusters are separated from each other. It is formulated as follows [56]:

$$Calinski-Harabasz\ index = \frac{SS_B}{SS_W} \times \frac{(N-k)}{(k-1)} \quad (10)$$

where:

SS_B – between-cluster variance, representing the overall dispersion among different clusters,

SS_W – within-cluster variance, indicating the total variance within clusters,

k – number of clusters,

N – total number of data points.

The total between-cluster variance SS_B is defined as [57]:

$$SS_B = \sum_{i=1}^{k} n_i m_i - m^2 \quad (11)$$

where:

n_i – number of data points in the i^{th} cluster,

m_i – centroid of the i^{th} cluster,

m – overall mean of the data,

k – the number of clusters,

$|m_i - m|$ – euclidean distance between the cluster centroid and the overall mean.

The total within-cluster variance SS_W is calculated as follows:

$$SS_W = \sum_{i=1}^{k} \sum_{x \in c_i} x - m_i^2 \quad (12)$$

where:

x – A specific data point,

c_i – The i^{th} cluster,

m_i – centroid of the i^{th} cluster,

k – number of clusters,

$|x - m_i|$ – euclidean distance between a data point and the cluster centroid.

A desirable clustering solution is characterized by high between-cluster variance SS_B and low within-cluster variance SS_w. Consequently, a higher CHI value indicates more distinct and well-separated clusters, reflecting better clustering performance. The Davies-Bouldin Index (DBI) evaluates the ratio of intra-cluster distances to inter-cluster distances, providing a measure of cluster compactness and separation. It is defined as [58]:

$$DBI = \frac{1}{k} \sum_{i=1}^{k} max_{j \neq i} \{D_{i.j}\} \quad (13)$$

where:

k – number of clusters,

D_{ij} – similarity measure between the i^{th} and j^{th} clusters,

calculated as:

$$D_{i.j} = \frac{(\overline{d_i} + \overline{d_j})}{d_{ij}} \quad (14)$$

where:

$\overline{d_i}$ – Average distance between each point in cluster i and its centroid,

$\overline{d_j}$ – average distance between each point in cluster j and its centroid,

d_{ij} – euclidean distance between the centroids of clusters i and j.

A lower DBI value indicates better clustering performance, as it reflects lower intra-cluster distances and higher inter-cluster separations. The Silhouette Score measures the consistency within

clusters by assessing the similarity of each point to its own cluster compared to other clusters. It is calculated as [59]:

$$Silhouette\ index\ (S_i) = {(b_i - a_i)}/{\max(a_i . b_i)} \quad (15)$$

where:

S_i – Silhouette value for the i^{th} data point,

a_i – mean distance from the i^{th} data point to all other points within the same cluster,

b_i – minimum average distance from the i^{th} data point to points in the nearest neighboring cluster.

The Silhouette score ranges from -1 to +1: High positive values indicate that data points are well-matched to their own cluster and poorly matched to neighboring clusters, implying high cohesion and separation. Negative values suggest that data points are likely assigned to the wrong clusters. Higher Silhouette Scores demonstrate a more effective clustering with well-separated and cohesive clusters.

The three-evaluation metrics (CHI, DBI, and Silhouette) collectively provide a robust framework for assessing clustering quality. In this study, these indices are employed to compare the performance of various clustering algorithms and to determine the optimal clustering strategy. By utilizing a combination of these metrics, the study ensures a comprehensive and rigorous evaluation of the clustering results.

Despite their widespread use, each of the employed clustering validity indices has specific limitations. The Davies-Bouldin index can be overly sensitive to cluster overlap and may not perform well when clusters vary in density or size. The Calinski-Harabasz index, while computationally efficient, assumes convex clusters and may misrepresent performance in irregular-shaped distributions. The Silhouette coefficient, though more robust, relies on average distances which can be skewed by outliers or non-uniform data dispersion. Therefore, relying on multiple indices provides a more balanced and comprehensive assessment of clustering quality.

3. Results

3.1. Determining the optimal number of clusters

The first step involved classifying the dataset into clusters ranging from 2 to 7 groups. For each clustering solution, the elbow index was calculated, as illustrated in Figure 8. Based on the analysis presented in the previous section, it was determined that four clusters are the optimal choice for the Sungun copper mine dataset. The graph shows a sharp and noticeable change at the point corresponding to four clusters, forming a distinct elbow shape. Beyond this point, the graph levels off and becomes nearly parallel to the X-axis, indicating that increasing the number of clusters further does not significantly improve the clustering solution.

