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Macro-comprehensive evaluation method of high rock slope stability in hydropower projects

Huaizhi Su · Jinyou Li · Jiping Cao · Zhiping Wen

Abstract Combining with the characteristics of the rock slope in hydropower engineering, the evaluation index system of rock slope stability in hydropower projects is determined based on multiple factors, and based on this, research, collect and establish the typical rock slope database of hydropower projects. Based on the fuzzy optimal recognition theory and Case-Based Reasoning, two different methods of slope stability evaluation are established respectively. Analyzing the rock slope stability of one hydropower project by the two methods, a comparison is made between the two methods and the effectiveness of the methods is verified.

Keywords High slope · Stability evaluation · Uncertainty analysis · Fuzzy optimal recognition method · Case-Based Reasoning method

H. Su (✉)
State Key Laboratory of Hydrology-Water Resources
and Hydraulic Engineering, Hohai University,
No. 1 Xikang Road, Nanjing 210098, China
e-mail: su_huaizhi@hhu.edu.cn

H. Su · J. Li
College of Water Conservancy and Hydropower Engineering,
Hohai University, Nanjing 210098, China

J. Cao
National Engineering Research Center of Water Resources
Efficient Utilization and Engineering Safety, Hohai University,
Nanjing 210098, China

Z. Wen
Department of Computer Engineering, Nanjing Institute
of Technology, Nanjing 211167, China

1 Introduction

China is constructing hydropower projects on a large scale, and engineering construction disturbs the original natural appearance of slope, making slope straying even far from equilibrium state, which brings some unsafe factors to construction and operation of the project. Built, being built or proposed large hydropower projects such as Laxiwa, Xiaowan, Jingping, Xiluodu and so on, are generally located in alpine valley region, where mountains high and steep, valleys narrow, earthquake fault zone developed, tectonic stress level high, engineering geologic conditions are very complex, and the issue of high rock slope is outstanding. For example, in May 2009 failure occurred on the surface of Guopu bank slope in Xiluodu hydropower station. The faulted rock mass with total volume of about 30 million m^3 had signs of global displacement and deformation. If the whole landslide took place, it will block channel and form the dammed lake in Laxiwa reservoir, which will cause Laxiwa and upstream Longyangxia losing the generating capacity. Instability of some important slopes will cause more serious consequences. Research on high rock slope in engineering has become the hot and difficult problem in the field of geotechnical engineering of the twenty-first century in China.

Slope is a nonlinear and uncertain dynamic system influenced by various factors. The stability evaluation is one of the important components and core contents of slope engineering, and it runs through the whole process of the slope engineering. Due to the incomplete and uncertainty information of slope, its stability evaluation has always been a quite complicated problem. In order to solve this problem, many scholars have done a lot of research on the evaluation method. The engineering analogy method, it is considered to be one of the most prevalent methods for

slope stability analysis in the current. But the method is different from person to person with its subjectivity. However, reliability method is basically limited to the research of the slope with potential dangerous sliding surface. The calculation method of reliability is quite different for different destruction form of rock mass, especially for rock slope due to its joint planes and cracks. Therefore, the characteristics of the rock mass is not only influenced by rock mechanical properties, but also constrained by the geometric distribution of the joint planes. The reliability method is hardly used in the slope with no potential sliding surface, such as jointed rock slope, canyon high steep slope (Wang et al. 2005; Li and Zhou 2009; Pantelidis 2009; Mert et al. 2011; Ghosh et al. 2010; He et al. 2011; Qin et al. 2001; Cai and Ugai 2004; Rahimi et al. 2011).

Because the rock slope of hydropower project usually have great height and complex rock structure, whose stability is influenced by geological and engineering factors. Slope stability evaluation is a multiple indexes and fuzzy comprehensive problem: the quality of rock mass, geometric properties of slope, construction methods and environmental conditions, etc. should be considered (Zou et al. 2012; Sadiq and Tesfamariam 2009; Su et al. 2010). The main problem of the traditional fuzzy comprehensive evaluation method of linear weighted average is that a reasonable evaluation can't be obtained easily, because the evaluation results tend to be homogenized by the linear weighted average. The direct method of fuzzy pattern recognition proposed by Lu (1991) is not used for unequally weighted, because it fails to consider the weight vector of each index. So its application is limited to the equally weighted of each index. Fuzzy optimal recognition method is suitable for multiple indexes evaluation system, which has been widely used in water quality evaluation, rock quality classification (Chen 1991, 2001). Due to the different dimension of influence indexes, each attribute is often normalized in evaluation method.

Case-Based Reasoning (CBR) was proposed by Shank in 1982, and it was applied to computer by Kolodnerin 1983. In CBR, the current problem or situation is called the target case, and the memory problem is called source case. Experience is captured and organized as a set of historical cases stored in a case base. From this base, source case is recalled either to resolve problems or provide recommendations for target case. Nowadays this method has been widely applied to the evaluation, diagnosis, decision-making problem in many fields such as environment, machinery, geotechnical engineering and so on (Kalapanidas and Avouris 2001).

For a long time, researchers have deeply studied on rock slope stability of a large number of hydropower project, and obtained some beneficial conclusions. All the rock slopes constitute a case base. It creates a reliable base for the slope stability evaluation with CBR. The knowledge representation in CBR is based on the case base. The acquisition of case base is much easier than rule, so the knowledge acquisition is simplified greatly. That is to say, CBR provides a feasible new way for slope stability evaluation (Begum et al. 2011; Watsona and Marir 1994; De Loor et al. 2011; Adam and Smith 2008).

