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Uncertainty Analysis of the Stability Parameters of Rock Walls

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The purpose of this paper is to investigate the effects of natural uncertainties and effective parameters on the stability of plate-type rock walls. For this, the effective factors and geo-mechanical properties in the study area were obtained using field experiments. Stability analysis of rock walls was investigated for 40 scenarios in dry and saturated states. These parameters were then evaluated using Easyfit software and Markov chain analysis and Monte Carlo simulation by Rock Plane software. Comparison of the results of numerical and uncertainty methods shows that the rock walls with 60-80 degree slope are stable; and In saturated state they require stability due to the reduction of shear strength. Fixation of the rock walls was also investigated, indicating an optimum angle of 30° for the installation of the rock screw. The results show that the Monte Carlo simulation provides a simpler interpretation and the uncertainty methods are more accurate and reliable than the numerical methods.

Keywords: Rock walls, Monte Carlo simulation, Markov chain model, Rock Plane software

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1. INTRODUCTION

Investigation of rock wall stability in geotechnical structures such as dams, tunnels, and mines etc. is very important [1]. The stability analysis of rock slopes is one of the most important parts. The study of the potential instability of these walls is one of the important issues of geology and lithology in recent decades [1-5]. Geological, hydrological, and topographic properties are studied using effective parameters. These parameters affecting the stability of rock slopes are:

Friction angle, adhesion coefficient, density, gradient topography, total solid altitude, surface, solid slope, fracture depth, total water pressure in the fracture, pore pressure, depth of water saturated fractures [6].

In recent decades, rock wall stability has been studied using various methods including fuzzy logic and artificial neural network [7-11].

However, in these studies the stability analysis of rock walls by different methods and their comparison in different modes has not been performed. Due to changes in parameters affecting rock walls stability, uncertainty methods are used [12-17].

Stability analysis of rock walls using manual calculations is time consuming and error-prone. With the advancement of computers and software, sophisticated and advanced numerical methods are being used.

The Stability analysis of rock walls is due to uncertainty and changes in physical and mechanical properties of rock parameters.

So for more accuracy and less error, we use reliable computational methods such as Monte Carlo method and Markov chain [18-21].

The Markov chain method is a powerful method for analyzing the stability of rock walls based on conditional probabilities and case transition matrices. In addition to reduce the model error, this method can increase the accuracy of the model by determining the value of each parameter [21].

The Monte Carlo simulation method is also more reliable than the safety factor derived from the deterministic analysis because of assigning the probability distribution function to each parameter in order to account the probability of instability. In this method, the influence of parameters is investigated simultaneously using Rock plane software [22].

The rock walls are stable in the dry state due to the shear strength parameters. These gradients are likely to be unstable due to increased pore pressure and decrease shear strength parameters [19].

In this paper, due to uncertainties and changes in the physical and mechanical properties of rock, the stability analysis of rock walls has been done using Markov chain methods, and Monte Carlo simulation has been done using Rock Scale software. In this analysis, for the slopes 60 to 80 degrees in dry and saturated mode, the effect of 11 effective parameters in 40 events is simultaneously investigated.

2. MATERIALS AND METHODS

The parameters such as geological, hydrological and tectonic parameters affect the stability or instability rock slopes. To calculate the coefficient of confidence, the ratio of shear strength to shear stress is calculated. Today, the different methods developed for calculation of instability rock slopes [1-5].

These methods sorted two analytical and numerical method categories. The analytical method is simple but this method cannot give the suitable error bar of the result. The results of numerical methods have a better agreement with experimental methods results than other methods.

The stability analysis of rock walls in the study area has been done using Markov chain methods, and Monte Carlo simulation has been done using Rock Scale software.

The area with coordinates of $49^{\circ}\ 41'\ 37''$ longitude and $32^{\circ}\ 54''\ 23''$ latitude is located in 100 km southern Aligoodarz, Lorestan province and within Zagros Mountains (Figure 1) [23].