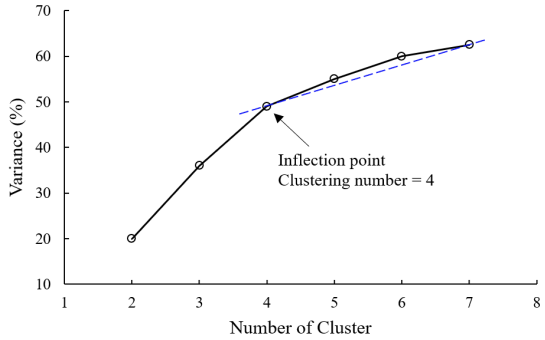


Figure 8. Data variance percentage versus the number of clusters

3.2. Preparation of clustering model based on FCM algorithm

The clustering process has unique characteristics, and its quality can be evaluated using various methods. Analyzing the spatial arrangement of the data enables an assessment of clustering quality and assignment accuracy by taking into account specific conditions and leveraging the data's geometric structure and location. However, visual quality assessment methods can sometimes be insufficient due to the large volume of data and its complex spatial distribution. To address this, several indicators and criteria are available to assess clustering quality. In this study, the values of three criteria were calculated to evaluate the efficacy and accuracy of each clustering method. Using the FCM method, the input data was clustered by determining the optimal number of clusters for the rock joint datasets. Figure 9 shows the classification of joints using FCM algorithms, effectively categorizing the rock joint data into four distinct groups. Table 2 presents the evaluation metrics for FCM-based data clustering. According to the table, the FCM method achieved the following values for the evaluation criteria: Davies-Bouldin Index: 0.88, Calinski–Harabasz Criterion: 346.05, Silhouette Score: 0.565. To further compare the results, it is recommended to utilize a hybrid fuzzy method combined with PSO and HS algorithms to evaluate the obtained cluster criteria more comprehensively.

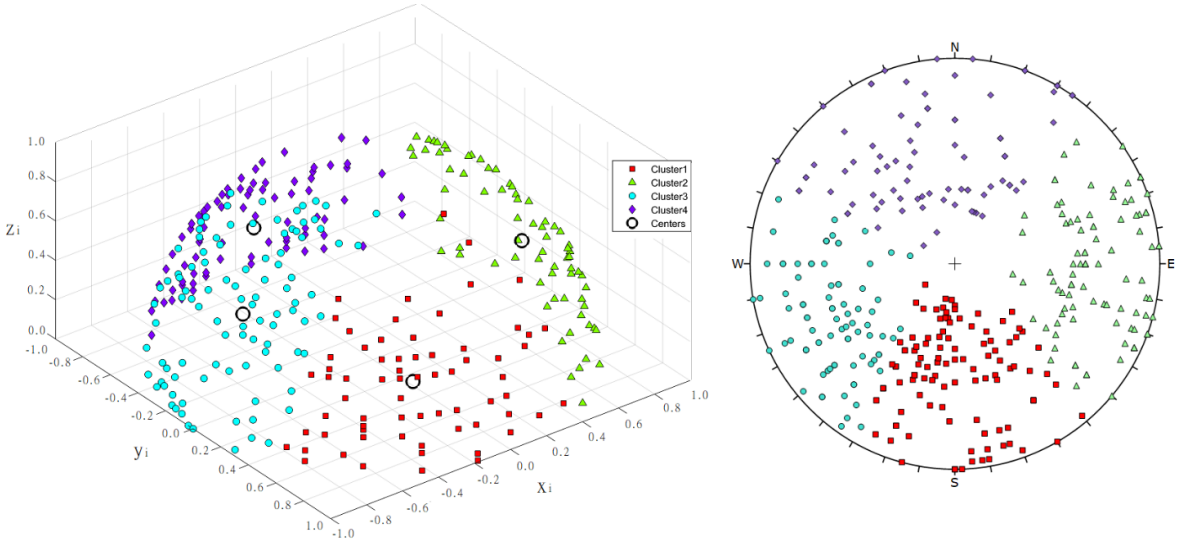


Figure 9. Stereographic plot of the clustering result fuzzy clustering method.

Table 2. Evaluation metric values for clustering using the fuzzy algorithm.

