Research Article

Application of an Improved Cloud Model and Distance Discrimination to Evaluate Slope Stability

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With the rapid development of China's economy, the construction of infrastructure has continuously improved. In the past few years, the construction of water conservancy projects has been constantly developing, and related geological disasters have become increasingly prominent. The stability of water conservancy slopes is related to whether water conservancy projects can be safely constructed and built to function safely and effectively, which has become a topic of increasing concern for geologists and related researchers. This paper selects the Jinping I Hydropower Station in Sichuan, China, for analysis. Four categories of evaluation factors (geological, engineering, environmental, and monitoring) and 24 subfactors (17 quantitative indicators and 7 qualitative indicators) are selected to ascertain the risk of the slope more accurately. By investigating the deficiencies of the traditional cloud model, the related concepts and computational models of a finite-area cloud model are proposed. By obtaining the characteristic parameters, the degrees of membership of the measurement samples belonging to different risk levels are further obtained. The weights of the indicators determined by the cloud processor and the weighted distance discriminant method are used to determine the final weights and achieve a final classification of the slope stability level. The research results demonstrate that the weighted distance discriminant algorithm combined with the improved finite-interval cloud model can consider the comprehensive information of each evaluation index and the degrees of mutual influence between the indicators, making the evaluation results more objective. Moreover, the proposed approach can quickly and accurately classify slope stability and deliver a prediction of the safety, thereby providing new ideas for evaluating the stability of slopes.

1. Introduction

The coincident improvements and construction of infrastructure and human engineering activities have greatly affected the geological environment, resulting in frequent slope failure disasters [1, 2]. In recent years, the scale of facilities such as roads, dams, railways, and underground tunnels has become increasingly broad. Hydropower stations are major projects for the benefit of the people, and their safety is also related to the personal and property safety of the surrounding people. However, dam abutments have complex geological structures, and the abutment dam slope is an important factor in resisting external forces to bear the load transmitted from a dam. Consequently, the slope stability has become an important factor of the construction process, and the control of the slope stability also affects the key to the success of the project [3, 4]. The instability mode of the slope has also recently received an increasing amount of attention.

The slope stability constitutes a systematic uncertainty that affects and threatens the safety of both human life and property. Slope stability analysis has become a key task in mining and geotechnical engineering [5]. Due to the randomness and complexity of the geological structure of a dam slope, it is very different from a soil slope. Therefore, geologists and related researchers in the fields of design and research are investigating slope stability in engineering construction projects with increasingly greater interest [6].

The main research object of initial landslide stability analyses was the soil; such analyses were based mainly on material mechanics, homogeneous elasticity, and elasto-plastic theory. Subsequently, scholars focused on evaluation methods applicable to the stability of not only soil slopes but also rock slopes [7]. Accordingly, analyses and investigations of the factors affecting slope stability were performed, and the stability and types of slopes were classified.

Three research methods are commonly employed to evaluate slope stability: the qualitative analysis method, the quantitative analysis method, and the uncertainty analysis method [8].

(a) *Qualitative Analysis Method.* Qualitative analysis is utilized mainly to conduct on-the-spot investigations and field investigations of the actual engineering geology and subsequently to determine the factors affecting slope stability. Through an analysis of the mechanical mechanisms of the instability and the failure mode, the evolution of both the slope body and the damage can be understood. Through qualitative analysis, it is possible to understand whether a slope is safe and the possible evolutionary characteristics of the slope. In addition, it is possible to comprehensively consider the factors that influence the slope stability. Examples of qualitative evaluations include analyses of the geological history, the engineering analogy method, and the graphical method, in addition to slope stability analysis databases and expert systems [9–11].

(b) *Quantitative Analysis Method.* Quantitative analysis is based on the mechanical properties of the slope body in consideration of various loads on the slope body, after which an appropriate mechanical model is selected for the analysis. Then, the appropriate parameters are used to quantitatively calculate slope stability. Finally, the calculation results are obtained by numerical simulation. Specific quantitative methods include the limit equilibrium method and numerical simulation method. The limit equilibrium method is relatively mature, and it is simple to meet the requirements of engineering applications using this approach. In contrast, due to the realization of geotechnical constitutive relationships, the numerical simulation method [12–14] is not sufficiently mature, which limits the reliability of its calculation results. Therefore, further research is needed.

(c) *Uncertainty Analysis Method.* Uncertainty is the main characteristic of most engineering problems, such as hydropower stations, and uncertainty is the characteristic of the evaluation method and the most prominent feature [15]. The use of measured natural data for slope stability evaluation is indeed full of uncertainty. The basic characteristics of uncertainty are the randomness and ambiguity discussed in probability theory and fuzzy mathematics, respectively. Slope rock and soil is an extremely complex geological medium, and its long-term geological action makes it one of the most complex materials in nature. Because its mechanical characteristic parameters, structural surface distribution law, and engineering geology are all complex and variable, the uncertainty of its evaluation mainly comes from the following three aspects: (1) the inherent heterogeneity of the rock and soil itself, (2) errors introduced by engineering parameter measurement and sampling, and (3) uncertainty caused by inaccurate models. Based on the characteristics of slope stability evaluation problems, many scholars have proposed many methods to improve their accuracy in the past few decades.

Since the 1990s, with the continuous development and augmentation of slope stability analysis theory, research regarding the evaluation of slope stability has gradually evolved from qualitative to quantitative research and from deterministic to uncertainty research [16, 17]. Since a slope essentially represents an extremely complex and variable system, the factors affecting slope stability are random, fuzzy, and uncertain. Therefore, the slope uncertainty can be effectively treated by an appropriate uncertainty analysis method. Hence, academic experts and scholars have proposed different theories based on this uncertainty to explore slope stability. Examples of uncertainty analysis methods include reliability analysis methods [18], fuzzy theory evaluation methods [19–21], grey system evaluation methods [22], neural network evaluation methods [23, 24], genetic algorithms [25, 26], and the analytic hierarchy process (AHP) [27].

For example, S. Song et al. [28] used the cusp catastrophe model to consider the correlation of an evaluation index through the catastrophe progression method and analysed the internal mechanism of a landslide system. Q. Huang et al. [29] combined matter-element theory with the correlation function and improved the extended slope stability evaluation model. X. Dai et al. [30] and C. Yan [31] constructed the edge of the weighted distance discriminant model for evaluating the slope stability; this method compensates for the shortcomings of the importance of using the magnitude distance method to ignore indicators. In addition, J. Zhang et al. [32] and F. Yan [33] combined the basic concepts of cloud models according to the characteristics of the different stability levels of indicators and proposed a cloud model evaluation method for the stability of a rock slope. Furthermore, J. Zhao et al. [34] proposed a cloud model evaluation model based on the improved entropy weighting method considering comprehensive information regarding actual evaluation indicators. All these theories and models have improved the system for evaluating slope stability to a certain extent; through them, a theoretical basis for the working safety of slopes has been proposed.

