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Construction of professional practice teaching system of urban underground space engineering based on clustering algorithm

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Abstract

As one of the ad hoc majors in urban underground space engineering, the construction and innovation of its practical teaching system is especially necessary. This paper introduces the principle mechanism of simulated annealing algorithm, proposes a K-means clustering method in collaboration with traditional particle swarm algorithm - PSK-means algorithm, overcomes the defect that particle swarm algorithm is easy to fall into local optimum, and optimizes the clustering center to get the optimal clustering result. And the improved algorithm as a teaching evaluation algorithm is combined with the practical teaching system of urban underground space engineering profession to build a practical teaching platform. Using the platform test for teaching evaluation, there are four students with high scores in learning attitude, and their scores are 43.2, 44.1, 41.5, 44.4. In the analysis of learning effect, also these four students with the best learning attitude are in the top, while the one with the worst learning attitude scores 19.2, and their learning effect is also the worst with 69.2. Based on the PSK-means algorithm and the teaching platform based on the combination of PSK-means algorithm and practical teaching system can carry out knowledge assessment statistics according to different knowledge points, thus reflecting the students' ability strengths and weaknesses in each knowledge point and reflecting the practicality of the practical teaching system of urban underground space engineering.

Keywords: *underground space engineering; practical teaching system; K-means clustering; particle swarm algorithm; PSK-means algorithm*

Introduction

With the increasing level of urbanization and the sudden growth of urban population, the original urban planning and construction area can no longer match the high-speed development of cities, so the construction of three-dimensional space has become one of the main directions of current urban expansion (Yuan H E 2017) (Chunguang L I 2016). Under the situation of high-speed urban development, underground engineering such as tunnels, subways, large underground parking lots, urban pipe corridors and underground oil reserve depots have been widely used (Hong-Lue Q U 2016). And the rise and rapid development of underground engineering requires a large number of professional and technical talents in urban underground space engineering, especially comprehensive technical talents with solid theoretical foundation, rich practical experience and outstanding innovation ability (C, 2015).

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Practical teaching is an important link in the cultivation of applied talents, and the current practical teaching of urban underground space engineering profession has problems that restrict the development of the profession, such as unclear teaching orientation, lack of practical teaching platform, insufficient innovation ability of students and single practical teaching content (Ma, Chen, & Lv, 2022) (Chen J 2015). And to complete the establishment and innovative reform of the practical teaching system, colleges and universities must closely follow the characteristics of the development of the times, grasp the requirements of society and enterprises for talents, optimize the curriculum system and practical links comprehensively, and cultivate sufficient professional talents for society while improving the employment competitiveness of graduates (Junlan, 2021) (Yang X U 2019). It can be said that the construction and reform of the practical teaching system of applied undergraduate urban underground space engineering majors is the key to cultivating applied undergraduate talents (Xiong J 2015).

Literature (Liu & Liao, 2017) The United States gradually entered a period of three-dimensional development and utilization of urban land after the 1920s, with the implementation of undergrounding of road traffic. For example, Boston's Central Avenue was transformed from an urban elevated road to an underground passage. Literature (Broere, 2016) The most important feature of Russia in the development and utilization of underground space is the construction of a well-developed subway system and a common urban trench system. In the literature (Attard, Winiarski, Rossier, & Eisenlohr, 2015), the main feature of underground space development and utilization in the Nordic countries is the effective integration with civil defense projects. For example, Finland attaches particularly high importance to the development and utilization of underground space, and its underground cultural, entertainment and sports facilities construction projects are very numerous and large in scale. Literature (Zargarian, Hunt, Braithwaite, Bobylev, & Rogers, 2016) A notable feature in the development and utilization of urban underground space in France is the development and utilization of abandoned mines, which are changed into urban sewers and air defense facilities. Literature (Xia, Lin, Liu, & Liu, 2022) Although the development of underground space in Japan started late, due to its lack of national resources, Japan pays great attention to the construction of underground railways, underground streets, underground stations and underground shopping malls, and is now in the leading position in the world. At the same time, Japan has also formed a set of relatively advanced underground commercial street development and utilization system in terms of legislation, planning and design. In particular, the number and quality of Japan's underground common ditch construction are at the forefront of the world.

Literature (Lu, Wu, Zhuang, & Rabczuk, 2016) The development and utilization of underground space is an important part of the sustainable development of urban space, and is closely related to the life of urban residents. It has made an indelible contribution to the expansion of survival, production and living space for urban residents, and has a broad development prospect. Literature (Zaini, Hussin, Jamalludin, & Zakaria, 2015) points out that in this era, urban

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development does not occur on the surface, but downward using underground space. There are good examples of underground space development worldwide, and the importance of developing underground space cannot be denied. Literature (Sterling et al., 2012) argues that underground spaces are those functional resources that do not need to be on the surface, that special climatic characteristics and favorable geotechnical structures are the driving forces for the development of underground spaces, and that the development of underground spaces can improve the image of cities. The literature (Volchko et al., 2020) argues that the world population is concentrating in urban agglomerations, and since land is a limited resource, the traditional methods of surface planning and land use differentiation can no longer solve the complex problems.

For urban planners, underground space is not a resource, but an agenda of last resort. The effective use of surface and underground space can solve the environmental problems of the built-up city and make the urban land use sustainable.

