Stability Assessment Model for Epimetamorphic Rock Slopes based on Adaptive Neuro-Fuzzy Inference System

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ABSTRACT

Neuro-fuzzy inference systems have been used in many areas in civil engineering applications. A stability assessment model for *epimetamorphic* rock slopes has been developed by using Adaptive Neuro-Fuzzy Inference System (ANFIS) for its capacity of dynamic nonlinear analyses. In the present study the inference system is employed to predict the stability of the slope by choosing bulk density γ, the height H, the inclination β, the shear strength parameters c and φ, of the slope as inputs, while the stability state as output. 53 slope cases in the author's research projects, i.e. 53 input-output data pairs were extracted, of which 41 pairs (training data set) were used for training the ANFIS while the remaining 12 pairs (checking data set) were used for validating the identified model. It is observed that the checking results of ANFIS model coincide with the actual stability state of epimetamorphic rock slopes, which outperforms the BP neural network model by contrast. Lastly, the ANFIS model was employed to predict the stability of Wangjiazhai slope, the fine prediction capability for the stability of epimetamorphic rock slopes was verified again.

KEYWORDS: Slope; Epimetamorphic rock; ANFIS; Prediction

INTRODUCTION

Epimetamorphic rock is widely distributed in mountainous area of southeast of Guizhou province in China. It occupies roughly a quarter of the aggregate area of this province. The analogical circumstance can also be seen in other regions of China such as Hunan and Guangxi.

Many engineering problems have come up due to the epimetamorphic rock, and generally they have such common properties as follows: the existence of a thicker weathered layer comparing to normal ones, and the presence of extremely broken rock mass. Both the two parts contribute to the instability of the weathered layer. It will probably lead to the failure of slopes or landslides. Only in Guizhou province, a number of large landslides can be found in weathered layer of epimetamorphic rock region (Fig. 1 illustrates a overview of epimetamorphic rock landslide after treatment).It not only results in a huge loss of highway construction and the increase of project cost, but prolong the construction duration also. Moreover, it seriously threatens the security of people's life and property.

Figure 1: Overview of an epimetamorphic rock landslide after treatment

A number of methods to assess slope stability are available. And the most used ones focus on some limit equilibrium methods such as Bishop Method [1] and Janbu Method [2]. Concerning that the structure of rock mass is of discontinuity in macroscopic perspective and its physical and mechanical properties are highly nonlinear in microscopic perspective, the stability of rock slopes is affected synthetically by both geological and engineering factors. Since these factors have characteristics of randomness, fuzziness, variableness and other uncertainty, stability assessment of slopes becomes a typical nonlinear problem. In other words, it is difficult to be presented by simple mechanical and mathematical models. Consequently, some researchers employ gray system theory (Chen 1999) [3], fuzzy methods (Zhang 2000) [4] and some other comprehensive assessment methods embedding experts' opinions to evaluate the stability of slopes. Whereas every expert would have different judgments, the results can be affected largely by the subjective factors of evaluators.

Artificial neural network (ANN) develops fast recently. It simulates the neural processing pattern of human's brain to conduct parallel process of information and nonlinear mapping, and possesses the capacity of large scale computations. Therefore, many investigators apply ANN to assess the stability of slopes (Mohammed A 2001, Wang 2006, H. Gomez 2005, and P. LU 2003)

[5-8]. More specially, BP neural network has an enhanced functionality of nonlinear analyses of its simple algorithm and fine feasibility. It is widely employed in geotechnical engineering including stability analysis of slopes (M. G. Sakellariou 2005, Wang 2005, Chen 2001) [9-11]. Generally, BP neural network is of low efficiency and likely to become trapped in local minima the training. Additionally it is difficult to determine the number of hidden layers. In order to make up for the insufficient of BPNN, some modified and novel assessment methods, e.g. generalized regressive neural network (LAN 2009) [12], RBF neural network (Fu 2003) [13], T-S fuzzy neural network (Chen 2005) [14], the combination of genetic algorithm with neural network (HE 2002, XUE 2007) [15-16], ant colony clustering algorithm (GAO 2009) [17]et.al. were developed for estimating the stability of slopes.