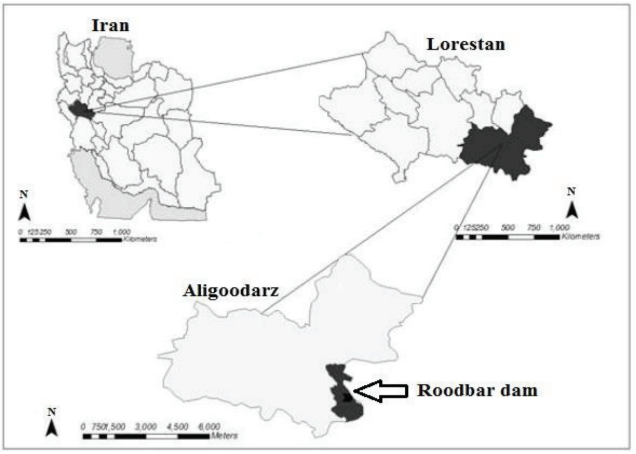

Fig. 1. Map of the position of study area

From the viewpoint of geology, the study area is located in the crush zone of Zagros. Often, the areas include an enormous mass of tectonized materials from the type of Dolomite and Dolomitic limestone fractured rocks. Structural properties such as slide dip and fracture depth are considered as determinants of the stability of rock instabilities in the area.

2.1. Methods used to analyze the stability of rock walls

Four common types of failures in the rock walls are: planar, wedge, Toppling and Circular failures. It's important to distinguish these four types of failures because stability analysis for each of these cases, are different (Figure 2) [24]. The proper analysis method is very important in design. In this study, an example of a planar failure is investigated. Using the obtained data from the study area, the stability analysis of the rock walls has been done.

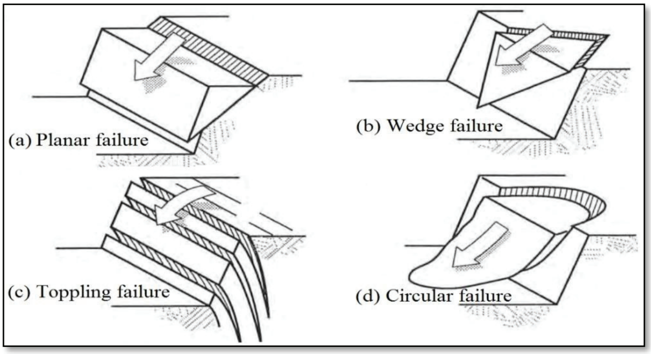

Fig. 2. Types of rock walls failures

2.1.1. Simulation of Monte Carlo using Rock Plane software

The Monte Carlo method can analyze probabilistic problems with any probability density function. Each parameter has a specific statistical distribution that should be identified. In order to use this method, at first, it is necessary to product the random numbers with any type of distribution using software such as Easyfit.

The Factor of safety without the maintenance system is obtained from equation 1 and with the maintenance system from equation 2 [25].

$$FS = \frac{cA+(W\cos\psi_P - U - V\sin\psi_P)\tan\varphi}{W\sin\psi_P + V\cos\psi_P} \quad (1)$$

$$FS = \frac{cA+(W\cos\psi P - U - V\sin\psi P + \mathrm{T}\sin(\psi\mathrm{T}+\psi P))\tan(\varphi)}{W\sin\psi P + V\cos\psi P - \mathrm{T}\cos(\psi\mathrm{T}+\psi P)} \quad (2)$$

Where c is adhesion, γ is Density, W is Weight, ψp is Slide Dip, Zw is Depth of Fractures Saturated by Water, T is the rock anchoring force, φ is the internal friction angle of the slider. A is the instability area and is obtained from the following equation:

$$A = (H + b\tan(\psi_s) - Z)(\csc(\psi_p)) \quad (3)$$

For depth Zw, the forces of U is Pore Water Pressure and V is Total Water Pressure in Fractures are calculated as follows:

$$U = \frac{1}{2}\gamma_w Z_w (H + b.\tan(\psi_s) - Z).csc(\psi_p) \quad (4)$$

$$V = \frac{1}{2}\gamma_w Z_w{}^2 \tag{5}$$

γw is specific gravity of water. The instability block weight force is also obtained as follows:

$$W = \gamma_r \left[\left(1 - \cot(\psi_f)\tan(\psi_p)\right)\left(bH + \frac{1}{2}H^2 \cot(\psi_f)\right) + \frac{1}{2}b^2\left(\tan(\psi_s) - \tan(\psi_p)\right) \right]$$

(6)

γr is specific gravity.

