

NEURAL NETWORK FOR ROCK SLOPE STABILITY EVALUATION

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ABSTRACT

An expert system has been developed for use in the stability evaluation of rock slopes under various geological conditions and engineering requirements. It is formed by neural network of paths and decision making procedures that use rock slope characteristics as input, evaluate the information, and lead to the output in form of the probability of failure. The input rock slopes are hierarchically characterized using various criteria, e.g., site characteristics, geological and hydrological conditions, mechanical properties, slope geometry, past failure, vegetation, ground vibration, engineering requirements, design constraints, and project goals, etc. The predictive capability of the proposed program has been verified by comparing with the actual rock slopes under stable and unstable conditions. The results are encouraging.

KEYWORDS: rock, slope, network, expert system, failure, stability, geology, hydrology

INTRODUCTION

Background

Expert system or knowledge base system is an intelligent computer program that uses knowledge and inference procedures to solve problems that are difficult enough to require significant human expertise for their solution. It is formed by a neural network, which is a part of the artificial intelligence approaches to problem. Knowledge necessary to perform at such level, plus the inference procedures used, can be thought of as a model of the expertise of the best practitioners of the field. The rules or heuristics that are used to solve problems in a particular area are stored in the system. It then tries to arrive at a conclusion from the known facts with the help of the knowledge base. The inference engine or the rule interpreter examines the existing facts in the working memory and the rules in the knowledge base. It determines the order in which the rules will be used. The inference engine carries out consultation with the user and informs the user when a conclusion is reached. If more information is required to invoke additional rules, it prompts the user accordingly (Harmon and King, 1985; Townsend and Feucht, 1986).

Moula et al. (1995) compile the names of numerous expert systems and knowledge base systems that have been developed for the analysis and design in geotechnical engineering. The application of the expert system in rock slope engineering however remains rare. For rock slope stability evaluation, classical methods and numerical analyses are often inadequate due to the geometric complexity, geological heterogeneity, engineering requirements, and time constraints. Such conventional approaches (e.g. Hoek and Bray, 1981; Goodman, 1989) also require a complete set of the representative rock properties, which often are difficult or uneconomically feasible to obtain. As a result, over 50% of rock slopes worldwide have been designed by experts. The expert can use their intuition, skills and

experience to arrive at the final conclusion of the design. Through the course of their profession they have developed their own criteria and decision-making rules for the analysis and design process. With the expert system such knowledge can be preserved indefinitely. The system is revisable and can be used to train new or inexperienced engineers. It will never omit relevant factors and rules needed in the evaluation and design of rock slopes, and hence minimizes the damage caused by erroneous design.

Objective

The objective of the present research is to develop a simple neural network for an expert system for the evaluation of rock slope stability. The proposed network is not based on the known analytical solutions or theories, but are based on the heuristic knowledge, inference procedure and experience of a slope expert backed by the rationale and logic. As a result, several relevant factors beyond those considered in the classical methods can be explicitly incorporated, e.g., slope history, excavation methods, joint spacing and apertures, existing vegetation, and current supports. Presented herein are the development of the system neural network and the verification of the system performance by comparing with the actual slope conditions.

MAIN NETWORK

Fig. 1 shows the main network linking four functional components used in the stability evaluation and support design of rock slopes obtained from the interview of a slope expert. These components are 1) data acquisition, 2) classification and preliminary evaluation, 3) stability evaluation, and 4) recommendations on support design. The system uses forward chaining strategy. The data are compiled and subjected to rules and conditions to obtain specific answers. Visual Basic software is used to create links and paths leading to the conclusions. The stability evaluation considers four modes of failure: plane sliding, wedge sliding, toppling failure, and circular failure. The system determines the possibility for each failure mode. If any mode is proved possible, it will determine the probability of the failure. Fuenkajorn and Kamutchat (2001) describe the recommendations on the support design.

Data acquisition

The system needs to know the general features of the rock slope that the user is dealing with. Such features include general geology, slope geometry, and engineering requirements. It first determines whether the slope problem is within the scope of its capability. If capable, it will further define the problem, and will try to match the input data with one of the preset conditions or slope types. This is achieved by posing a selected sequence of questions to the user. The questions in each set will be arranged into relevant categories, and from the most general to specific. The user can respond to each question by selecting one of the several prescribed answers. An option of 'unknown answer' is also available. The main categories whose questions belong to are summarized as follows.