The slope stability analysis method is starting from certainty to uncertainty analysis due to the emergence of some new theories and new methods. At the same time, because of the complexity of the slope engineering, slope stability evaluation can't only rely on a single method. The combination of two or more methods has become a trend for slope stability evaluation. Comprehensively considering the influence on the slope stability such as rock mass structure, orientation of advantage discontinuities, geometric properties of slope, construction methods and environment conditions, this paper constructs the evaluation index system of rock slope stability based on multiple factors, discusses the method of indexes normalization and researches the rock slope stability evaluation method based on the fuzzy optimal recognition theory and CBR, respectively, based on researching and collecting many typical cases of rock slope in hydropower engineering. At last, the validity and consistency of two methods are verified.

2 System of index affecting rock slope stability

The stability of rock slope not only depends on RQD (Rock Quality Designation) of its own, but also on geometric properties of slope and the relative relation between the orientation of control- and excavation discontinuities, etc., so it is necessary to build a comprehensive evaluation index system considering many factors, when making a macro-assessment on the stability of slopes.

Based on referencing to domestic and foreign literature (Romana 1993; Liu et al. 2005) and according to the deformation mechanism of rock slope and engineering geological and hydrogeology conditions, the important factors influencing the stability of rock slope are summed up as follows: slope height, rock mass structure of the slope, slope angle, failure mode, dip of slip plane, sliding plane types, landslide inducing factors (rainfall, groundwater, reservoir storage, construction methods, earthquake), etc. According to the characteristic of each factor, Fig. 1 lists various conditions of every factor.

Several attributes can be comprehensively considered to simplify analysis. According to the mutual relationship of tendency and dip between the intersection of discontinuities, two or more discontinuities and slope surface;
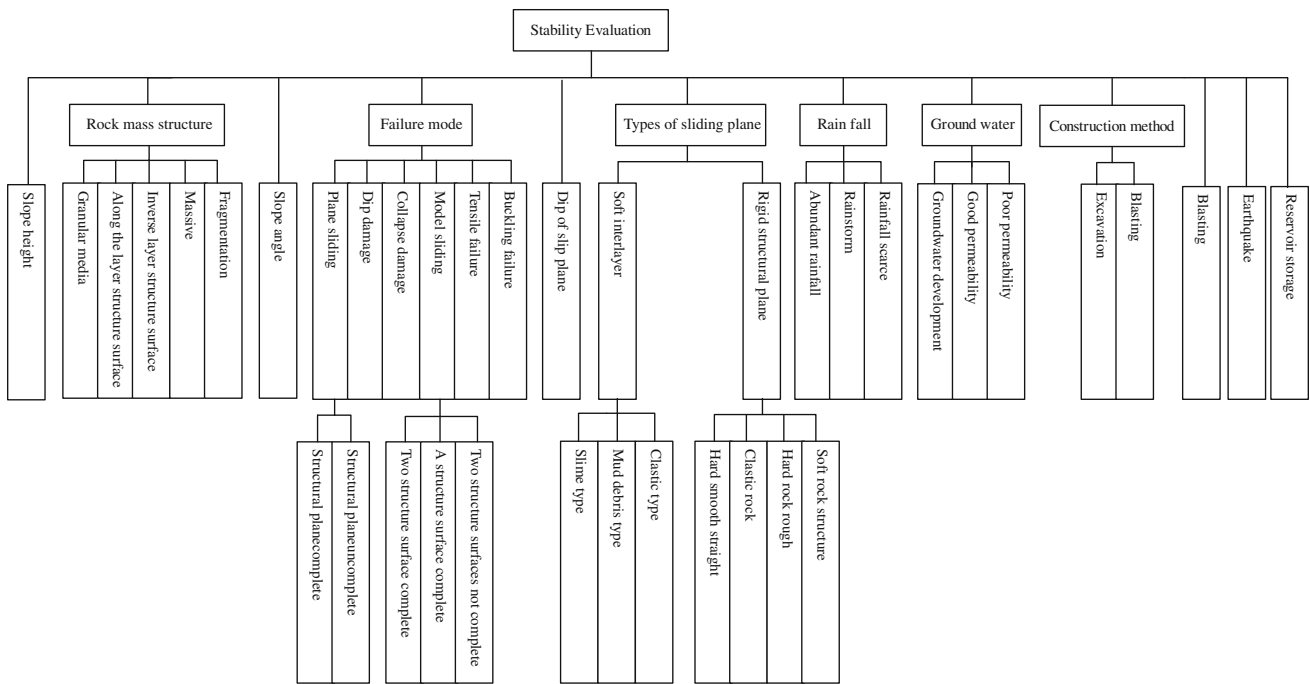
Fig. 1 System of indexes affecting rock slope stability in hydropower engineering

comprehensively considering the assemblage characteristics and whose combination relation with slope (Zhu and Mo 2004), it is defined as position indicator of advantage discontinuities F.

$$F = \frac{F_1 F_2 F_3}{60}, \tag{1}$$

$$F_1 = (1 - \sin A)^2 \quad F_2 = \tan^2 \beta_j, \tag{2}$$

where F_1 indicates the relationship of dip direction between discontinuities and slope, $F_1 \in [0.15, 1]$; F_2 indicates the influence of the dip of discontinuities, $F_2 \in [0.15, 1]$; if toppling model, then $F_2 = 1$; F_3 indicates the mutual relationship between the slope angle and the dip of discontinuities, $F_3 \in [-60, 0]$ and $[0, 60]$; A is the angle between the dip direction of discontinuities and slope, β_j is the dip of discontinuities.

