Journal of Engineering and Applied Sciences 12 (9): 2361-2366, 2017
ISSN: 1816-949X

The Stability Analysis of Rok Walls by Artificial Markov Chains in the Roodbar in Lorestan, Iran

[1]Sina Mokhtar, [2]Mostafa Yousefi Rad and [2]Sayyed Hamid Lajevardi
[1]Department of Civil, Faculty of Earth Sciences, Islamic Azad University, Arak Branch, Arak, Iran
[2]Department of Geology, Faculty of Earth Sciences, Arak University of Technology, Arak, Iran

Abstract: Identifying the effective factors in evaluating the stability of stone walls is one of the main problems in geology however there are many different methods to interpret the stability of stone gables quantitatively. Despite the simple modeling process, conventional methods are not able to estimate the error or accuracy of resulting model, so they are used for continuous variables. But probabilistic methods can quantify and estimate the possibility of accuracy of the model, also examine the value of each piece of information in increasing the accuracy of the model. Markov chain can be used as a powerful way to analyze the stone walls based on conditional probabilities and providing the states transition matrix. Since this method is better utilized for discrete variables in lithology, the aim of this study is to provide more accurate results and simpler geological interpretation. In the study, it is investigated 11 intrinsic and geometric parameters influencing on the walls of Roodbar dam located in a distance of about 100 km from Southern Aligudarz, Lorestan Province, Iran. The factors were identified by using the available data and their analysis and complementation by field records. Then, the effect of each resistance parameters on the stability was examined by MATLAB7.1 Software in order to analyze the artificial Markov chains. The results indicate that the slopes of the area in a dry state are stable at 17 modes and unstable at 3 modes and in a saturated state are stable at 14 modes and unstable at 6 modes and have generally a little stability. The study indicates that the network has the ability to predict the degree of stability of rock slopes.

Key words: Rock slope, artificial Markov chains, roodbar, Lorestan, network

INTRODUCTION

Due to a variety of factors such as angle of slope and height, geomechanical properties of materials and water table, analyzing the stability of rock instabilities is among most important parts of designing in the projects in which there is likely a slide potential on the slopes of the instabilities (Khajehzadeh *et al.*, 2010). Rock instabilities in dry state are essentially more stable than the instabilities in saturation state. Among the slopes, it can be mentioned the slopes that are stable in dry state and in saturated state, they create an unstable mass because of reduced shear strength parameters.

Lithological, meteorological and morphological conditions of the area are the most important factors that cause the instabilities to occur.

Study area: In the study, it has been attempted to analyze the stability of rock instabilities in dry and saturation states in Roodbar dam using the artificial Markov chains. The area with a coordinates of 49°41'37" longitude and

Fig. 1: The position of the study area (no scale)

32°54'23" latitude is located in 100 km Southern Aligudarz, Lorestan province and within Zagros Mountains (Fig. 1).

MATERIALS AND METHODS

It is essential to use the accurate and convenient methods to assess slope instability because of existence of different conditions and parameters such as geological,

Corresponding Author: Sina Mokhtar, Department of Civil, Faculty of Earth Sciences, Islamic Azad University, Arak Branch, Arak, Iran

hydro-geological and tectonic involved in scope instability. Today, a variety of methods are used for quantitative interpretation (Sarkar *et al*., 2012). These methods generally divided into two categories; deterministic and probabilistic. Unlike simple modeling process, deterministic methods are not able to estimate the error or accuracy of the resulting model. But using probabilistic methods can be quantified the error of the model and estimated the possibility of its accuracy, also examined the value of any of the information in increasing the accuracy of the model (Mukerji *et al*., 2001). Markov chain method named in honor of Andry Markov, a Russian mathematician is a probabilistic approach; its application in the earth sciences has increased rapidly over the last few years. This method is used in geology for modeling the discrete variables such as lithology and faces. Geological modeling by Markov chain does not use the vario-grams and quantity-grams but it is based on conditional probabilities. In addition to more accurate results, the conditional probabilities provide the simpler geological interpretation and this is the reason that Markov chain is popular among geologists. Many researchers have used this method to analyze the sedimentary strata and faces modeling using data of outcrops and exploratory estimations. Also, projects and studies relating to expansion of the dimensions of modeling have been conducted using this method (Li and Zhang, 2008).

