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Application of K-PSO Clustering Algorithm and Game Theory in Rock Mass Quality Evaluation of Maji Hydropower Station

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Abstract: In this study, the K-means algorithm based on particle swarm optimization (K-PSO) and game theory are introduced to establish the quality evaluation model of a rock mass. Five evaluation factors were considered, i.e., uniaxial saturated compressive strength of rock, discontinuity spacing, acoustic velocity, rock quality designation (RQD), and integrity coefficient. The rock mass of an elevation adit at the abutment of Maji hydropower station was taken as a case study. The subjective weight of the evaluation factor was determined by the weighted least squares method, and the objective weight of the evaluation factor was determined by the entropy method. The combined weights of each influencing factor were determined by game theory to be 0.142, 0.179, 0.035, 0.116, and 0.108. The rock mass quality evaluation in the study area was analyzed by K-PSO algorithm. The results indicate that the K-PSO clustering results are almost the same as the evaluation results of the traditional basic quality (BQ) classification method and the widely used extension evaluation method and are consistent with the preliminary judgment of the expert field. The results are consistent with the field observation law. It is considered that the K-PSO clustering theory can reflect the engineering geological characteristics of the rock mass of the hydropower project in the rock mass quality evaluation.

Keywords: K-PSO; rock mass quality classification; entropy method; the weighted least-square method; clustering model

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1. Introduction

With the development of hydropower energy, the rock mass problems encountered when constructing hydropower stations have become increasingly complex. By evaluating rock mass quality, rock mass engineering can be reasonably designed based on the project quality. In evaluating the geological engineering conditions and obtaining the engineering characteristics of rock mass, the evaluation and classification of rock mass quality are critical. The quality of dam abutment rock mass is related to the safety, stability, and economic benefits of hydropower projects. Thus, it is necessary to reasonably evaluate the quality of rock.

The results of the study on the quality of engineering rock mass, from the rock mass rating (RMR) method and tunneling quality index (Q) classification, have been presented in previous studies (Barton N, 1974; Bieniawski Z T, 1973,1989) [1–3]. Rehman reviewed the rock mass rating and tunnel construction quality index system of tunnel design, including

development, improvement, application and limitations [4]. Hafeezur Rehman discussed the application of Q classification and RMR classification in tunnel rock mass [5,6]. To date, many researchers have carried out significant research work. At the same time, the national ministries and commissions have also proposed classification methods for evaluating rock mass quality according to specific conditions. These classification methods achieved good results in practical engineering applications. In most previous studies, qualitative or quantitative methods have been used to evaluate rock mass quality. The main considerations were rock strength, the development of structural planes, the geological environment in which the rock mass occurs, and certain other factors. Many methods are combined with these factors, such as the sum-difference method, cumulative quotient method or their combination. However, these methods have many shortcomings, which need to be further developed and improved.

Many system theories have been introduced for rock mass quality evaluation. Extension theory is a widely used nonlinear method [7–10]. In addition, there unascertained measure theory [11], rough set and artificial neural network [12], reduction concept lattice, and fuzzy optimization are used [13]. The existing research methods only consider the influence of one of the factors at a time. Also, the geological conditions of the rock mass are very complex. Therefore, using previous research methods is not appropriate when considering the influence of only one factor alone. Moreover, the study of the rock mass quality problem [14,15] is a very complex contradictory problem, and the results of different index evaluations may differ greatly.

Data mining plays an important role in the computer field. It automatically searches the process of special relational information hidden in a large number of data and obtains the best information. Clustering analysis is an effective data mining algorithm. The K-PSO clustering algorithm is an optimized K-means algorithm based on the particle swarm optimization (PSO) algorithm [16–19], which has the characteristics of stable convergence and high computational efficiency.

The PSO algorithm is a new optimization technology, whose idea comes from artificial life and evolutionary computation theory. PSO completes the optimization by following the optimal solution found by the particle and the optimal solution of the whole group. The algorithm is simple and easy to implement, with few adjustable parameters, and has been widely studied and applied. In this paper, the K-means algorithm of particle swarm optimization (KPSO) is used to evaluate and analyze the rock mass quality classification in the study area. Compared with the traditional classification method, the new method is not sensitive to the initial clustering center, and overcomes the shortcomings of the difficulty in selecting the initial clustering center. In addition, the PSO algorithm is a global optimization method.

The engineering rock mass classification method provides a simple and rapid way to understand the quality of rock mass. From its development process, it can be seen that people's understanding of rock mass quality is constantly deepening and expanding. This is not only the direction of geotechnical workers' efforts, but also the inevitable trend of engineering rock mass classification to further understand the potential failure mechanism of the existing evaluation systems, and establish and improve the evaluation criteria of each evaluation system and the internal relationship between them, to seek a unified rock mass quality evaluation method. Secondly, in addition to the traditional RMR, Q classification and BQ classification, in recent years, various mathematical methods, such as fuzzy theory, data mining and extension theory, have been used to study more and more rock mass quality evaluation methods. The K-PSO clustering algorithm is a typical data mining method.

This kind of method quantitatively solves the inconvenience caused by some 'uncertain factors' in the classification system so that the rock mass classification results are more reasonable and operational than the traditional classification. Research in this area needs to further improve the rock mass classification system, which is also an important development direction of the rock mass classification method.