Geologic features. There are six types of rock allowed by the system: 1) massive rock, 2) blocky rock, 3) bedded rock, 4) heavily-jointed rock, 5) soft rock, and 6) hard-soft interbedded rock. If the input slope problem does not fall into one of these types, the system will immediately admit that it can not solve that problem.

Safety requirements. The system classifies the engineering applications of rock slope into four levels of safety, based on the types of engineering structures (e.g., railroad, home, major highway, spillway, dam abutment, mined road, etc.) and on the distance between these structures and the slope toe.

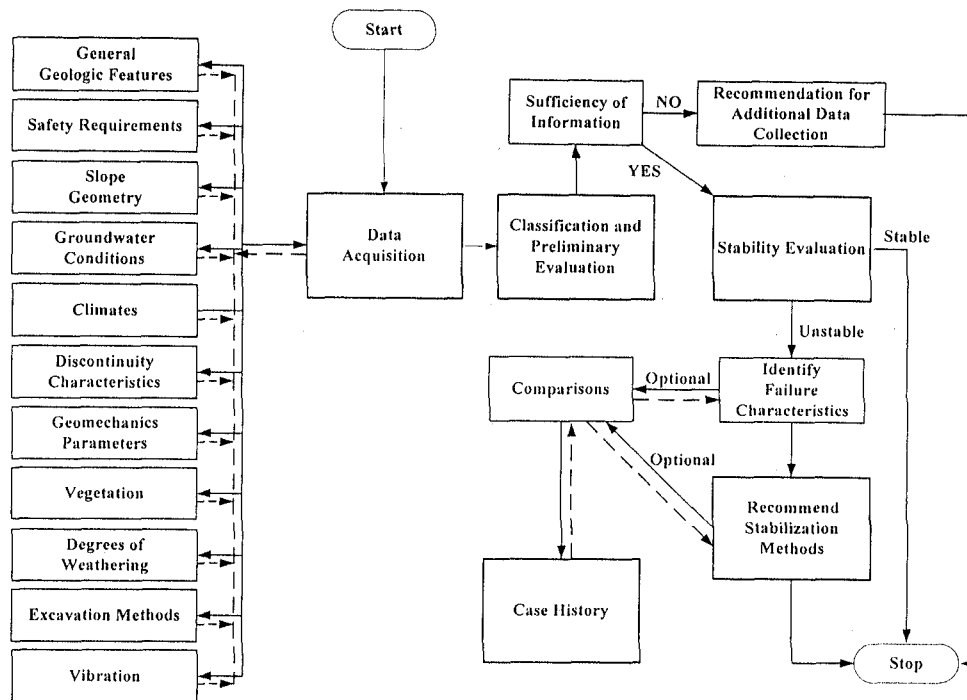


Fig. 1 Main network

Groundwater conditions. The system classifies the groundwater in terms of its level as compared to the slope height. The options are from completely dry to water level up to 25%, 50%, 75%, or 100% of the slope height. If the condition is unknown, the system will further inquire the climate where the slope is situated. Two options are available here: tropical and arid.

Slope geometry. This crucial information includes the slope orientation, height, angle, and curvature. Three slope shapes are available: convex, concave and straight faces. Topography of the upper slope face and near the slope toe can be inserted as an option. The system can also design the optimum slope geometry, if requested.

Joint characteristics. The user must provide orientation, average spacing, continuity, aperture, filling, and roughness of all joint sets.

Geomechanics parameters. Rock density, uniaxial compressive strength, and shear strength of all joint sets should be provided. If they are unknown, the system will further ask about the types of rock forming the slope, and then will extract the missing information from its database. A conservative set of geomechanics parameters will be selected.

Supplementary information. Some information can be of useful, but not necessary. These are available as input options, e.g., the past failure, vegetation, methods of excavation, and current support. They may be used in the stability evaluation when applicable.

To gain trust and understanding from the user, instead of answering the question asked by the system, user may ask why the system is asking a particular question. The system will give the reasoning or basis for what the particular answer will be used, or the rule it is trying to satisfy. This makes it user-friendly and helps the user to understand and rely on the system.