However, due to the complexity of the factors affecting the stability of slopes, it is still difficult to overcome the defects inherent in the abovementioned theories. When evaluating actual working conditions, deviations from the actual situation are still evident. For instance, the fuzzy mathematical model of the cusp catastrophe model does not consider the weight of an index; rather, it measures only the relative importance of the index and is thus subjective. Moreover, the extension model still adopts a subjective assignment, and the method of weighting ignores some important constraints during the calculation process. In addition, the coupled neural network algorithm is computationally complex. Meanwhile, the sample obtained using this algorithm is not representative, and the fitting speed is difficult to control. Additionally, the normal cloud model ignores the correlations among the evaluation indicators, and the distribution of indicators is not completely normal.

Based on the existing limitations of the research methods discussed above, this paper cites a finite-area cloud model as an improved cloud model that obeys a uniform distribution in combination with the actual evaluation indicators. The cloud model discussed herein is a conceptual model for addressing fuzzy problems proposed by D. Li et al. [35, 36], who addressed the ambiguity and randomness of data from a membership perspective. This cloud model has been applied to various engineering problems, such as the prediction of rock burst [37, 38], the stability analysis of surrounding rock [39], the quality classification of rock masses, and the evaluation of the spontaneous combustion tendency of ore. This model has also been widely used in military fields and has achieved good results for power grid performance, agricultural production, water quality assessment, and other areas [40–47]. However, the cloud model exhibits deficiencies when addressing unilateral issues. When the traditional cloud model is in a unilateral interval, that is, when it is in the interval of either $[0, C]$ or $[C, \infty]$, the index distribution of the edge is still the same as that of the traditional normal distribution. Thus, the simulation results under this theory often demonstrate a large deviation from the actual situation; therefore, a cloud model with a finite interval is introduced. The weighted distance discriminant algorithm [48, 49], which considers the degree of mutual influence between the levels to enhance the accuracy of the calculation results, is used to calculate the index weights. Finally, the application of this mathematical model to an evaluation of the slope of a hydropower station in China verifies the effectiveness of the proposed slope stability analysis technique [6].

2. Methodology

2.1. Basic Concept of the Cloud. A cloud model can be defined as a fuzzy model transformed by an uncertainty relationship represented by three mathematical descriptive symbols. Cloud theory forms the basis of generating a cloud model [35]. The normal cloud model describes qualitative concepts through parameter symbols of different features. Although the traditional cloud model can describe the uncertainty and randomness between evaluation indicators, it fundamentally assumes that the indicators tend to be normally distributed; in reality, however, the evaluation indicators do not completely obey a normal distribution and are limited. Rather, the interval obeys a near-normal distribution, and thus it is difficult to correctly describe the difference between the characteristics of the simulated object and the actual situation by using the traditional normal cloud model. According to the same principle, an already-determined index x_0 may be adjacent to but not on the actual level at which it is really located. Thus, the original infinite interval is converted into a finite interval, and the modified cloud model is converted into a finite interval.

Let U be a quantitative set of exact numerical representations [35], where $U=\{x\}$ and c are qualitative concepts on U . If there are arbitrary quantitative elements and x has a stable tendency, a random number $\mu(x) \in (0,1)$ is a random implementation of the qualitative concept C among them:

$$\mu : U \longrightarrow [0, 1], \quad \forall x \in U, \quad x \longrightarrow \mu(x) \quad (1)$$

Then, the distribution of x on the set U is called a cloud, and each point $(x, \mu(x))$ is called a cloud drop.

2.2. Digital Features. According to the previous basic concept, the cloud model concept is expressed mainly by three basic digital features, namely, the expectation E_x , the entropy E_n , and the super entropy H_e [37, 50]. The expectation E_x represents the intermediate position of the qualitative concept, which is the central value of the universe. In a geometric sense, the random value corresponding to the highest point of an image determines the position of the cloud droplet distribution. The entropy E_n is characterized in the domain interval. The value range of the cloud droplets expressed by this concept reflects the ambiguity and randomness of the basic concept. The value of E_n also determines the degree of chaos among the cloud droplets. The larger the width of a cloud map is, the larger the value range of the cloud droplets. Accordingly, as the qualitative concept becomes more blurred, the cloud droplets become more discrete, and vice versa. The super entropy H_e , which is the entropy of the entropy, indicates the uncertainty in the entropy. In a cloud image, H_e usually indicates the thickness of the cloud. The larger the super entropy is, the thicker the cloud.

According to the distribution of the risk level, a magnitude interval such as $[C_{\min}^k, \infty]$ or $\text{sum}[0, C_{\max}^k]$ exists, and the index variable at this time no longer obeys the traditional cloud model distribution. Therefore, the edge blur $\mu(x)$ interval should be transformed into a uniform distribution with a certainty degree of 1; this interval is usually described by a half-litre trapezoidal cloud and a half-falling trapezoidal cloud [30]. It is easy to prove that the finite-interval $[\gamma]$ -order normal density function has the same variance and expectation as the infinite-interval $[\gamma]$ -order normal distribution density function, and the following equations used to calculate the corresponding set of cloud characteristic parameters can be obtained:

$$E_x^k = \frac{C_{\max}^k + C_{\min}^k}{2} \quad (2)$$

$$E_n^k = \frac{C_{\max}^k - C_{\min}^k}{2\sqrt{[\gamma] + 3}} \quad (3)$$

$$H_e^k = \lambda E_n^k \quad (4)$$

In the above formulas, C_k is the half-length of the K th level; $C_{\max}^k$ and $C_{\min}^k$ are the upper and lower bounds, respectively, of the rank interval; $[\gamma]$ is the order of the normal density function in the finite interval taking the largest integer of γ ; and λ is an empirical value (taken in this paper to be 0.01) that can be adjusted according to the fuzzy degree of the index variable. Let the indicator limit value belong to the same level as two levels of 0.5. The algorithm of the order of its normal distribution function is recorded as follows [51]:

$$[\gamma] = \frac{\lg 0.5}{\lg \{1 - [2(C^k - E_x^k)/\xi_k]^2\}} \quad (5)$$

In the above formula, ξ_k is the endpoint of the level interval K . When the evaluation indicator type is larger, the indicator value and the level interval increase. Then, the lengths ξ_k^l and ξ_k^r of the left- and right-hand intervals of level K are as follows:

$$\begin{aligned}\xi_k^r &= C_{\max}^{k+1} - E_x^k; \\ \xi_k^l &= E_x^k - C_{\min}^{k-1}\end{aligned}\quad (6)$$

