Classification of underground engineering surrounding rock based on Gaussian cloud model

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Abstract. Based on the Gaussian cloud model, an integrative evaluation method for the stability classification of surrounding rock was presented. Selecting five factors, i.e. rock quality designation, uniaxial compressive strengthen, integrality coefficient, strengthen coefficient of structural plane and seepage measurement of groundwater to be the evaluation indicators. According to the Gaussian cloud model and the information entropy theory, the data were normalized and the comprehensive certainty was calculated, then a Gaussian cloud model was obtained to classify the stability classification of surrounding rock. 14 samples of the first stage project in Guangzhou pump accumulator electricity station and 16 samples produced by the interpolation method were taken as the training samples. 12 samples of the second stage project were selected to verify the model. Compared with the artificial neural network (ANN) method and support vector machine (SVM) method, the results show the gauss cloud method has excellent performance and high prediction accuracy, and the method is of practical value, can be applied to evaluate the stability of surrounding rock in underground engineering.

1. Introduction

With the development of society and the acceleration of economic construction, the utilization of space is becoming more and more diversified and stereoscopic. The development and utilization of underground space has been paid more and more attention, and the underground space engineering disasters are also increasing. Therefore, how to evaluate the stability of underground cavern objectively and scientifically is particularly important [1]. The stability of underground space engineering includes many kinds, and the stability analysis of surrounding rock is one of the most important. At present, there are many methods for engineering surrounding rock stability classification at home and abroad. The traditional evaluation methods include RQD method, RMR method, Q classification method and so on [2], these traditional evaluation methods are simple and fast, but it is difficult to make an accurate classification of surrounding rock stability due to less factors considered. With the deepening of research, some new theories are applied to the stability evaluation of surrounding rock.

Wang Mingwu et al. [3] discussed the multi-dimensional connection cloud evaluation model of cavern rock mass quality based on entropy weight; Sheng Jiliang [4] established the fuzzy comprehensive evaluation model of surrounding rock stability classification, and applied it to engineering practice; Gong Fengqiang et al. [5] comprehensively applied catastrophe theory and fuzzy
mathematics theory to establish the surrounding rock stability. Hu Jianhua et al. [6] established the engineering rock mass quality classification model based on RS-TOPSIS method by integrating rough set theory and approximate ideal solution sorting method; the introduction of artificial neural network into the evaluation of surrounding rock stability is based on its strong ability to deal with nonlinearity. This method has strong systematic characteristics, Cai Guangkui [7] established the BP neural network model of surrounding rock classification based on the principle of artificial neural network method; Sun Lianying [8] established the spatial intelligence model of rock mass stability; Yuan Ying et al. [9] applied the support vector machine method to the evaluation of engineering surrounding rock, and achieved good results. It can be found that the previous methods rarely consider the influence of fuzziness and randomness in the process of surrounding rock stability classification on the evaluation results at the same time. Therefore, it is necessary and urgent to introduce a new evaluation method to study the stability classification of surrounding rock of underground engineering.

Cloud theory is an intelligent evaluation method developed on the basis of uncertain artificial intelligence theory [10], which can comprehensively consider the fuzziness and randomness of concepts in the evaluation process. Yang Shuai et al. [11] proposed a new Gaussian Gaussian cloud model is proposed to optimize the computation. Therefore, this paper applies the cloud theory to the evaluation of surrounding rock stability, uses the entropy weight method to determine the weight of each index, and then establishes the Gaussian cloud model of surrounding rock stability evaluation, and verifies the feasibility and effectiveness of the model through engineering examples, so as to provide a new idea for the evaluation of surrounding rock stability of underground engineering.

2. Gaussian cloud method for stability classification of surrounding rock

2.1. Cloud theory

Cloud model is a mathematical model proposed by Academician Li Deyi [10] on the basis of in-depth study and analysis of stochastic theory and fuzzy mathematics to deal with the qualitative and quantitative transformation of uncertain knowledge. The model has been successfully applied to the fields of energy evaluation, long-term and short-term variable prediction, image processing and geotechnical engineering.

(1) Cloud model concept

Let Z be a quantitative set expressed by exact value, Z={x}, which is called universe. For any element x in Z, there exists a random number with stable tendency μ(x) ∈ [0,1], it is called the degree of certainty of x to Z, and the distribution of the degree of certainty on Z is called cloud [12].

