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Evaluation of Slope Stability under Geological Conditions using Multi-Factorial Fuzzy Classification System

Morteza Niromand[1], Reza Mikaeil[2*], Mehran Advay[1], and Masoud Zare Naghadehi[3]

1. Department of mining, Ahar Branch, Islamic Azad University, Ahar, Iran
2. Faculty of Environment, Urmia University of Technology, Urmia, Iran
3. Mackay School of Earth Sciences and Engineering, University of Nevada, Reno, NV, USA

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Abstract

Slope instability can occur due to external loads such as earthquakes, explosions, and pore pressures. In addition, under natural conditions, slope instability can be caused by factors such as the erosion of some parts of the slope due to water or wind currents and the gradual rise of groundwater levels. Another factor leading to slope instability is human activities involving various types of loading and unloading on the slope. The instability of slopes may be associated with limited or large displacements, which either can cause problems or damage structures on the slope. Therefore, this phenomenon needs due care at all slope design and implementation stages. In general, slope stability is influenced by natural factors such as rock type (lithology), tectonic conditions of the area, rock mass joint conditions, and climatic conditions of the area. Furthermore, it is a function of design factors such as dip, height, explosive pattern, and explosion method. The present study offers a multi-factorial fuzzy classification system using the multi-criteria fuzzy approach to evaluate the slope stability. The evaluation is performed in five classes, namely “high stability”, “stable”, “relatively stable”, “unstable”, and “highly unstable”. Next, the viability of 28 slopes of 8 large open-pit mines in different parts of the world was evaluated. According to the fuzzy classification results, 4 and 6 slopes were evaluated in relatively stable and unstable conditions, respectively, with the other slopes classified as stable class. Afterward, the developed fuzzy classification system was assessed based on the actual behavior of the slopes. The results revealed a general large and local failure in most slopes in unstable and relatively stable conditions. Hence, a non-linear multi-factorial fuzzy classification system with good reliability can be used to evaluate the stability of the slopes.

1. Introduction

Designing a slope in open-pit mines involves many challenges such as increasing the slope depth. This issue increases the waste volume and the mining costs. Increasing the slope dip can lower the factor of safety (FOS), thereby, increasing the risk of slope failure. Fractures that occur in open-pit slopes are usually large-scale with complex mechanisms. These large fractures in the slope also cause economic and human losses. For instance, a large-scale slope failure in a porphyry copper mine in South Africa has caused extensive damage to the mine [1]. Regarding the significant impact of slope stability on the open-pit mines economy, it is necessary to continuously monitor the stability conditions to detect the necessary signs of instability for its prediction and prevention. Thus selecting a sustainable optimum slope is required to avoid high mining costs and lower the risk of slope instability. Analysis of slope stability in open mines is possible through empirical methods, limit equilibrium, numerical modeling methods, and systematic methods. In this respect, classification systems are among the most primitive methods for evaluating slope

Corresponding author: Reza.mikaeil@gmail.com (R. Mikaeil)

stability. Of the extensive studies conducted for this purpose, some are mentioned below.

Hack et al. (2002) developed a slope stability probability classification (SSPC) to classify slopes. This system assesses the probability of slope stability based on rock mass characteristics. In addition, several conversion coefficients were applied across different stages depending on the current or future weathering and the extent of rock mass damage due to drilling. Finally, the slope stability is expressed as the probability of the occurrence of various failure mechanisms. This research was conducted for four years in the Falset area of Tarragona, Spain, and was then implemented in Australia, South Africa, New Zealand, and the Netherlands Antilles [2]. Goshtasebi et al. (2008) investigated the critical circular slip surface and slope surface modification in a heavily jointed rock mass using a genetic algorithm (GA). According to the obtained results, the modified slope angle of the wall was determined to be 48.44° [3]. Ataei and Bodaghabadi (2008) investigated slope stability and determined stable slopes in the Chador Malo iron ore mine using numerical and limit equilibrium methods. The results showed that some instability problems occur with increasing slope height. Therefore, stable slopes for each geotechnical zone and prepared sections were calculated and presented as a function of slope height [4]. Daftaribesheli et al. (2011) assessed rock slope stability using the Fuzzy Slope Mass Rating (FSMR) system. According to the results, the FSMR method provides a better assessment of slope stability than other slope stability classification systems and can also predict rock slope failure [5]. Zare Naghadehi et al. (2011) applied a probabilistic systems methodology to assess the importance of factors affecting the stability of rock slopes by nine parameters. These parameters were considered the main factors in modeling the stability of the slope system. This research selected slopes in the Khosh-Yeylagh region in Iran as a case study. The results showed that this new approach was a simple but efficient tool for evaluating the parameters affecting the stability of slopes [6]. Zare Naghadehi et al. (2013) and Zare & Jimenez (2015) developed a new Mine Slope Instability Index (MSII) to evaluate the stability conditions of slopes in open pit mines. Slope stability was assessed by comparing the MSII values and those of the actual behavior for 12 case histories, which showed a good agreement [7, 8]. Taherynia et al. (2014) investigated slope stability classification systems and risk analysis to determine the degree of risk of rock slope instability. They performed their study on the Lashter Pass (located on the Shiraz-Isfahan highway, Iran), which has a high potential for instability. To this end, they applied several classification methods and Rock-Fall software for risk analysis [9]. Friedoni et al. (2015) examined the application of the modified Q classification system and its composite parameters for analyzing and deducing field data for estimating slope stability. According to their research, the Q classification system can be promising in evaluating rock mass quality. In addition, by modifying the parameters of the Q classification system, they introduced a modified mass rock classification system called the slope quality rating (SQR) [10].