Method	Values of criteria of data		
	Silhouette	Davies-Bouldin	Calinski–Harabasz
Fuzzy algorithm (FCM)	0.565	0.82	346.05

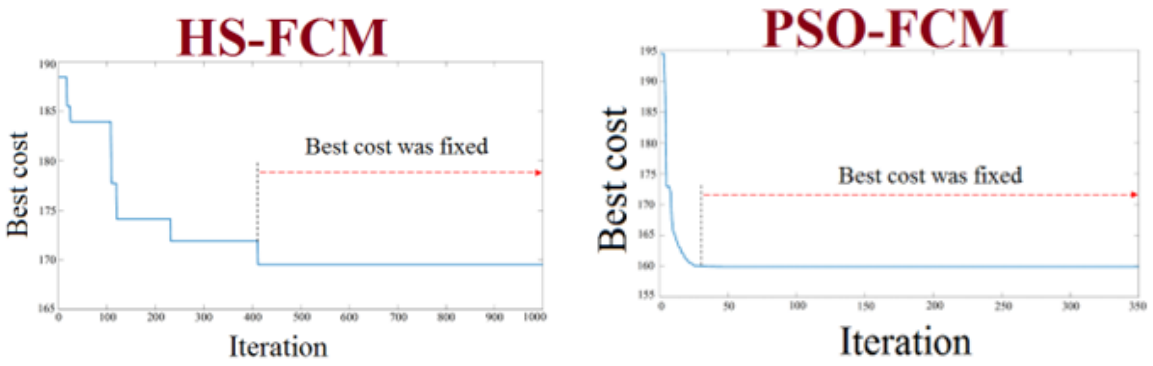
3.3. Optimizing fuzzy clustering using HS and PSO algorithms

This study explored the potential of combining the Harmony Search (HS) and Particle Swarm Optimization (PSO) algorithms with Fuzzy C-Means (FCM) algorithms. The objective was to develop an unsupervised clustering technique for rock joints using datasets collected from case studies. Consequently, it was crucial to determine the control parameters of these algorithms. The control parameters significantly influence the optimal results and convergence speed of the algorithms. However, in this context, specific equations and rules are often absent. Therefore, expert judgment and trial-and-error techniques are typically used, depending on the datasets. For the HS algorithm, the key control parameters are as follows: Harmony Memory Size (HMS), Maximum Number of Iterations (Maxit), Harmony Memory Consideration Rate (HMCR), and Pitch Adjustment Rate (PAR). For the PSO algorithm, the main control parameters are as follows: Inertia Weight (W), Swarm Size (PS), Inertia Weight Damping Rate (WDR), and Maximum Number of Iterations (Maxit). The maximum number of iterations was set to 1000. The Pitch Adjustment Rate (PAR) was set to 0.1, allowing a 10% probability for selecting neighboring values. Additionally, previous research indicates that the Harmony Memory Size (HMS) typically falls within the range of 40 to 100. In this study, a value of 50 was determined through trial and error. Table 3 summarizes the parameter values used in the HS and PSO algorithms.

Table 3. Parameter values for the HS and PSO algorithms.

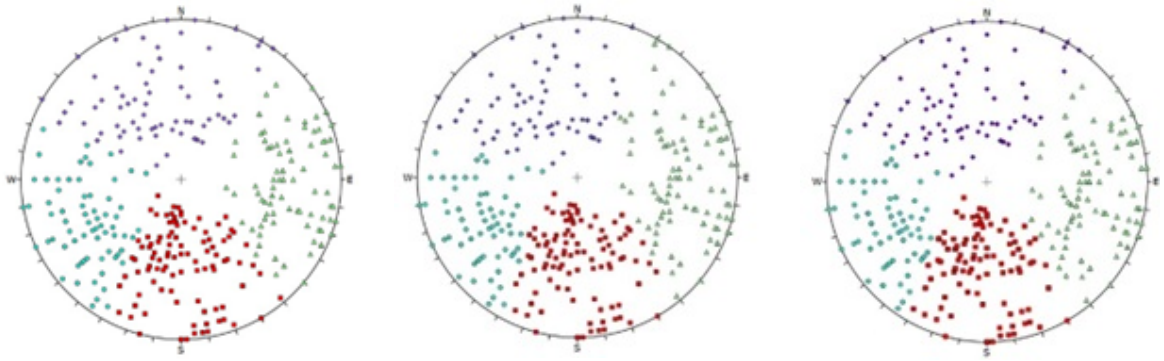
Metaheuristic algorithm	Hyperparameters	Values
HS	HMS	50
	Maxit	1000
	HMCR	0.2
	PAR	0.1
PSO	W	1
	PS	50
	WDR	0.99
	Maxit	350

Figure 10 illustrates the iteration-based optimization process, while Figure 11 presents the stereographic plot of the clustering results for all methods. As shown in Figure 10, the HS-FCM clustering process reached its optimal cost after 416 iterations, yielding a value of 169. In contrast, the PSO-FCM method achieved its optimal cost after 48 iterations, resulting in a value of 160. These figures clearly indicate that the PSO algorithm converges faster than the HS algorithm due to its lower cost. It's important to note that the optimal value is dimensionless. Additionally, the optimization process stabilizes when the difference between the outcomes of two consecutive iterations is smaller than the minimum acceptable precision. Figure 11 shows that all clustering techniques effectively classified the rock joint datasets from the case studies. Finally, Table 4 and Figure 12 present the clustering results based on the three evaluation criteria mentioned earlier.