The three digital features of cloud are expected $E_x$, entropy $E_n$ and hyper entropy $H_e$. The expected $E_x$ represents the central value of the concept in the universe space; the entropy $E_n$ represents the value range of cloud droplets that can be accepted by qualitative concepts in the universe space; the super entropy $H_e$ is the entropy of the entropy $E_n$, which reflects the dispersion degree of cloud droplets. Li Deyi et al. [13] have proved that the elements in $[Ex-3En, Ex+3En]$ interval exceed 99.73%, which is called "3 $E_n$ principle". According to the concept of cloud model and "3 $E_n$ principle", the cloud digital characteristics of surrounding rock stability classification index can be calculated according to Formula (1) ~ Formula (3):

$$E_x = \frac{C_{max} + C_{min}}{2}$$ (1)

$$E_n = \frac{C_{max} - C_{min}}{6}$$ (2)

$$H_e = K$$ (3)

Where $C_{max}$ and $C_{min}$ are the maximum and minimum boundary values of the corresponding grade standard respectively; $k$ is a constant, which can be adjusted according to the fuzzy threshold of the variable, and 0.01 is taken in this paper. For variables with unilateral boundaries, such as $(-\infty, C_{max}]$, the default boundary parameters can be determined according to the upper and lower limits of the variables, and then the numerical characteristics of the cloud model can be calculated according to Formula (1) ~ Formula (3) [14].
If the cloud distribution satisfies: \( x \sim N(E_x, E_n^2) \), where \( E_n' \sim N(E_n, H_e^2) \), and the uncertainty of \( C \) satisfies:

\[
\mu(x_j) = e^{-\frac{(x_j-E_n')^2}{2E_n'^2}}
\]

(4)

The distribution on the universe \( U \) is called Gaussian cloud [15]. Academician Li Deyi [10] has demonstrated the universality of Gaussian cloud model by analyzing the universality of Gaussian distribution and bell shaped membership function in detail. Therefore, this paper uses Gaussian cloud model to study the stability classification of surrounding rock of underground engineering.

2) X-conditional forward cloud generator

Cloud generator [16] is the key to the application of cloud model in practice. It includes forward cloud generator, reverse cloud generator and condition cloud generator (X condition cloud generator, Y condition cloud generator). Among them, the X-condition forward cloud generator [17] generates the cloud drop \((x, \mu(x))\) satisfying the condition through the given three cloud model digital features \((E_x, E_n, H_e)\) and specific X value. For the same input value \(X\), the X-condition forward cloud generator has the characteristics of slight change of certainty, which can reflect people's different views on the same data belonging to a certain concept degree, and make the combination of fuzziness and randomness better. Due to the fuzziness and randomness of surrounding rock stability classification, and belongs to qualitative to quantitative transformation, this paper uses X-condition forward cloud generator for surrounding rock stability classification. The algorithm is as follows:

Step 1: determine three digital features \((E_x, E_n, H_e)\) and specific data \(x\) of Gaussian cloud model;

Step 2: generate a model with \(E_n\) as expectation and \(H_e\) as variance normal random number \(E_n' = \text{NORM}(E_n, H_e)\), and then calculate its expected value \(\mu(x) = \exp[-(x - E_x)^2/2(E_n')^2]\). Then a cloud drop \((x, \mu(x))\) is produced;

Step 3: Iterate until N cloud droplets are generated.

2.2. Selection of surrounding rock stability evaluation index

There are many factors affecting the stability of surrounding rock. According to the current domestic specifications, combined with the existing research results and Literature [5-7, 18] the rock quality index \(R_{QD}\), uniaxial saturated compressive strength \(R_w\), integrity coefficient \(K_v\), structural plane strength coefficient \(K_f\) and groundwater seepage quantity \(\omega\) are selected as the indexes of surrounding rock stability classification. According to the previous research results, combined with the characteristics of cloud discriminant model, the surrounding rock of underground engineering is divided into five levels, namely: Level I (stable), level II (relatively stable), level III (basically stable), level IV (unstable), level V (extremely unstable), and the corresponding relationship between the surrounding rock stability grade and each evaluation index is established, as shown in Table 1.