Current research studies devote into the integration of artificial neural network and fuzzy inference system. And it is referred to as adaptive neuro-fuzzy inference system (ANFIS) (Jang JRS 1993) [18]. ANFIS have such excellent properties that it is able to give a quick convergence a fine stability and its training results are of uniqueness etc.. By embedding the experts' fuzzy inference process into neural network, it gives specific physical significances to the nodes and weighs of neural network. Simultaneously the system has both the adaptive capability and ability of neural network, which overcomes the insufficient of bad learning ability in conventional fuzzy inference system. Hence, ANFIS has been used to deal with some practical problems in geotechnical engineering [19-22], but in available literatures, there is no application example which employs ANFIS in stability assessment of slopes.

Therefore, being supported by the Project of Science and Technology of West of the Ministry of Transportation of China with the title as slope stability of embankments in weathered layer of epimetamorphic rock series of mountainous area in Guizhou province (Project No. 200631880237), we made detailed investigation of 53 slopes in the vicinity of Kaili-Sansui highway in epimetamorphic rock region. In the course of this work, firstly we selected such parameters of the slope from the obtained data, as bulk density γ, the height H, the inclination β, cohesion c and internal friction angle φ to form the input vector, and the stability state be the only output variable. Secondly from the 53 data pairs of slopes, we used 41 ones for forming the data set while the remaining 12 ones for validating the prediction, i.e. checking data set. Then on ANFIS, we established a stability assessment model for epimetamorphic rock slopes. Lastly identified model was tested in the prediction of stability of Wangjiazhai slope.

FUNDAMENTALS AND ARCHITECTURE OF ANFIS

ANFIS is a branch of fuzzy inference system which mostly utilizes Sugeno and Takagi's of fuzzy reasoning (Jang JSR 1993) [18]. It comprises of premise part and consequent part with simplified fuzzy if-then rules as follows:

If x is A and y is B, then $z = f(x, y)$.

where A and B are the fuzzy sets in precise part, and $f(x, y)$ is a nonfuzzy equation in consequent part. Generally, $f(x, y)$ is a polynomial of input variables A and B. If $f(x, y)$ is a first-order polynomial, the generated fuzzy inference system is called first-order Sugeno and Takagi (ST) fuzzy model.

Fig. 2a utilizes a two-rule two-input first-order ST fuzzy model to illustrate the fuzzy reasoning mechanism. It has two input variables x and y, one output variable z, and contains two if-then fuzzy rules:

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$;
Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$.