Preliminary evaluation

After the data have been systematically stored, the system first determines 1) whether the information is sufficient to evaluate the stability, 2) whether there is any conflict between the input parameters, and 3) whether the input parameters are valid. If it decides that the information is insufficient, it will skip the evaluation process, and will recommend the user to acquire the missing information. The system will resolve the conflicts and will check the validity of the input data. For example, if the user assigns unrealistic friction angles, or if two joint sets have identical attitudes, it will prompt the user to recheck or correct his input.

As the data collection progresses, the system evaluates the incoming information and tries to classify the slope to narrow down the types of problem. The next question to the user will therefore be partly dictated by the previous answers. This strategy is adopted to make the neural network efficient and to reach the final conclusions quickly.

STABILITY EVALUATION

The system classifies each factors considered in the stability evaluation into small ranges or sub-divisions, mainly to convert the input slope characteristics into quantitative form. The classification follows as much as practical the suggested methods by the International Society of Rock Mechanics (ISRM - Brown, 1981). A set of rating is then assigned to these parameters for each failure mode considered. Recognizing that the significance of these parameters can be at different degrees for different conditions of the rock mass, a set of influencing factors is also defined as multiplying factors for the corresponding parameter. The probability of failure $P\{f\}$ in percent for each mode can then be calculated by

$$P\{f\} = \Sigma \{R_n * I_n\},$$

where R_n is the rating for each parameter, I_n is the influencing factor for the corresponding parameter, and n represents type or number of the parameters considered for each slope (varying from 1, 2, 3, 4,..... n). Tables 1 and 2 list the rates and influencing factors to calculate the probability of the circular failure. In this case, the value n equals to 7. The calculations of the probability of failure for plane and wedge sliding use 12 parameters, and hence $n = 12$. Detailed classifications, rating, and influencing factors for the plane and wedge sliding and toppling failure evaluation are given in Tables 3 through 6.

To correlate the probability of failure to the factor of safety, the system defines that the factor of safety is 1.0 when $P\{f\}$ equals to 50%. The system recommendations also compare the calculated $P\{f\}$ against the degrees of safety required for four types of engineering application. For Type A where the slope toe is nearby the residential structures or power plant facilities, $P\{f\}$ should be less than 10%. Type B is for the slopes along the main highways, railroads, and large bridges, which requires the $P\{f\}$ less than 30%. Type C is for the slopes along the small roads and reservoirs, which requires the $P\{f\}$ less than 50%. Type D requires $P\{f\}$ less than 70% which is defined for the temporary access or small roads in open pit mines.

VERIFICATIONS

The predictive capability of the proposed neural network has been assessed by comparing the calculated probability of failure with the actual slope conditions. Table 7 tabulates some selected case studies showing the actual modes of failure. The network predictions agree reasonable well with the actual failure conditions. The system uses the slope characteristics and material property data and calculates the probability of failure for

Table 1 Rating factors for evaluation of circular failure

Slope height		Slope face angle		Groundwater Table		Degree of weathering	
(m)	Rate	Degrees	Rate	(%)	Rate	Conditions	Rate
2-5	1	20-25	0	0	0	Fresh	2
5-10	5	25-30	1	25	5	Slightly	4
10-15	8	30-35	2	50	10	Moderately	6
15-20	10	35-40	3	75	10	Highly	8
>20	10	40-45	5	100	10	Completely	10
		45-50	6	Unknown	10	Unknown	5
		50-55	8				
		55-60	9				
		60-65	9				
		65-70	10				
		>70	10				
Vegetation		Excavation		Vibration			
Conditions	Rate	Methods	Rate	Conditions	Rate		
No vegetation	10	Blasting with Pre-splitting	5	Near Blasting sites, earthquake	10		
Only grass	7	Blasting without pre-splitting	10	Near main highway	5		
Grass with small trees	5	Backhoe	0	No vibration	0		
Full grown trees	0	Unknown	5	Unknown	5		
Unknown	5						