(a) (b)

Figure 10. Best cost-per-iteration provided by algorithms. (a) HS-FCM (b) PSO-FCM.

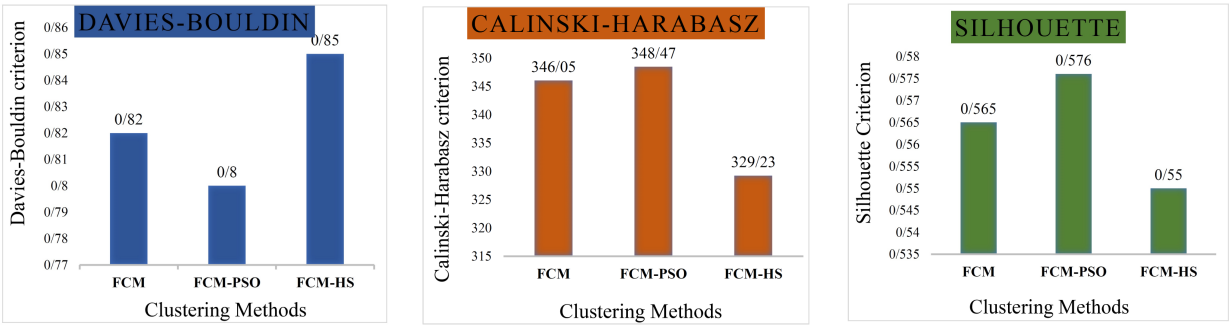


(a) (b) (c)

Figure 11. Comparison of the clustering methods (a) FCM method (b) FCM-HS method (c) FCM-PSO method.

Table 4. Evaluation metrics for different clustering methods.

Clustering method	Evaluation criteria		
	Silhouette	Calinski–Harabasz	Davies-Bouldin
FCM	0.565	346.05	0.82
FCM-PSO	0.576	348.47	0.80
FCM-HS	0.550	329.23	0.85



(a) (b) (c)

Figure 12. The results relate to the current research's evaluation criteria for clustering methods. (a) Davies-Bouldin criterion (b) Calinski–Harabasz criterion (c) Silhouette criterion.

4. Discussion

Based on the results presented in Table 4 and Figure 12, it is evident that the FCM-PSO method outperforms the other approaches in clustering joint set data. According to the Davies-Bouldin criterion, the FCM-PSO method, with the lowest value of 0.80, achieves the best performance among all methods. However, the FCM-HS method shows no improvement compared to the standard FCM. Specifically, the FCM method outperforms the FCM-HS method in this criterion, with a value of 0.82. The PSO algorithm enhances the efficiency of the FCM method compared to the HS algorithm, as the Davies-Bouldin index decreases from 0.85 to 0.80. Regarding the Calinski–Harabasz criterion, the FCM-PSO and FCM methods rank first and second, with values of 348.47 and 346.05, respectively. Conversely, the FCM-HS method performs worse than the FCM method based on this criterion. In analyzing the silhouette criterion, the FCM-PSO method demonstrates superior performance with a value of 0.576. In contrast, the FCM-HS method yields lower results compared to the other approaches, with a silhouette index value of 0.550. Consistency in clustering performance is crucial when evaluating data clustering methods. The FCM-PSO clustering method consistently demonstrates superior performance across all three evaluation criteria. It slightly outperforms the other two methods in accurately assigning joint sets to their nearest neighbors.

The practical implications of the proposed FCM-PSO clustering method are particularly significant for real-world mining operations. Accurate identification of joint sets plays a crucial role in assessing rock mass behavior, optimizing excavation strategies, and ensuring the stability of underground structures. The enhanced clustering performance enables geotechnical engineers to better characterize joint orientations, which directly impacts slope design, tunnel alignment, and safety risk mitigation. Moreover, the hybrid algorithm's ability to handle noisy and overlapping data improves the reliability of structural models in complex geological settings.