This paper creates a teaching platform based on the combination of the improved clustering algorithm and the newly constructed professional practice teaching system of urban underground space engineering. The proposed K-means clustering algorithm based on the synergy of particle swarm and simulated annealing uses the probabilistic burstiness of simulated annealing to co-evolve with the particle swarm algorithm. According to the dynamic change of the number of particles in the evolution process, the global search ability of the algorithm is enhanced, and then the clustering center of clustering is optimized to achieve the optimal clustering result, which is used as the teaching evaluation algorithm of the urban underground space engineering teaching platform. Finally, through the evaluation analysis of the students who use the teaching platform's teaching, this verifies the feasibility of the practical teaching system for space engineering majors.

Professional practice teaching platform of urban underground space engineering

Construction of professional practice teaching system of urban underground space engineering

The principles of constructing the professional practice teaching system of urban underground space engineering are comprehensiveness, wholeness, independence and scientificity. The principle of comprehensiveness means that urban underground space engineering integrates the professional contents of urban planning, structural engineering and geotechnical engineering, etc. The principle of wholeness should reflect the overall function of combining practice and theory on teaching. Due to the small class size, students can complete most of the practical teaching links independently, that is, students have more independent practice opportunities, reflecting a better independence. The scientific nature is to require the construction and implementation of the practical teaching links to be gradual and scientific and reasonable.

As an ad hoc major, the professional practice teaching system of urban underground space engineering should be forward-looking and systematic, with innovative practice teaching

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contents, closely related to urban planning and construction, actively innovating engineering design and construction technology, and cultivating excellent underground engineers who meet the requirements of the major and the needs of the society. To this end, according to the requirements of the Urban Underground Space Engineering program, the teaching system should be systematic. To this end, according to the cultivation program of urban underground space engineering, the professional practice teaching system of urban underground space engineering is constructed as shown in Fig. 1. it creates various independent practice opportunities for students to integrate knowledge, ability and quality, and enhances students' ability to complete their work independently.

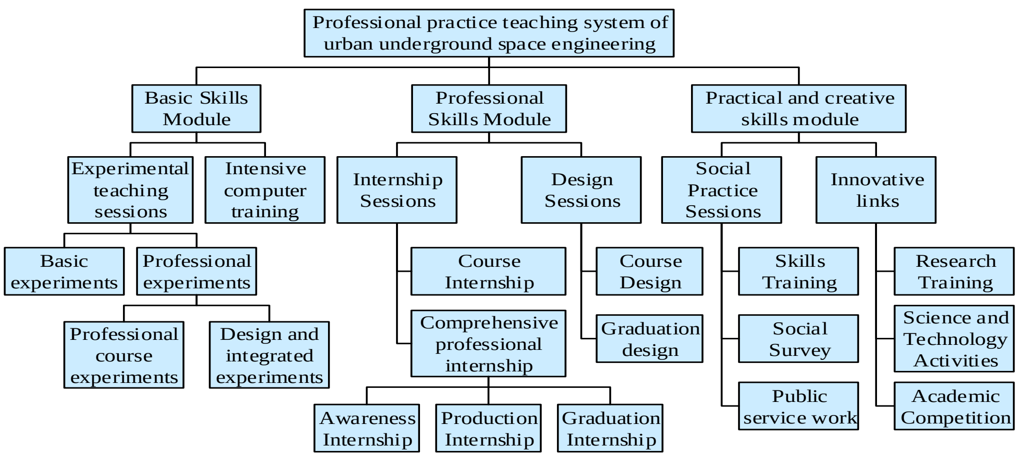

Figure 1 Composition of practical teaching system

Particle swarm algorithm

The particle swarm optimization algorithm simulates the graceful and unpredictable motion of a flock of birds, which can be described as follows: a group of particles flying in n-dimensional space at a certain speed, and a population $X=\{X_1,X_2,\cdots,X_n\}$ consisting of N particles, where $X_i=\{x_{i1},x_{i2},\cdots,x_{in}\}$ represents the position of each particle, considered as a feasible solution to the optimization problem. The particles need to complete the search for the optimal solution by continuously adjusting their positions x_{id}. Each particle has a memory function during the evolutionary process, which can remember the optimal position it has searched, i.e., the local optimal solution, denoted as Pd, and the optimal position experienced by the global particle, i.e., the global optimal solution, denoted as P_{id}. In addition, the velocity of each particle, denoted as $V_i=\{v_{i1},v_{i2},\cdots,v_{in}\}$, determines the direction and distance the particle moves, and each particle updates its velocity according to Equation (1). The motion state of the particles can be described by Eqs. (1) and (2).

$$V_{id}^{t+1} = \omega V_{id}^{t} + \lambda_1 r_1()\left(P_{id} - X_{id}^{t}\right) + \lambda_2 r_2()\left(P_{gd} - X_{id}^{t}\right) \tag{1}$$

$$X_{id}^{t+1} = X_{id}^{t} + V_{id}^{t+1} \tag{2}$$

where V_{id}^{t} denotes the velocity of the particle in dimension d at t iterations, X_{id}^{t} denotes the position of the particle in dimension d at t iterations, P_{id} and P_{gd} denote the current local optimum and global optimum of the particle, respectively, parameter ω is the inertia weight, λ_1 and λ_2 are learning factors that regulate the relative importance of P_{id} and P_{gd}, respectively, and $r_1()$ and $r_2()$ are random functions with values between $(0,1)$.