Table 2 Influencing factors for evaluation of circular failure

Rock grade	Slope height	Slope face angle	Groundwater	
R0	3.02	3.02	3.11	
R1	2.82	2.82	2.51	
R2	2.58	2.58	2.01	
R3	2.23	2.23	1.71	
Rock grade	Weathering	Vegetation	Excavation	Vibration
R0	0	0.5	0	0.35
R1	0.1	1.1	0.1	0.55
R2	0.4	1.28	0.4	0.75
R3	0.7	1.42	0.7	1.01

each mode. In the case where some parameters are not available, it assumes such parameters and continues to evaluate the slope stability. It should be noted that most of the presented cases can not be analyzed by the classical methods due to the incompleteness of the material property data. The details are given in the table.

Table 3 Rating factors for evaluation of plane and wedge sliding

Number of other discontinuity		Spacing of the analyzed set		Apertures of the analyzed set		Infilling of the analyzed set	
Sets	Rate	(mm)	Rate	(mm)	Rate	Type	Rate
1	2	< 20	10	<0.1	1	Calcite	0
2	6	20-60	10	0.1-0.25	2	Nothing	5
3	10	60-200	8	0.25-0.5	3	Sand, Silt	10
4	10	200-600	6	0.5-2.5	5	Clay	10
Unknown	8	600-2000	5	2.5-10	8	Unknown	5
		2000-6000	5	>10	10		
		>6000	2	Unknown	5		
		Unknown	6				
Persistence		JRC		$(\psi_p - \phi)^*$		Weathering	
%	Rate		Rate	Degrees	Rate	Conditions	Rate
0-20	1	0-2	10	70-80	10	Fresh	2
20-40	5	2-4	10	60-70	10	Slightly	5
40-60	5	4-6	9	50-60	10	Moderately	8
60-80	5	6-8	7	40-50	10	Highly	10
80-100	10	8-10	6	30-40	9	Completely	10
Unknown	5	10-12	5	20-30	7	Unknown	8
		12-14	4	10-20	5		
		14-16	3	0-10	1		
		16-18	2	-10-0	0.5		
		18-20	1	<-10	0		
		Unknown	5				
Groundwater Table		Slope shape		Vegetation		Excavation	
(%)	Rate	Shape	Rate	Conditions	Rate	Methods	Rate
0	1	Concave	5	No vegetation	10	Blasting with pre-splitting	5
25	5	Straight	7	Only grass	7	Blasting without pre-splitting	10
50	10	Convex	10	Grass & small tree	5	Backhoe	0
75	10			Full grown tree	0	Unknown	5
100	10			Unknown	5		
Unknown	10						
<p>Notes: * ψ_p = sliding plane angle; ϕ = friction angle of joint</p>							

Table 4 Influencing factors for evaluation of plane and wedge sliding

Rock grade	Other discontinuity	Spacing	Aperture	Infilling	Persistence	JRC first set
R2	0.27	0.56	0.57	0.47	0.66	1.15
R3	0.46	0.35	0.96	0.96	0.98	1.52
R4	0.58	0.2	1.35	1.35	1.2	1.75
R5	0.72	0.2	1.6	1.6	1.41	1.98
R6	0.78	0.2	1.6	1.6	1.42	2

Rock grade	$\psi_p - \phi$	Degree of weathering	Groundwater Table	Slope shape	Vegetation	Excavation methods
R2	1.54	1.00	2.34	0.37	0.40	0.64
R3	1.82	0.40	1.40	0.21	0.40	0.54
R4	2.1	0.33	0.53	0.11	0.10	0.4
R5	2.29	0	0	0	0	0.2
R6	2.3	0	0	0	0	0.1

Table 5 Rating factors for evaluation of toppling failure

Number of other discontinuity		Spacing of other set		Apertures of the analyzed set		Infilling of the analyzed set	
Sets	Rate	(mm)	Rate	(mm)	Rate	Type	Rate
1	0	< 20	10	<0.1	1	Calcite	0
2	5	20-60	10	0.1-0.25	5	Nothing	10
3	10	60-200	10	0.25-0.5	10	Sand, Silt	10
4	10	200-600	5	0.5-2.5	10	Clay	10
Unknown	5	600-2000	5	2.5-10	10	Unknown	10
		2000-6000	1	>10	10		
		>6000	1	Unknown	10		
		Unknown	5				