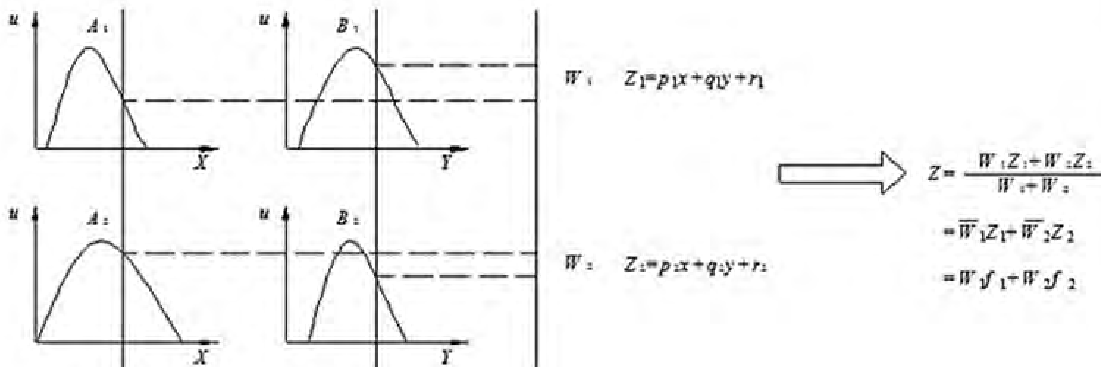

Figure 2 (a): The first-order ST fuzzy model

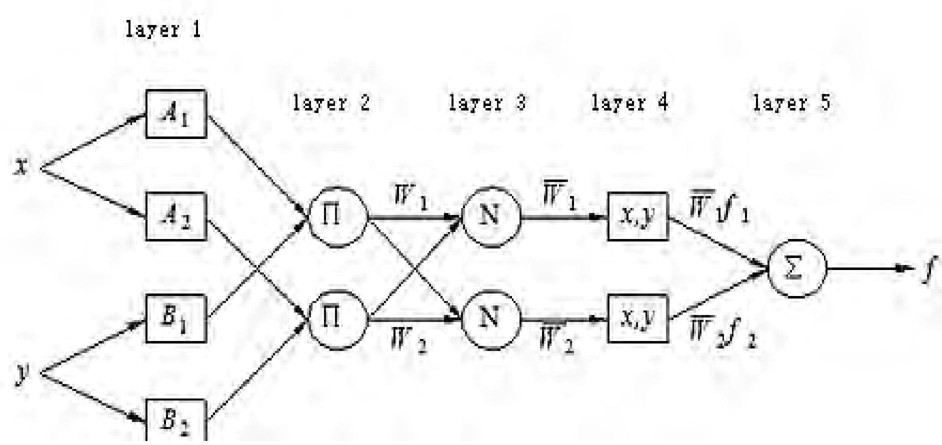

Figure 2 (b): Corresponding ANFIS architecture

The corresponding equivalent ANFIS architecture is shown in Fig. 2b. The ANFIS has 5 layers, node function in the same layer are of the same function family as described below. Note that O_{ij} denotes the output of the ith node in layer j.

Layer 1: Every node i in this layer is an adaptive (square) node with a node function

$$O_{1i} = u_{Ai}(x),\ i = 1,2 \tag{1}$$

where x is the input to node i, and A is the linguistic label (small, large, etc.) associated with this node function. In other words, O_{1i} is the membership function of A_i and it specifies the degree to which the given x satisfies the quantifier A_i. In fact, any continuous and piecewise differentiable functions are qualified for node functions in this layer, such as usually used bell-shaped function with maximum equal to 1 and minimum equal to 0, as follows:

$$u_A(x) = \frac{1}{1+\left|\frac{x-c_i}{a_i}\right|^{2b_i}} \tag{2}$$

where $\{a_i, b_i, c_i\}$ is the parameter set. As the values of these parameters change, the bell-shaped functions vary accordingly, thus exhibiting various forms of membership functions on linguistic label A_i. Parameters in this layer are referred to as the 'premise parameters'.

Layer 2: Each node in this layer calculates the 'firing strength' of each rule via multiplication:

$$O_{2i} = u_{A_i}(x)u_{B_i}(y), i = 1, 2 \tag{3}$$

Layer 3: The ith node in this layer calculates the ratio of the ith rule's firing strength to the sum of all rules' firing strengths:

$$O_{3i} = \overline{w} = \frac{w_i}{w_1 + w_2}, \quad i = 1, 2 \tag{4}$$

For convenience, outputs in this layer will be called 'normalized firing strength'.

Layer 4: Every node i in this layer is an adaptive (square) node with a node function:

$$O_{4i} = \overline{w}_i f_i = \overline{w}_i (p_i x + q_i y + r_i) \tag{5}$$

where $\overline{w}_i$ is the output of layer 3, and $\{p_i, q_i, r_i\}$ is the parameter set. Parameters in this layer will be referred to as 'consequent parameters'.