From Eqs. (1) and (2), it can be seen that the velocity of the particle for the next iteration is determined by three components: the current velocity of the particle itself V_{id}^{t}, the difference between the local optimal solution and the current position $P_{id} - X_{id}^{t}$, and the difference between the global optimal solution and the current position $P_{gd} - X_{id}^{t}$, and its relative importance is determined by the weighting factor ω, and the learning factors λ_1 and λ_2, respectively. Figure 2 shows a schematic diagram of the movement of each particle, represented as a weighted summation of the three movement directions.

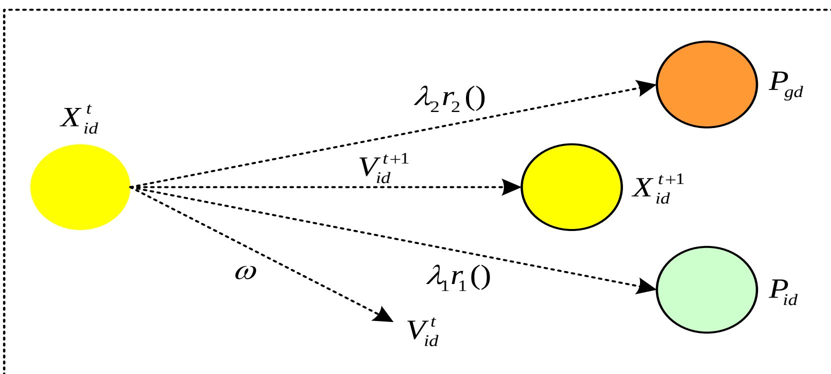

Figure 2 Schematic diagram of the movement of particles

The basic steps of the particle swarm optimization algorithm are as follows:

1) Initialize the particle swarm, including randomly initializing the position X and velocity V of

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the particles.

2) Calculate the fitness value of each particle by the well-defined fitness function.

3) Update of local extremes: for each particle, compare the fitness value of its current position with the fitness value of its best experienced position P_{id}, if better, update P_{id} otherwise, keep the original P_{id}.

4) Update of global extremes: For each particle, compare the fitness value of its current position with the fitness value of the best experienced position of the population, Pgi, and if better, update P_{gd}, otherwise, keep the original P_{gd}.

5) Each particle has a velocity, and the position of the particle is updated by changing the velocity of the particle, and the velocity and position of the particle are adjusted according to equations (1) and (2).

6) Determine whether the end condition is reached, if yes, end, otherwise go to step 2). (The end condition is usually set as: maximum number of evolutionary generations or a good enough position).

The basic flow of the particle swarm optimization algorithm is shown in Figure 3.

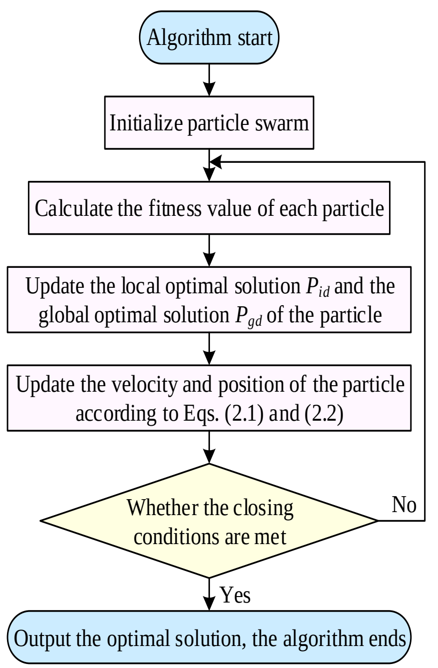

Figure 3 Flow chart of particle swarm optimization algorithm

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K-means clustering

The K-means algorithm is to divide the set of n data objects into k classes with k as the input parameter, so that the data objects in the same class have the highest similarity and the data objects between classes have the lowest similarity. The similarity is the average of the data objects in the same class and is called the cluster center. Since the value of k is often unknown and the user-defined value of k is not always exactly equal to the actual number of classes, resulting in the K-means algorithm is not very stable in terms of the effect and quality of clustering a pair of data sets. Therefore, the study of parameter k is a key part of the K-means algorithm, which is a local search algorithm, and the clustering result is directly related to the selection of the initial point, and the initial point also affects the running time of the whole algorithm. Therefore, the selection of initial points is also a key part of K-means algorithm research. At present, the main methods for the selection of initial points are distance optimal method, density valuation method, and random selection method.

In K-means clustering analysis, let the data set be $X=\{X_i, i=1,2,\cdots,n\}$, where each data object X_i is a vector of dimension d. The clustering of data set X is to find a reasonable division $C=\{C_1,C_2,\cdots,C_k\}$ that maximizes the intra-class similarity and inter-class variability of the division results. The following relationship is satisfied:

$$X=\bigcup_{i=1}^{k}C_1 \tag{3}$$

$$C_i \neq \varnothing (i=1,2,\cdots,k) \tag{4}$$

$$C_i \cap C_j = \varnothing (i,j=1,2,\cdots,k, i\neq j) \tag{5}$$

And, so that the total inter-class dispersion and the value of Sum are minimized, the solution for Sum is performed according to Equation (6).

$$Sum=\sum_{r-1}^{k}\sum_{X_i\in C_r} d(X_i,Z_r) \tag{6}$$

where Z_r is the cluster center of class r, $d(X_i,Z_r)$ is the distance from data sample X_i to the corresponding cluster center Z_r, and Sum, as the objective evaluation function of clustering, is the sum of the distances from each type of data sample to the corresponding cluster center.