5. Conclusions

Rock joints significantly influence rock mass behavior in open-pit mining, necessitating precise classification. This study introduces a novel hybrid clustering method, integrating Particle Swarm Optimization (PSO) with Fuzzy C-Means (FCM) to enhance classification accuracy. Dip and dip direction data from 19 steps of the Sungun copper mine ramp were analyzed using FCM, with the elbow index confirming a four-class clustering approach. To optimize FCM, Harmony Search (HS) and PSO minimized clustering errors, assessed through Davies-Bouldin, Calinski–Harabasz, and silhouette indices. The FCM-PSO method outperformed others, achieving the lowest Davies-Bouldin index (0.80), highest Calinski–Harabasz score (348.47), and optimal silhouette value (0.57). Compared to traditional clustering methods' the PSO-optimized FCM approach effectively identifies noise and outliers, ensuring robust classification. Additionally, metaheuristic algorithms demonstrate superior convergence speed and are easily implemented using computational tools such as MATLAB and R. Given its strong performance, the FCM-PSO method presents a highly effective approach for rock joint classification, with future research focusing on broader comparative analyses and machine learning applications for enhanced clustering precision.

This study presented a novel hybrid clustering approach based on Fuzzy C-Means (FCM) and Particle Swarm Optimization (PSO) for the

classification of joint sets in rock mass structures. The key contributions of the work include (1) the integration of PSO to optimize cluster centers and enhance the convergence behavior of FCM, (2) the application of comprehensive validity indices to evaluate clustering quality, and (3) the demonstration of the method's effectiveness in real-world mining scenarios with complex, overlapping data.

The proposed FCM-PSO method outperformed traditional clustering algorithms in terms of compactness and separation, providing a more accurate representation of joint orientations. This advancement holds direct implications for geotechnical engineering, particularly in the planning and safety assessment of mining excavations.

Future research can explore the integration of deep learning-based feature extraction with the clustering framework to handle more complex geological datasets. Moreover, applying the hybrid method to 3D orientation data and comparing its performance with other metaheuristic optimization techniques, such as Genetic Algorithms or Grey Wolf Optimizer, could further validate its generalizability and robustness.

References

[1] Wu, N., Liang, Z., Zhang, Z., Li, S., & Lang, Y. (2022). Development and verification of three-dimensional equivalent discrete fracture network modelling based on the finite element method. *Engineering Geology*, *306*, 106759.

[2] Junaid, M., Abdullah, R. A., Abdelrahman, K., Ullah, A., Mahmood, S., Sa'ari, R., & Islam, A. (2024). Assigning resistivity values to rock quality designation indices using integrated unmanned aerial vehicle and 2D electrical resistivity tomography in granitic rock. *Geocarto International*, *39*(1), 2343019.

[3] Fattahi, H. (2017). Prediction of slope stability using adaptive neuro-fuzzy inference system based on clustering methods. *Journal of Mining and Environment*, *8*(2), 163-177.

[4] Schmidt, W. (1925). Gefugestatistik. *Tschermaks Mineral. Petrogr. Mitt.*, *38*, 342-423.

[5] Shanley, R. J., & Mahtab, M. A. (1976). Delineation and analysis of clusters in orientation data. *Journal of the International Association for Mathematical Geology*, *8*, 9-23.

[6] Mahtab, M. A., & Yegulalp, T. M. (1982, August). A rejection criterion for definition of clusters in orientation data. In *ARMA US Rock Mechanics/Geomechanics Symposium* (pp. ARMA-82). ARMA.

[7] Chen, J. P., Shi, B. F., & Wang, Q. (2005). Study on the dominant orientations of random fractures of fractured rock masses. *Yanshilixue Yu Gongcheng Xuebao/Chin. J. Rock Mech. Eng.*, *24*(2), 241-245.

[8] Klose, C. D., Seo, S., & Obermayer, K. (2005). A new clustering approach for partitioning directional data. *International Journal of Rock Mechanics and Mining Sciences*, *42*(2), 315-321.

[9] Zhan, J., Xu, P., Chen, J., Wang, Q., Zhang, W., & Han, X. (2017). Comprehensive characterization and clustering of orientation data: A case study from the Songta dam site, China. *Engineering Geology*, *225*, 3-18.

[10] Harrison, J. P. (1992). Fuzzy objective functions applied to the analysis of discontinuity orientation data. In *ISRM symposium: Eurock'92* (pp. 25-30).

[11] Hammah, R. E., & Curran, J. H. (1998). Fuzzy cluster algorithm for the automatic identification of joint sets. *International Journal of Rock Mechanics and Mining Sciences*, *35*(7), 889-905.

[12] Hammah, R. E., & Curran, J. H. (1999). On distance measures for the fuzzy K-means algorithm for joint data. *Rock Mechanics and Rock Engineering*, *32*(1), 1-27.