Layer 5: The single node in this layer is a fixed (circle) node labeled Σ that computes the 'overall output' as the summation of all incoming signals, i.e.

$$O_{5i} = \sum \overline{w}_i f_i = \frac{\sum w_i f_i}{\sum w_i} \tag{6}$$

Thus, an adaptive network is constructed which is functionally equivalent to the ST fuzzy model. But the adaptive architecture is not exclusive, we can merge layer 3 and layer 4 and obtain an equivalent architecture with 4 layers. Similarly, the weight normalization can be performed in the last layer of the network. Most extremely, we can even reduce the whole network to a single adaptive node with the same parameter set (Jang JSR 1997) [23].

There exit mainly two methods to generate the training structure of ANFIS, i.e. grid partition method and clustering method. While the learning rules are focused on error back-propagation learning rule and hybrid learning rule (Jang JSR 1997) [23].

DEVELOPMENT OF STABILITY ASSESSMENT MODEL OF SLOPES BASED ON ANFIS

Preparation of the database

We have investigated 53 typical slopes in detail on the sides of Kaili-Sansui highway (see Fig. 3) which located in epimetamorphic rock region and obtained primary data. On the basis of these data, we extracted such 5 parameters of the slope as bulk density γ, height H, inclination β, cohesion c and internal friction angle φ to form the input vector (for a part of slopes which have weak structural plane, c and φ are the cohesion and internal friction angle of weak structural plane, respectively), while the stability state of slope to be the output (0 denotes the failure of slope and 1 denotes the stable slope). The total 53 data pairs of slopes were divided into two parts, 41 pairs were used to train the ANFIS model, while the remaining 12 pairs to test the prediction. Training data set and checking data set are presented in Table 1 and Table 2, respectively.

(a) Location of Guizhou province in China

(b) Location of Kaili-Sansui highway in Guizhou

Figure 3: Specific location of Kaili-Sansui highway

Table 1: Training data set of epimetamorphic rock slopes

Code	Location of slope	Bulk density/ (kN/m3)	Height/m	Inclination /(°)	Cohesion /kPa	Internal friction angle/ (°)	Actual stability state of slope
1	Slope in Tailie elementary school	20	10	10	8	20	Failure(0)
2	Slope on the right of Circle E of Tailie Overpass	27.3	30	30	37.3	31	Stable(1)
3	Landslide on the left of	20.6	35	25	26.31	22	Failure

	K71+625～K71+700						(0)
4	Slope of Pingxite Bridge	21.6	50	40	6.5	19	Failure (0)
5	Slope on the right of K76+085～K76+200	22.4	35	28	28.9	24	Failure (0)
6	Slope on the left of K77+920～K78+100	23.2	33	30	31.2	23	Failure (0)
7	Slope on the left of K79+165～K79+300	26.8	26	30	37.5	32	Stable (1)
8	Slope on the right of K79+920～K80+035	27.4	42	25	38.1	31	Stable (1)
9	Landslide on the right of ZAK0+315～ZAK0+407	21.8	50	50	32.7	27	Failure (0)
10	Slope on the left of K83+260～K83+360	21.8	60	35	27.6	25	Failure (0)
11	Slope on the right of K88+300～K88+420	26.5	21	30	35.4	32	Stable (1)
12	Slope on the right of K88+700～K88+876	26.5	39	35	36.1	31	Stable (1)
13	Slope on the right of K89+730～K89+841	27	69	30	35.8	32	Stable (1)
14	Slope on the right of K90+225～K90+345	27	22	25	38.4	33	Stable (1)
15	Slope on the left of K98+520～K98+710	21.4	52	50	28.8	20	Failure(0)
16	Slope on the left of K99+120～K99+260	26	55	38	42.4	37	Stable(1)
17	Slope on the left of K100+280～K100+410	26	30	25	39.4	36	Stable(1)
18	Slope on the left of K100+615～K100+915	25.6	26	25	38.8	36	Stable(1)
19	Landslide on the left of K103+330～K103+450	20	53	45	30.3	25	Failure(0)
20	Slope on the left of K104+610～K104+805	25.8	50	30	34.7	33	Stable(1)
21	Landslide on the left of K104+892～K105+052	21.8	99	35	28.8	26	Failure(0)
22	Landslide on the left of K105+260～K105+330	21.8	60	30	31.2	25	Failure(0)
23	Slope on the left of K106+268～K106+577	24	51	30	41.5	36	Stable(1)
24	Slope on the left of K106+992～K107+085	24	50	35	40.8	35	Stable(1)
25	Landslide on the left of K107+856～K107+968	20.6	70	35	27.8	27	Failure(0)
26	Landslide on the left of K108+960～K109+010	20.6	55	35	32.4	26	Failure(0)
27	Slope on the left of K109+841～K109+900	25.8	40	27	38.2	33	Stable(1)
28	Slope on the left of K110+200～K110+274	25.8	45	25	39.4	33	Stable(1)
29	Landslide on the left of	21.1	31	40	33.5	28	Failure(0)