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Here $d\left(X_i, Z_r\right)$ is the distance in Euclidean space, i.e. $d\left(X_i, Z_r\right) = \| X_i - Z_r \|$.

Particle swarm and simulated annealing based cooperative K-means clustering (PSK-means) algorithm

Simulated annealing algorithm

The simulated annealing algorithm starts from a certain sufficiently high temperature, performs a random search in the solution space using the Metropolis sampling strategy and receives the worse solution with a certain probability, and the sampling process is repeated as the temperature keeps decreasing to finally obtain the global optimal solution. The simulated annealing algorithm is robust, has implied parallelism and global convergence, can handle different types of optimal design variables, and has no requirement for the objective function. The simulated annealing algorithm can converge to the global optimal solution with probability 1 under the condition that the initial temperature is high enough and the temperature decreases slowly enough.

The basic steps of the simulated annealing algorithm are as follows:

1) Initialization: Randomly select the initial solution m_0 and evaluate m_0 with the evaluation function $C\left(m_0\right)$. Initial temperature T so that its value is large enough; initial number of evolutionary generations N for each temperature T.

2) For current temperatures T and $i = 1, \cdots\cdots, N$, perform steps 3) to 6).

3) Generate a new solution $m_1 = m_0 + \Delta m$ by perturbation and calculate the evaluation function $C\left(m_1\right)$.

4) Calculate increment $\Delta C = C\left(m_l\right) - C\left(m_0\right)$.

5) If increment $\Delta C < 0$, accept m_1 as the new current solution, i.e., $m_0 = m_1$. Otherwise, accept m_1 as the new current solution with probability $\exp(-\Delta C / T)$, i.e., when the probability value is greater than $(0,1)$ between a random number rand, also accept m_1 as the new current solution, let $m_0 = m_1$; otherwise, keep m_0 as the current solution.

6) If the predefined termination condition is met, the current solution m_0 is output as the optimal solution and the program is terminated. (The termination condition is set as follows: several new solutions m_1 are not accepted in succession)

7) Temperature T gradually decreases and cannot drop below zero degrees, i.e., $T>0$, and then goes to step 2). (The algorithm is often terminated by setting the number of iterations, or the end temperature)

Synergistic mechanism of particle swarm and simulated annealing

The simulated annealing algorithm has the advantages of global convergence, while the particle swarm algorithm has the advantages of easy implementation, fast local convergence, and less parameters to be adjusted. By completing the iterative process cooperatively, we can avoid the defects of particle swarm algorithm which is easy to fall into local optimum, and also improve the convergence speed of particle swarm algorithm at the late stage of evolution.

In the particle swarm and simulated annealing collaborative process, during the initialization phase of the algorithm, half of the particles undergo PSO iteration, and for each particle, its fitness is compared with the fitness of its best experienced position and the fitness of the best experienced position of the population, respectively, and if better, P_{id} and P_{gd} are updated, otherwise, no change is made. The other half of the particles are subjected to SA random sampling using the fitness function $fitness()$ evaluation function with an initial solution of P_{id}. A further search is performed to obtain a new solution Y. If $fitness\left(P_{id}\right)-fitness(Y)<0$, the new solution Y is received as the global optimal position and made $P_{id}=Y$. Otherwise, Y is received as the global optimal position with probability $\exp\left(-\left(fitness\left(P_{id}d\right)-fitness(Y)\right)/T\right)$. Then, the optimal solution is selected from the population as the global optimal solution. When the change in the optimal fitness value is less than some fixed value dis (set according to the algorithm) for q consecutive iterations (set according to the algorithm), the number of particles in the PSO iteration is dynamically reduced and the number of particles in the SA sampling is increased according to the ratio of the average fitness change for q consecutive generations. The change in the number of particles can be based on Equation (7):

$$N=fix\left(\mu N\times\frac{\sum_{i=2}^{q}\frac{Pbest(i-1)}{Pbest\ (i)}}{q-1}\right) \tag{7}$$

where μ is the conditioning factor, fix is the rounding function, N is the number of particles for PSO iterations, q is the number of consecutive evolutionary generations, and $Pbest$ is the set of optimal fitnesses for q consecutive generations.

Improved PSK-means algorithm

Let $X=\{X_i, i=1,2,\cdots,m\}$ be the set of data samples, where the data samples X_i have the same dimensionality, are d -dimensional vectors, and $d=1,2,3\cdots n$. The result of clustering is to find a reasonable division $D=\{D_l, D_2,\cdots,D_k\}$ and such that the division satisfies the following relation:

$$\begin{aligned} &X=\bigcup_{i=1}^{k} D_i \\ &D_i \neq \varnothing (i=1,2,\cdots,k) \\ &D_i \cap D_j = \varnothing (i,j=1,2,\cdots,k, i\neq j) \end{aligned} \tag{8}$$

and minimizes the sum Sum of the distances from class k data samples to the corresponding cluster centers:

$$Sum=\sum_{r=1}^{k}\sum_{X_i\in D_r}\left\|X_i-Z_r\right\| \tag{9}$$

Where k is the number of cluster divisions, Z_r is the r rd cluster center, $\left\|X_i-Z_r\right\|$ is the Euclidean spatial distance from each data sample to its cluster center, and Sum, also known as the sum of interclass dispersions, is the sum of the Euclidean distances of the data samples from the k classes.