Factors affecting stability of rock instabilities in study area: Structural (geology), geotechnical, topographical and hydrogeological properties are among the most important factors affecting the stability. In this study, having changed each of the characteristics, the instabilities were analyzed and the safety factor for each of them was obtained.

Structural (geological) properties: From the viewpoint of geology, the study area is located in crush zone of Zagros. Often, the areas include an enormous mass of techtonizated materials from the type of dolomite and dolomitic limestone fractured rocks. Structural properties such as sliding slope and fracture depth are considered as determinants of the stability of rock instabilities in the area. The results of the studies suggest the rock instability in the slopes above 60°. The properties of the lithologic units are shown in Table 1.

Geotechnical properties: Since, the geotechnical properties are effective on the stability of rock instabilities, various geotechnical tests were done on the rock samples in the area. Finally, the numeral values for the factors as friction angle, adhesion coefficient and density were determined using the rock lab software (Table 2).

Table 1: Structural properties of lithologic units of study area

Factor	Fracture depth (Z) (m)	Slide Dip (Ψp) (°)
Values	5	60

Table 2: Numeral values for geotechnical properties using rock lab software

Factor	Adhesion coefficient (C) (MPa)	Friction Angle (Ψp) (°)	Density (γ) (kg/m^3)
Values	0.4	40	2330

Table 3: Numeral values for topographical properties of study area

Factor	Topography slope (Ψf) (°)	Total height of slid (H) (m)	Area (A) (m^2)
Values	69	15	2

Table 4: Numeral values for hydrogeologycal properties in dry and saturation state area

Factors	Total water pressure in fractures (V) (KPa)	Pore water pressure (U) (KPa)	Depth of saturated fractures by water (Zw) (m)
Value indry state	4	0	2
Value in saturation state	108	20	2

Topographical properties: Topographical properties are among the factors affecting the stability of rock instabilities. The results indicate that there are almost identical values for topography slope (Ψf) 60-80° total height of slid (H) and area (A) for any factor (Table 3).

Hydrogeological properties: Hydrogeologycal properties as total water pressure in fractures (V), pore water pressure (U) and depth of fractures saturated by water (Zw) are the most important factors affecting the instability of rock instabilities. The values for the factors are quietly different before dam inundation (dry state) and after it (saturated state) (Table 4).

RESULTS AND DISCUSSION

Statistical analysis using Markov chain model: Markov chain model includes a system in which a series of changes from one state to another occurs over time that can be measured in discrete intervals. Available discontinuous states (Wt) is used to predict the expected and the next state (Wt+1) by multiplying the transition probability matrix relating the current state of the time t:

$$Wt+1 = Wtpt$$

Where:

- Wt = A n×1 state vector at time t
- pt = A n×n transition probability matrix
- n = Maximum discontinuous states in a chain model
- P_{ij} = Probability of transition of discontinuous states from state i to state j between time t and t+1 (ij = n)

$$P_t = \begin{bmatrix} p_{11}\ p_{12} \cdots p_{1n} \\ p_{21}\ p_{22} \cdots p_{2n} \\ p_{n1}\ p_{n2} \cdots p_{nn} \end{bmatrix} \quad (1)$$