2.1.2. Markov Chains models

The Markov chain model includes a system in which a series of changes from one state to another occurs over time. these changes can be measured at discrete intervals. (Wt) discontinuous modes are available and (Wt+1) is used to predict the next state by multiplying the probability matrix by the time t. t: Wt+1 = Wpt where Wt is an n × 1 state vector at time t, Pt is a n×n transition probability matrix, and n is maximum discontinuous states in a chain model. Pij is probability of transition of discontinuous states from state i to state j between time t and t + 1 [26].

(ij ≤ n)

$$P_t = \begin{bmatrix} p_{11} & p_{12} & \cdots & p_{1n} \\ p_{21} & p_{22} & \cdots & p_{2n} \\ \vdots & & & \\ p_{n1} & p_{n2} & \cdots & p_{nn} \end{bmatrix} \tag{7}$$

For the desired time period:

$t\,(t = 1, 2, \ldots, k)$

The transition probability matrix is as follows:

$$\left\{ p_{ij} \geq 0, \forall i, j \in 1, \ldots, N \right\}$$

$$\sum_{j=1}^{N} p_{ij}(t) = 1 \tag{8}$$

If the transition probabilities do not change over time K, the process will be as $W(t+k) = W(t)P_k$. In other words, the probability of being in a state depends on the knowledge of existing state and knowing the earlier states of the system does not change the mentioned possibility anything.

If the states of the system are as {A1, A2 , ..., Ak}, then the probability that the system be in state Aj at time t, and in state Ai at the time t + 1, will be PjPji. So the probability that the system be in state Ai at time t + 1 can be obtained from the following equation:

$$P_i = \sum_{j=1}^{k} P_j P_{ji} \tag{9}$$

Where Pi is obtained by multiplying the vector P in column of the matrix P. As a result, the probability in time t + 1 is:

$$P(t+1) = (\sum_{j=1}^{k} P_j P_{j1}, \sum_{j=1}^{k} P_j P_{j2}, \ldots, \sum_{j=1}^{k} P_j P_{jk}) \tag{10}$$

In this paper, direct field data were used to make the transition probability model. In this method, transfer matrix Pij is obtained directly from field data (Table 2).
Discontinuous transition probability matrix, transmission sequence Zij from the replacement of discontinuous state i, for each time interval Δt is calculated by state j during the time Δt [7].

$$P_{ij} = \frac{Z_{ij}}{\sum_j Z_{ij}} \tag{11}$$

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. Pij values were 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. Structural (geology), geotechnical, topographical and hydrogeological properties are among the most important factors affecting the stability. In this section, having changed each of the characteristics, the instabilities were analyzed and the safety factor for each of them was obtained.
The results of the studies suggest the rock instability in the slopes above 60 degrees. The properties of the lithological units are shown in Tables 1and 2.
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.

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 to 80 degrees, the total height of slid (H) and area (A) for any factor.

Hydro geological properties as total water pressure in fractures (V), cavity water pressure (U) and depth of fractures saturated by water (Zw) are the most important factors in rock instability.

The parameters that influence the stability of the rock walls as input data in dry and saturated state are shown in Tables 1 and 2.