The encoding of particles in the PSK-means algorithm is based on the clustering center, which consists of k class of clustering centers for each particle, and since the data sample is a d - dimensional vector, the number of dimensions that determine the position and velocity of the particle is $k\times d$. In addition, each particle has its fitness value for use $fitness()$. The encoding structure of the particles is derived as follows:

$$Z_1 Z_2\cdots Z_{1d} Z_{21} Z_2 \ldots Z_{2d}\cdots Z_{k1} Z_{k2}\cdots Z_{kl} V_1 \ldots V_{k\times d}\ fitness\ (X) \tag{10}$$

The adaptation values of individual particles are calculated as follows:

1) The formula of cluster center Z_r is:

$$Z_r = \frac{1}{n_r} \sum_{\forall x_i \in C_r} x_i \qquad (11)$$

where n_r is the number of samples in cluster r.

2) When the clustering center is determined, the clustering division for that particle is determined by the nearest neighbor rule formula (12) if X_i, j is satisfied:

$$\left\| X_i - Z_j \right\| = \min_{k=1,2,\cdots,n} \left\| X_i - Z_k \right\| \qquad (12)$$

Then X_i belongs to category j.

3) Based on the clustering of the data set, the inter-class dispersion and Sum are calculated according to Equation (9), and the smaller the value of Sum indicates the better result of clustering.

4) The particle fitness is calculated according to Equation (13), where Sum is the inter-class dispersion and the smaller the value of Sum, the greater the fitness.

$$fitness = \frac{1}{Sum} \qquad (13)$$

The algorithm steps of K-means clustering based on particle swarm and simulated annealing synergy are as follows:

1) When initializing the population, the initial clustering division is based on generating random numbers to classify the sample set, calculating the cluster centers of each category according to Equation (11), and encoding k cluster center in turn as the initial position of the particle. After randomly initializing the velocity of the particle, the dimension is the same as the position of the particle. Then calculate the fitness of the particles according to equations (9) and (13), and encode them according to the encoding structure of the particles. The above steps are repeated to generate an initial particle population of size $2N$, determine the local optimum P_{id} and global optimum P_{gd} for each particle. order $N_L = N; N_2 = N$, initial temperature $T = t_0$.

2) PSO iterations are performed for the first N_1 particle to update the local optimal position P_{id} and the global optimal position P_{gd}. And update the velocity and position of the particle

according to Eqs. (1) and (2), where ω decreases from the maximum inertia weight $\omega_{\max}$ to the minimum inertia weight $\omega_{\min}$ with the evolutionary generation according to Eq. (14), i.e:

$$\omega = \omega_{\max} - t \times \frac{\omega_{\max} - \omega_{\min}}{MaxT} \tag{14}$$

where t is the current evolutionary generation and $MaxT$ is the total evolutionary generation.

3) $Y = P_{id}$, perform the sampling process of SA for the latter N_2 particles and adjust the relevant parameters of SA: the temperature value T and the new solution Y of the search.

4) Select the global optimal position P_{gd} from the whole population.

5) The new clustering centers are derived based on the reverse inference of the encoding method of the new generation of particles and K-means clustering is performed.

6) If the change in the optimal fitness value for q consecutive generation is less than some fixed value dis, the particles are dynamically assigned according to Equation (7) to obtain N_1 and N_2.

7) Determine whether the set maximum number of evolutionary generations is reached, and if so, end the algorithm iteration. Otherwise, turn to step 2) to iterate.

The PSK- means algorithm flow chart is shown in Figure 4.

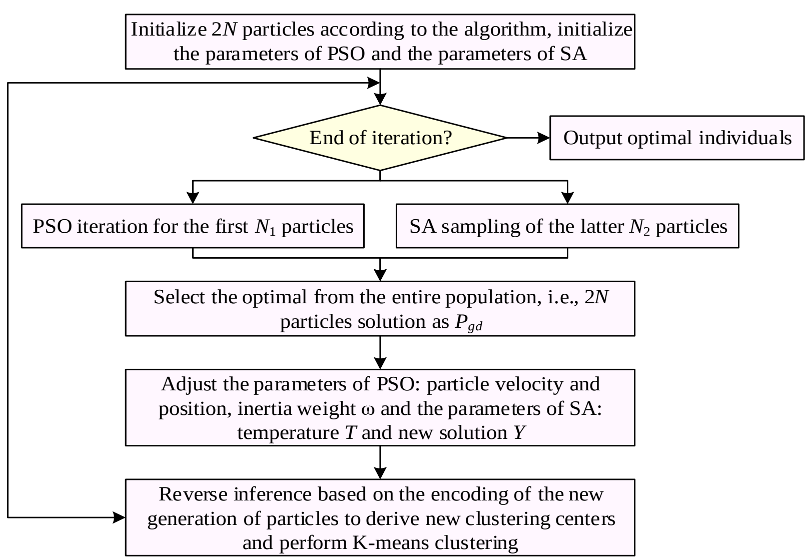

Figure 4 Flow chart of PSK-means algorithm

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Teaching evaluation based on PSK-means algorithm