Table 5: Data inputs for scenarios fourty in the area

Scenario	Adhesion coefficient (C)	Friction angle (ϕ)	Topography Dip (Ψf)	Slide dip (Ψp)	Total water pressure in fractures (V)	Pore water pressure (U)	Fracture depth (Z)	Depth of fractures saturated by water (Zw)	Total height of slid (H)	Density (γ)	Area (A)
1	0.41	40	63	61	41	78	4.3	2.0	15	2330	2
2	0.43	42	61	60	48	72	4.2	2.0	15	2330	2
3	0.43	42	60	62	23	76	4.5	2.0	15	2330	2
4	0.45	44	62	61	25	74	4.1	2.0	15	2330	2
5	0.41	42	61	61	45	79	4.4	1.0	15	2330	2
6	0.40	41	64	60	50	73	4.5	1.0	15	2330	2
7	0.44	42	63	60	24	77	4.6	1.0	15	2330	2
8	0.42	41	61	62	23	72	4.4	1.0	15	2330	2
9	0.42	41	65	60	43	78	4.6	2.0	15	2330	2
10	0.41	42	64	61	25	75	4.3	2.0	15	2330	2
11	0.41	39	66	65	24	80	4.9	2.0	15	2330	2
12	0.40	39	68	64	23	73	5.0	2.0	15	2330	2
13	0.38	37	69	66	42	81	5.1	1.0	15	2330	2
14	0.37	38	68	68	39	73	5.2	1.0	15	2330	2
15	0.38	36	70	67	24	83	5.0	1.0	15	2330	2
16	0.44	42	63	62	24	75	4.3	1.0	15	2330	2
17	0.43	43	66	61	50	77	4.1	2.3	15	2330	2
18	0.45	41	64	60	38	74	4.3	2.2	15	2330	2
19	0.45	42	64	60	24	78	4.1	2.1	15	2330	2
20	0.39	38	62	64	25	73	4.7	2.5	15	2330	2
21	0.42	43	65	60	32	81	4.3	2.3	15	2330	2
22	0.43	41	63	61	43	75	4.1	3.1	15	2330	2
23	0.43	43	66	60	23	83	4.2	3.2	15	2330	2
24	0.38	39	68	65	24	74	4.9	3.6	15	2330	2
25	0.43	42	63	60	36	84	4.4	3.3	15	2330	2
26	0.45	43	65	61	38	74	4.3	1.0	15	2330	2
27	0.44	41	64	60	24	72	4.3	1.0	15	2330	2
28	0.43	42	64	60	25	73	4.1	1.0	15	2330	2
29	0.38	40	66	68	39	78	4.8	3.0	15	2330	2
30	0.37	38	68	66	38	75	4.6	2.8	15	2330	2
31	0.38	36	67	69	24	79	4.9	3.0	15	2330	2
32	0.37	37	67	71	24	73	4.5	2.7	15	2330	2
33	0.36	39	68	68	36	83	4.8	3.1	15	2330	2
34	0.38	38	66	60	40	73	4.7	3.1	15	2330	2
35	0.40	36	68	72	23	81	4.6	3.1	15	2330	2
36	0.39	38	68	70	25	75	4.9	3.3	15	2330	2
37	0.39	39	67	67	42	80	4.8	4.2	15	2330	2
38	0.38	38	70	66	46	75	4.6	4.1	15	2330	2
39	0.37	36	68	68	24	82	4.7	4.4	15	2330	2
40	0.40	38	69	69	24	74	5.0	4.3	15	2330	2

For the desired time period:

$$t(t = 1, 2, ..., k)$$

The transition probability matrix is as:

$$\{P_{ij}(t) \geq 0, \forall i, j \in 1, ..., N\}$$

$$\sum_{J=1}^{N} P_{ij}(t) = 1 \quad (2)$$

If the transition probabilities do not change over time K, the process will be as W(t + k) = W(t) pk. In other words, the probability of being in a state depends on the knowledge of existing state and knowing the earlier states of system does not change the mentioned possibility anything (Table 5). If the states of the system are as $\{A_1, A_2, ..., A_k\}$, then the probability that the system be in state A_j at time t and in state A_i at the time t+1 will be $P_j P_{ji}$. So, the probability that the system be in state A_i at time t+1 can be obtained from the following equation:

$$P_i = \sum_{J=1}^{N} P_j P_{ji} \quad (3)$$

It can be seen that Pi is obtained from multiplying the vector P in ith column of the matrix P. As a result, the probability in time t+1 is:

$$P(t+1) = \left(\sum_{j=1}^{k} p_j p_{j1}, \sum_{j=1}^{k} p_j p_{j2}, ..., \sum_{j=1}^{k} p_j p_{jk}\right) \quad (4)$$

In this study, first hand and direct field data were used to make the transition probability model. In this method, transfer matrix P_{ij} is obtained directly from field data (Table 2).