| Category | \(R_{QD}/\%\) | \(R_w/\text{MPa}\) | \(K_v\) | \(K_f\) | \(\omega/\text{[L·(min·10 m)\(^{-1}\)]}\) |
|----------|----------------|-------------------|--------|--------|-----------------|
| I        | 90~100         | 120~200           | 0.75~1 | 0.8~1  | 0~5             |
| II       | 75~90          | 60~120            | 0.45~0.75 | 0.6~0.8 | 5~10            |
| III      | 50~75          | 30~60             | 0.3~0.45 | 0.4~0.6 | 10~25           |
| IV       | 25~50          | 15~30             | 0.2~0.3  | 0.2~0.4 | 25~125          |
| V        | 0~25           | 0~15              | 0~0.2   | 0~0.2  | 125~300         |

2.3. Determination of index weight based on entropy weight method

Weight calculation methods can be divided into two categories: subjective method and objective methods. Subjective method is greatly influenced by human factors, so it has a great influence on the weight and the result of discrimination. Objective evaluation method can eliminate the influence of human factors. In this paper, entropy weight method [19] is selected as the method to calculate the
weight of evaluation index. The calculation steps are as follows: ① construct the original evaluation index data matrix \( X=(x_{ij})_{m \times n} \) according to the evaluation object and evaluation index; ② normalize the matrix \( X \); ③ calculate the entropy value \( E_j \) and deviation degree \( d_j \) of each index; ④ calculate the weight according to the deviation degree of each index.

Use the method of deviation standardization to normalize the original data, the formula is as follows:

(The bigger the better)

\[
y_{ij} = \max_j(x_{ij}) - x_{ij} \]

(The smaller the better)

\[
y_{ij} = \frac{x_{ij} - \min_j(x_{ij})}{\max_j(x_{ij}) - \min_j(x_{ij})}
\]

The calculation formulas of entropy value, deviation degree and entropy weight of each evaluation index are shown in Formula (7) ~ Formula (9).

\[
E_j = - \ln(m)^{-1} \sum_{i=1}^{m} P_{ij} \ln P_{ij}
\]

\[
d_j = 1 - E_j
\]

\[
w_j = d_j / (n - \sum E_j)
\]

Where \( m \) is the number of evaluation objects, \( n \) is the number of evaluation indexes in each evaluation object, \( P_{ij} = y_{ij} / \sum_{i=1}^{m} y_{ij} \), if \( P_{ij} = 0 \), then define \( \ln P_{ij} = 0 \).

2.4. Calculation of comprehensive certainty

According to the X-condition forward cloud generator algorithm, the evaluation index data \( x \) belongs to the stability classification level of certainty degree of a surrounding rock. Combined with the index weight obtained by entropy weight method, the comprehensive certainty degree \( U \) is calculated according to Formulas (4) ~ (9).

\[
U = \sum_{i=1}^{m} \mu(x)w_j
\]

Where, \( \mu(x) \) is the uncertainty of each index and \( w_j \) is the weight of the evaluation index.

2.5. Classification process

The basic process of the stability classification model of surrounding rock of underground engineering based on Gaussian cloud theory is shown in Figure 1.
3. Establishment and test of cloud model for surrounding rock stability classification

3.1. Modeling
Based on the theory of Gaussian cloud model and Formulas (2) ~ (4), the cloud model parameters $E_n$, $E_o$ and $H_e$ are determined, use the calculation flow in Figure 1, and the corresponding cloud models are established for the five indexes of rock quality index, rock uniaxial saturated compressive strength, integrity coefficient, structural plane strength coefficient and underground water quantity, as shown in Figure 2. The abscissa in the figure represents the values of each classification index, and the ordinate represents the corresponding uncertainty. In Figure 2(a), 2(b), 2(c) and 2(d), from left to right, the clouds corresponding to stability classification indexes level I-V are respectively represented, and in Figure 2(e), from left to right, the clouds corresponding to stability classification indexes level V-I are respectively represented.

![Clouds for each evaluation factor](image)

**Figure 2.** Cloud for each evaluation factor.

3.2. Model checking
In order to test the feasibility and effectiveness of the application of Gaussian cloud model in the classification of surrounding rock stability, the underground engineering of Guangzhou Pumped Storage Power Station is taken as an engineering example [7] to study the classification of surrounding
rock stability. Guangzhou Pumped Storage Power Station is mainly composed of upper reservoir, lower reservoir, underground powerhouse and underground passages. It is built in two phases. The lithology of the surrounding rock of the cavern in the project area is mainly slightly weathered granite; the geostress is mainly gravity stress, and the geostress of each part of the surrounding rock of the project has little difference; and the underground water is exposed between the fracture zones of the cavern. The first 14 groups of data in Table 2 are the measured parameters of phase 1 project. Considering the completeness and uniformity of samples, the last 16 groups of data are constructed by interpolation method.