Persistence		JRC		Dip of first the analyzed set		Degrees of weathering	
%	Rate		Rate	Degrees	Rate	Conditions	Rate
0-20	2	0-2	10	80-90	3	Fresh	2
20-40	2	2-4	10	30-80	8	Slightly	5
40-60	6	4-6	9	0-30	10	Moderately	8
60-80	8	6-8	5			Highly	10
80-100	10	8-10	5			Completely	10
Unknown	6	10-12	5			Unknown	8
		12-20	2				
		Unknown	5				

Table 5 Rating factors for evaluation of toppling failure (continue)

Groundwater Table		Vegetation		Excavation methods		Vibration	
(%)	Rate	Conditions	Rate	Methods	Rate	Conditions	Rate
0	1	No vegetation	10	Blasting with pre-splitting	5	Near blasting sites/ Earthquake	10
25	5	Only grass	7	Blasting without pre-splitting	10	Near main highway	5
50	5	Grass & small tree	5	Backhoe	0	No vibration	0
75	5	Full grown tree	0	Unknown	5		
100	10	Unknown	5				
Unknown	5						

Table 6 Influencing factors for evaluation of toppling failure

Rock grade	Other discontinuity	Spacing	Aperture	Infilling	Persistence	JRC
R2	0.82	0.52	0.9	0.09	0.51	0.22
R3	1.01	0.61	0.79	0.15	0.62	0.29
R4	1.16	0.72	0.68	0.21	0.75	0.37
R5	1.3	0.85	0.6	0.29	0.89	0.49
R6	1.43	1.02	0.52	0.41	1.05	0.68

Rock grade	Dip of first set	Degree of weathering	Groundwater	Vegetation	Excavation methods	Vibration
R2	3	1.1	0.64	0.98	0.55	0.67
R3	3	0.91	0.46	0.97	0.41	0.78
R4	3	0.67	0.34	0.89	0.3	0.91
R5	3	0.4	0.22	0.71	0.2	1.05
R6	3	0	0.14	0.43	0.1	1.22

CONCLUSIONS

A simple form of neural network for an expert system has been developed for evaluating the mechanical stability of rock slopes. The input parameters are hierarchically characterized into several groups and sub-groups, using various criteria, i.e., site characteristics, geological and hydrological conditions, mechanical properties, slope geometry, past failure, vegetation, ground vibration, engineering requirements, design constraints, and project goals. The kinematic analysis is first performed to identify the possibility of all potential modes of failure. Specific sets of rating and influencing factors are assigned to these parameters for each rock condition and each failure mode considered. The probability of failure is the summation of the multiplied products between the rating and the corresponding influencing factor. The predicted results agree reasonably well with the actual slopes under a range of stability conditions.