The purpose of evaluation is to promote better development of students. After determining the practical teaching system of urban underground space engineering and the implementation plan of teaching evaluation based on PSK-means algorithm, the determination of evaluation indexes and data processing of evaluation are the basis of teaching evaluation, and the precise evaluation of teaching subjects based on teaching objectives is the main research content of this chapter.

eaching evaluation index design

Combining the teaching system of urban underground space engineering and the teaching platform of PSK-means algorithm, the primary evaluation indexes of learning attitude and learning effect are formed under the guidance of constructivist teaching theory with learning path and teaching activities as the basic units, and the learning effect is judged according to professional ability.

The learning attitude is divided according to students' autonomy, with mandatory learning activities (necessary learning activities), autonomous learning activities, and the initiative to explore the unknown as secondary evaluation indicators, and the corresponding quantitative evaluation indicators are established according to the actual teaching process.

The embodiment of learning effect is from the degree of control of learning content, combined with the original evaluation methods of universities to evaluate students' mastery of relevant subject knowledge, according to the necessary evaluation scheme and independent knowledge evaluation to build secondary evaluation indexes based on knowledge mastery and deep processing feedback, a process-oriented teaching evaluation index system is constructed, and the indexes.

Learning attitude

a. Mandatory learning activities: This evaluates students' engagement and participation in required learning activities such as attending lectures, completing assignments, and participating in group discussions. Quantitative indicators can include attendance rates, submission rates, and active participation in class discussions.

b. Autonomous learning activities: This evaluates students' ability to take initiative in their learning process, such as conducting additional research, seeking additional resources, and engaging in self-directed learning. Quantitative indicators can include the number of additional resources accessed, self-study hours, and the quality of self-generated learning materials.

c. Initiative to explore the unknown: This evaluates students' curiosity, creativity, and willingness to explore beyond the provided materials. Quantitative indicators can include the number of questions asked, engagement in independent research projects, and the level of critical thinking demonstrated in class discussions.are shown in Table 1.

Table 1 Teaching evaluation index based on clustering algorithm

Tier 1 Indicators	Tier 2 Indicators	Evaluation data items	Quantification Methods
Learning Attitude	Necessary activity initiative	Class attendance rate	Number of check-ins/total number of classes
		Pre-learning before class	Number of pre-tests before class
		Classroom tests	Number of class tests taken
		Assignment completion	Number of homework assignments completed on time
		Questionnaire	Number of questionnaires taken
	Self-directed learning initiative	Resource Access	Number of hours of resource viewing
			Number of resource visits
		Self-directed exercises	Length of self-practice
			Number of self-practice
	Explore the initiative	Questions and Answers	Number of individual questions
			Number of individual answers
Learning Effect	Knowledge Learning	Prep self-test scores	Related scores
		Class test scores	——
		After-class assignments	——
		Midterm and Final Grades	——
	Further processing feedback	Self-administered Unit Tests	——
		Error Review	——

Analysis of learning attitude evaluation

Teaching under the practical teaching system of urban underground space engineering, the learning activities are quantified according to three parts: before class, during class and after class, and the attendance rate, pre-course pre-test, participation in pre-course test, homework completion and questions and answers in class can be obtained to reflect students' learning attitudes.

According to the initiative of learning, there are three types of learning activities: necessary activities, independent learning, and active exploration, and the corresponding secondary evaluation indexes are set up, so that students' learning attitudes are defined by the initiative of their participation in learning activities, which are "initiative of necessary activities", "initiative of

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independent learning", and "initiative of exploration". Therefore, students' learning attitudes are defined by their participation in learning activities, namely "necessary activity initiative", "independent learning initiative", and "exploration initiative", and then the evaluation indexes are set up according to their actual learning behavior activities.

The experiment counted the teaching data of urban underground space engineering courses on the teaching platform, and collected "attendance score", "chapter study", "homework submission" and "questionnaire" as the evaluation indexes of learning attitude according to the actual teaching situation. "questionnaire" as the evaluation index of learning attitude. We can set $1 \le j \le 32$ (32 times of class attendance), $j = 33$ for the number of chapter study, $34 \le j \le 49$ (16 times of after-class homework), $50 \le j \le 65$ (16 times of questionnaire), a total of 65 actual evaluation indicators for this cycle of learning attitude assessment data items, each indicator refers to the corresponding quantitative criteria to calculate the score composition matrix A_1, the weight value of each indicator composition matrix W_1. intercepted students numbered 15-24 a total of 10 students data display.

Table 2 shows the description of each indicator of learning attitude, including the specific quantification strategy and the related indicator weight value setting.