| Sample | \(R_{QD}/\%\) | \(R_w/\text{MPa}\) | \(K_v\) | \(K_t\) | \(\omega/[\text{L} \cdot (\text{min} \cdot 10 \text{ m})^{-1}]\) | Actual level |
|--------|----------------|-----------------|-------|-------|----------------|--------------|
| 1      | 71.8           | 90.1            | 0.57  | 0.45  | 0              | II           |
| 2      | 51             | 40.2            | 0.38  | 0.55  | 10.5           | III          |
| 3      | 52             | 25              | 0.22  | 0.52  | 12             | III-IV       |
| 4      | 68             | 90              | 0.38  | 0.38  | 21             | III          |
| 5      | 28             | 40              | 0.32  | 0.3   | 18.5           | III-IV       |
| 6      | 51             | 45              | 0.15  | 0.3   | 5              | III          |
| 7      | 76             | 95              | 0.7   | 0.55  | 12             | II           |
| 8      | 87             | 95              | 0.7   | 0.5   | 9.8            | II           |
| 9      | 76             | 90              | 0.57  | 0.5   | 11             | II-III       |
| 10     | 50             | 35              | 0.3   | 0.35  | 20             | III-IV       |
| 11     | 68             | 90              | 0.57  | 0.35  | 18.5           | II-III       |
| 12     | 82             | 95              | 0.7   | 0.35  | 0              | II           |
| 13     | 75             | 87.3            | 0.3   | 0.63  | 0              | II           |
| 14     | 30.2           | 8.4             | 0.18  | 0.18  | 50             | V            |
| 15     | 100            | 200             | 1     | 1     | 0              | I            |
| 16     | 97.5           | 180             | 0.94  | 0.95  | 1.3            | I            |
| 17     | 95             | 160             | 0.88  | 0.95  | 2.5            | I            |
| 18     | 92.5           | 140             | 0.81  | 0.85  | 3.8            | I            |
| 19     | 86.3           | 105             | 0.68  | 0.75  | 6.3            | II           |
| 20     | 82.5           | 90              | 0.6   | 0.7   | 7.5            | II           |
| 21     | 78.8           | 75              | 0.53  | 0.65  | 8.8            | II           |
| 22     | 68.8           | 52.5            | 0.41  | 0.55  | 13.8           | III          |
| 23     | 62.5           | 45              | 0.38  | 0.5   | 17.5           | III          |
| 24     | 56.3           | 37.5            | 0.34  | 0.45  | 21.3           | III          |
| 25     | 43.8           | 26.3            | 0.28  | 0.35  | 50.6           | IV           |
| 26     | 37.5           | 22.5            | 0.25  | 0.3   | 75             | IV           |
| 27     | 31.3           | 18.8            | 0.23  | 0.25  | 100            | IV           |
| 28     | 18.8           | 11.3            | 0.15  | 0.15  | 169            | V            |
| 29     | 12.5           | 7.5             | 0.1   | 0.1   | 213            | V            |
| 30     | 6.3            | 0.8             | 0.05  | 0.05  | 256            | V            |

Entropy weight method is used to calculate the weight of each evaluation index. When normalizing the data, the smaller the groundwater seepage \(\omega\), the better, Formula (6) is used to normalize the smaller the groundwater seepage, and Formula (5) is used to normalize the other four factors. The entropy value, deviation degree and entropy weight of each evaluation index are shown in Table 3.

Take sample 1 as an example to illustrate the calculation process of each sample's uncertainty. Firstly, according to the five evaluation index data of cloud model and sample, the uncertainty of each index value belonging to each stability level is generated, as shown in Table 4.
### Table 3. The entropy coefficients of evaluation indexes.

| Index          | $R_{QD}$ | $R_w$ | $K_v$ | $K_f$ | $\omega$ |
|----------------|----------|-------|-------|-------|----------|
| Entropy        | 0.9595   | 0.9176| 0.9368| 0.9481| 0.9806   |
| Deviation degree | 0.0405 | 0.0824| 0.0632| 0.0519| 0.0194   |
| Entropy weight  | 0.1575   | 0.3202| 0.2455| 0.2015| 0.0753   |