The K-PSO clustering algorithm plays an important role in the field of data mining. However, there is little research on rock mass quality evaluation using the K-PSO clustering algorithm. Since rock mass is an intrinsically complex body, the rationality of the selected impact indicators in evaluating rock mass quality and the fuzziness and randomness of each indicator often need to be fully valued. According to the characteristics of the study area, the evaluation index of rock mass quality was determined, and the weight of the influence index of rock mass quality was determined using game theory. Further, considering the fuzziness and randomness in the evaluation process, the K-PSO clustering model of each evaluation factor was obtained according to each evaluation index. The K-PSO clustering algorithm was also used to explore the uncertainty problem of rock mass quality evaluation from a new perspective.

2. Methods

2.1. K-Means Algorithm

The main idea of the K-means algorithm is to divide the data set into different categories through the iterative process, so that the criterion function for evaluating the clustering performance is optimized and each generated cluster is compact and independent. It was first proposed by Bezdek in his doctoral dissertation. The steps are as follows [20,21].

For a rock mass of tunnel section data set $X = \{X_1, X_2, \text{or } X_n\}$, it can be divided into c classes, expressed as $C = (C_1, C_2, \ldots, C_c)$, and the division matrix $U(X)$ is obtained, expressed as $U(X) = [u_{ij}]_{c\times n}$ ($I = 1, \ldots, c$, $j = 1, \ldots, n$), where u_{ij} is the membership degree of the sample x_j to the C_i class. The division result needs to meet the following conditions:

$$\begin{cases} U_{i=1}^{c} C_i = X \\ C_i \cap C_j = \varnothing, i, j = 1, \cdots, c; i \neq j \\ C_i \neq \varnothing \qquad i = 1, \cdots, c \end{cases} \tag{1}$$

Using this method to divide the number of rock mass quality classification can be achieved by the following steps:

1. Initialize the basic parameters of Fuzzy C-means clustering algorithm to determine the number of cluster centers c ($2 \leq c \leq n$).
2. Calculate the membership u_{ij} and the initial clustering center y_i of each cluster according to the results of the initial division.

$$u_{ij} = 1 / \sum_{l=1}^{c} \left[d(x_j, y_i) / d(x_j, y_l) \right]^{\frac{1}{m-1}} \tag{2}$$

$$y_i = \sum_{j=1}^{n} (u_{ij})^m x_j / \sum_{j=1}^{n} (u_{ij})^m \tag{3}$$

where u_{ij} is the membership degree of the jth rock mass belonging to the ith subset C_i, m is the fuzzy weighted index, and the general value is 2; $d(x_j,y_i)$ represents the distance from the jth rock mass to the cluster center of the ith subset.

3. Compute the distance from each discontinuity to each cluster center, and then reclassify this according to the new distance. That is, each discontinuity is divided with the nearest group.
4. Solve and update the membership u_{ij} and clustering center y_i using Equations (2) and (3).
5. Solve the objective function by:

$$J(U, Y) = \sum_{i=1}^{c} \sum_{j=1}^{n} (u_{ij})^m d(x_j, y_i) \tag{4}$$

6. Repeat Steps (3), (4), and (5) to minimize the objective function.

7. When it cannot be reassigned to different clusters, the iteration process ends.

2.2. PSO Method

Particle swarm optimization (PSO) is an evolutionary computation technique, which was proposed by Dr. Eberhart and Dr. Kennedy in 1995 [16]. It derives from the study of bird predation behavior. The algorithm was originally inspired by the regularity of bird swarm activities, then a simplified model was established using swarm intelligence. Based on the observation of the activity behavior of animal clusters, the particle swarm optimization algorithm uses the sharing of information by individuals in the group to make the movement of the whole group evolve process from disorder to order in the problem-solving space, so as to obtain the optimal solution.

In PSO, we call the population formed by all particles a group. Each particle in the population can be regarded as the potential solution to a problem. The position and velocity of particle i in D-dimensional space are expressed as $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$ and $V_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$, respectively. The particles are constantly flying in the search space, and the speed is modified with their own flight experience and the experience of their peers. The particles continuously search according to the modified position; the change in position is realized by the change in velocity. The change in particle velocity and position is calculated by Equations (5) and (6) [19,22].

$$v_{id} = wv_{id} + \mu_1 r_1(p_{id} - x_{id}) + \mu_2 r_2(p_{gd} - x_{id}) \tag{5}$$

$$x_{id} = x_{id} + v_{id} \tag{6}$$

where d is the search direction ($d = 1, 2, \ldots, D$), w is the inertia weight ranging from 0.4 to 0.9, μ_1 and μ_2 are positive constants for learning ($\mu_1 = \mu_2 = 2$), and r_1 and r_2 are two random numbers in the range [0, 1] [23]. The parameter w reflects the influence of the previous velocity of the particle on the current velocity. When the w value reaches the maximum, the PSO algorithm plays a leading role in the global optimization ability, and the smaller inertia weight will be beneficial to the local search ability.

2.3. K-PSO Method

The particle swarm optimization K-means algorithm (KPSO) improves the global search ability of the K-means algorithm and can effectively solve the problem whereby the local convergence of the algorithm and the classification results are affected by the initial clustering center [23]. In the K-PSO algorithm, the particles need to be encoded. In this paper, the coding method based on clustering center is adopted: the position of each particle is composed of the centers of K rock mass quality classification groups; each particle has a certain velocity V to adjust its position; in addition, each particle also has a fitness to evaluate the adaptability of the current position of the particle (i.e., the validity of the clustering results). In the process of rock mass quality classification, the fitness of particles is calculated by Equation (4). In this way, each particle represents a possible classification result, and the fitness of the particle is used to evaluate the classification result. Since the rock mass of different sections is divided into K groups, the position and velocity of the particles are $3 \times K$ dimensional variables. Each particle is encoded using the structure shown in the following Figure 1.