3 Typical cases of rock slope in hydropower engineering and normalization of data and indexes

3.1 Cases of high slope

Case base is an essential part and the knowledge base of CBR. It can be extracted from feature-rich database, and also can be obtained from all kinds of method of knowledge acquisition. By searching documents, 13 source cases from the rock slope of hydropower project are summarized,

which include deeper case study and definite conclusion. The stability grading of rock slope is the stability evaluation from the macro-comprehensive, which provides a theoretical reference for the slope excavation and experience design. The grading methods of slope rock can be divided into RMR, SMR and CSMR method (Sun and Chen 1997; Li and Li 2001). The modified grading method of hydropower slope rock is introduced in this article which is proposed by Zhang and Shen (2011). It is consistent with the experience score of slope actual situation. Combining with above method, macro-stable state of slope, namely evaluation category, is divided into four situations: unstable, not stable, basically stable and stable. According to Sect. 2, main influence factors of rock slope stability state in hydropower engineering are summarized as follows: slope height, dip of slope plane, advantage discontinuities combinations, types of sliding plane, failure mode, groundwater, rainfall and construction methods, and the classification standard, totally 8, is shown in Table 1. Researching and collecting the data of very clear and typical high slope stable state in hydropower engineering, case base of typical high rock slope in hydropower engineering is built. The attribute parameters of source case and stable state are listed in Table 2.

3.2 Normalization of data and index

Normalization of data and index means scaling the data into a smaller specified interval. Due to the units of each

Table 1 Classification standard of high rock slope stability single index

Evaluation index	Stability types			
	Stable	Basically stable	Not stable	Unstable
Slope height (m)				
Standard value	80–100	100–150	150–260	>260
Normalized number	1.0–0.9	0.9–0.8	0.8–0.7	0.7–0
Dip of slope plane (°)				
Standard value	0–30	30–45	45–60	>60
Normalized number	1.0–0.9	0.9–0.75	0.75–0.6	0.6–0
Advantage discontinuities azimuth				
Standard value	Very suitable	Suitable	General suitable	Unsuitable
Normalized number	1.0–0.85	0.85–0.7	0.7–0.4	0.4–0
Types of sliding plane				
Standard value	Joint	Level	Fault	Weak intercalation
Normalized number	1.0–0.9	0.9–0.8	0.8–0.7	0.7–0
Failure mode				
Standard value	Crack, buckling	Dumping, collapse	Wedge shape sliding	Plane sliding
Normalized number	1.0–0.9	0.9–0.75	0.75–0.6	0.6–0
Groundwater				
Standard value	Groundwater undeveloped	Strong permeability	Groundwater developed	Extremely developed
Normalized number	1.0–0.9	0.9–0.75	0.75–0.5	0.5–0
Rainfall				
Standard value	Rainfall scarce	Rainfall abundant	Rainstorm	Infrequent rainstorm
Normalized number	1.0–0.9	0.9–0.8	0.8–0.7	0.7–0
Construction method				
Standard value	Natural slope	Peripheral pre-blasting	Conventional blasting	Defects
Normalized number	1.0–0.9	0.9–0.8	0.8–0.7	0.7–0

evaluation index of the rock slope stability of hydropower project are different. The evaluation index is needed to be normalized in order to make it suitable for evaluation calculation. Based on the given classification standard value of index (as shown in Table 1) and sample index data, suppose that y_{ih}, $y_{i,h+1}$ ($i = 1, 2,...,m$; $h = 1, 2,...,c+1$), respectively represent upper and lower limit of the hth classification standard value for the ith evaluation index, x_{ij} is the ith index value of sample j (Zhang 1996).

Assuming the membership of stability is 1 that the upper limit y_{i1} of 1 standard for index i, the membership of stability is 0 that the lower limit $y_{i,c+1}$ of c standard for index i, the membership of stability for $y_{i1} \sim y_{i,c+1}$ is between 1 and 0, the membership is defined as:

$$s_{ih} = \frac{y_{ih} - y_{i,c+1}}{y_{i1} - y_{i,c+1}}, \tag{3}$$

where S_{ih} is the membership of stability for index classification standard value, $h = 1, 2,...,c+1$.

As far as engineering security is concerned, take the upper limit of index as the standard value at all levels, and then the standard index membership matrix is as follows:

$$S = \begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1c} \\ s_{21} & s_{22} & \cdots & s_{2c} \\ \cdots & \cdots & \cdots & \cdots \\ s_{m1} & s_{m2} & \cdots & s_{mc} \end{bmatrix} = (s_{ih}) \quad h = 1, 2, \ldots, c. \tag{4}$$

The index value of sample j is defined as:

$$\vec{x}_j = \left(x_{1j}, x_{2j}, \ldots, x_{mj} \right)^T. \tag{5}$$

After normalization, Eq. (5) changes to:

$$\vec{r}_j = \left(r_{1j}, r_{2j}, \ldots, r_{mj} \right)^T. \tag{6}$$

In Eq. (4), S is the standard membership of c stable categories, and $\vec{r}_j$ indicates the membership of stability for sample j every index.