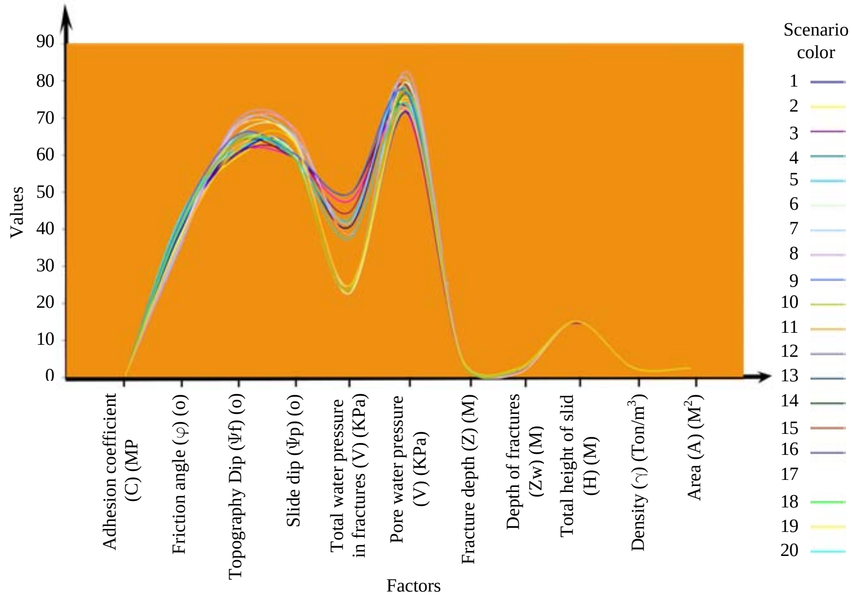

Fig. 2: Data inputs for scenarios in the dry state

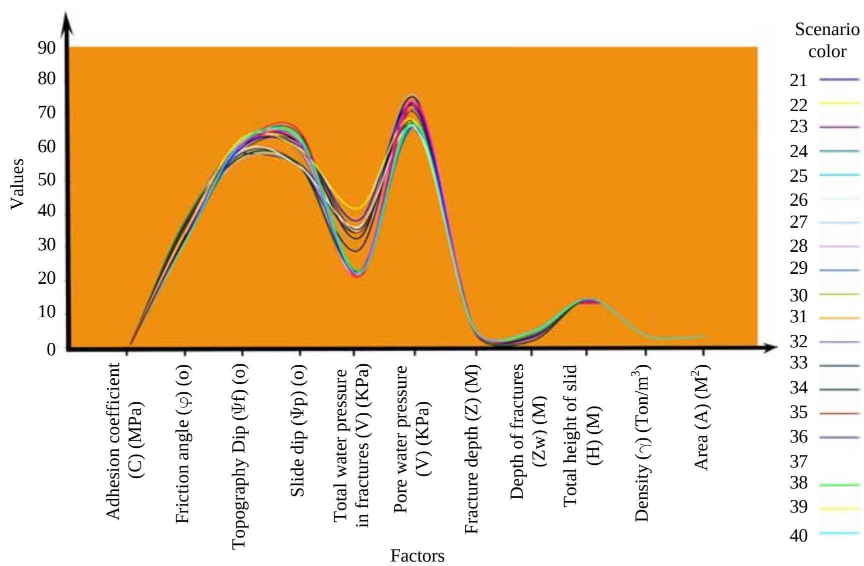

Fig. 3: Data inputs for scenarios in the saturation state

Discontinuous transition probability matrix, transmission sequence Z_{ij} from replacement of discontinuous state i for each time interval Δt is calculated by state j during the time Δt:

$$P_{ij} = \frac{Z_{ij}}{\Sigma_j Z_{ij}} \tag{5}$$

In this method, the sequence data are related to changes of observed data rates of discrete states over time. Using these data can estimate the values of transmission possibility by linear programming optimization method. P_{ij} values was limited between [0, 1] and transition probability matrix was repeated for several periods to determine the rates of changes. This method is based on the assumption that the possibility of transmission is fixed and does not change over time. This method is used studies repeatedly (Yemshanov and Perera, 2002). To compare the different structures, some indices are required to evaluate the function of the proposed model in the entire data model and compared with experimental results (Fig. 2 and 3). These data were