### Table 4. Membership of evaluation indexes of sample 1.

| Index | $R_{QD}$ | $R_w$ | $K_v$ | $K_f$ | $\omega$ |
|-------|----------|-------|-------|-------|----------|
| $\mu(I)$ | 0       | 0.1208| 0.0247| 0     | 0.5023   |
| $\mu(II)$ | 0.2439 | 1     | 0.9732| 0.0176| 0.002    |
| $\mu(III)$ | 0.6405 | 0.002 | 0.0265| 0.837 | 0.0238   |
| $\mu(IV)$ | 0.0053 | 0     | 0     | 0.2103| 0.2108   |
| $\mu(V)$ | 0       | 0     | 0     | 0.0007| 0.0258   |

### Table 5. Evaluated results of stability of surrounding rock.

| Sample | Comprehensive certainty | Paper result | Actual level |
|--------|-------------------------|--------------|--------------|
|        | $U(I)$ | $U(II)$ | $U(III)$ | $U(IV)$ | $U(V)$ |        |        |
| 1      | 0.0824 | 0.6016 | 0.2847 | 0.0589 | 0.0021 | II | II |
| 2      | 0.0009 | 0.1758 | 0.8404 | 0.1164 | 0.0046 | III | III |
| 3      | 0.0002 | 0.0473 | 0.4613 | 0.5927 | 0.1001 | III-IV | III-IV |
| 4      | 0.0385 | 0.39   | 0.5214 | 0.175  | 0.0069 | II-III | III |
| 5      | 0.0006 | 0.0713 | 0.5632 | 0.4327 | 0.0814 | III-IV | III-IV |
| 6      | 0.0387 | 0.1059 | 0.4399 | 0.3259 | 0.2215 | III-IV | III |
| 7      | 0.1203 | 0.64   | 0.2903 | 0.0287 | 0.0029 | II | II |
| 8      | 0.1467 | 0.6751 | 0.2485 | 0.0368 | 0.0027 | II | II |
| 9      | 0.0445 | 0.6864 | 0.3235 | 0.0382 | 0.0028 | II | II-III |
| 10     | 0.0004 | 0.0492 | 0.5619 | 0.472  | 0.0246 | III-IV | III-IV |
| 11     | 0.0445 | 0.5713 | 0.2618 | 0.2014 | 0.0071 | II | II-III |
| 12     | 0.139  | 0.6544 | 0.0728 | 0.1835 | 0.0052 | II | II |
| 13     | 0.0721 | 0.5571 | 0.2795 | 0.159  | 0.0188 | II | II |
| 14     | 0      | 0.0036 | 0.0141 | 0.3782 | 0.6479 | V | V |
| 15     | 0.5033 | 0.0071 | 0.0020 | 0.0158 | 0.0019 | I | I |
| 16     | 0.8398 | 0.0239 | 0.0037 | 0.0167 | 0.002  | I | I |
| 17     | 0.9967 | 0.064  | 0.0062 | 0.0175 | 0.0021 | I | I |
| 18     | 0.838  | 0.2175 | 0.0105 | 0.0184 | 0.0022 | I | I |
| 19     | 0.2148 | 0.8363 | 0.0325 | 0.0203 | 0.0024 | II | II |
| 20     | 0.0706 | 1      | 0.0659 | 0.0213 | 0.0025 | II | II |
| 21     | 0.0209 | 0.8448 | 0.1639 | 0.0225 | 0.0026 | II | II |
| 22     | 0.0023 | 0.2528 | 0.8482 | 0.0358 | 0.0037 | III | III |
| 23     | 0.0011 | 0.1409 | 0.9993 | 0.0657 | 0.0052 | III | III |
| 24     | 0.0005 | 0.0757 | 0.8490 | 0.1794 | 0.01  | III | III |
| 25     | 0.0001 | 0.0266 | 0.2196 | 0.8326 | 0.0464 | IV | IV |
| 26     | 1E-04  | 0.0169 | 0.1427 | 1      | 0.1111 | IV | IV |
| 27     | 6E-05  | 0.0111 | 0.0756 | 0.8595 | 0.2433 | IV | IV |
| 28     | 3E-05  | 0.0035 | 0.0125 | 0.1868 | 0.8377 | V | V |
| 29     | 0      | 0.0019 | 0.0047 | 0.0489 | 1      | V | V |
| 30     | 0      | 0.0008 | 0.0008 | 0.0071 | 0.7553 | V | V |
Then the entropy weights of each evaluation index in Formula (10) and Table 3 are used to calculate the comprehensive degree of certainty 

\[ U = [0.082, 0.6016, 0.285, 0.059, 0.002] \]

\[ U_2 > U_3 > U_1 > U_4 > U_5 \]

indicates that the surrounding rock stability level of sample 1 belongs to class II (relatively stable) with the greatest degree of certainty, and it is possible to belong to class III (basically stable), while it is less likely to belong to class I, class IV and class v. Finally, according to the maximum comprehensive certainty value, the surrounding rock stability level of sample 1 is class II.