Similarly, the larger the index value is, the smaller the level interval, and the lengths of the left- and right-hand intervals of level K are as follows:

$$\begin{aligned}\xi_k^l &= E_x^k - C_{\min}^{k+1}; \\ \xi_k^r &= C_{\max}^{k-1} - E_x^k\end{aligned}\quad (7)$$

2.3. Cloud Generator. The cloud generator is the key to utilizing the cloud model for purposes ranging from theoretical to practical applications [52]. Usually, the cloud generator includes both a forward cloud generator and a reverse cloud generator. A forward cloud generator CG usually uses cloud characteristic parameters $N(E_x, E_n, H_e)$ to generate cloud droplets $P(x_i, \mu_i)$ ($i=1,2,3,\dots,n$). Usually, this process is a transformation from a qualitative analysis to a quantitative calculation. In contrast, a reverse cloud generator CG^{-1} uses the three cloud characteristic parameters of the cloud drop graph to transform them into qualitative concepts. Therefore, the combination of these two cloud generators can be utilized to generate different types of cloud models using different qualitative concepts and quantitative calculations.

Using the above description, the digital features of the cloud are expressed as $x \sim (E_x, E_n, H_e)$. Combined with the index-level feature, the fitting can be performed by MATLAB programming with the help of the digital features and the number of cloud droplets N to be generated (this article takes $N=5000$). When the indicator is within the interval between the mean cloud values of the two edges, the mathematical conceptual model can be defined as follows: let U be a quantitative set of exact numerical representations, $U=\{x\}$, where C represents qualitative concepts on U . If there is any quantitative element x and if x has a stable tendency, the random number $\mu(x) \in [0, 1]$ is a stochastic implementation of the qualitative concept C . Here, if x satisfies $x \sim (E_x, E_n'^2)$, as follows from set pair theory, the same indicator can belong only to the adjacent level interval, and it cannot belong to the infinite level interval. Therefore, the infinite interval can be converted into a finite interval. Furthermore, the evaluation index x can be transformed from a normal distribution over an infinite interval into a normal distribution over a finite interval. The certainty of x in C is satisfied as follows:

$$\mu = \exp\left(\frac{-(x - E_x)^2}{2E_n'^2}\right) \quad (8)$$

When the indicator is far from the expected value of E_x , x obeys a uniform distribution with a certainty degree of 1.

FIGURE 1: Traditional cloud model and finite-interval cloud model.

In summary, the distribution of x obeys the following (in this article, $km_{ax}=5$):

$$\begin{aligned}\mu &= 1 \quad x \in [C_{\min}^{k_{\max}}, \infty) \cup (0, C_{\max}^{k_{\min}}] \\ \mu &= \exp\left(\frac{-(x - E_x)^2}{2E_n'^2}\right) \quad x \in \text{other interval}\end{aligned}\quad (9)$$

According to (9), we can see that when the indicator is far away from the expectation, then x obeys a uniform distribution with a certainty degree of 1.

As shown in Figure 1, the quantitative element x in two diagrams represents the quantitative random number on the

domain interval U , and $\mu(x)$ indicates that the quantitative element x corresponds to the interval membership degree, which ranges from 0~1. The horizontal coordinates represent the range of the selected evaluation indicators. In the first picture, the expectation of the adjacent two interval ranges is E_x , the distance between them is $3E_n$, the longitudinal coordinate represents the membership degree, and the x of the peak place corresponds to the E_x point. In the cloud model parameters, E_n represents the thickness of the curve, representing the physical meaning of the degree of confusion of the cloud droplets. The improved cloud model diagram indicates that when the quantitative element x is in the edge interval (the artificially specified maximum and minimum levels), it can be determined that the quantitative element x is subject to a uniform distribution at E_x as the dividing point, at which point the interval membership degree is 1.

Using the forward cloud generator and the characteristic parameter values, the degrees of membership corresponding to different measured evaluation indexes can be further obtained. The specific algorithm and steps are as follows.

(1) Review the relevant literature in addition to specific engineering surveys and data to obtain measured data and further calculate the entropy E_n and super entropy H_e . Because the super entropy is characterized by the thickness of the cloud, we can temporarily take $\lambda=0.01$.

(2) According to the improved formula, the cloud characteristic parameter can be obtained, as can the random number $E_n^f \sim N(E_n, H_e^2)$ of the normal distribution.

(3) According to the actual survey index x , in addition to (9) and using the specific grading standard of the hazard of the slope risk to obtain E_x , the hazard level membership degree of the measured index can be obtained in combination with the cloud droplet map.

The application of the improved forward normal cloud model to slope stability analysis is based on the following four reasons.

(1) The slope risk classification is full of uncertainty, and thus the cloud model is used to study the uncertainty in the concept of human cognition through three numerical characteristics: expectation, entropy, and super entropy.

(2) The normal cloud model is based on a normal distribution and is the most commonly used cloud model. It exhibits universality, and the expected curves of the cloud model with many qualitative concepts in the natural sciences approximately obey normal distributions. Following further improvement, the curve will become more subordinate to the actual situation.

(3) The cloud model is a two-way cognitive model of qualitative and quantitative conversions that is divided into positive clouds and reverse clouds. The slope risk classification constitutes a transformation from qualitative to quantitative research corresponding to the forward cloud model.

(4) The stability of a slope is a problem in which a variable is affected by multiple factors. The improved normal cloud model can treat each factor as a variable, enabling it to intuitively and quickly address the slope stability prediction problem; moreover, the improved model can reflect the extent to which different slopes belong to the same slope risk level.