Table 2 Typical cases and stability state of slope in hydropower projects

Numbers	Index	Slope height	Dip of slope plane	Advantage discontinuities azimuth	Types of sliding plane	Failure mode	Groundwater	Rainfall	Construction method	Stability state
1										
	y	180	40	Unsuitable	Stone joint	Plane sliding	Developed	Abundant	Defect	Unstable
	s	0.758	0.8	0.35	0.9	0.55	0.7	0.85	0.65	4
2										
	y	255	45	General suitable	Clastic weak plane	Plane sliding	Deeper	Less	Nature	Not stable
	s	0.703	0.75	0.55	0.65	0.55	0.91	0.91	1.0	3
3										
	y	210	40	Unsuitable	Mud weak plane	Plane sliding	Deeper	Less	Nature	Unstable
	s	0.731	0.8	0.38	0.6	0.55	0.91	0.91	1.0	4
4										
	y	124	51	Very suitable	Slime dissection	Plane sliding	Developed	Abundant	Defect	Basically stable
	s	0.843	0.69	0.9	0.5	0.55	0.7	0.85	0.65	2
5										
	y	120	55	Suitable	Level	Wedge shape sliding	Deeper	Abundant	Defect	Stable
	s	0.852	0.65	0.8	0.85	0.7	0.91	0.85	0.65	1
6										
	y	150	40	Suitable	Fault	Wedge shape sliding	Deeper	Less	Defect	Not stable
	s	0.795	0.8	0.8	0.78	0.7	0.91	0.91	0.65	3
7										
	y	200	30	Unsuitable	Clastic weak plane	Plane sliding	Developed	Abundant	Defect	Unstable
	s	0.739	0.9	0.35	0.65	0.55	0.7	0.88	0.68	4
8										
	y	150	75	Very suitable	Clastic weak plane	Plane sliding	Developed	Abundant	Defect	Stable
	s	0.795	0.3	0.9	0.65	0.55	0.7	0.85	0.68	1
9										
	y	200	40	Very suitable	Clastic weak plane	Dumping	Deeper	Less	Defect	Stable
	s	0.739	0.8	0.9	0.65	0.85	0.91	0.91	0.68	1
10										
	y	445	40	General suitable	Mud weak plane	Collapse	Deeper	Less	Nature	Stable
	s	0.644	0.8	0.55	0.6	0.85	0.91	0.91	1	1

Table 2 continued

Numbers	Index	Slope height	Dip of slope plane	Advantage discontinuities azimuth	Types of sliding plane	Failure mode	Groundwater	Rainfall	Construction method	Stability state
11										
	y	120	55	Suitable	Clastic weak plane	Collapse	Developed	Abundant	Defect	Unstable
	s	0.852	0.65	0.8	0.65	0.85	0.7	0.85	0.65	4
12										
	y	120	30	General suitable	Slime dissection	Collapse	Strong permeability	Less	Defect	Unstable
	s	0.852	0.9	0.55	0.5	0.85	0.8	0.91	0.3	4
13										
	y	218	45	Suitable	Mud weak plane	Plane sliding	Deeper	Less	Defect	Not stable
	s	0.725	0.75	0.75	0.65	0.55	0.91	0.91	0.65	3

Slope height, m; dip, °; y, standard value; s, normalized number

4 High rock slope stability evaluation method based on fuzzy optimal recognition theory

The classification problem about high rock slope stability can be summed up as: according to the membership matrix S of classification standard for stability, make an optimum recognition of classified sample j which is expressed by m index memberships (Lu 1991).

Normally, m index memberships of sample j will not fall into the standard value range of same index membership in matrix S, but irregularly into the different standard ranges of classification index membership in matrix S. Assume that sample j falls into different categories of matrix S whose upper and lower limit are respectively a_1, a_2 (positive integer), and $1 < a_1 < a_2 < c$.

Suppose that the vector consisting of classification memberships for sample j is:

$$\vec{u}_j = (u_{1j}, u_{2j}, \ldots, u_{cj}) \quad \sum_{h=1}^{c} u_{hj} = 1. \tag{7}$$

Suppose that the weight vector of m indexes of sample j is:

$$\omega_j = (\omega_{1j}, \omega_{2j}, \ldots, \omega_{mj}) \quad \sum_{i=1}^{m} \omega_{ij} = 1. \tag{8}$$

And then the difference between sample j and the hth classification can be expressed as Euclidean distance:

$$d_{hj} = \sqrt{\sum_{i=1}^{m} \left[\omega_{ij}(r_{ij} - s_{ih}) \right]^2}. \tag{9}$$

In order to show the difference between samples much more reasonable, according to the hth membership of sample j in Eq. (7), the weighted Euclidean distance can be obtained:

$$D(\vec{r}_j, \vec{s}_h) = u_{hj} \sqrt{\sum_{i=1}^{m} \left[\omega_{ij}(r_{ij} - s_{ih}) \right]^2}. \tag{10}$$

Meanwhile, to solve Eq. (10), the optimal classified membership vector should be solved first. The objective function of this optimization problem is defined as: square sum of weighted Euclidean distance between classification upper and lower limit are respectively a_1, a_2 for sample j is minimum:

$$\min\left\{ F(u_{hj}) = \sum_{h=a_1}^{a_2} \left[u_{hj} \sqrt{\sum_{i=1}^{m} \left[\omega_{ij}(r_{ij} - s_{ih}) \right]^2} \right] \right\}. \tag{11}$$

The constraint conditions of the optimization problem:

$$\sum_{h=a_1}^{a_2} u_{hj} = 1. \tag{12}$$

Lagrange function is constructed:

$$L(u_{hj}, \lambda) = \sum_{h=a_1}^{a_2} u_{hj}^2 \cdot \sum_{i=1}^{m} \left[\omega_{ij}(r_{ij} - s_{ih}) \right]^2 - \lambda \left(\sum_{h=a_1}^{a_2} u_{hj} - 1 \right). \tag{13}$$