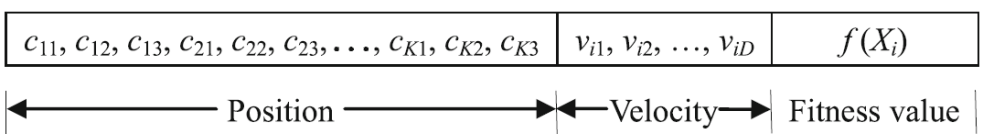

Figure 1. Particle coding.

where $cj = (cj_1, cj_2, cj_3)$ represents the center of the jth cluster ($1 \leq j \leq K$) and $D = 3 \times K$. The flow chart of the K-PSO algorithm is shown in Figure 2. The specific operation process is described as follows [24–26].

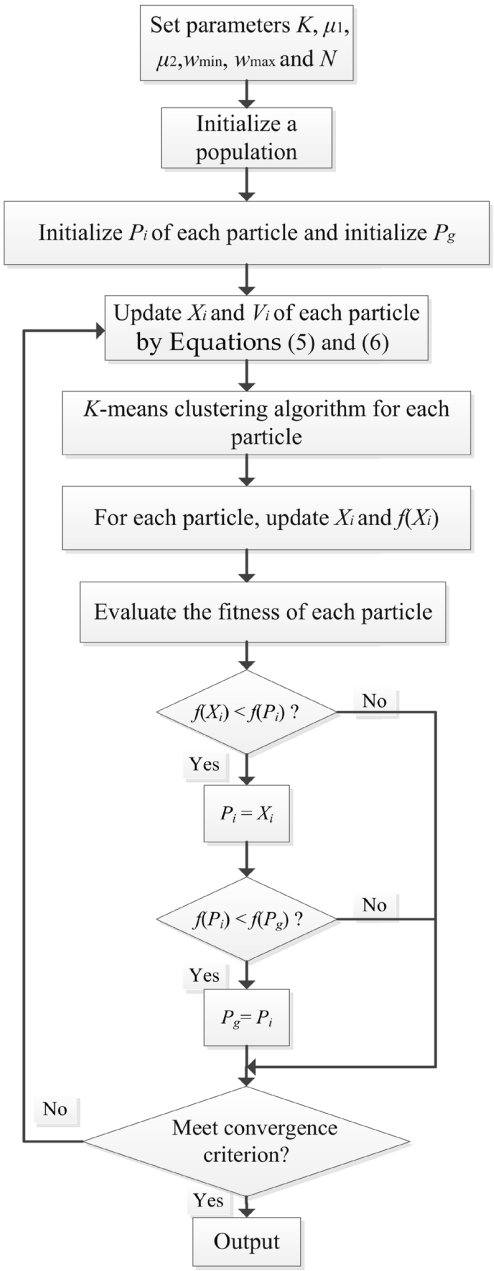

Figure 2. Flow chart of K-PSO method (adapted with permission from Ref. [23] Li, Y.Y. 2015).

Step 1: The number of groups K is determined, which is the initial value of the parameter setting, including learning factor (μ_1, μ_2), inertia weight ($w_{\min}$, $w_{\max}$), and the total number of particles N in the particle swarm.

Step 2: Population initialization. For example, the initialization of particle i (i = 1, 2, …, N) in the population can be achieved by the following steps: (a) The rock mass of different sections is divided into K groups, and the clustering center of each group is calculated by eigenvalue analysis method; (b) according to the calculated clustering center of K group rock mass, the particle position is coded as $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$, and the velocity of randomly initialized particles is $V_i = (v_{i1}, v_{i2}, \ldots, v_{iD})$; (c) according to the classification results, the fitness $f(X_i)$ of the particles is calculated according

to Equation (4). Repeating the above steps N times, a particle swarm containing N particles can be generated:

$$POP = \begin{bmatrix} x_{11}, x_{12}, \cdots, x_{1D}, v_{11}, v_{12}, \cdots, v_{1D}, f(X_1) \\ x_{21}, x_{22}, \cdots, x_{2D}, v_{21}, v_{22}, \cdots, v_{2D}, f(X_2) \\ \cdots \\ x_{N1}, x_{N2}, \cdots, x_{ND}, v_{N1}, v_{N2}, \cdots, v_{ND}, f(X_N) \end{bmatrix} \quad (7)$$

where (x_{i1}, x_{i2}, …, x_{iD}) = (c_{11}, c_{12}, c_{13}, c_{21}, c_{22}, c_{23},…, c_{K1},c_{K2}, c_{K3}) and $D = 3 \times K$.

Step 3: Initialize the individual optimal position P_i of each particle and the optimal position P_g of the population. For each particle i, let $P_i = X_i$; comparing the fitness of each particle, the position of the particle with the smallest fitness value is assigned to P_g.

Step 4: The position and velocity of particles are updated by Equations (5) and (6).

Step 5: For each particle i, conduct the following operation:

(a) Calculate the distance from the rock mass of different tunnel sections to the K latest clustering centers, and divide the rock mass of the tunnel section into the nearest group;

(b) Update the clustering center according to the grouping results;

(c) Calculate the fitness value.

Step 6: According to the classification results in Step (5), the position and fitness value of the particles are updated.

Step 7: For each particle i, compare the fitness value of its current position X_i with that of its previous personal best position P_i. If $f(X_i)/f(P_i)$, then assign X_i to P_i (let $P_i = X_i$).