3. Finite-Area Cloud Model and Distance Discrimination for Building a Weighted Model

3.1. Construction of the Slope Stability Evaluation System.

The stability evaluation and analysis of a slope ultimately constitutes a fuzzy problem. The stability of a slope can be considered to characterize its safety factor. By analysing several articles [53–57] evaluating the stability of rock slope, we find the following: (1) The factors affecting the stability of rock slope are related to the geometry of the slope, the excavation process, and engineering support. (2) Its stability is related to stratum structure and rock lithology. (3) Among the many evaluation factors, its stability is related to the regional environment where the slope is located, such as the local rainfall and earthquakes. The stability coefficients of different working conditions can be represented by a unified function:

$$F_s = g(X) = g(C, \varphi, H, \alpha \dots) \quad (10)$$

In the above function, X represents all the evaluation factors that affect slope stability. For example, C is the cohesive force of rock and soil, φ denotes the internal friction angle of a rock mass, H is the slope height, α is the slope angle, and $g(X)$ is the function used to calculate the stability quantitatively. Under actual working conditions, many influencing factors are ambiguous; thus, many qualitative factors are represented by fuzzy values and can be written as follows:

$$\vec{F}_s = \overrightarrow{g(X)} = g(\vec{C}, \vec{\varphi}, H, \alpha \dots) \quad (11)$$

Slope stability is affected by its own complex characteristics and the available engineering technology. The most important factors include the geological features of the slope, the hydrological structure, and the external environment, which encompass human production activities, geological disasters, and precipitation. To date, no uniform standards to determine the stability of slopes have been presented in the academic or geological engineering circles. The current slope safety assessment method fails to integrate the complex rock mass stress, slope characteristics, rock properties, rock mass structure, natural factors, and human activities and other factors, so it is difficult to objectively and comprehensively evaluate the overall stability of the slope, especially the choice of the slope impact factors of hydropower stations; therefore, the choice of factors in this paper is mainly limited to hydropower projects involving rock slopes. According to established grading standards, the evaluation indicators should satisfy the five following principles: representativeness, relevance, quantifiability, accessibility, and reservability. Therefore, for improving the accuracy of the evaluation, this paper selects the following evaluation indicators for analysis:

(a) Geological factors ($P1$): deformation modulus (X_{1-1}); integrity index of the rock mass (X_{1-2}); rock quality designation (RQD) (X_{1-3}); uniaxial compressive strength (UCS) (X_{1-4}); initial index (X_{1-5}); and condition of discontinuities (X_{1-6}).

(b) Engineering factors ($P2$): slope height (X_{2-1}); slope angle (X_{2-2}); reinforcements (X_{2-3}); drainage condition (X_{2-4});

FIGURE 2: The comprehensive evaluation indicators.

excavation method (X_{2-5}); and excavation intensity and volume (X_{2-6}).

(c) Environmental factors ($P3$): mean annual precipitation (X_{3-1}); saturated water content of the slope (X_{3-2}); rainfall duration and intensity (X_{3-3}); water table (X_{3-4}); daily maximum rainfall (X_{3-5}); seismic acceleration (X_{3-6}); catchment area (X_{3-7}); and vegetation type (X_{3-8}).

(d) Monitoring factors ($P4$): surface deformation rate (X_{4-1}); prestressed anchorage force (X_{4-2}); internal deformation rate (X_{4-3}); and route inspection of the slope condition (X_{4-4}).

A comprehensive graph of the evaluation indicators is shown in Figure 2 [6].

According to the characteristics of the rock slope in an engineering project, the selection criteria for the evaluation indicators are selected in consideration of the systematic comprehensiveness, concise scientificity, relative independence, and flexible operability of the modelling process. Macrofactors should be selected while avoiding specific physical and mechanical properties. The indicators should

be comprehensive, representative, and coordinated but also encompass the main influencing factors as much as possible; the greater the independence of the factors, the better the correlation. Moreover, the factors should be combined to avoid difficulties when selecting a fuzzy synthetic model.

3.2. Grading Criteria for Evaluation Indicators. Due to the randomness and ambiguity of the factors that affect the rock slope stability, stability changes both with the time and with the environment. The basis of the grading standard is usually related to the actual situation of the rock slope and the discontinuous geological conditions. In general, as a result of different engineering backgrounds, many potential factors will affect the actual working conditions. Consequently, the slope is divided into five grades, namely, completely stable (I), stable (II), partially stable (III), unstable (IV), and completely unstable (V), according to the classification criteria of the engineering rock mass, thereby forming a single-factor slope stability evaluation index according to different classification level standards. The specific descriptions of the different levels

are listed in Table 1 [21, 58], and the specific parameters are reported in Table 2 [59, 60].

3.3. Evaluation Factor Weight Calculation. For any evaluation method, especially for the target evaluation index, considering the weights of numerous different evaluation factors is usually required. These so-called weights refer to the relative importance of the evaluation factors that affect the problem in the evaluation process. Descriptions of the weights can be either qualitative or quantitative. However, the qualitative description of a weight is subjective, and thus the weight of an indicator in an actual process is usually expressed by a specific algorithm. Commonly used methods for calculating index weights include the AHP [61, 62], the entropy weight method [63, 64], and the RS method [65, 66], among others [67–70]. However, most of these methods are subjective, and thus it is difficult to obtain objective and accurate results. In addition, while the entropy weight method is a commonly used objective weighting technique, this approach usually considers only the amount of information regarding the indicators; in other words, the correlations among the evaluation indicators are not considered. Accordingly, this paper adopts another objective weighting method known as the weighted distance discriminant method. The specific steps of this method are as follows [30]:

Step 1. Solution of the normal membership degree (determination degree): according to the measured value corresponding to each index E_i of the evaluation object, refer to the method of improving the characteristic parameters of the cloud model; then, the membership degree of the corresponding risk level K to which each evaluation index belongs can be obtained.

Step 2. Calculating the distance between two indicators: assuming that m_i^k and m_j^k are the basic probability distribution functions of the two levels corresponding to the two indicators E_i and E_j , respectively, the distance between the two indicators can be expressed as follows:

$$D(E_i, E_j) = \sqrt{\frac{1}{2} (\|m_i^k\|^2 + \|m_j^k\|^2 - 2 \langle m_i^k, m_j^k \rangle)} \quad (12)$$

In this formula, $\|m_j^k\|^2 = \langle m_j^k, m_j^k \rangle$ is the inner product of two vectors. The level of the hazard corresponding to the evaluation object selected in this paper is 5; thus, $K=5$, and the distance between the two indicators $D(E_i, E_j)$ can be obtained from the above formula.