Let $\frac{\partial L(u_{hj}, \lambda)}{\partial u_{hj}} = 0$, $\frac{\partial L(u_{hj}, \lambda)}{\partial \lambda} = 0$, the following can be got

$$u_{hj} = \frac{\lambda}{2 \sum_{i=1}^{m} \left[\omega_{ij}(r_{ij} - s_{ih}) \right]^2}, \tag{14}$$

$$\sum_{h=a_1}^{a_2} u_{hj} - 1 = 0. \tag{15}$$

And from Eq. (14), the following can be obtained

$$\sum_{h=a_1}^{a_2} u_{hj} = \frac{\lambda}{2} \sum_{h=a_1}^{a_2} \frac{1}{\sum_{i=1}^{m} \left[\omega_{ij}(r_{ij} - s_{ih}) \right]^2}. \tag{16}$$

Combining Eqs. (15) and (16), we can get

$$\lambda = \frac{2}{\sum_{h=a_1}^{a_2} \frac{1}{\sum_{i=1}^{m} \left[\omega_{ij}(r_{ij} - s_{ih}) \right]^2}}. \tag{17}$$

Substituting Eq. (17) into Eq. (14), we can get

$$u_{hj} = \frac{1}{\sum_{i=1}^{m} \left[\omega_{ij}(r_{ij} - s_{ih}) \right]^2 \sum_{h=a_1}^{a_2} \frac{1}{\sum_{i=1}^{m} \left[\omega_{ij}(r_{ij} - s_{ih}) \right]^2}}$$
$$= \frac{1}{d_{hj}^2 \cdot \sum_{k=a_1}^{a_2} d_{kj}^{-2}}, \tag{18}$$

where $h = a_1, a_1 + 1, \ldots, a_2$, and serial number k can be discontinuous.

Equation (18) can be applied to classification and recognition of high slope stability in hydropower projects. The specific steps of recognition can be described as follows.

(1) Establish the classification standard of each individual index influencing high rock slope stability in hydropower engineering and each index value of sample.
(2) According to the upper and lower limit of each individual index, normalize the standard value of index.
(3) Process and normalize the index value of sample.
(4) Obtain memberships corresponding indexes, and determine the weight of each index to get index weight vector.
(5) Substitute relevant data into fuzzy optimal recognition method and obtain the stability classification of sample.

5 High rock slope stability evaluation method based on CBR

CBR is a kind of analogy inference method, whose core idea is that the current problem need to be solved is called

target case and the problem in the memory is called source case (Lekkas et al. 1994; Khajotia et al. 2007). The key technical problems for realizing CBR method are the establishment of case base and the calculation of attribute weight and similarity, respectively.

The foundation of CBR is the establishment of case base. In this article, the case base is the 13 source cases from the rock slope of hydropower project, which includes deeper case study and definite conclusion. A source case is the rock slope stability of one hydropower project which including the slope height, dip of slope plane, advantage discontinuities azimuth, types of sliding plane, failure mode, groundwater, rainfall, construction method and the evaluation grade of slope stability. A target case is a rock slope of hydropower project and its stability needs to be estimated by CBR method.

Another key problem of CBR is to determine the weight of attribute, which is used to measure the relative importance of each affecting factor. Evaluation method based on CBR using weight to reflect the influence of attribute on classification discriminant. If some attribute has little influence on classification discriminant, the weight is small. Otherwise, the weight is large. The slope stability evaluation method based on CBR using variable weight to reflect the influence of attribute on classification discriminant, and the calculation method of attribute weight is presented by the concept of variable weight. Which are calculated according to the concept of variable weight:

$$\omega_h = \sum_{i=1}^{n} \left[\frac{N_h(T, C_i)}{\sum_{j=1}^{n} N_h(T, C_j)} \right]^2, \tag{19}$$

$$N_h(T, C_j) = \text{Num}\left(\{ r | r \in C_j \text{ and } (v_r(h) = v_T(h) \text{ or } v_r(h) \in [L, U]) \} \right), \tag{20}$$

where ω_h is the weight of the attribute h; T is target case; n is the number of evaluation categories; C_i, C_j are the ith and jth evaluation categories, respectively; $N_h(T, C_j)$ is the record number of T in the C_j; $v_r(h)$ is the value of slope source case r for the attribute h; $v_T(h)$ is the value of target case T for the attribute h; $[L, U]$ is the range of target case T for the attribute h.

$$\left\{ \begin{array}{ll} L = \inf\left[\bigcap_{k=1}^{n} \text{dom}_k(h) \right], & v_T(h) \in \text{dom}_k(h) \\ U = \sup\left[\bigcap_{k=1}^{n} \text{dom}_k(h) \right], & v_T(h) \in \text{dom}_k(h) \end{array} \right\}, \tag{21}$$

where $\text{dom}_k(h)$ is the range of evaluation category C_k for the attribute h; L, K are respectively the supremum and infimum of intersection for the whole $\text{dom}_k(h)$, $k = 1, 2, \ldots, n$ including $v_T(h)$.

$N_h(T, C_i)$ expresses the frequency that target case T for the attribute h belongs to category C_k; $\sum N_h(T, C_j)$ shows

the sum of frequencies that target case T for the attribute h belongs to all categories. That is, $N_h(T, C_i)/\sum N_h(T, C_j)$ shows the probability that target case T for the attribute h belongs to category C_k.