	K110+421～K110+500						
30	Landslide on the left of K110+980～K110+240	21.1	75	30	34.2	26	Failure(0)
31	Slope on the right of K112+720～K112+815	26.6	52	25	42.4	37	Stable(1)
32	Slope on the left of K113+500～K113+580	26.6	42	35	44.1	38	Stable(1)
33	Slope on the left of K114+060～K114+167	26.6	60	35	40.7	35	Stable(1)
34	Slope on the left of K114+224～K114+258	25.8	40	30	41.2	35	Stable(1)
35	Slope on the left of K117+200～K117+412	25.8	33	30	43.3	37	Stable(1)
36	Front slope of tunnel in SongjieyaK122+310	21.7	60	45	32	27	Failure(0)
37	Landslide on the right of K122+350～K122+455	20.6	65	40	28.5	27	Failure(0)
38	Landslide on the left of K127+440～K127+590	21.5	70	40	29.8	26	Failure(0)
39	Slope on the left of K127+761～K127+882	26.5	36	34	42.9	38	Stable(1)
40	Landslide on the left of K137+650～K137+730	20.8	45	30	15.6	20	Failure(0)
41	Landslide on the left of K138+624～K138+797	20.8	40	30	14.8	21	Failure(0)

Table 2: Checking data set of epimetamorphic rock slopes

Code	Location of slope	Bulk density/ (kN/m^3)	Height/m	Inclination /(°)	Cohesion /kPa	Internal friction angle/ (°)	Actual stability state of slope
1	Landslide on the right of K75+760～K76+000	19.6	58	40	29.6	23	Failure(0)
2	Slope on the right of ZBK0+000～ZBK0+185	25.4	35	20	33	33	Stable(1)
3	Landslide on the left of K84+602～K85+185	22.4	50	50	29.3	26	Failure(0)
4	Slope on the right of K91+614～K91+660	26.2	30	35	41.5	36	Stable(1)
5	Slope on the right of K91+720～K91+771	26.2	36	23	42.3	36	Stable(1)
6	Slope on the left of K100+950～K101+300	25.6	32	30	39.8	36	Stable(1)
7	Slope on the left of K102+691～K102+880	25.6	60	35	36.8	34	Stable(1)
8	Slope on the right of K118+360～K118+549	26.2	37	30	42.8	37	Stable(1)
9	Slope on the right of	26.2	68	35	43.8	38	Stable(1)

	K119+823～K119+951						
10	Landslide on the right of K124+340～K124+562	20.6	42	30	32.4	26	Failure(0)
11	Slope on the right of K131+280～K131+380	26.5	54	42	41.8	36	Stable(1)
12	Landslide on the left of K138+840～K138+930	20.8	53	30	15.4	21	Failure(0)

Architecture of ANFIS model

The 5 quantities mentioned above were chosen as input variables, and the stability state of epimetamorphic rock slope as output variable. Each input variable had two membership functions of Gaussian type. The grid partition method was utilized to generate the training structure, and the hybrid learning rule was employed in the learning procedure. The training data set was performed learning and training constantly till the error measure of output was tolerant; the checking data set was used to test the prediction capability and give a cross validation of the ANFIS model. The schematic of the architecture of ANFIS is illustrated in Fig. 4.