[13] Zhou, W., & Maerz, N. H. (2002). Implementation of multivariate clustering methods for characterizing discontinuities data from scanlines and oriented boreholes. *Computers & Geosciences*, *28*(7), 827-839.

[14] Jimenez-Rodriguez, R., & Sitar, N. (2006). A spectral method for clustering of rock discontinuity sets. *International Journal of Rock Mechanics and Mining Sciences*, *43*(7), 1052-1061.

[15] Jimenez, R. (2008). Fuzzy spectral clustering for identification of rock discontinuity sets. *Rock Mechanics and Rock Engineering*, *41*(6), 929.

[16] Yu, F. E. N. G., Fengshan, M. A., Chengcheng, G. O. N. G., Jie, G. U. O., Shanfei, W. A. N. G., & Zicheng, L. I. U. (2011). Data analysis method for optimized and dominant orientations of joints in rock mass. *Journal of Engineering Geology*, *19*(6), 887-892.

[17] Qin, S. W., Chen, J. J., Chen, J. P., Han, X., Zhang, W., & Liu, X. (2016). Fuzzy C-means cluster analysis based on rough set for grouping of discontinuities. *J. Cent. South Univ.(Sci. Technol.)*, *9*, 3125-3130.

[18] Wang, S., Dong, F., Zhang, Z., Yang, B., & Hou, Q. (2023). Multi-index dominant grouping of rock mass discontinuities based on the combined weighting method: A case study for the Huayang tunnel. *Tunnelling and Underground Space Technology*, *139*, 105211.

[19] Cui, X., & Yan, E. C. (2020). Fuzzy C-means cluster analysis based on variable length string genetic algorithm for the grouping of rock discontinuity sets. *KSCE Journal of Civil Engineering*, *24*(11), 3237-3246.

[20] Li, Y., Wang, Q., Chen, J., Xu, L., & Song, S. (2015). K-means algorithm based on particle swarm optimization for the identification of rock discontinuity

sets. *Rock Mechanics and Rock Engineering*, *48*, 375-385.

[21] Ma, G. W., Xu, Z. H., Zhang, W., & Li, S. C. (2015). An enriched K-means clustering method for grouping fractures with meliorated initial centers. *Arabian Journal of Geosciences*, *8*, 1881-1893.

[22] Song, S., Wang, Q., Chen, J., Li, Y., Zhang, W., & Ruan, Y. (2017). Fuzzy C-means clustering analysis based on quantum particle swarm optimization algorithm for the grouping of rock discontinuity sets. *KSCE Journal of Civil Engineering*, *21*, 1115-1122.

[23] Pu, C., Zhan, J., Zhang, W., & Peng, J. (2024). Characterization and clustering of rock discontinuity sets: A review. *Journal of Rock Mechanics and Geotechnical Engineering*, *17*(2), 1240–1262.

[24] Xu, L. M., Chen, J. P., Wang, Q., & Zhou, F. J. (2013). Fuzzy C-means cluster analysis based on mutative scale chaos optimization algorithm for the grouping of discontinuity sets. *Rock Mechanics and Rock Engineering*, *46*, 189-198.

[25] Ding, Q., Huang, R., Wang, F., Chen, J., Wang, M., & Zhang, X. (2018). Multi-Parameter Dominant Grouping of Discontinuities in Rock Mass Using Improved ISODATA Algorithm. *Mathematical Problems in Engineering*, *2018*(1), 5619404.

[26] Shirazy, A., Hezarkhani, A., Shirazi, A., Khakmardan, S., & Rooki, R. (2022). K-means clustering and general regression neural network methods for copper mineralization probability in Chahar-Farsakh, Iran. *Türkiye Jeoloji Bülteni*, *65*(1), 79-92.

[27] Mikaeil, R., Haghshenas, S. S., Haghshenas, S. S., & Ataei, M. (2018). Performance prediction of circular saw machine using imperialist competitive algorithm and fuzzy clustering technique. *Neural Computing and Applications*, *29*, 283-292.

[28] Song, T., Chen, J., Zhang, W., Xiang, L. J., & Yang, J. H. (2015). A method for multivariate parameter dominant partitioning of discontinuities of rock mass based on artificial bee colony algorithm. *Rock and Soil Mechanics*, *36*, 861–868.

[29] Xu, L. M., Chen, J. P., Wang, Q., & Zhou, F. J. (2013). Fuzzy C-means cluster analysis based on mutative scale chaos optimization algorithm for the grouping of discontinuity sets. *Rock Mechanics and Rock Engineering*, *46*, 189-198.