Derivation shows that $\omega_h \in [1/4, 1]$ $(n = 4)$, if $\omega_h = 1.0$, which explains the important features of the attribute for classification, the weight is maximum; if $\omega_h = 0.25$, which explains the attribute occurs equally in every classification, the weight is minimum.

The third key problem of CBR is to calculate the similarity, and the calculation of similarity has many kinds of methods, such as Euclidean-, Manhattan- and the Infinite Module distances. Euclidean distance formula:

$$d_{iT} = \left\{ \sum_{h=1}^{n} \omega_h (v_i(h) - v_T(h))^2 \right\}^{1/2}, \qquad (22)$$

where d_{iT} is the Euclidean distance between target case T and case i in the source case; $v_i(h)$, $v_T(h)$ are the values of case i in the source case and attribute h of target case; n is the total number of attributes; ω_h is the weight of attribute.

When using Euclidean distance to calculate similarity, each attribute value should be normalized. The Euclidean distance d_{iT} between target case and source case is calculated and sorted. The smaller the Euclidean distance is, the more similar the target case and source case are. Seeking the minimum among those distances, the corresponding slope is the most similar slope to target case. So, the most similar source case is identified from the case base. Finally, the stability of target case can be estimated.

The specific steps of high rock slope stability evaluation method based on CBR can be described as follows.

(1) Determine attributes and evaluation category, normalize attributes, calculate the weights of attributes, and establish case base;
(2) Input the attribute parameters of target case, calculate similarity, and seek the most similar case base;
(3) Obtain the warning criterion of target case and judge the stability of target case.

6 Example analysis

6.1 Engineering situation

One hydropower station is located in Yalong River upstream; southwest Sichuan Province, engineering geology condition very complex. The left bank of nodal region is high and steep slope; bedrock bare; palisades towering. Upper and lower parts of formation lithology are respectively sandy slate and marble, rock with a small amount of intrusive lamprophyre veins, and there is greenschist interlayer between marble interlayer. Rock general occurrence is N 0°–30° E, NW from ∠25° to 45° which is a typical inverse layer slope. Slip-outward countertendency joints developed in the rock mass, and the faults of f5, f8, f9, and etc. close to the building developed.

6.2 Engineering geological conditions

The left bank is reverse slope, where under EL. 1,820–900 m is marble exposed section, terrain is complete, the gradient of slope is 55°–70°, and above is sandy slate exposed section, the gradient of slope is 35°–45°, terrain integrity is poor. Figures 2 and 3 describe the distribution of f42-9, f5, SL44-1, lamprophyre veins X advantage discontinuities in the left bank high slope. After left bank slope excavation, because "rock wall" as a resistance in the lateral of fault f5 will be stripped, fault f42-9 will be directly exposed in excavation face, and the wedge body composed of fault f42-9 and SL44-1 possesses sliding free face. Fault f42-9 is distributed in EL. 1,800–2,020 m, the types of fault discontinuities mostly rock fragments with little mud, and attitude of the fault is N 80°–90° E, SE ∠45°–55°. Fault f5 is throughout the left shoulder of dam and slope excavation above EL. 1,885 m, the types of fault discontinuities mostly rock fragments with little mud, and attitude of the fault is N 40°–50° E, SE ∠70°–75°. Fault SL44-1 deep tensile fracture zone develops in about EL. 1,800–2,000 m of sandy slate, mainly extending in the slope body, not exposed in the slope which is not excavated, with hollow units, and the general attitude is about SN–N 20° W, E(NE) ∠55°–60°. The attitude of lamprophyre veins is N 45°–55° E, SE ∠65°–70°.

The global stability of slope is mainly controlled by deformation tensile fracture rock composed of fault f42-9, lamprophyre veins and SL44-1 deep tensile fracture zone in the left bank dam. The possible deformation instability sliding failure mode is wedge-shaped body sliding failure mode that SL44-1 relaxation tensile fracture zone is upstream boundary, fault f42-9 is downstream boundary and slipping surface, and lamprophyre veins are trailing edges cut plane. Typical geological sections are shown in Fig. 3. According to the combination of discontinuities in the left bank slope, the maximum possible global instability mode of deformation tensile fracture rock in the left bank dam comes down to wedge-shaped body sliding failure mode.

At the same time, the groundwater in high slope of left bank activities obviously, which is one of the important factors influencing slope stability, therefore, multiple measures such as cutting off water, anti-seepage and drainage measures are adopted.