Table 7 Comparisons between neural network predictions and actual conditions

Rock Types/ Locations (References)	Slope Characteristics	Actual Conditions	Neural Network
Limestone/ Kao Som Pot Quarry, Thailand (Kamutchat, 2003)	H = 90 ft, $\delta_f = 85^\circ$ $\psi_f = 80^\circ$, J1 = 7°/24° J2 = 138°/77°; J3 = 78°/84° J4 = 221°/78°, Saturated	1) plane failure along J2 2) wedge failure between J2 & J3, J3 & J4	1) plane failure along J2 : $P_f = 75\%$ 2) wedge failure between J2 & J3, J3 & J4: $P_f = 77\%$
Shale/ Phetchabun province, Thailand (Kamutchat, 2003)	H = 48 ft, $\delta_f = 200^\circ$ $\psi_f = 48^\circ$; J1 = 309°/42° J2 = 182°/72°; J3 = 47°/78° Saturated	1) circular failure 2) wedge failure between J1&J2	1) circular failure: $P_f = 70\%$ 2) wedge failure between J1 & J2: $P_f = 78\%$
Schist/ Tak province, Thailand (Kamutchat, 2003)	H = 48 ft, $\delta_f = 215^\circ$ $\psi_f = 79^\circ$, J1 = 052°/31° J2 = 154°/79°; J3 = 241°/74° Saturated	1) plane failure along J3 2) wedge failure between J2&J3	1) plane failure along J3: $P_f = 65\%$ 2) wedge failure between J2 & J3: $P_f = 68\%$.
Sandstone/ Khon Kean province, Thailand (Kamutchat, 2003)	H = 50 ft, $\delta_f = 110^\circ$ $\psi_f = 72^\circ$, J1 = 116°/26° J2 = 360°/83°; J3 = 279°/76° Saturated	stable	failure not possible
Dolomite/ Theodore Roosevelt Dam, USA (Scott, 1995)	H = 110 ft, $\delta_f = 360^\circ$ $\psi_f = 84^\circ$, J1 = 050°/25° J2 = 180°/70°; J3 = 318°/83° J4 = 058°/31°, $\phi = 35^\circ$ Saturated	1) plane failure along J3 2) toppling failure between J2&J4	1) plane failure along J3: $P_f = 55\%$ 2) Insufficient data
Calcite Silicate/ South Foot Wall, South Africa (Bye and Bell, 2001)	H = 40 ft, $\delta_f = 355^\circ$ $\psi_f = 51^\circ$, J1 = 087°/86° J2 = 196°/79°; J3 = 124°/61° $\phi = 32^\circ$, $\sigma_c = 140$ MPa c = 2000-200000 psf Saturated	1) wedge failure between J1&J2 and J1&J3	1) wedge failure between J1&J2: $P_f = 76\%$ and J1&J3: $P_f = 60\%$
Marl/ Eskihisar (Yatagan-Mugla), Turkey (Sonmez and Ulusay, 1999)	H = 81 ft, $\psi_f = 78^\circ$ $\sigma_c = 4.15$ MPa, Slightly Weathered, Dry	1) circular failure	1) circular failure: $P_f = 66\%$
H = Slope Height ψ_f = Dip Angle of Slope Face δ_f = Dip Direction of Slope Face σ_c = Uniaxial Compressive Strength c = Cohesion ϕ = Friction angle		FS = Factor of Safety P_f = Probability of Failure J1, J2, J3 and J4 = Joint Set Number (dip direction / dip angle) S1, S2, S3 and S4 = Joint Spacing for set 1, 2, 3 and 4	

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REFERENCES

- Brown, E.T. (1981) *Rock Characterization Testing and Monitoring*. ISRM Suggested Methods, Pergamon Press, Oxford.
- Bye, A.R. and Bell, F.G. (2001) Stability assessment and slope design at Sandstoot open pit, South Africa. *International Journal of Rock Mechanics and Mining Sciences* Vol. 38. Elsevier Science Ltd: pp.449-466.
- Fuenkajorn, K. and Kamutchat, S. (2001) Rock slope design using expert system: ROSES program. *Sixth Mining, Metallurgical, and Petroleum Engineering Conference*. Bangkok, Thailand, October 24-26.
- Goodman, R.E. (1989) *Introduction to Rock Mechanics*, John Wiley and Sons, Inc., Singapore.
- Harmon, P. and King, D. (1985) *Expert System, Artificial Intelligence in Business*, John Wiley and Sons, Inc., New York, 283 pp.
- Hoek, E. and Bray, J.W. (1981) *Rock Slope Engineering*, Institution of Mining and Metallurgy, London.
- Kamutchat, S. (2003) Rock Slope Design Using Expert System. M.S. Thesis, Suranaree University of Technology, Nakhon Ratchasima, Thailand.
- Moula, M., Toll, D.G. and Vaptismas, N. (1995) Knowledge-based systems in geotechnical engineering. *Geotechnique*, Vol. 45, No. 2, pp. 209-221.
- Scott, G.A. (1995) Rock slopes: Some construction case histories. Daeman & Schultz (eds). *Rock Mechanics*, Rotterdam: pp. 65-70.
- Sonmez, H. and Ulusay, R.(1999) Modifications to the geological strength index (GSI) and their applicability to stability of slopes. *International Journal of Rock Mechanics and Mining Sciences*. Vol. 36. Elsevier Science Ltd: pp.743-760.
- Townsend, C. and Feucht, D. (1986) *Designing and Programming Personal Expert Systems*. Tab books, Inc., Blue Ridge Summit, Pennsylvania.