Table 1. Network inputs for scenarios in the dry state in the area

Scenario	Geotechnical Properties			Topographical Properties			Geological Properties		Hydrogeological Properties		
	Friction Angle (ϕ) (o)	Adhesion Coefficient (C) (t/m^3)	Density (γ) (t/m^3)	Topography Dip (ψf) (o)	Total Height of Slid (H) (m)	Area (A) (m)	Slide Dip (ψp) (o)	Fracture Depth (Z) (m)	Depth of Fractures Saturated by Water (Zw) (m)	Pore Water Pressure (U) (kPa)	Total Water Pressure in Fractures (V) (kPa)
1	40.0	4.1	2.3	63.0	15.0	2.0	61.0	4.3	2.0	8.0	8.0
2	42.0	4.3	2.3	61.0	15.0	2.0	60.0	4.2	2.0	2.0	10.0
3	42.0	4.3	2.3	60.0	15.0	2.0	62.0	4.5	2.0	6.0	9.0
4	44.0	4.5	2.3	62.0	15.0	2.0	61.0	4.1	2.0	4.0	8.0
5	42.0	4.1	2.3	61.0	15.0	2.0	61.0	4.4	1.0	5.0	11.0
6	41.0	4.0	2.3	64.0	15.0	2.0	60.0	4.5	1.0	3.0	9.0
7	42.0	4.4	2.3	63.0	15.0	2.0	60.0	4.6	1.0	7.0	13.0
8	41.0	4.2	2.3	61.0	15.0	2.0	62.0	4.4	1.0	5.0	9.0
9	41.0	4.2	2.3	65.0	15.0	2.0	60.0	4.6	2.0	7.0	8.0
10	42.0	4.1	2.3	64.0	15.0	2.0	61.0	4.3	2.0	5.0	12.0
11	39.0	4.1	2.3	66.0	15.0	2.0	65.0	4.9	2.0	4.0	14.0
12	39.0	4.0	2.3	68.0	15.0	2.0	64.0	5	2.0	7.0	13.0
13	37.0	3.8	2.3	69.0	15.0	2.0	66.0	5.1	1.0	12.0	12.0
14	38.0	3.7	2.3	68.0	15.0	2.0	68.0	5.2	1.0	11.0	19.0
15	36.0	3.8	2.3	70.0	15.0	2.0	67.0	5	1.0	11.0	24.0
16	42.0	4.4	2.3	63.0	15.0	2.0	62.0	4.3	1.0	7.0	24.0
17	43.0	4.3	2.3	66.0	15.0	2.0	61.0	4.1	2.3	7.0	10.0
18	41.0	4.5	2.3	64.0	15.0	2.0	60.0	4.3	2.2	4.0	18.0
19	42.0	4.5	2.3	64.0	15.0	2.0	60.0	4.1	2.1	8.0	14.0
20	38.0	3.9	2.3	62.0	15.0	2.0	64.0	4.7	2.5	12.0	25.0

Table 2. Network inputs for scenarios in the saturate state in the area

Scenario	Geotechnical Properties			Topographical Properties			Geological Properties		Hydrogeological Properties		
	Friction Angle (ϕ) (o)	Adhesion Coefficient (C) (t/m³)	Density (γ) (t/m³)	Topography Dip (ψf) (o)	Total Height of Slid (H) (m)	Area (A) (m)	Slide Dip (ψp) (o)	Fracture Depth (Z) (m)	Depth of Fractures Saturated by Water (Zw) (m)	Pore Water Pressure (U) (kPa)	Total Water Pressure in Fractures (V) (kPa)
1	42.0	4.2	2.3	65.0	15.0	2.0	60.0	4.3	2.3	15.0	82.0
2	41.0	4.3	2.3	63.0	15.0	2.0	61.0	4.1	3.1	14.0	83.0
3	40.0	4.3	2.3	66.0	15.0	2.0	60.0	4.2	3.2	13.0	79.0
4	39.0	3.8	2.3	68.0	15.0	2.0	65.0	4.9	3.6	14.0	74.0
5	42.0	4.3	2.3	63.0	15.0	2.0	60.0	4.4	3.3	12.0	76.0
6	43.0	4.5	2.3	65.0	15.0	2.0	61.0	4.3	1.0	14.0	68.0
7	41.0	4.4	2.3	64.0	15.0	2.0	60.0	4.3	1.0	13.0	77.0
8	42.0	4.3	2.3	64.0	15.0	2.0	60.0	4.1	1.0	13.0	75.0
9	40.0	3.8	2.3	66.0	15.0	2.0	68.0	4.8	3.0	18.0	99.0
10	38.0	3.7	2.3	68.0	15.0	2.0	66.0	4.6	2.8	19.0	98.0
11	36.0	3.8	2.3	67.0	15.0	2.0	69.0	4.9	3.0	19.0	94.0
12	37.0	0.37	2.3	67.0	15.0	2.0	71.0	4.5	2.7	20.0	94.0
13	39.0	3.6	2.3	68.0	15.0	2.0	68.0	4.8	3.1	18.0	96.0
14	38.0	3.8	2.3	66.0	15.0	2.0	60.0	4.7	3.1	17.0	90.0
15	36.0	4.0	2.3	68.0	15.0	2.0	72.0	4.6	3.1	17.0	93.0
16	38.0	3.9	2.3	68.0	15.0	2.0	70.0	4.9	3.3	19.0	95.0
17	39.0	3.9	2.3	67.0	15.0	2.0	67.0	4.8	4.2	15.0	72.0
18	38.0	3.8	2.3	70.0	15.0	2.0	66.0	4.6	4.1	14.0	76.0
19	36.0	3.7	2.3	68.0	15.0	2.0	68.0	4.7	4.4	16.0	74.0
20	38.0	4.0	2.3	69.0	15.0	2.0	69.0	5.0	4.3	19.0	94.0