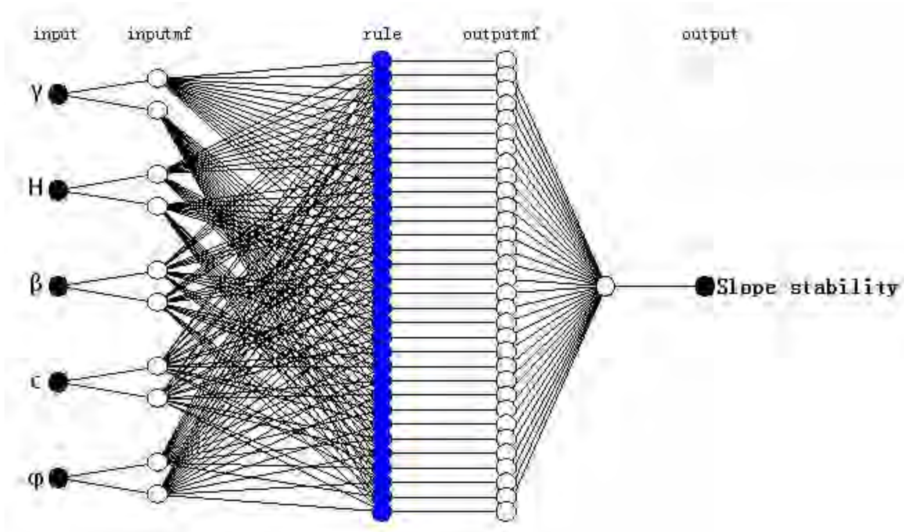

Figure 4: Schematic of the architecture of ANFIS model

Evaluation of the model

The training and checking error curves are shown in Fig. 5, which demonstrates that the training and checking error converge simultaneously, thus the same inherent law is shared by the training and checking data within the precision requirement of engineering.