For each particle i, the fitness value of its current position X_i is compared with the fitness value of the particle's historical optimal position P_i. If $f(X_i) < f(P_i)$, let $P_i = X_i$.

Step 8: For each particle i, the fitness value of its individual optimal position P_i is compared with the fitness value of the optimal position P_g of the particle swarm. If $f(P_i) < f(P_g)$, then $P_g = P_i$.

Step 9: Check the convergence criterion, which is a maximum number of iterations. If converged, output the clustering results; otherwise, loop to Step 4.

If the termination condition is satisfied, the program stops running; otherwise, return Step (4) to continue running. It should be noted that when running Step (5), empty groups are sometimes generated. If there is an empty class, randomly select a rock mass from other non-empty groups as the cluster center of the empty group. The flow chart of K-PSO algorithm is shown in Figure 2.

2.4. Determining the Weight of the Impact Factor

(1) Weight-based least squares method to determine the objective weight

In 1979, A.T.W. CHU proposed the theory of the weighted least squares method [27], which is a new ranking method in the analytic hierarchy process. The traditional analytic hierarchy process greatly interferes with human factors and lacks the necessary theoretical basis. The weighted least square method can solve this problem. It calculates the minimum solution ω_θ of the judgment matrix function relationship under the limited constraints and solves the ranking weight vector. The detailed method is described as follows.

(a) Construction of judgment matrix A

Judgment matrix A is constructed considering the influence of multiple parameters on rock mass quality evaluations.

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{21} & \cdots & a_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ a_{n1} & a_{n1} & \cdots & a_{nn} \end{bmatrix} \quad (8)$$

Each element in the judgment matrix A is assigned a value, referring to the assignment table in Table 1.

Table 1. Quantitative assignment table of index importance.

The Value of a_{ij}	**Description of the Importance of Indicator *i* Relative to Indicator *j***
1	equal importance
3	a little important
5	obviously important
7	strongly important
9	top importance
2, 4, 6, 8	the intermediate values of 1–3, 3–5, 5–7, 7–9 are denoted by 2, 4, 6, 8, respectively
reciprocal	If the importance of index i relative to index j is a_{ij}. The importance of indicator j relative to indicator i is $a_{ji} = 1/a_{ij}$

(b) Solving Function Minimization ω_θ.

The function relation is $J = \sum_{i=1}^{n} \sum_{j=1}^{n} \left(\omega_i - a_{ij}\omega_j\right)^2$. The constraint condition is $\sum_{i=1}^{n} \omega_i = 1$, minimization $\omega_\theta = (\omega_1, \omega_2, \ldots, \omega_n,)^T$. According to Wang Zhiren's [28] solution of the above relation, the formula of ω_θ is given in Equation (9).

$$\omega_\theta = \frac{C^{-1}e}{e^T C^{-1} e} \tag{9}$$

where C and e are

$$C = \begin{bmatrix} \sum_{i=1}^{n} a_{i1}^2 + n - 2 & -(a_{12} + a_{21}) & \cdots & -(a_{1n} + a_{n1}) \\ -(a_{21} + a_{12}) & \sum_{i=1}^{n} a_{i2}^2 + n - 2 & \cdots & -(a_{2n} + a_{n2}) \\ \cdots & \cdots & \cdots & \cdots \\ -(a_{n1} + a_{n1}) & -(a_{n2} + a_{2n}) & \cdots & \sum_{i=1}^{n} a_{in}^2 + n - 2 \end{bmatrix} \tag{10}$$

$$e = (1, 1, \ldots, 1)^T \tag{11}$$

(2) Information entropy determines the objective weight of the evaluation index.

As a means of objective weighting, the information entropy is used to determine the weight of influencing factors. Its evaluation process relies entirely on the laws of objective data, making the weight absolutely objective, and thus avoiding the interference of human factors to a large extent. The specific operation steps are given as follows.

There are m evaluation objects and n evaluation indexes in the system to be evaluated, then the entropy value H_i [29,30] of the ith evaluation index is given in Equation (12).

$$H_i = -k \sum_{j=1}^{m} P_{ij} \ln P_{ij} \tag{12}$$

where $H_i > 0$; $P_{ij} = u_{ij} / \sum_{j=1}^{n} u_{ij}$; $k = 1/\ln m$; when $\mu_{ij} = 0$, $\mu_{ij} \ln \mu_{ij} = 0$, $(i = 1, 2, \ldots, n)$.

$$\theta_i = \frac{d_i}{\sum_{i=1}^{n} d_i} = \frac{1 - H_i}{n - \sum_{i=1}^{n} H_i} \tag{13}$$

where $d_i = 1 - H_i$.

(3) Combined weighting determined by game theory

For a weight vector $\delta_i = \{\delta_1, \delta_2, \ldots \delta_n\}$, the linear combination is

$$\delta = \sum_{k=1}^{n} \alpha_k \delta_k^T (\alpha_k > 0) \tag{14}$$

where a_k is the weight coefficient.

$$\min = \left\| \sum_j^n \alpha_j \times \delta_j^T - \delta_i^T \right\|_2 (i = 1, 2, \ldots, n) \tag{15}$$

According to the properties of the matrix differential, the first-order derivative of Equation (15) is obtained. Thus, Equation (16) is obtained.