[30] Zarean, A., & Poormirzaee, R. (2016). Joint inversion of ReMi dispersion curves and refraction travel times using particle swarm optimization algorithm. *Journal of Mining and Environment*, *7*(1), 67–79.

[31] Mousavi, S. S., Nikkhah, M., & Zare, S. (2019). A comparative study of two meta-heuristic algorithms in optimizing cost of reinforced concrete segmental lining. *Journal of Mining and Environment*, *10*(1), 95-112.

[32] Sharifi, F., Arab Amiri, A. R., & Kamkar Rouhani, A. (2019). Using a combination of genetic algorithm and particle swarm optimization algorithm for GEMTIP modeling of spectral-induced polarization data. *Journal of Mining and Environment*, *10*(2), 493-505.

[33] Rezaei, M., & Asadizadeh, M. (2020). Predicting unconfined compressive strength of intact rock using new hybrid intelligent models. *Journal of Mining and Environment*, *11*(1), 231-246.

[34] Esmaeilzadeh, A., & Shahriar, K. (2019). Optimized fuzzy cmeans–fuzzy covariance–fuzzy maximum likelihood estimation clustering method based on deferential evolutionary optimization algorithm for identification of rock mass discontinuities sets. *Periodica Polytechnica Civil Engineering*, *63*(2), 674-686.

[35] Saeidi, O., Torabi, S. R., & Ataei, M. (2014). Prediction of the rock mass diggability index by using fuzzy clustering-based, ANN and multiple regression methods. *Rock Mechanics and Rock Engineering*, *47*, 717-732.

[36] Lotfi Godarzi, J., Sayadi, A. R., Mousavi, A., & Nehring, M. (2025). Simultaneous Optimization of Mine Production Rate and Cut-off Grade using Particle Swarm Optimization. *Journal of Mining and Environment*, *16*(2), 583-598.

[37] Nikakhtar, L., Zare, S., & Mirzaei, H. (2023). Performance comparison of particle swarm optimization and genetic algorithm for back-analysis of soil layer geotechnical parameters. *Journal of Mining and Environment*, *14*(1), 217-232.

[38] Hu, Y., Wang, X., & Zhong, Z. (2022). Investigations on the jointed influences of saturation and roughness on the shear properties of artificial rock joints. *Geomechanics and Geophysics for Geo-Energy and Geo-Resources*, *8*(4), 115.

[39] Nabavi, Z., Mirzehi, M., Dehghani, H., & Ashtari, P. (2023). A hybrid model for back-break prediction using XGBoost machine learning and metaheuristic algorithms in Chadormalu iron mine. *Journal of Mining and Environment*, *14*(2), 689-712.

[40] Ruan, Y., Chen, J., Fan, Z., Wang, T., Mu, J., Huo, R., ... & Sun, Y. (2023). Application of K-PSO clustering algorithm and game theory in rock mass quality evaluation of Maji Hydropower Station. *Applied Sciences*, *13*(14), 8467.

[41] Ruan, Y., Liu, W., Wang, T., Chen, J., Zhou, X., & Sun, Y. (2023). Dominant Partitioning of Discontinuities of rock masses based on DBSCAN algorithm. *Applied Sciences*, *13*(15), 8917.

[42] Wang, R., Ni, Y., Zhang, L., & Gao, B. (2025). Grouped machine learning methods for predicting rock mass parameters in a tunnel boring machine-driven tunnel based on fuzzy C-means clustering. *Deep Underground Science and Engineering*, *4*(1), 55-71.

[43] Yong, R., Wang, H., Ye, J., Du, S., & Luo, Z. (2024). Neutrosophic genetic algorithm and its application in clustering analysis of rock discontinuity sets. *Expert Systems with Applications*, *245*, 122973.

[44] Lu, G., Cao, B., Zhu, X., Lin, Z., Bai, D., Tao, C., & Li, Y. (2024). Identification of rock mass discontinuity from 3D point clouds using improved fuzzy C-means and convolutional neural network. *Bulletin of Engineering Geology and the Environment*, *83*(5), 159.

[45] Aggarwal, V., Gupta, V., Singh, P., Sharma, K., & Sharma, N. (2019, April). Detection of spatial outlier by using improved Z-score test. In *2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI)* (pp. 788-790). IEEE.

[46] Wong, L. N. Y., & Liu, G. (2010, June). An improved K-means clustering method for the automatic grouping of discontinuity sets. In *ARMA US Rock Mechanics/Geomechanics Symposium* (pp. ARMA-10). ARMA.