Fig. 2 Engineering geological schematic plan
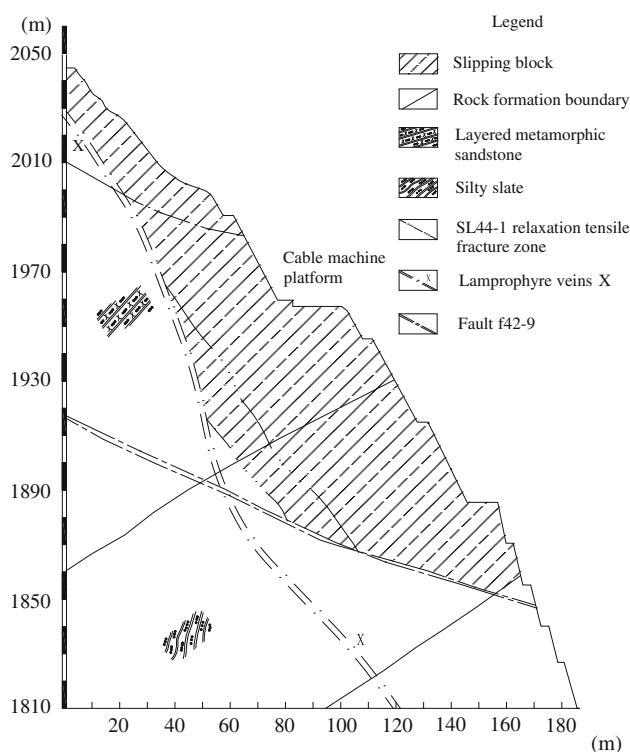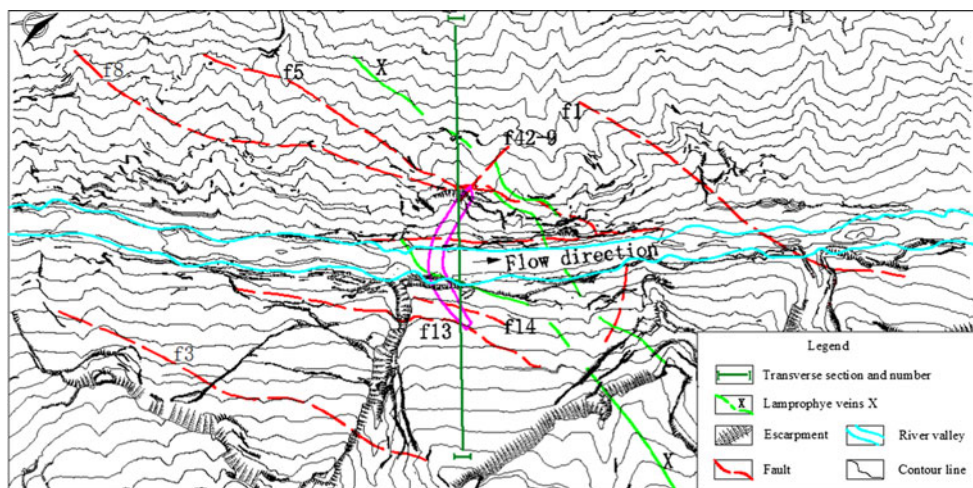
Fig. 3 Typical geological section drawing in the left bank high slope

6.3 Normalization of index parameters

Figure 1 summarizes the important factors influencing stability of high rock slope: slope height, rock mass structure, slope angle, failure mode, dip of slip plane, types of sliding plane and inducing factors of landslide (rainfall, groundwater, reservoir storage, construction methods, earthquake). As mentioned previously, to eliminate the influence of different dimensions, index data needs to be normalized (Sadiq and Tesfamariam 2009).

For slope stability, the higher the slope, the greater probability of cutting disadvantage discontinuities, the more unstable the slope, the correction coefficients of rock mass are used to describe the influence of slope mass height on the stability, the following empirical formula is used:

$$\xi = 0.57 + 33.8H^{-1}, \tag{23}$$

where H is the height of slope.

The influence of various types of discontinuities such as faults, mud intercalation, bedding and joints on the stability of slope rock mass is not the same. The property data of discontinuities are processed as follows: faults, mud intercalation, $\lambda = 0.7$; bedding plane $\lambda \in [0.8, 0.9]$; joint plane $\lambda = [0.9, 1.0]$.

Groundwater is the main inducing factor of landslide in reservoir bank, and reservoir storage affects the stability of the slope by groundwater. Developed groundwater, undeveloped groundwater with strong permeability and undeveloped groundwater with poor permeability are processed as follows: developed groundwater $\gamma = 0.7$; undeveloped groundwater with strong permeability $\gamma = [0.8, 0.9]$; undeveloped groundwater with poor permeability $\gamma = [0.9, 1.0]$.

6.4 Preliminary evaluation of stability based on the fuzzy optimum recognition theory

In Sect. 3, the stable state of slope is divided as four kinds of situations: unstable, not stable, basically stable and stable. According to Sects. 3.1 and 6.3, with reference to relevant literatures, by the classification standard of single index or factor (Table 1), the following can be obtained: $c = 4$, $m = 8$.

From Sect. 6.2, it is known that the main influencing factors of high slope stability in the hydropower project which is studied in this paper can be summed up as follows: the gradient of slope 40°–50°, maximum excavation height 225 m above EL. 1,885 m, the maximum possible

global instability mode coming down to wedge-shaped body sliding failure mode, the types of fault discontinuities mostly rock fragments with little mud, attitude of the fault f42-9 N80–90° E, SE ∠45°–55°, groundwater developed, taking a variety of anti-seepage and drainage measures.

According to Table 1, standard index membership matrix:

$$S = \begin{bmatrix} 1 & 0.9 & 0.8 & 0.7 \\ 1 & 0.9 & 0.75 & 0.6 \\ 1 & 0.85 & 0.7 & 0.4 \\ 1 & 0.9 & 0.8 & 0.7 \\ 1 & 0.9 & 0.75 & 0.6 \\ 1 & 0.9 & 0.75 & 0.5 \\ 1 & 0.9 & 0.8 & 0.7 \\ 1 & 0.9 & 0.8 & 0.7 \end{bmatrix} = (s_{ih}) \quad h = 1, 2, 3, 4. \tag{24}$$

Measured values of engineering sample are processed by normalization method, corresponding number of normalization:

$$\vec{r} = (r_1, r_2, \ldots, r_8)^T$$
$$= (0.72, 0.75, 0.65, 0.6, 0.65, 0.95, 0.85, 0.85)^T. \tag{25}$$

Comparing Eqs. (24) and (25), the index distribution of research object is quite dispersive, specifically speaking, index 1, 2, 3, 5 fall into 3–4 class, index 7, 8 fall into 2–3 class, index 4 falls into 4 class, index 6 falls into 1–2 class, so $a_1 = 1$, $a_2 = 4$.