Step 3. Calculating the similarity: according to the distance between the two indicators E_i and E_j obtained with the previous formula, the similarity $S(E_i, E_j)$ between these two indicators can be obtained as follows:

$$S(E_i, E_j) = 1 - D(E_i, E_j) \quad (13)$$

Step 4. Calculating the support level of the indicators: according to the above calculation formula, the smaller the distance between the indicators is, the greater the similarity

and the better the consistency between them. Then, the support level of the calculated indicators is as follows:

$$\sup(E_i) = \sum_{j=i, j \neq i}^n S(E_i, E_j) \quad i = 1, 2, 3 \dots n \quad (14)$$

Step 5. Calculating the weights of the evaluation indicators: normalization can further yield the credibility $\omega(E_i)$ of each indicator E_i (the weights of the different evaluation factors):

$$\omega(E_i) = \frac{\sup(E_i)}{\sum_{i=1}^n \sup(E_i)} \quad i = 1, 2, 3 \dots n \quad (15)$$

3.4. Determination of Comprehensive Weights. After the expansion and calculation of the above steps, we can conclude that the measured data x of different evaluation indicators belongs to a specific certainty degree in the cloud $\mu(x)$. Then, we can employ the weighted distance discriminant method to calculate the weights of the different evaluation indicators using the final comprehensive determination formula:

$$\mu_k = \sum_{j=1}^m \omega(E_j) \cdot \mu_{k,j} \quad (16)$$

In the above formula, $\mu_{k,j}$ is the certainty of the measured value of the j th indicator of the sample, and $\omega(E_j)$ is the weight of the j th evaluation index of the sample.

According to the final comprehensive determination and the principle of maximum membership, we can determine the membership level of the sample as follows:

$$L = \max(\mu_1, \mu_2, \mu_3 \dots \mu_k) \quad (17)$$

3.5. Framework for Calculating and Evaluating Slope Stability. (a) According to research concerning slope stability analysis performed by many scholars and geologists, a risk classification standard is established for landslide evaluation indicators.

(b) The cloud characteristic parameters of the classification index are determined, and the cloud generator is used to draw the cloud droplet map to generate a cloud model.

(c) The degree of certainty corresponding to each indicator is calculated based on the measured data of the sample.

(d) The weight of each evaluation index is calculated by using the algorithm of the improved weighted distance discriminant method.

(e) The comprehensive weight values are calculated, and the slope hazard level is determined according to the principle of maximum membership.

The specific operation flow chart is shown in Figure 3.

4. Engineering Applications

4.1. Background Information of the Jinping 1 Hydropower Station. The Jinping 1 Hydropower Station [6, 71, 72], a massive controlled-reservoir cascade hydropower station situated in the lower reaches of the Yalong River (Kala to Jiangkou section), is in Yanyuan County and Muli County, Liangshan

TABLE 1: Slope stability grades and empirical descriptions.

Rank	Description	Stability	Safety	Failures	Treatment
I	Very favourable	Completely stable	Completely safe	None	None
II	Favourable	Stable	Safe	Some blocks	Occasional
III	Fair	Partially stable	Moderately safe	Some joints or many wedges	Systematic
IV	Unfavourable	Unstable	Unsafe	Planar or big wedges	Important/corrective
V	Very unfavourable	Completely unstable	Dangerous	Big planar, soil-like failures	Re-excavation

TABLE 2: Single-factor slope stability evaluation index.

Rating factor	Ranking grade				
	I	II	III	IV	V
<i>Geological factors (P1)</i>					
Deformation modulus (X_{1-1}) (GPa)	33.0-50.0	20.0-33.0	6.0-20.0	1.3-6.0	0-1.3
Integrity index (X_{1-2})	0.75-1	0.55-0.75	0.35-0.55	0.15-0.35	0-0.15
RQD (X_{1-3})	90-100	75-90	50-75	25-50	0-25
UCS (X_{1-4}) (MPa)	>250	100-250	50-100	25-50	0-25
Initial geo-stress (X_{1-5}) (MPa)	0-2	2-8	8-14	14-20	20-25
Discontinuities (X_{1-6})					
Cohesion (X_{1-6-1}) (MPa)	0.22-0.32	0.12-0.22	0.08-0.12	0.05-0.08	0-0.05
Friction angle (X_{1-6-2}) ($^{\circ}$)	37-45	29-37	21-29	13-21	0-13
Volumetric count (X_{1-6-3})	0-3	3-10	10-20	20-35	>35
Integrity description (X_{1-6-4})	Very good	Good	Moderate	Bad	Very bad
Distance between the dip direction of the discontinuity and cutting face (X_{1-6-5})	Very far	Far	Fair	Close	Very close
<i>Engineering factors (P2)</i>					
Slope height (X_{2-1}) (m)	0-30	30-45	45-60	60-80	80-100
Slope angle (X_{2-2}) ($^{\circ}$)	0-20	20-35	35-45	45-60	60-80
Reinforcements (X_{2-3})	Surplus	Sufficient	Fair	Insufficient	Barely
Drainage condition (X_{2-4})	Very favourable	Favourable	Fair	Unfavourable	Very unfavourable
Excavation method (X_{2-5})	No excavation	Manual	Mixed	Explosion	Large explosion
Excavation intensity and volume (X_{2-6})	Very favourable	Favourable	Fair	Unfavourable	Very unfavourable
<i>Environmental factors (P3)</i>					
Mean annual precipitation (X_{3-1}) (mm)	0-600	600-800	800-1,100	1,100-1,500	1,500-2,000
Saturated water content of the slope (X_{3-2}) (%)	0-20	20-40	40-55	55-75	75-100
Rainfall duration and intensity (X_{3-3})	Very favourable	Favourable	Fair	Unfavourable	Very unfavourable
Water table (X_{3-4})	Very low	Low	Fair	High	Very high
Daily maximum rainfall (X_{3-5}) (mm)	0-25	25-50	50-70	70-100	100-150
Seismic acceleration (X_{3-6}) (g)	0-0.05	0.05-0.1	0.1-0.15	0.15-0.20	0.20-0.40
Catchment area (X_{3-7})	Very favourable	Favourable	Fair	Unfavourable	Very unfavourable
Vegetation type (X_{3-8})	Very favourable	Favourable	Fair	Unfavourable	Very unfavourable
<i>Monitoring factors (P4)</i>					
Surface deformation rate (X_{4-1}) (mm/m)	0-2	2-3	3-5	5-8	8-10
Pre-stressed anchorage force (X_{4-2}) (%)	0-8	8-15	15-20	20-25	25-30
Internal deformation rate (X_{4-3}) (mm/m)	0-0.3	0.3-0.8	0.8-1.5	1.5-2	2-3
Route inspection of slope condition (X_{4-4})	Very good	Good	Moderate	Bad	Very bad

FIGURE 3: Framework for calculating and evaluating slope stability.