$$\begin{bmatrix} \delta_1 \cdot \delta_1^T & \delta_1 \cdot \delta_2^T & \cdots & \delta_1 \cdot \delta_n^T \\ \delta_2 \cdot \delta_1^T & \delta_2 \cdot \delta_2^T & \cdots & \delta_2 \cdot \delta_n^T \\ \vdots & \vdots & \vdots & \vdots \\ \delta_n \cdot \delta_1^T & \delta_n \cdot \delta_2^T & \cdots & \delta_n \cdot \delta_n^T \end{bmatrix} \begin{bmatrix} \alpha_1 \\ \alpha_2 \\ \vdots \\ \alpha_n \end{bmatrix} = \begin{bmatrix} \delta_1 \cdot \delta_1^T \\ \delta_2 \cdot \delta_2^T \\ \vdots \\ \delta_n \cdot \delta_n^T \end{bmatrix} \tag{16}$$

Finally, the equations are solved and normalized to obtain the combined weight value.

$$\delta^* = \sum_{k=1}^{n} \alpha_k^* \cdot \delta_k^T \tag{17}$$

2.5. The Basic Quality of Rock Mass (BQ)

The basic quality (BQ) system is considered to be China's national rock mass quality classification system (GB/T50218-2014 2014) [31], which can be applied to most types of rock mass engineering. Two basic parameters, uniaxial compressive strength (UCS) and rock integrity index (Kv), are considered when evaluating the basic BQ value. For rock slope engineering, considering the adverse effects of existing geological conditions, by introducing five correction factors, the BQ value is adjusted to the correction value [BQ] to determine the grade of rock slope. The BQ system is only suitable for rock slopes with a height of less than 60 m, and is a sliding failure mode [32,33].

The BQ system comprehensively refers to the classification basis of rock mass quality at home and abroad, adopts the classification method combining qualitative and quantitative aspects, and closely combines the engineering characteristics of rock mass engineering in China, which has strong scientificity and practicability. However, the content of the qualitative description is complicated, and the classification basis is relatively general. The calculation of quantitative index BQ needs to consider the corresponding constraints, which limits its practicability [33,34].

3. Example Analyses

3.1. Overview of Maji Hydropower Station and Classification Standards and Parameters

Maji Hydropower Station is located in Mujiajia Village, Maji Township, Fugong County, Yunnan Province (Figure 3). The proposed dam site is a concrete double-curvature arch dam with a design height of 300 m. The project area is located southeast of the Qinghai–Tibet Plateau and belongs to the Hengduan Mountains in western Yunnan. The terrain is generally high in the north and low in the south. The dam site area mainly develops into alpine canyons. The mountains on both sides of the river are distributed above 3000 m–4000 m, and the relative height difference is 1500 m–2500 m, which belongs to the alpine canyon geomorphic unit. The overall flow direction of Nujiang River is roughly SE130°–SE170°. The valley slopes on both sides are steep, and the slope is generally 45°–60°. The cliffs are more common, showing a symmetrical 'V' shape (Figure 4).

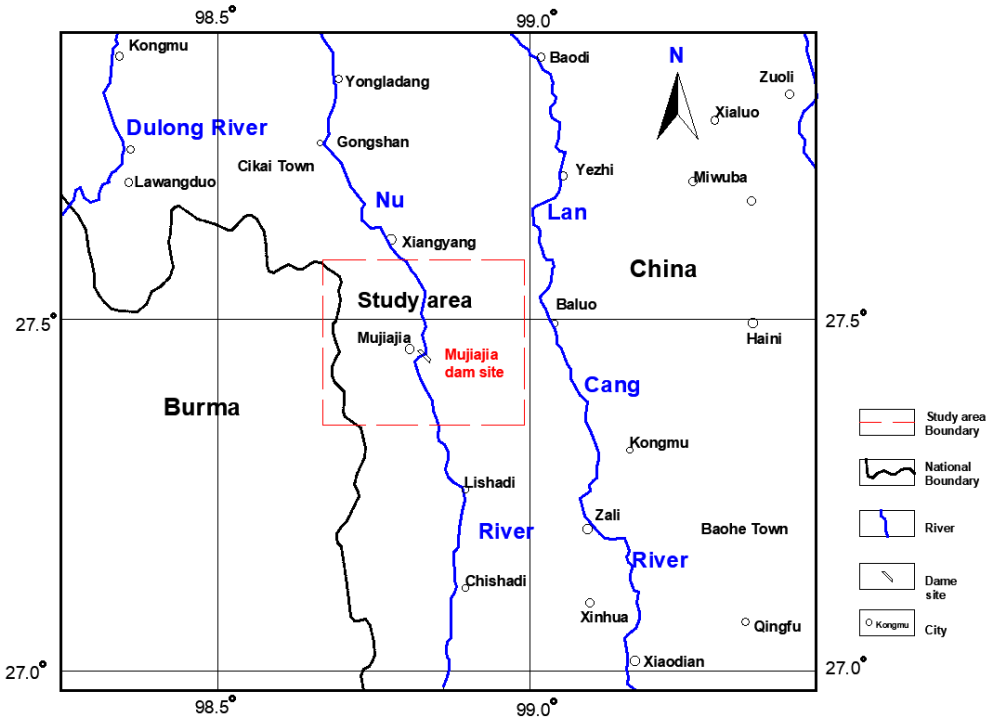

Figure 3. Traffic location diagram of Maji hydropower station.



Figure 4. Geomorphology and geology of the dam site.

The strata in the area are relatively developed and are exposed from Proterozoic to the Quaternary. The metamorphic deformation of the strata is quite different. The changes in lithology and lithofacies are extremely complex. Magmatic, metamorphic, and sedimentary rocks are all exposed (Figure 5). The groundwater in the reservoir area mainly includes bedrock fissure water and loose rock pore water, mainly bedrock fissure water. According to Reference [35], an engineering geological classification scheme of the dam foundation rock mass was carried out. The quantitative standard of rock mass quality classification of the Maji hydropower station was determined, as shown in Table 2.