[47] Ketchen, D. J., & Shook, C. L. (1996). The application of cluster analysis in strategic management research: an analysis and critique. *Strategic Management Journal*, *17*(6), 441-458.

[48] Adolfsson, A., Ackerman, M., & Brownstein, N. C. (2016). To cluster, or not to cluster: How to answer the estion. *TKDD*, *17*, 1-9.

[49] Bezdek, J. C., Ehrlich, R., & Full, W. (1984). FCM: The fuzzy c-means clustering algorithm. *Computers & Geosciences*, *10*(2-3), 191-203.

[50] Kennedy, J., & Eberhart, R. (1995, November). Particle swarm optimization. In *Proceedings of ICNN'95-international conference on neural networks* (Vol. 4, pp. 1942-1948). ieee.

[51] Fathi, M., Alimoradi, A., & Hemati Ahooi, H. R. (2021). Optimizing extreme learning machine algorithm using particle swarm optimization to estimate iron ore grade. *Journal of Mining and Environment*, *12*(2), 397-411.

[52] Kennedy, J. (1998, March). The behavior of particles. In *International conference on evolutionary programming* (pp. 579-589). Berlin, Heidelberg: Springer Berlin Heidelberg.

[53] Geem, Z. W., Kim, J. H., & Loganathan, G. V. (2001). A new heuristic optimization algorithm: harmony search. *Simulation*, *76*(2), 60-68.

[54] Wang, X., Gao, X. Z., & Zenger, K. (2015). *An introduction to harmony search optimization method*. New York: Springer International Publishing.

[55] Haghshenas, S. S., Haghshenas, S. S., Geem, Z. W., Kim, T. H., Mikaeil, R., Pugliese, L., & Troncone, A. (2021). Application of harmony search algorithm to slope stability analysis. *Land*, *10*(11), 1250.

[56] Caliński, T., & Harabasz, J. (1974). A dendrite method for cluster analysis. *Communications in Statistics-theory and Methods*, *3*(1), 1-27.

[57] Davies, D. L., & Bouldin, D. W. (1979). A cluster separation measure. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 2, 224-227.

[58] Rousseeuw, P. J. (1987). Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. *Journal of Computational and Applied Mathematics*, *20*, 53-65.

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شناسایی دسته درزه‌ها با استفاده از خوشه‌بندی فازی بهینه‌شده توسط الگوریتم ازدحام ذرات (مطالعه موردی: معدن مس سونگون)

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کلمات کلیدی

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چکیده

شناسایی دسته درزه‌ها نقش مهمی در زمین‌شناسی مهندسی به‌ویژه در رده‌بندی توده‌سنگ و تحلیل پایداری شیب‌ها در معادن دارد. خوشه‌بندی دقیق این دسته‌ها براساس شیب و امتداد شیب، درک بهتری از رفتار توده‌سنگ فراهم کرده و موجب بهبود ایمنی دیواره‌های معدنی می‌شود. در این پژوهش، رویکرد خوشه‌بندی جدیدی با ترکیب الگوریتم‌های جستجوی هارمونی (HS) و بهینه‌سازی ازدحام ذرات (PSO) برای طبقه‌بندی دسته درزه‌ها در معدن مس سونگون ارائه شده است. ابتدا ویژگی‌های درزه‌ها با استفاده از روش خوشه‌بندی فازی (FCM) گروه‌بندی شدند و با بهره‌گیری از روش آرنج، چهار خوشه تعیین شد. سپس برای بهینه‌سازی خوشه‌بندی، روش FCM با الگوریتم‌های HS و PSO ترکیب شد. عملکرد روش‌ها با شاخص‌های دیویس-بولدین، کالینسکی–هاراباز و سیلوئت ارزیابی شد. نتایج نشان داد روش ترکیبی FCM-PSO با امتیازهای ۰/۸۰ ، ۳۴۷/۴۸ و ۰/۵۷، عملکرد بهتری نسبت به سایر روش‌ها داشته و خوشه‌بندی دقیق‌تری ارائه داده است. در مقابل، روش FCM-HS عملکرد ضعیف‌تری نسبت به FCM داشت. با در نظر گرفتن این نتایج مشخص می‌شود که روش ترکیبی FCM-PSO توانایی بالایی در طبقه‌بندی دسته درزه‌ها دارد و می‌تواند دیدگاه‌های معتبری درباره رفتار توده‌سنگ در معدن مس سونگون ارائه دهد. استفاده از این روش می‌تواند تحلیل‌های زمین‌شناسی را بهبود بخشیده و موجب افزایش ایمنی و کارایی در عملیات‌های معدنی شود.

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