According to the above process, the surrounding rock stability judgment results of 30 groups of engineering data are obtained and compared with the actual stability level of surrounding rock, as shown in Table 5. The analysis shows that the classification results of the model are basically consistent with the actual level, which indicates that the Gaussian cloud model is feasible for surrounding rock stability classification. At the same time, the application of cloud model can transform the qualitative concept of surrounding rock stability into the quantitative value of certainty, which can reflect the fuzziness and uncertainty of surrounding rock stability and has certain advantages. The results are convenient for engineering application and have certain application significance in practical engineering.

4. Engineering application

The established Gaussian cloud model is applied to classify the surrounding rock of some tunnel sections of Guangzhou Pumped Storage Power Station Phase 2 project, and the results are compared with those of BP neural network method [7] and support vector machine method [9]. The results are shown in Table 6.

| Footage | Weathering alteration situation | \( R_{\text{QD}}/\% \) | \( R_{\text{w}}/\text{M Pa} \) | \( K_r \) | \( K_i \) | \( \omega/\left([\text{L}^{-1}\text{(min·10 m)}^{-1}]\right) \) | Paper result | BP | SVM |
|---------|---------------------------------|----------------|-----------------|-----|-----|-----------------|-------------|-----|-----|
| 0+000~0+067 | Moderately and weakly weathered fault alteration zone | 26 | 36 | 0.22 | 0.35 | 5 | IV | IV | IV |
| 0+067~0+130 | Weak weathering | 52 | 25 | 0.2 | 0.5 | 5 | III-IV | III | III |
| 0+130~0+198 | Breeze | 75 | 95 | 0.7 | 0.5 | 0 | II | II | II |
| 0+198~0+297 | Fault alteration zone | 50 | 70 | 0.5 | 0.25 | 5 | II | III-II | III |
| 0+297~0+406 | Breeze | 85.5 | 94 | 0.65 | 0.55 | 0 | II | II | II |
| 0+406~0+426 | Fault alteration zone | 35 | 70.5 | 0.35 | 0.3 | 10 | IV | IV | III |
| 0+426~0+560 | Breeze | 85 | 93 | 0.6 | 0.5 | 0 | II | II | II |

The results show that the classification results of surrounding rock stability of Guangzhou Pumped Storage Power Station Phase 2 project based on Gaussian cloud model are consistent with those of BP neural network method, among the 12 groups of data, 10 groups are consistent, and 2 groups are close to each other; while in the results of support vector machine (SVM), 10 groups are consistent, one group is close, and one group is different. Therefore, the classification method of surrounding rock...
stability based on Gaussian cloud model has certain advantages over support vector machine (SVM), and has certain application significance in practical engineering.

5. Conclusions
(1) The rock quality index $R_QD$, rock uniaxial saturated compressive strength $R_w$, integrity coefficient $K_v$, structural plane strength coefficient $K_f$ and groundwater seepage quantity $\omega$ are selected to establish the classification index system of surrounding rock stability of underground engineering. The entropy weight method is used to mine and process 30 groups of measured data of surrounding rock of Guangzhou Pumped storage power station phase 1 project, and the weights of 5 indexes affecting the surrounding rock stability of underground engineering are obtained Heavy.
(2) Based on the Gauss cloud theory of uncertainty, the classification Gauss cloud model of underground engineering surrounding rock stability is established. Through the back inspection of 30 groups of Guangzhou Pumped Storage Power Station Phase 1 project samples, the results are basically consistent with the actual level of surrounding rock stability, which proves the accuracy and reliability of the evaluation model.
(3) The Gauss cloud model of surrounding rock stability classification is used to classify the surrounding rock stability of Guangzhou Pumped Storage Power Station Phase 2 project, and the results are consistent with BP neural network The classification results of neural network method and support vector machine method are consistent, which shows that the classification method of surrounding rock stability based on Gaussian cloud model has a certain practical value, and provides a feasible quantitative method for the classification of surrounding rock stability.

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