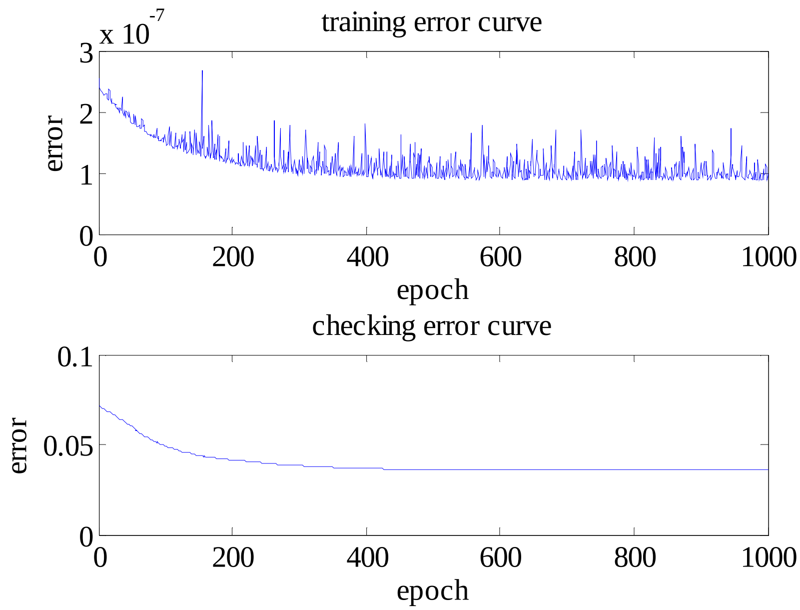

Figure 5: Error curves of ANFIS model

In order to demonstrate the superiority of ANFIS model, a BP neural network (BPNN) model was established by contrast. In BPNN, inputs are also bulk density γ, height H, inclination β, cohesion c and internal friction angle φ, of the slope and the stability state of the slope is output (0 denotes the failure of slope and 1 denotes the stable slope). There are 10 hidden layers, except for that transfer function of output layer is purelin function, transfer functions of other layers are tansig function; learning function employs learngdm function; training function adopts trainlm function and error performance function uses mse function. The specific theory and method of BP neural network can refer to these literatures: M.G.SAKELLARIOU 2005, Wang 2005, and Chen 2001[9-11].

Fig. 6 shows the comparison of training values of ANFIS model and BP neural network model with actual stability state values of epimetamorphic rock slopes. It is found that both ANFIS and BPNN can achieve fine training precision, i.e. the training values dramatically coincide with the actual values.

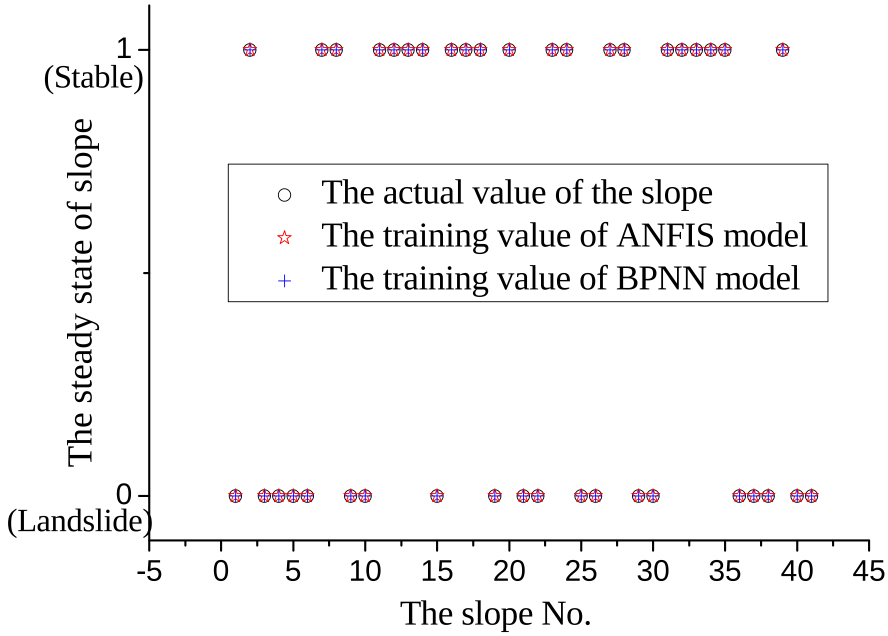

Figure 6: Comparison of training values of ANFIS and BPNN with actual values

The checking results of ANFIS model and BPNN model are compared with the actual stability state value as illustrated in Fig. 7. It is observed that with respect to the same checking data set, the checking results of ANFIS model are perfectly identical to the actual stability state values of slopes, whereas BPNN model makes a wrong prediction which is not agree with the actual stability state of a slope. More specifically, the error rate of BPNN reaches 8.3 per cent. Hence, due to its higher accuracy rate of prediction, it is feasible to employ ANFIS model to assess the stability of epimetamorphic rock slopes.