Then using Easyfit software, the best statistical distributions were identified and their distribution parameters were noted. Then their mean and standard deviation of them were obtained, and finally, based on this information the case study is modeled using the Monte Carlo method in Rock Plane software, which is specially designed for the fracture of the rock plate. After calculating the safety factor and the probability of failure, the results of each calculation are recorded. Finally, the most appropriate and safe mode was selected.

2.2. Identify the best statistical distribution of each parameter by EasyFit software

In EasyFit software, the statistical distribution of each random variable and the probability of the variable being within a specified interval are examined.
This software is designed to provide reliable data analysis and select the best model. Using EasyFit software makes it easier and faster to choose the best probability distribution for the data. The analysis time and error are also greatly reduced.
The best distribution for the adhesion parameters and friction angle is a uniform distribution, and for topography dip is a normal one. The best distribution for slide dip is a normal log, and for the pore water pressure in the stretching failure and in planar failure is the beta distribution.

2.3. Calculating the average value and standard deviation of each parameter by SPSS software

Due to the fact that Easyfit software does not show the mean and standard deviation of beta and normal log distributions, SPSS software is used. The mean and standard deviation of the three parameters total water pressure in fractures, pore water pressure and depth of fractures saturated by water are calculated and shown in Table 3.
After performing statistical operations on data using Easyfit software, data is prepared to enter the Rock Plane software, as shown in Table 3.

Table 3. Variable parameters obtained to enter the Rock Plane software

Parameter	Statistical distribution	Average	Standard deviation	Minimum amount	Maximum amount
Adhesion Coefficient (C) (t/m^3)	Uniform	4.10	-	3.60	4.50
Friction Angle (ϕ) (o)	Uniform	39.97	-	36.00	44.00
Topography Dip (ψ_f)) (o)	Normal log	65.45	2.86	60.00	70.00
Depth of Fractures Saturated by Water (Z_w) (m)	Normal log	2.70	1.15	1.00	4.40
Slide Dip (ψp) (o)	Normal log	64.27	3.42	60.00	72.00
Pore Water Pressure (U) (kPa)	Beta	11.75	5.34	2.00	0.200
Total Water Pressure in Fractures (V) (kPa)	Beta	47.49	3.46	8.00	99.00

Parameters total height of slid, area, fracture depth, density which are fixed are shown in Table 4.

Table 4. Fixed parameters obtained to enter the Rock Plane software

Parameter	Density (γ) (t/m^3)	Total Height of Slid (H)(m)	Area (A) (m)	Fracture Depth (Z)(m)
Value	2.33	15.00	2.00	5.00

3. Discussion

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 (as shown in tables 2 and 3).

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

3.1. Analysis of the stability of rock walls using Markov chain method

This slope stability analysis has been done considering the safety factor. Due to the instability factors in the region, rock slope safety factors were evaluated using Markov chain 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.

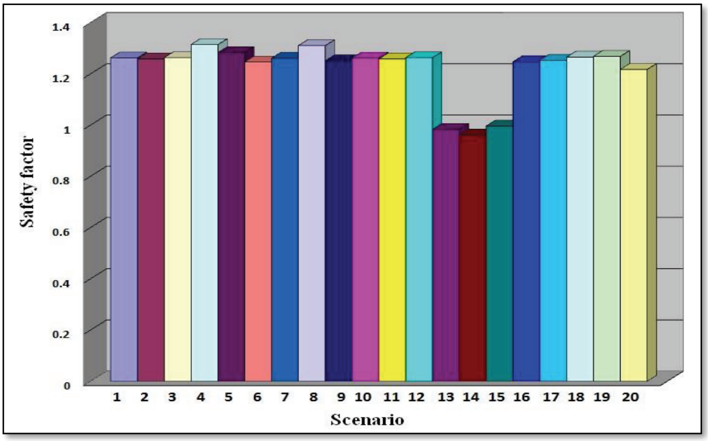

Fig. 3. Safety factor for scenarios in the dry state

In a saturated state, they are stable at 14 modes and unstable at 6 modes. The study indicates that the Markov chain method has the ability to predict the degree of stability of rock slopes.