(**a**) (**b**)

Figure 5. Granitic gneiss; (**a**) Lenticular biotite plagioclase amphibolite xenolith (residual body) in granitic gneiss; (**b**) Lenticular biotite plagioclase amphibolite xenolith (residual body) in granitic gneiss.

Table 2. Rock mass quality assessment standard of Maji hydropower station.

Rock Classification		Saturated Compressive Strength R_c (MPa)	Spacing D (m)	Wave Velocity v (m/s)	RQD (%)	Integrity Coefficient K_v
I		>120	>1.0	5100~6200	>90	>0.75
II		100~120	0.5~1.0	4800~5100	90~75	0.75~0.55
III	III_1	70~100	0.4~0.5	4400~4800	75~60	0.55~0.45
	III_2	30~70	0.4~0.3	3700~4400	60~45	0.45~0.35
IV		15~30	0.3~0.1	2000~3700	45~25	0.35~0.15

The evaluation of rock mass quality is closely related to the selection of evaluation indexes. These indexes mainly include geological factors and engineering factors. Geological factors include rock mass characteristics, stress state and joint surface distribution. Engineering factors refer to the external factors that are artificially formed in the later period of rock mass without disturbance. The rock mass quality evaluation index is very complex and diverse. In this paper, the rock mass quality evaluation index is determined according to the geological environment of the actual project, focusing on the study of rock mass characteristics before engineering activities. Based on the widely used specifications, combined with previous experience and a comprehensive consideration of the relevant literature, the rock mass quality classification of PD105 is taken as an example in this paper. Five evaluation indexes were used: saturated compressive strength (C_1/MPa), fracture spacing (C_2/m), acoustic wave velocity (C_3/m/s), RQD (C_4/%) and integrity coefficient (C_5) of rock [10,35–37]. The weight of each evaluation index was determined by game theory, and the K-PSO clustering algorithm was used to evaluate the rock mass grade. The quality evaluation indexes of the rock mass are as follows (Figure 6).

1. Rock uniaxial saturated compressive strength R_c (MPa) reflects the degree of hardness of rock and rock characteristics.
2. Structural plane spacing J_d (m) represents the characteristics of the geological structure and rock mass structure.
3. Acoustic wave velocity V (m/s) can comprehensively reflect rock mass quality.
4. The RQD index reflects the size and integrity of rock mass.
5. Integrity coefficient K_v can be used to classify the rock mass integrity.

Considering that the units of each evaluation factor are different, the classification criteria are dimensionless to eliminate the dimension of the index. The dimensionless treatment formulae are shown in Equations (18) and (19):

Benefit indicators:

$$A = (M - M_{min})/(M_{max} - M_{min}) \quad (18)$$

Cost indicators:

$$A = (M_{max} - M)/(M_{max} - M_{min}) \quad (19)$$

where A is the value after dimensionless processing; M is the boundary value or sample data value of each evaluation factor in each rock mass quality grade; M_{max} and M_{min} are the maximum and minimum values of the processing range of each evaluation factor.

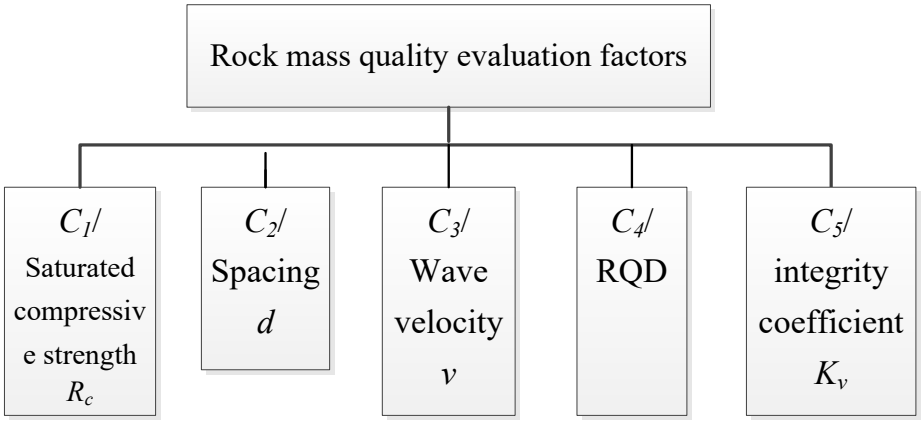

Figure 6. Rock mass quality evaluation indexes.

In this paper, the uniaxial saturated compressive strength R_c, structural plane spacing J_d, RQD, integrity coefficient Kv and acoustic longitudinal wave velocity V_p of rock are dimensionless and processed by Equation (18). The processing results are shown in Table 3.

Table 3. Rock mass quality classification standard.

Rock Classification	Saturated Compressive Strength R_c (MPa)	Spacing D (m)	Wave Velocity v (m/s)	RQD (%)	Integrity Coefficient K_v
I	>1	>1.0	0.82~1.0	0.9~1.0	0.75~1.0
II	0.83~1	0.5~1.0	0.77~0.82	0.9~0.75	0.75~0.55
III III_1	0.58~0.83	0.4~0.5	0.71~0.77	0.75~0.6	0.55~0.45
III III_2	0.25~0.58	0.4~0.3	0.60~0.71	0.6~0.45	0.45~0.35
IV	0.125~0.25	0.3~0.1	0.32~0.60	0.45~0.25	0.35~0.15
V	0~15	0~0.1	0~0.32	0~0.25	0~0.15

3.2. Selection of Rock Mass Samples

According to the field investigation and experimental tests, the average value of each evaluation index of PD105 per 10 m (from 150 m) was obtained. Each section is named P_1, P_2, . . ., P_{15}, in order [38–44]. The rock mass parameters of each section are shown in Table 4. The parameters of the sample data after dimensionless processing are listed in Table 5.