Table 2 Description of learning attitude indicators

Quantitative Metrics	Quantitative Strategies	w_j
Attendance Score	Attendance / Total number of courses	0.1
Chapter Study	Number of studies *0.5	0.4
Assignment Submission	The positive or negative difference between the actual submission time and the estimated submission time for a single job value	0.4
Questionnaire	Whether to participate in the questionnaire* Questionnaire score/ Total questionnaire score	0.1

Figure 5 shows the learning attitude ratings of students numbered 11-25 obtained from the evaluation function of the teaching platform based on the PSK-means algorithm. It can be seen that the comparative graph of learning attitude evaluation reflects the positive learning attitude of students during the examination cycle, and it can be seen that students number 13, 14, 15 and 23 have higher scores in all categories and positive attitudes.

In contrast, student #17 had several absences from class, and his learning attitude score was low and his attitude was negative. The data indicate that the assessment system does quantify the students' attitude ratings.

This quantitative result can provide data support for the learning intervention.

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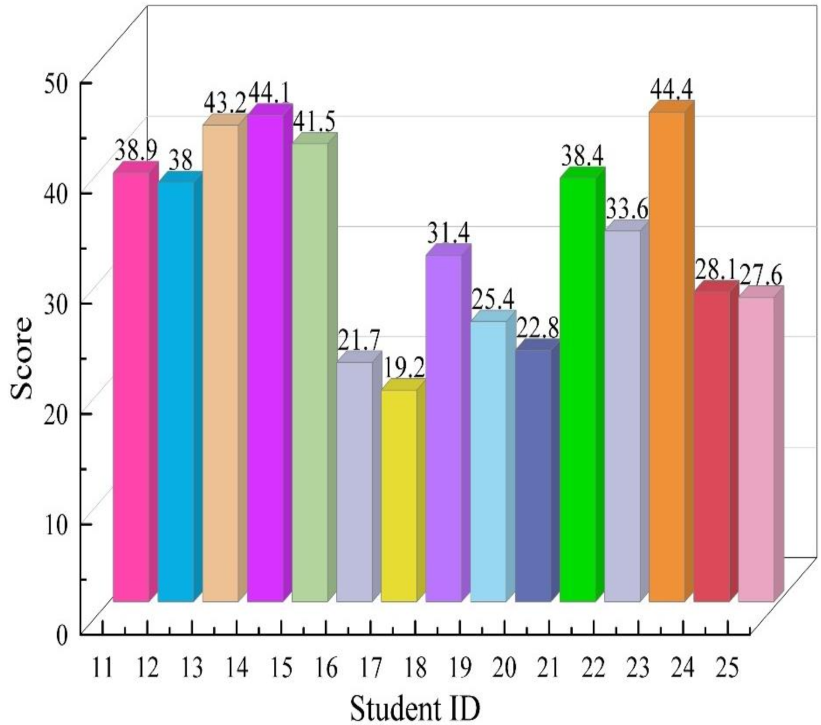

Figure 5 Learning attitude rating results

Analysis of learning effect evaluation

The numerical calculation of the learning effect is also based on the PSK-means algorithm of the learning evaluation function of the teaching platform, and the numerical calculation of the learning effect is based on 17 assignments of students numbered 11-25 in 202218-20200521.

When setting the evaluation index n, 17 assignments with 107 questions were used as the evaluation index. The learning effect scores of 15 students numbered 11-25 are shown in Figure 6.

From the results of the assessment comparing the actual scores of the students, it can be seen that students No. 13, 14, 15 and 23 learn well. While student number 17 has the worst learning effect, this data can correctly reflect the learning effect of students.

The teaching platform based on PSK-means algorithm can carry out knowledge assessment statistics according to different knowledge points, thus reflecting the strength of students' ability in each knowledge point. For teachers, it is convenient for them to grasp students' mastery in each knowledge point so that they can make timely teaching adjustments.

For students, they can know their weak points of knowledge control through data query, so that they can study and correct themselves in time. On the teaching platform, the statistical results can be used as the data base for the personalized push module.

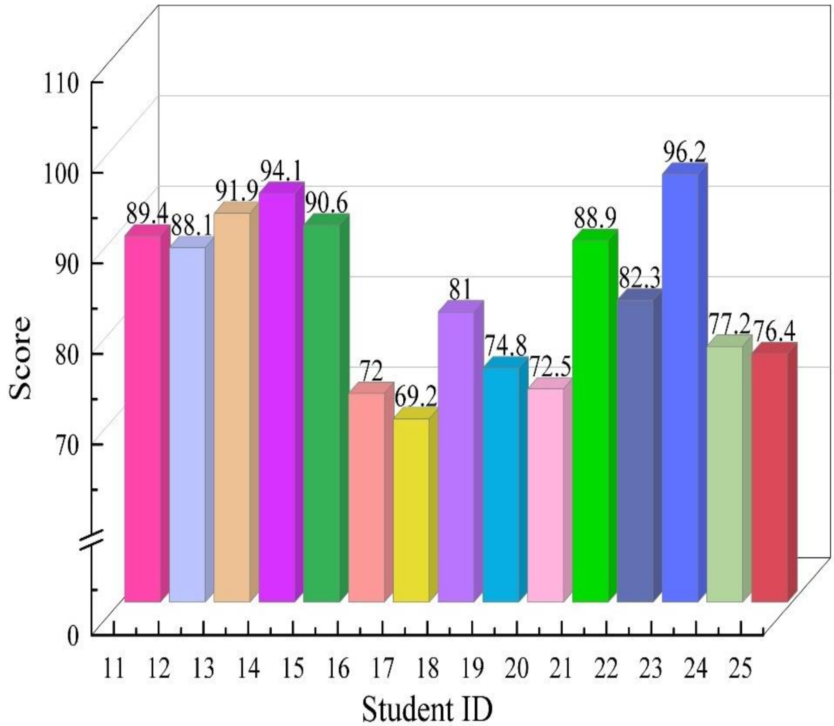

Figure 6 Learning Effect Evaluation Results

Conclusion

In this paper, we construct a professional practice teaching system of urban underground space engineering as the basis of practice teaching platform, and propose a K-means clustering algorithm based on the synergy of particle swarm and simulated annealing - PSK-means algorithm applied to the platform teaching evaluation.