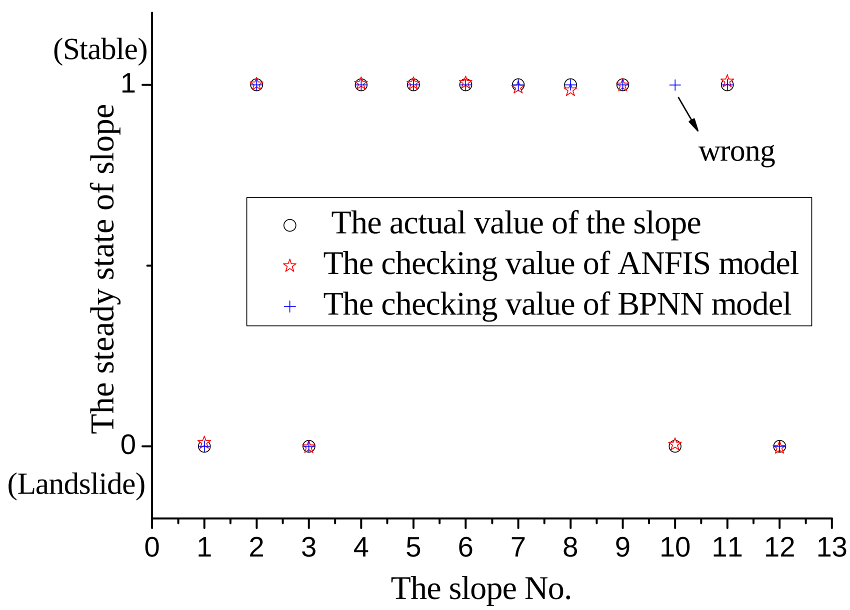

Figure 7: Comparison of checking results of ANFIS and BPNN with actual values

Influence factors on model precision

The author figures out the following factors which can influence the performance of network:

(1) Accuracy of data set and the number of data pairs. ANFIS is based on the training data set. It is able to elect rules in learning procedure of structure and eliminate a part of data pairs, but the prediction precision of system is determined by the accuracy of data population. Additionally, a smaller number of data pairs will lead to an inferior learning capability, thus the system stability cannot be guaranteed.

(2) The number of input variables of ANFIS. When the number of inputs increases, accordingly the number of dimensions of the system will increase, the learning procedure will be more complicated. Especially, when there is not sufficient accuracy of data pairs, the checking precision is very likely to fail to satisfy the requirement and even cannot converge.

(3) The number of membership functions pertaining to each input. Theoretically, more membership functions amount to a smaller fuzzy interval, which will contribute to a higher training precision. However, it should be kept in mind that the checking precision will probably decrease along the increasing number of membership functions. Generally, two membership functions for each input will be in the tolerance of engineering requirement.

Engineering application of ANFIS model

Take Wangjiazhai Slope (see Fig. 8) in the vicinity of Kaili-Sansui highway for example to test the prediction capability of ANFIS model established herein for the safety of epimetamorphic rock slopes. The inputs values of model for this slope are such as follows: γ= 19.8 kN/m^3, H = 98 m, β = 26° , c = 8.6kPa, φ = 17.8° . Loading the above data into the ANFIS model developed in the previous context, we can obtain the output value for -0.07 i.e. the slope is of failure which comes agree with the actual circumstance. Actually, Wangjiazhai slope is a landslide (Jia 2009) [24]. It is a proof to indicate the fine prediction function of ANFIS model developed in this work for stability assessment of slopes in epimetamorphic rock region.

Figure 8: Location of Wangjiazhai slope

CONCLUSIONS

(1) With respect to the complex nonlinear relationship of influence factors on slopes, this paper devotes into the establishment of ANFIS model to perform the stability assessment of epimetamorphic rock slopes by taking advantage of the dynamic nonlinear analyses capability of ANFIS.

(2) A stability assessment model for epimetamorphic rock slopes based on ANFIS was established. In this model, 5 parameters which had significant influence on the stability of epimetamorphic rock slopes were selected to form the input vector, while the stability state of the slope be the output variable; 41 engineering cases were used for training the model, and 12 engineering cases for checking the system. By contrast with the most common BP neural network model, the ANFIS model is observed to outperform the BPNN.

(3) An engineering project was employed to test the prediction capability of ANFIS model developed in this work for the safety of epimetamorphic rock slopes. A fine prediction performance of this ANFIS model was found for stability assessment of slopes in epimetamorphic rock region.

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