Table 4. The rock mass parameters of each section in PD105.

Zone	C_1/Saturated Compressive Strength R_c (MPa)	C_2/Spacing D (m)	C_3/Wave Velocity v (m/s)	C_4/RQD (%)	C_5/Integrity Coefficient K_v
P_1	5	0.08	1443	22	12
P_2	15	0.13	2224	24	16
P_3	31	0.21	2645	50	28
P_4	35	0.4	3505	55	48
P_5	50	0.35	3034	46	36
P_6	80	0.45	4355	66	53
P_7	75	0.56	4677	81	64

Table 4. *Cont.*

Zone	C_1/Saturated Compressive Strength R_c (MPa)	C_2/Spacing D (m)	C_3/Wave Velocity v (m/s)	C_4/RQD (%)	C_5/Integrity Coefficient K_v
P_8	103	0.8	4789	79	68
P_9	110	0.83	5890	88	82
P_{10}	98	0.69	5342	78	78
P_{11}	116	0.97	5203	90	75
P_{12}	120	1.1	5578	93	79
P_{13}	134	0.94	5275	88	76
P_{14}	145	1.5	6085	95	88
P_{15}	143	1.43	5765	94	80

Table 5. The rock mass parameters of each section in PD105.

Zone	C_1/Saturated Compressive Strength R_c (MPa)	C_2/Spacing D (m)	C_3/Wave Velocity v (m/s)	C_4/RQD (%)	C_5/Integrity Coefficient K_v
P_1	0.04	0.08	0.23	0.22	0.12
P_2	0.13	0.13	0.36	0.24	0.16
P_3	0.26	0.21	0.43	0.50	0.28
P_4	0.29	0.4	0.57	0.55	0.48
P_5	0.42	0.35	0.49	0.46	0.36
P_6	0.67	0.45	0.7	0.66	0.53
P_7	0.63	0.56	0.75	0.81	0.64
P_8	0.86	0.8	0.77	0.79	0.68
P_9	0.92	0.83	0.95	0.88	0.82
P_{10}	0.82	0.69	0.86	0.78	0.78
P_{11}	0.97	0.97	0.84	0.90	0.75
P_{12}	1	1.1	0.9	0.93	0.79
P_{13}	1.12	0.94	0.85	0.88	0.76
P_{14}	1.21	1.5	0.98	0.95	0.88
P_{15}	1.19	1.43	0.93	0.94	0.80

3.3. Determination of Weight and Results of Cluster Analysis

3.3.1. Determination of Weight (w_1)

(1) Weight-based least squares method to determine the objective weight

In this paper, five factors of saturated compressive strength (R_c), spacing (D), wave velocity (v), rock quality designation (RQD) and integrity coefficient (Kv) are considered to evaluate the quality of rock mass. According to the importance of each factor, they are compared in turn to establish judgment matrix A, as follows:

$$A = \begin{bmatrix} 1 & 3 & 5 & 3 & 4 \\ 1/3 & 1 & 3 & 1 & 2 \\ 1/5 & 1/3 & 1 & 1/3 & 1/2 \\ 1/3 & 1 & 3 & 1 & 1 \\ 1/4 & 1/2 & 2 & 1/2 & 1 \end{bmatrix}$$

The intermediate matrix C is solved by Formula (10), as follows:

$$C = \begin{bmatrix} 4.32 & -3.33 & -5.2 & -3.33 & -4.25 \\ -3.33 & 14.36 & -3.33 & -2 & -2.5 \\ -5.2 & -3.33 & 51 & -3.33 & -2.5 \\ -3.33 & -2 & -3.33 & 14.36 & -2.5 \\ -4.25 & -2.5 & -2.5 & -2.5 & 28.25 \end{bmatrix}$$

The weight values of the five parameters can be calculated by Formula (9), w_1, as shown in Table 6.

Table 6. Rock quality evaluation parameter weights based on the weighted least-squares method.

Index	C_1/Saturated Compressive Strength R_c	C_2/Spacing D	C_3/Wave Velocity v	C_4/RQD	C_5/Integrity Coefficient K_v
Weight	0.471	0.172	0.076	0.172	0.109

(2) Information entropy determines the objective weight of the evaluation index (w_2).

The rock mass quality data of 15 tunnel sections were transformed into standard data, and the objective weight w_2 of rock mass quality evaluation index was 0.305, 0.113, 0.074, 0.103, 0.124, using the entropy method combined with Formulas (12) and (13).

(3) Combined weighting (w) determined by game theory

In this paper, game theory was used to determine the comprehensive weight of sample rock mass quality. According to the least square and entropy methods, the subjective weight value and objective weight value of five evaluation indexes of rock mass quality evaluation were obtained. Game theory was used to establish the optimal combination coefficient equations:

$$\begin{cases} aw_1w_1^T + bw_1w_2^T = w_1w_1^T \\ aw_2w_1^T + bw_2w_2^T = w_2w_2^T \end{cases}$$

According to Formula (17), the comprehensive weight (w) of the evaluation factor was calculated to be 0.142, 0.179, 0.035, 0.116, and 0.108.