Figures 3 and 4 shows safety factor prepared of Markov chain at dry state and saturated state respectively.

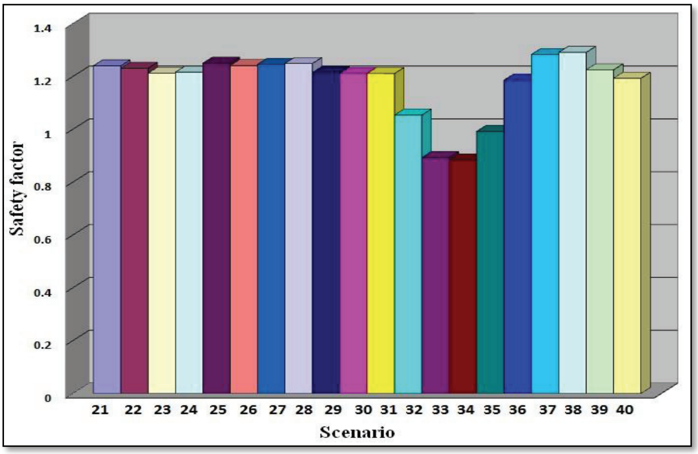

Fig. 4. Safety factor for scenarios in the saturated state

Considering the safety factors in the area, the parameters affecting the stability of rock instabilities were studied using the method. 11 effective parameters for rock walls stability in 20 dry states and 20 saturated scenarios are investigated (as shown in Figures 3 and 4).

3.2. Sustainability Analysis of rock walls Using Monte Carlo Simulation with Rock plane Software

The stability analysis of rock walls was done using Monte Carlo simulation with deterministic and probabilistic methods. The probability of failure of the rock walls of the studied area using a maintenance system or without a preservation system has been investigated**.**

3.2.1. Analysis of the stability of rock walls by a definite method and without maintenance

In the final analysis, only the average of 40 samples is taken into account, and uncertainty on the rock walls is not considered. By entering the available data into Rock Plane software using the definite method and without maintenance system, a safety factor is 1.28 in the dry state, and 0.98 in saturated state.

3.2.2. Analysis of rock walls with Monte Carlo probabilistic method without maintenance system

This probabilistic analysis is performed using Monte Carlo simulation based on random number generation. The results are more accurate but increase the time of computer analysis. So they are important for many computers. Under these conditions, the probability of failure is calculated based on a larger number of samples. Also the best statistical behavior and distribution is selected based on the statistical data. The Monte Carlo method is used to enter mean data and other statistical parameters for each particular distribution and has been performed 1000 times with different random numbers over time. Using this method, the probability of failure in dry state was 17% and in saturated state 36.35%.

The number of samples using the Monte Carlo method is important in determining integers. The number of sampling and comparison of results convergence is shown in Table 5.

Table 5. Comparing the convergence of the results with the number of samples

Scenario	Probability of Failure (%)	Random numbers
1	43.86	100
2	38.46	500
3	37.58	1000
4	36.89	2000
5	36.60	20000
6	36.35	100000
7	36.35	200000

According to the above table and the number of random numbers obtained from the software, the probabilities of failure with 100000 and 200000 numbers are equal, and converge to 36.35 %. Thus, the highest number of random samples needed to analyze the stability of the confined rock walls in this study is 100,000.

3.2.3. Analysis of rock walls with Monte Carlo probabilistic method with maintenance system

Due to the probability of a planar failure in the saturate state, the maintenance system should be designed for slopes 60 to 80 degrees. Here, by the installation of 11 Rock bolts with the specifications given in Table 5, despite the safety factor of 5.022 in the deterministic method, in the probability method, the probability of failure for the dry state still was 3.41 % and for the saturated state was 7.58%.