Yi Autonomous Prefecture, Sichuan Province. The stream and the valleys along the path of the Yalong River are deep, and the river presents many rapids; thus, navigation is not possible. The land along the river is sparsely populated, and cultivated land is scattered along the stream. There are no important towns or industrial mining enterprises. The main task of the development of the hydropower project is power generation, although it is also expected to serve as a flood storage reservoir during the flooding season, thereby reducing the flood control burden on the middle and lower reaches of the Yangtze River. The 305-m high hub building of the Jinping 1 Hydropower Station is the world's tallest arch dam. The hub area, which is affected by complex topographic and geological conditions, is a V-shaped canyon with steep slopes and micro-geomorphic features. The geological structures in the valley are both soft and hard, the topography dips in opposite directions, and the upper part of the hub area is open and narrow. The stream of the Yalong River rapidly downcuts, and the region is pervaded by a high-stress background; thus, deep cracks are developed along the deep slope of the left bank. Through scientific research tracking, safety monitoring feedback, dynamic design technology, and construction technology research, the slope can be smoothly designed and constructed, and it can be controlled safely and effectively. To explore the actual degree of danger associated with the arch dam, this paper selects the improved cloud model and weighted distance discriminant method to ascertain the hazard of the arch dam.

The measured values of the indicators are listed in Table 3. For some indicators that can be only qualitatively described,

we can assume that the probabilities that these evaluation factors are qualitatively described within these intervals are subject to different levels since the range of weights is between 0 and 1. We can then assign values according to the classification method; that is, we can divide the interval $[0, 1]$ into five equal subintervals: $[0, 0.2]$, $[0.2, 0.4]$, $[0.4, 0.6]$, $[0.6, 0.8]$, and $[0.8, 1.0]$. Then, we can assign values to the qualitative indicators according to their quantitative descriptions, whereas the values of the remaining quantitative indicators can be obtained through actual survey and research data [6].

4.2. Standardized Processing of Measured Sample Data. To eliminate the dimensional differences between different indicators, it is necessary to normalize the sample data. In this paper, the Z-score method is used to normalize the data samples. The specific formula can be expressed as follows:

$$x^* = \frac{x - \mu}{\sigma} \quad (18)$$

where μ is the mean of all sample data and σ is the standard deviation of all sample data; they are defined as follows:

$$\mu = \frac{1}{m} \sum_{i=1}^m x_i$$

$$\sigma = \sqrt{\frac{1}{m-1} \sum_{i=1}^m (x_i - \mu)^2} \quad (19)$$

4.3. Generation of the Cloud Droplet Graph. To verify the reliability and effectiveness of the proposed method, this

TABLE 3: Actual evaluation values of different evaluation indicators.

Evaluation factor	Original	Evaluation factor	Original
Deformation modulus (X_{1-1})	1.9 GPa	Reinforcements (X_{2-3})	0.70
Integrity index (X_{1-2})	0.72	Drainage effect (X_{2-4})	0.75
RQD (X_{1-3})	85%	Mean annual precipitation (X_{3-1})	607 mm
UCS (X_{1-4})	105 MPa	Water content (X_{3-2})	13%
Initial geo-stress (X_{1-5})	21.49 MPa	Daily maximum rainfall (X_{3-5})	49.2 mm
Cohesion (X_{1-6-1})	0.02 MPa	Seismic acceleration (X_{3-6})	0.1 g
Friction angle (X_{1-6-2})	16.7°	Surface deformation rate (X_{4-1})	1.89 mm/m
Volumetric count (X_{1-6-3})	17/m ³	Pre-stressed anchorage force (X_{4-2})	8.73%
Integrity description (X_{1-6-4})	0.60	Internal deformation rate (X_{4-3})	0.27 mm/m
Slope height (X_{2-1})	110 m	Route inspection (X_{4-4})	0.75
Slope angle (X_{2-2})	50°		

```

ExK = a;
EnK = b;
HeK = c;
for i = 1 : 5000;
    EnnK = randn(1) * HeK + EnK;
    xN(i) = randn(1) * EnnK + ExK;
    if xK(i) >= m or xK(i) <= m
        yK(i) = 1;
    else
        yK(i) = exp(-((xK(i) - ExK)^2) / (2 * EnnK^2));
    end
figure
plot(xK, yK, 'y.')
axis([0 C 0 1])
legend('T')
xlabel('Evaluation index')
ylabel('Membership')

```

ALGORITHM 1

paper selects the Jinping I Hydropower Station as the research background and uses its indicator system and measured data for a verification and comparative analysis. According to the finite-area cloud model and grading standards, the cloud feature parameters are determined by using (2)-(7). The generated cloud droplet map is shown in Figure 4, in which the abscissa indicates the evaluation indicator and the ordinate indicates the degree of certainty determined by the evaluation indicators with different values, that is, the degree of membership. Because the specific values of some qualitatively described indicators in this article are obtained according to the classification method and by assignment, only the quantitative descriptions of those indicators and the quantitative evaluation factors with specific survey values are described by the cloud map in Figure 4. According to the cloud characteristic parameters and the forward cloud generator, a cloud droplet graph is generated. The specific algorithm is as shown in Algorithm 1.

4.4. Determination of the Weights of the Evaluation Indicators. According to the cloud droplet graph and the membership

formula generated in Figure 3, the measured values of the samples evidently belong to different hazard levels.

$$R = \begin{matrix} & \begin{matrix} T & I & II & III & IV & V \end{matrix} \\ \begin{matrix} X_{1-1} \\ X_{1-2} \\ X_{1-3} \\ X_{1-4} \\ X_{1-5} \\ X_{16-1} \\ X_{16-2} \\ X_{16-3} \\ X_{2-1} \\ X_{2-2} \\ X_{3-1} \\ X_{3-2} \\ X_{3-5} \\ X_{3-6} \\ X_{4-1} \\ X_{4-2} \\ X_{4-3} \end{matrix} & \begin{bmatrix} 0 & 0 & 0.19 & 0.71 & 0.1 \\ 0.32 & 0.67 & 0.01 & 0 & 0 \\ 0.05 & 0.85 & 0.1 & 0 & 0 \\ 0 & 0.60 & 0.40 & 0 & 0 \\ 0 & 0 & 0 & 0.19 & 0.81 \\ 0 & 0 & 0 & 0.03 & 0.97 \\ 0 & 0 & 0.04 & 0.81 & 0.15 \\ 0 & 0 & 0.78 & 0.21 & 0.01 \\ 0 & 0 & 0 & 0.11 & 0.89 \\ 0 & 0 & 0.06 & 0.89 & 0.05 \\ 0.45 & 0.53 & 0.02 & 0 & 0 \\ 0.88 & 0.12 & 0 & 0 & 0 \\ 0 & 0.54 & 0.45 & 0.01 & 0 \\ 0 & 0.51 & 0.46 & 0.03 & 0 \\ 0.59 & 0.37 & 0.04 & 0 & 0 \\ 0.37 & 0.63 & 0 & 0 & 0 \\ 0.60 & 0.39 & 0.01 & 0 & 0 \end{bmatrix} \end{matrix} \quad (20)$$