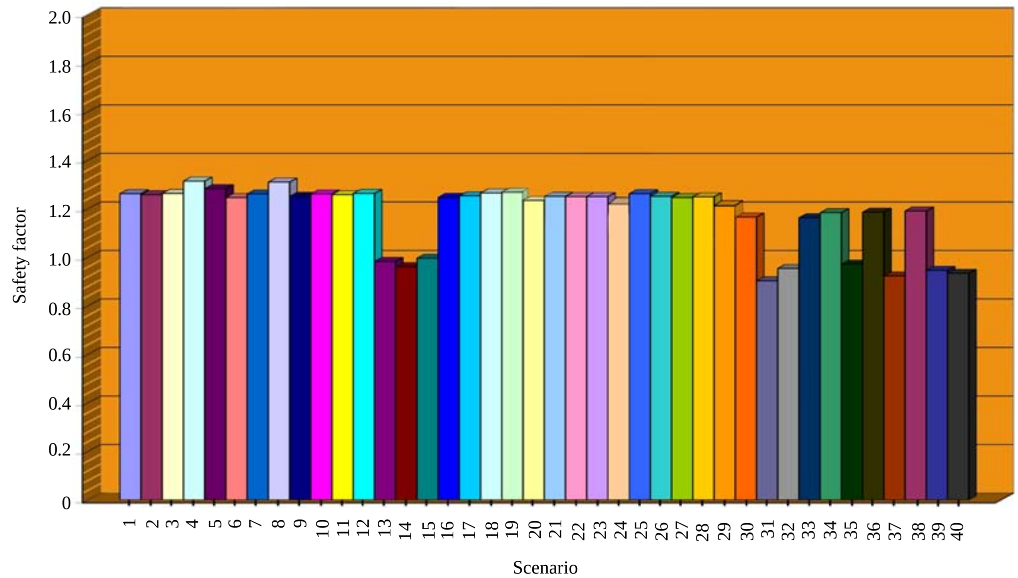

Fig. 4: Safety factor for scenarios fourty in the area

obtained in wet and dry conditions showing there are changes in adhesion, friction angle, tilt and slope failures in scenarios 1-20 in the dry state and there are increasing the water pressure in the joints and poring water pressure in failure surface in scenarios 21-40 wet state.

Safety factor: This slope stability analysis has been done considering the confidence coefficient. Considering the factors of instability in the area, the parameters affecting stability of rock instabilities were studied using the method. The occurrences in the area are 40 scenarios based on 11 factors.

The results indicate that the slopes of the area in a dry state are stable at 17 modes and unstable at 3 modes and in a saturated state are stable at 14 modes and unstable at 6 modes and have generally a little stability. The study indicates that the network has the ability to predict the degree of stability of rock slopes (Fig. 4).

CONCLUSION

The results obtained from the study show that the stability has decreased due to reduced adhesion and friction angle and increased failure slope and land slope, so that the confidence coefficient is varied between 0.9-0.99 and it has decreased in the case of 30-40 due to increased water pressure in the joints and water pore pressure in the failure surface and cracks depth so that the confidence coefficient varies between 0.9-1.18. Considering the stability analysis, the range is between 0.9-1.3 that it indicates the stability of the majority of slope with the joints of 60-80° in the dry state and instability on the most slopes in saturated state. The simulation results indicate that the proposed artificial Markov chains is able to withstand slope.

The model behavior complies with the laws and principles of mechanics. Finally, it can be said that the neural model has ability to model through the simple parameters usually done at early stages of explorations.

REFERENCES

Khajehzadeh, M., E.A. Shafie and M.R. Taha, 2010. Modified particle swarm optimization for probabilistic slope stability analysis. Int. J. Phys. Sci., 5: 2248-2258.

Li, W. and C. Zhang, 2008. A single-chain-based multidimensional markov chain model for subsurface characterization. Environ. Ecol. Statist., 15: 157-174.

Mukerji, T., A. Jorstad, P. Avseth, G. Mavko and J.R. Granli, 2001. Mapping lithofacies and pore-fluid probabilities in a North Sea reservoir: Seismic inversions and statistical rock physics. Geophys., 66: 988-1001.

Sarkar, K., T.N. Singh and A.K. Verma, 2012. A numerical simulation of landslide-prone slope in Himalayan region-a case study. Arabian J. Geosci., 5: 73-81.

Yemshanov, D. and A.H. Perera, 2002. A spatially explicit stochastic model to simulate boreal forest cover transitions: General structure and properties. Ecol. Modell., 150: 189-209.