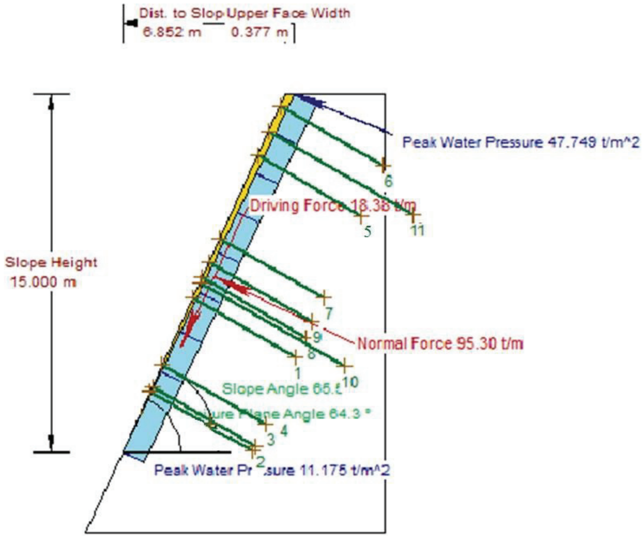

Fig. 5. A view of the shape of the rock walls and rock bolts installed using the Rock Plane software

Therefore, it can be concluded that probabilistic methods for rock mechanics are more rational than because of uncertainty in geology. Based on the frequent application of the software, the best Rock Bolt mounting angles were obtained at 30 degrees (best safety coefficient) shown in Figure 5 and Table 6.

Table 6. Specifications of installed rock bolts for the stability of rock walls in a probabilistic method

Number	Angle (°)	Capacity (t/m)	Length (m)	Anchlength (m)
1	30.0	20.00	5.00	4.943
2	30.0	20.00	5.00	4.938
3	30.0	20.00	5.00	4.917
4	30.0	20.00	5.00	.4671
5	30.0	20.00	5.00	.4671
6	30.0	20.00	5.00	.4671
7	30.0	20.00	5.00	.4796
8	30.0	20.00	5.00	.4834
9	30.0	20.00	5.00	.4820
10	30.0	20.00	7.00	.4839
11	30.0	20.00	7.00	.4853

3.3. Comparison of the probability of failure of rock walls using Markov chain methods and Monte Carlo simulation

The probability of failure of the rock walls of the studied area was obtained using Markov chain and Monte Carlo simulation with maintenance system and without.
The Monte Carlo simulation method shows a higher probability of failure, which suggests a more cautious approach (as shown in Table 7).

Table 7. The probability of failure rock walls using probabilistic Markov methods and Monte Carlo simulation

state	Simulate Monte Carlo with Rock Plane Software		Markov chain method
	With maintenance system	No maintenance system	No maintenance system
In dry state	3.41 %	17.00 %	00.15 %
In saturated state	7.58 %	36.35 %	30.00 %

4. Results

In this paper, it was shown that with increasing cavity water pressure, the reliability index decreases. Given the speed of as well as the advancement of software programs, the use of numerical techniques such as the Monte Carlo simulation method seems to be better than the other classical probabilistic methods.
In scenarios 13, 14 and 15 in the dry state, due to the decrease in the parameters of friction angle and adhesion coefficient, the safety factor decreased to 0.92. Also, in the saturation mode the safety coefficients of scenarios 32 to 36 and 40 decreased to 0.87 due to the increase in parameters Total Water Pressure in Fractures and Pore Water Pressure.
This decrease indicates the importance and influence of these parameters on the stability of the rock walls.
Finally, based on the Markov chain method and the Monte Carlo simulation method using the Rock plane software in dry and saturated states, we conclude:
The results show that probabilistic methods are more prudent than deterministic methods. Also the stability values obtained from probabilistic methods are less than deterministic methods. Therefore, probabilistic methods are more reliable than deterministic methods.

Given that rock failure is a natural phenomenon, the results indicate a very good match between numerical and software methods with the rules and principles of rock mechanics, so it has the ability to predict the stability of rock walls. Finally, it can be said that the proposed method has the ability to model based on effective parameters that are commonly used in the early stages of exploration.

Using the results obtained from the Markov chain and the Monte Carlo simulation using the Rock plane software, we can say that the rock walls are more stable in a dry state than in saturated state. In the saturated state, the coefficient of reliability decreases due to the reduction of the shear strength parameters.

The results show that in Markov chain method, given that each mode has a greater impact than the previous one, it is a suitable method for the stability of rock walls, but the Monte Carlo simulation is more cautious. To reduce the cost of laboratory sampling, fewer samples can be taken, but instead of the deterministic method, probabilistic methods and software, that is a virtual lab, can be used.

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LIST OF FIGURES AND TABLES:

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