The data samples are normalized by using (18)-(19). In addition, the basic probability distribution matrix and formula obtained by using (12)-(13) are used to calculate the distance D between the indicators and their similarity S . For example, the UCS (influencing factor X_{1-4}) has a value of 105 MPa, whereas the initial geo-stress (influencing factor X_{1-5}) has a value of 20.49 MPa. According to the theory of the cloud model and the generated cloud droplet map, the degree of certainty between the two different risk levels can be calculated separately. The UCS evaluation indicator belongs to the 2nd and 3rd levels, with relative importance of 0.60 and

FIGURE 4: Continued.

FIGURE 4: Generation of the cloud droplet graph.

0.40, respectively. The initial geo-stress evaluation indicator belongs to the 4th and 5th hazard levels, with degrees of certainty of 0.19 and 0.81, respectively. According to (12)-(13), the distance and similarity between these two evaluation factors can be calculated as $D(X_{1.4}, X_{1.5}) = 0.606$ and $S(X_{1.4}, X_{1.5}) = 0.394$, respectively. The same approach can be used to calculate the distances and similarities between the remaining indicators in addition to the normalized measured values of the indicators. The specific results are reported in Table 4.

According to the calculation results presented in Table 4, by summing the similarities E_i between a certain evaluation indicator $S(E_i, E_j)$ and all of the other indicators and then obtaining the support degree of the index, the same approach can be used to obtain the support degrees of the remaining evaluation indicators according to the calculated results. The weight formula (15) can provide the support degrees of all evaluation indicators. The weights of the final evaluation factors are listed in Table 4.

4.5. Final Classification Level Determination. According to the cloud model, Table 2 can be used to derive the threshold values of different evaluation indicators belonging to different hazard levels. The characteristic parameters of each level can

be obtained using (2)-(4), and the measured values of the forward cloud model generator and of different evaluation factors are calculated accordingly. The sample data belong to different degrees of certainty; thus, the comprehensive certainty can be obtained by calculating the final certainty of the evaluation object according to the principle of maximum membership in (17). The calculation process is illustrated by taking evaluation factor $X_{3.1}$ as an example. According to the cloud model, the degrees of certainty that $X_{3.1}$ belongs to different hazard levels are $\mu_1 = 0.45$, $\mu_2 = 0.53$, $\mu_3 = 0.02$, and $\mu_4 = \mu_5 = 0$. From this evaluation factor, we can speculate that the degree of certainty that the sample data belong to the first level of danger is 0.45, the degree of certainty that the data belong to the second level is 0.53, the degree of certainty that the data belong to the third level is 0.02, and the degrees of certainty that the data belong to the fourth and fifth levels are 0. According to this one indicator, the sample data most likely belong to the second level of danger; however, the data may belong to the first level, and there is a small possibility that the data belong to the third level. Additionally, it is impossible that the data belong to the 4th or 5th level. Based on the attributes of the other indicators, the final samples belong to specific certainty degrees; ultimately,

TABLE 4: Distances between indicators and the final weights of the evaluation indicators.

Indicator distance																	
	X_{1-1}	X_{1-2}	X_{1-3}	X_{1-4}	X_{1-5}	X_{1-6-1}	X_{1-6-2}	X_{1-6-3}	X_{2-1}	X_{2-2}	X_{3-1}	X_{3-2}	X_{3-5}	X_{3-6}	X_{4-1}	X_{4-2}	X_{4-3}
—	—	0.549	0.624	0.459	0.405	0.628	0.022	0.303	0.510	0.670	0.513	0.670	0.430	0.403	0.511	0.542	0.527
X_{1-1}	—	—	0.057	0.130	0.622	0.747	0.615	0.594	0.678	0.674	0.018	0.308	0.157	0.166	0.082	0.002	0.078
X_{1-2}	0.551	—	—	0.077	0.714	0.838	0.706	0.616	0.770	0.761	0.134	0.616	0.111	0.124	0.263	0.080	0.261
X_{1-3}	0.376	0.943	—	—	0.606	0.731	0.595	0.274	0.662	0.635	0.176	0.582	0.003	0.006	0.265	0.149	0.040
X_{1-4}	0.541	0.870	0.923	—	—	0.026	0.410	0.624	0.006	0.536	0.588	0.741	0.591	0.577	0.589	0.613	0.602
X_{1-5}	0.595	0.378	0.286	0.394	—	—	0.640	0.781	0.006	0.795	0.713	0.865	0.718	0.706	0.714	0.738	0.727
X_{1-6-1}	0.372	0.253	0.162	0.269	0.974	—	—	—	0.006	—	0.713	—	0.610	0.581	0.640	0.666	0.655
X_{1-6-2}	0.978	0.385	0.294	0.405	0.590	0.360	—	0.486	0.519	0.009	0.581	0.734	0.574	0.547	0.582	0.606	0.595
X_{1-6-3}	0.697	0.406	0.384	0.726	0.376	0.219	0.514	—	0.696	0.679	0.553	0.721	0.220	0.198	0.538	0.593	0.575
Similarity between indicators	X_{2-1}	0.490	0.322	0.230	0.338	0.994	0.481	0.304	—	0.659	0.644	0.797	0.648	0.635	0.645	0.669	0.658
	X_{2-2}	0.370	0.326	0.239	0.365	0.464	0.205	0.991	0.321	0.341	—	0.640	0.794	0.610	0.581	0.640	0.666
	X_{3-1}	0.487	0.982	0.866	0.824	0.412	0.287	0.419	0.447	0.356	0.360	—	0.177	0.199	0.023	0.008	0.021
	X_{3-2}	0.330	0.692	0.384	0.418	0.259	0.135	0.266	0.279	0.203	0.206	0.823	—	0.570	0.074	0.260	0.076
	X_{3-5}	0.570	0.843	0.889	0.997	0.419	0.282	0.426	0.780	0.352	0.390	0.806	0.391	—	0.472	0.174	0.288
	X_{3-6}	0.597	0.834	0.876	0.994	0.423	0.294	0.453	0.802	0.365	0.419	0.801	0.430	0.999	—	0.182	0.289
	X_{4-1}	0.489	0.918	0.737	0.735	0.411	0.286	0.418	0.462	0.355	0.360	0.977	0.926	0.528	0.727	—	0.001
	X_{4-2}	0.458	0.998	0.920	0.851	0.387	0.262	0.394	0.407	0.331	0.334	0.992	0.740	0.826	0.818	0.941	—
	X_{4-3}	0.473	0.922	0.739	0.960	0.398	0.273	0.405	0.425	0.342	0.345	0.979	0.924	0.712	0.999	0.945	—
Normalized post-evaluation indicators																	
	-0.442	-0.451	0.150	0.292	-0.303	-0.456	-0.337	-0.335	0.328	-0.100	3.866	-0.363	-0.105	-0.455	-0.442	-0.394	-0.454
Support for each indicator																	
	8.374	10.448	9.34	9.535	7.163	6.249	7.575	8.076	5.926	7.494	8.55	10.165	10.353	9.858	10.658	10.552	10.552
Weight of each evaluation factor																	
	0.056	0.069	0.062	0.063	0.047	0.041	0.050	0.054	0.039	0.050	0.057	0.067	0.069	0.065	0.071	0.070	0.070