Considering engineering safety, the bigger the classes where membership value r_{ij} of index i falls, the more harmful to the engineering safety, the index should be given a greater weight value. When determining the index weight, take 1–0 as the concept of scale, and provide: index r_{ij} equal or less than the cth classification standard value S_{ic} of index i, unnormalized weight $\omega_{ij} = 1$, and each descending a class, weight reduces 0.1, then the weight of S_{i1}, S_{i2}, S_{i3}, S_{i4} are respectively 0.7, 0.8, 0.9, 1.0. Meanwhile, the weight of r_{ij} falling into the hth and $h + 1$th classification standard value $S_{ih} \sim S_{i(h+1)}$:

$$\omega_{ij} = 0.6 + 0.1 \left(h + \frac{s_{ih} - r_{ij}}{s_{ih} - s_{i(h+1)}} \right), \tag{26}$$

where $h = 1, 2, 3$; $i = 1, 2, \ldots, 8$.

The membership of index 1 $r_1 = 0.72$, falling into the third and fourth classification standard value 0.8–0.7, substituting $h = 3$ and relevant data into Eq. (26), the unnormalized weight of index can be obtained:

$$\omega_1 = 0.6 + 0.1 \left(3 + \frac{0.8 - 0.72}{0.8 - 0.7} \right) = 0.98. \tag{27}$$

Similarly, the unnormalized weights of the other indexes

can be obtained respectively: 0.9, 0.932, 1.0, 0.967, 0.75, 0.85, 0.85, namely

$$\omega = (0.98, 0.9, 0.932, 1.0, 0.967, 0.75, 0.85, 0.85),$$

which is normalized, then get the index weight vector

$$\omega = (0.136, 0.124, 0.129, 0.138, 0.134, 0.1, 0.12, 0.119),$$

Substituting data into Eq. (18), it is can be obtained $u_1 = 0$, $u_2 = 0.251$, $u_3 = 0.643$, $u_4 = 0.106$ when $h = 1, 2, 3, 4$.

Consequently, the high rock slope after excavation is identified the third class by fuzzy optimum recognition theory, in not stable state, needed reinforcement measures.

6.5 Preliminary evaluation of stability based on CBR

Selecting Sect. 3.1 research collection of rock slope as source case, the left bank high slope of the hydropower project which is discussed in this paper is target case. Influencing factors of typical high rock slope stability, the data after normalization of influencing factors and stable state are listed in Table 2. Influencing factors of target case and the normalized data are as mentioned in Sect. 6.4. According to Eq. (19) calculate index weight of each influencing factors, and the results are 0.344, 0.28, 0.5, 0.29, 0.5, 0.39, 0.347, 0.3.

According to Eq. (22) calculate the Euclidean distance of target case and source case, and the results are 0.114, 0.019, 0.05, 0.082, 0.052, 0.038, 0.09, 0.129, 0.067, 0.036, 0.073, 0.141, 0.025. From Sect. 5, it can be seen that the closer the Euclidean distance, the more similar with source case and target case, that is, the target case is most similar with source cases 2#, 13#, 10# and 6#, and the stability state of source cases 2#, 13#, 10# and 6# are not stable, not stable, stable and not stable. The 2#, 13# and 6# are in the same stability state, and 10# is the exception. Despite these differences, the extremely conservative from stable slope (1) to the unstable slope (4) and extremely dangerous from unstable slope (4) to the stable slope (1) does not appear in evaluation. The similar slopes already include all not stable slopes of the case base. Therefore, the macro-comprehensive evaluation of the stability state for target slope is not affected. Thereby, it can be initially determined that the high slope excavation without support in the left bank of engineering has instability risk, and reinforcement measures shall be taken, basically consistent with the conclusion in Sect. 6.4.

In CBR, when retrieved case is used to a new problem, the solving result must first be evaluated. If successful, the solution result is no need to adjust or modify. Otherwise you need to adjust or modify it. Once the new problem is solved, the solution process may be used for similar problems in the future. Therefore, it is necessary to add the

new problem to case base. Seeing from the calculation result above, the case retrieval proved to be successful. There is no need to adjust or modify, the target case can also be used as a typical case added to the hydropower engineering slope case base.

7 Conclusions

Combining with deformation mechanism of rock slope in hydropower project, the index system of high rock slope stability is put forward. For existing numerous uncertainties in high rock slope stability, research the preliminary evaluation method of high rock slope stability based on fuzzy optimal recognition theory and the one based on CBR, respectively.

(1) Surveying and collecting domestic typical rock slope cases in hydropower engineering, provide a strong basis for the preliminary evaluation method.

(2) On the basis of typical high rock slope cases, put forward the normalization method of influencing factors on high rock slope stability, establish the preliminary evaluation method of slope stability based on fuzzy optimum recognition theory, and the example analysis shows that the method whose physical conception is clear, is simple and practical.

(3) Construct CBR method of high rock slope in hydropower engineering, which makes the studied high rock slope as target case, through the similarity calculation, get the most similar source case with target case, so as to achieve the preliminary forecast, evaluation on the stability of slope.

(4) The example analysis finds that index weights of two methods do not fit well in a certain extent, and the accuracy of methods needs further study.

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