3.3.2. Results of Cluster Analysis

The rock mass quality in the study area was divided into grade I, grade II, grade III_1, grade III_2, grade IV, and grade V. The K-PSO clustering results of rock mass quality in the study area are shown in Table 7.

Table 7. Classification comparison table of different methods of 15 sections in PD105.

Zone	C_1	C_2	C_3	C_4	C_5	The New Method	BQ	Extension Evaluation	Field Discrimination
P_1	0.04	0.08	0.23	0.22	0.12	V	V	V	IV~V
P_2	0.13	0.13	0.36	0.24	0.16	IV	IV	IV	IV~V
P_3	0.26	0.21	0.43	0.50	0.28	IV	IV	IV	IV~V
P_4	0.29	0.4	0.57	0.55	0.48	III_2	III_2	III_2	III_1~III_2
P_5	0.42	0.35	0.49	0.46	0.36	III_2	IV	III_2	III_2~IV
P_6	0.67	0.45	0.7	0.66	0.53	III_1	III_2	III_1	III_1~III_2
P_7	0.63	0.56	0.75	0.81	0.64	II	II	II	II~III_1
P_8	0.86	0.8	0.77	0.79	0.68	II	II	II	II~III_1
P_9	0.92	0.83	0.95	0.88	0.82	II	I	II	I~II
P_{10}	0.82	0.69	0.86	0.78	0.78	II	II	II	I~II
P_{11}	0.97	0.97	0.84	0.90	0.75	II	II	II	II~III_1
P_{12}	1	1.1	0.9	0.93	0.79	I	I	I	I~II
P_{13}	1.12	0.94	0.85	0.88	0.76	I	I	I	I~II
P_{14}	1.21	1.5	0.98	0.95	0.88	I	I	I	I~II
P_{15}	1.19	1.43	0.93	0.94	0.80	I	I	I	I~II

Under the conditions of high stress and a high ground temperature, the rock damage of the RMR system is aggravated, which shows that the rock characteristics change from brittleness to plasticity, and the rheological effect of rock is enhanced. Therefore, the system has poor applicability to deep underground engineering. The Q system can be seen from its system composition. Except for the RQD value, a quantitative index, the other five indexes are qualitatively obtained by field investigation, which has a certain level of experience. At the same time, there are some shortcomings in the application of Q system in high-stress areas. The BQ classification method of rock mass comprehensively refers to the classification basis of rock mass quality at home and abroad, adopts the classification method combining qualitative and quantitative factors, and closely combines the engineering characteristics of rock mass engineering in China, which has strong scientificity and practicability. Therefore, combined with the evaluation parameters of rock mass quality in the study area, this paper chose BQ classification for the comparison of new methods, and further verified the accuracy of the new method when applied to rock mass quality evaluation in combination with field investigation [1–6,45].

In this paper, the method was compared with the two methods: the traditional BQ classification method and the nonlinear extension theory commonly used at present. Through comparison, the K-PSO clustering results are generally found to be consistent with the results of the traditional BQ classification method, and consistent with the preliminary judgment of the expert field.

The results show that with the increase in the depth of the tunnel, the quality of the rock mass is improving, showing good regularity, and consistent with the trend of rock mass weathering. This indicates that the new method combines the weighting method and K-PSO clustering algorithm to evaluate the construction of a hydropower station. The rock mass quality evaluation model is feasible and can reflect the actual rock mass quality grade. The evaluation results are reasonable and effective.

4. Conclusions

In this paper, a new method for evaluating rock mass quality based on the K-PSO clustering algorithm is proposed. The subjective and objective weights of evaluation factors are determined by the weighted least squares method, the objective weights are determined by the entropy method, and the combined weights of each influencing factor are determined by game theory.

(1) This is based on multi-factors and multi-angles. The number and type of rock mass quality parameters are freer, and can truly and objectively reflect the field investigation results. The proposed method can fully use the information obtained from engineering investigation and solve the past classification of rock mass quality deficiencies and defects, which used only fixed factors.

(2) The weight of the rock mass quality evaluation factor is determined to be 0.142, 0.179, 0.035, 0.116, and 0.108 using game theory to combine the least-square method and the entropy method. This method can overcome the shortcomings of subjective and objective weighting and is suitable for dealing with complex, multi-objective decision-making problems.

(3) The factors affecting the evaluation of rock mass quality are uncertain, nonlinear and fuzzy. Using a clustering model to evaluate rock mass quality can effectively solve the problem of uncertainty between factors. Especially when there is a lack of geological data, this method can quickly and reasonably analyze the rock mass quality of the tunnel section.

(4) In traditional rock engineering, the methods of rock mass quality evaluation include the BQ classification method, RMR classification method, and Q classification method. Most of them use qualitative or quantitative methods to evaluate the quality of the rock mass. However, the rock mass quality problem is a complex contradictory problem, and the results of different indexes may be different. Clustering analysis is

an effective data mining algorithm. The K-PSO clustering algorithm is an optimized K-Means algorithm based on the PSO algorithm, which has the characteristics of stable convergence and high computational efficiency. It can quickly and accurately classify rock mass quality and determine the evaluation grade of rock mass quality. The evaluation results are consistent with the traditional BQ classification method and the widely used extension theory evaluation results. They show that using the combination weighting method and K-PSO clustering algorithm is feasible to evaluate and construct the rock mass quality evaluation model for a hydropower station, truly reflecting the actual rock mass quality grade. The evaluation results were found to be reasonable and effective.

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