TABLE 5: The final weights belonging to different hazard levels.

Comprehensive certainty					Final rating
μ_1	μ_2	μ_3	μ_4	μ_5	
0.2196	0.3429	0.1535	0.1528	0.1297	II

the comprehensive evaluation determines the risk of the evaluation object. According to the maximum membership principle based on the comprehensive membership degree in (16) in combination with the weight of each indicator obtained by the weighted distance discriminant method and the degrees of certainty of the evaluation factors, the final slope stability of the Jinping 1 Hydropower Station can be evaluated and rated. The final weights belonging to the different hazard levels are reported in Table 5.

According to the maximum membership principle, the certainty of the sample data belonging to the second level is 0.343, and the degree of certainty belonging to the first level is 0.22, whereas the final membership degrees of the other three levels are relatively small. Therefore, the final judgment is rated as the second level. Based on the final evaluation results and the actual construction conditions of the specific project, we can conclude that the improved cloud model with the weighted distance discriminant method is effective. Therefore, this mathematical method can be applied to the slope stability analysis of various engineering applications. This approach also provides new methods and ideas for similar issues.

In this paper, the distance discriminant method is used to obtain the weight. Compared with other weighting methods, the degree of mutual influence between each level of each index can be comprehensively considered, such that the determined weight is more reasonable and the accuracy of the evaluation method is improved. According to the measured value of the index, the weight of the index is obtained, which avoids the subjectivity of the traditional empowerment and the risk of being separated from the actual.

At the same time, the relationship between the indicators, the standard levels of the indicators, and the distributions of the indicators are considered, which avoids the defects that are easy to be partial in the process of empowerment.

Since the slope stability is a qualitative concept, the classification of its hazard level will be affected and controlled by many uncertain factors. The finite cloud generator is used to convert its ambiguity and randomness into the certainty degree, which reveals the evaluation process. The method of improving the feature parameters reduces the error of the calculation result to a certain extent, but it still cannot completely eliminate the gray feature of its existence. In addition, the actual distribution form of the slope stability evaluation index will have an impact on the evaluation results. The cloud model generated by the combination of the uniform distribution and the normal distribution reflects the actual situation more reasonably. Therefore, it is necessary to further improve the parameter method to make the result more accurate. Third, the evaluation factor should also be selected according to the actual project conditions, and it

cannot be done overnight, because the influence factors of different types of slope engineering will be slightly different.

5. Conclusions

(1) This paper uses the weighted distance discriminant algorithm to calculate the weights of evaluation factors and selects the arch dam slope of the Jinping 1 Hydropower Station in Sichuan, China, as the research background. The degrees of influence of various evaluation index factors are comprehensively considered, and the accuracy of the evaluation index weights is improved. According to an analysis of the final evaluation results, the proposed algorithm can be employed not only to evaluate the safety of a slope but also to reveal the tendency of the risk of the sample to be evaluated and to obtain a prediction of the safety.

(2) According to the uncertainties in slope stability analysis, four evaluation indexes and 17 index factors (evaluation indicators) affecting slope stability are selected to make the evaluation results more reasonable. Moreover, the evaluation index system improves the credibility of the evaluation. At the same time, the method can also be applied to the safety evaluation of other hydraulic structures. For the slope stability analysis of other engineering types, the evaluation factors should also be selected according to their different natures.

(3) According to the traditional normal cloud model, the improved finite-area cloud model utilized in this paper can make the probability of membership of the evaluation index system more reasonable and accurate, thereby compensating for the fact that the theoretical distribution does not conform with the actual distribution and eliminates the possibility that the simulation results in the theoretical model may exceed the actual range of risk. At the same time, in combination with the weighted distance discriminant algorithm, the simulation results are more consistent with the actual situation. Combined with a variety of analysis methods, the prediction results of this method are relatively accurate and provide a feasible quantitative analysis method for engineering slope stability analysis.

(4) The safety evaluation model of rock slope stability based on the combination of an improved cloud model and a distance discriminant weighting method is based on multiangles and multifactors. The types and quantities of selected parameters are not limited, avoiding the one-sidedness and subjective decision-making of single-factor decision-making. This model can be applied to the specific characteristics of different rock mass engineering and can accurately and scientifically predict the safety status of rock slope engineering. It has good applicability in both the construction and operation phases. Using this method, a safety preevaluation of the slope construction project can be achieved; before the project is constructed, the basic data of the evaluation factors affecting the slope stability can be collected to judge its stability, and then the feasibility of the project can be determined. It also provides a relatively reliable method for the preassessment of other projects.

Data Availability

The [DATA TYPE] data used to support the findings of this study have been deposited in the Comprehensive Stability Evaluation of Rock Slope Using the Cloud Model-Based Approach repository (DOI: 10.1007/s00603-013-0507-3).

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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