In the evaluation of students' learning attitudes, among them, students 13, 14, 15 and 23 scored more than 40 points, and only student 17 scored less than 20 points. From the evaluation of learning effectiveness, the same four students No. 13, 14, 15 and 23 scored more than 90 points, while only No. 17 scored less than 70 points. The results processed by the teaching evaluation function of the teaching platform can show that the learning attitude affects the learning effect to a certain extent.

Therefore, teaching under the professional practice teaching system of urban underground space engineering can classify students or teachers with the help of the teaching evaluation function of the platform, and then instruct or put forward improvement suggestions according to the class, which can better guide the teaching work and improve the teaching quality.

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References

Attard, G., Winiarski, T., Rossier, Y., & Eisenlohr, L. (2015). *Urban underground space management: an approach by indicators for groundwater protection*. Paper presented at the Engineering Geology for Society and Territory-Volume 3: River Basins, Reservoir Sedimentation and Water Resources.

Broere, W. (2016). Urban underground space: Solving the problems of today's cities. *Tunnelling and Underground Space Technology, 55*, 245-248.

C, Y. (2015). Cultivation mechanism of innovative talents of urban underground space engineering specialty. *Journal of Architectural Education in Institutions of Higher Learning*.

Chen J , G. Y. (2015). Research and practice of curriculum system construction for urban underground space engineering specialty. *Journal of Architectural Education in Institutions of Higher Learning*.

Chunguang L I , Z. Z., Guicheng H E , et al. (2016). Practicum mode based STC in urban underground space engineering. *Journal of Architectural Education in Institutions of Higher Learning*.

Hong-Lue Q U , Z. J. W., Zhu D P , et al. (2016). Education Reform Exploration on the Construction Course for the Major of City Underground Space Engineering. *Journal of Hubei Correspondence University*.

Junlan, Z. (2021). *Practice and Teaching Reform of Engineering Geology for Urban Underground Space Engineering1*. Paper presented at the IOP Conference Series: Earth and Environmental Science.

Liu, J., & Liao, Y. (2017). *Research and Application of Indexes System of Comprehensive Benefit of Large Urban Underground Space Development*. Paper presented at the Proceedings of the 20th International Symposium on Advancement of Construction Management and Real Estate.

Lu, Z., Wu, L., Zhuang, X., & Rabczuk, T. (2016). Quantitative assessment of engineering geological suitability for multilayer Urban Underground Space. *Tunnelling and Underground Space Technology, 59*, 65-76.

Ma, Y., Chen, N., & Lv, H. (2022). Back propagation mathematical model for stock price prediction. *Applied Mathematics and Nonlinear Sciences, 7*(1), 165-174.

Sterling, R., Admiraal, H., Bobylev, N., Parker, H., Godard, J.-P., Vähäaho, I., . . . Hanamura, T. (2012). Sustainability issues for underground space in urban areas. *Proceedings of the Institution of Civil Engineers-Urban Design and Planning, 165*(4), 241-254.

Volchko, Y., Norrman, J., Ericsson, L. O., Nilsson, K. L., Markstedt, A., Öberg, M., . . . Tengborg, P. (2020). Subsurface planning: Towards a common understanding of the subsurface as a multifunctional resource. *Land Use Policy, 90*, 104316.

Xia, H., Lin, C., Liu, X., & Liu, Z. (2022). Urban underground space capacity demand forecasting based on sustainable concept: A review. *Energy and Buildings, 255*, 111656.

Xiong J , W. Z., Liu S , et al. (2015). Reform and exploration on engineering survey teaching of urban underground space engineering specialty. *Journal of Architectural Education in Institutions of Higher Learning*.

Yang X U , S. P., Sun X. (2019). Innovation and Practice of Graduation Design in Urban Underground Space Engineering Specialty of Applied Undergraduate University. *Education Teaching Forum*.

Yuan H E , Z. L., Shi-Xiong X U. (2017). SEVERAL PROBLEMS AND COUNTERMEASURES AGAINST URBAN UNDERGROUND SPACE ENGINEERING MANAGEMENT. *Architecture Technology*.

Zaini, F., Hussin, K., Jamalludin, N. A., & Zakaria, S. R. A. (2015). The principle of depth for underground land development: A review. *Jurnal Teknologi, 75*(10), 71-78.

Zargarian, R., Hunt, D. V., Braithwaite, P., Bobylev, N., & Rogers, C. D. (2016). *A new sustainability framework for urban underground space*. Paper presented at the Proceedings of the Institution of Civil Engineers-Engineering Sustainability.