Khosravi et al. (2017) investigated the influence of the counterweight balance size on the stability of the undercut slopes through a series of numerical model tests using FLAC3D software. The results showed a significant relationship between counterweight balance size and maximum stable undercut span, where increasing a counterweight balance size results in a wider stable span. Finally, a non-linear relationship was proposed between counterweight balance size and maximum stable undercut span [11]. Fattahi (2017) explored slope stability prediction using an adaptive neuro-fuzzy inference system (ANFIS) based on clustering methods. In this research work, three ANFIS models were developed including grid partitioning (GP), subtractive clustering method (SCM), and fuzzy c-means clustering method (FCM). Comparing these three models revealed that the ANFIS-SCM model outperforms the other two models [12]. Samieinejad et al. (2017) conducted field investigations using digital terrestrial photogrammetry to characterize the geometric properties of discontinuities in open-pit slopes. The results showed that this new method can be used to estimate the structural parameters of the rock mass for the analysis of steep slopes in open pits [13]. Zebarjadi Dana et al. (2018) investigated the effects of geometric and geomechanical properties on the slope stability of open pit mines using two-dimensional and three-dimensional finite difference methods. Finally, it was observed that considering the real slope geometry, the FOS3D/FOS2D ratio (3D effect) is greater than 1 in all cases [14]. Fattahi et al. (2018) used a Monte Carlo simulation technique to assess earthquake-induced displacement of slopes (EIDS). This study was conducted to predict EIDS using the Monte Carlo simulation method (MCSM). The results showed that the stochastic approach can successfully reproduce EIDS values and calculate confidence intervals [15]. Evangelin & Thirukumaran (2018) investigated the sustainability of slopes along roads in India using RMR, SMR, and continuous slope mass rating (CSMR). The results showed that since the CSMR classification represented continuous slope stability conditions, it seems more appropriate for developing spatial databases and cutting roads. Therefore, the steep slope of the walls affected the slope stability significantly [16]. Azarfar (2019) and Azarfar et al. (2018; 2019) conducted broad research on the effect of faults on open pit slope stability by employing numerical and experimental methods. They carried out sensitivity and comparative analyses for the numerical simulations to investigate the stability of rock slopes on large and small scales (overall open-pit slope and bench slope) and the fault zones. The sensitivity analysis results showed that choosing an adequately low convergence ratio is critical for estimating FOS [17-19]. Santos et al. (2019) proposed a methodology to evaluate slope stability using two techniques of multivariate statistics: principal component analysis (PCA) and discriminant analysis. The results showed that the proposed methodology provides a powerful tool for slope hazard assessment in surface mines [20]. Khorasani et al. (2019) investigated the effect of large block positions on the stability analysis of block-in-matrix slopes using physical and numerical models. The results showed that the position of large blocks significantly influenced the slope stability [21]. Shafiei Ganjeh et al. (2019) conducted a numerical modeling to investigate the effects of earthquake and blasting on the slope stability of the Chadormello open pit mine. According to the results, seismic study and dynamic slope stability should be considered as part of the computational design of the mine [22]. Sarfaraz et al. (2019) investigated the slide-head-toppling failure through a series of numerical modeling. The results showed the accuracy of the finite element method (FEM) for evaluating the stability analysis of slopes with the potential of slide-head-toppling failure [23].

Alikhani et al. (2020) assessed the influence of the overall slope angle on the economics of open-pit mines using the limit equilibrium methods (modified Bishop and modified Janbu) and numerical models for slope stability analysis [24]. Sarfaraz and Amini (2020) investigated the field of numerical modeling of rock slopes with the potential of block-flexural toppling failure. According to these authors, although the mechanism of block-flexural toppling failure is complicated, the numerical code can analyze this failure efficiently [25]. Sarfraz (2020) presented a theoretical model for block-flexural toppling failure according to the erosion phenomenon. The results showed that the presented model is conservative in analyzing the block-flexural toppling failure; however, it can be used to evaluate this failure [26]. Shah et al. (2020) investigated rock slope stability in tropical climates in Lafarge Quarry, Perak, Malaysia. The results showed that the kinematic analysis combined with the rock mass classification system provides a better insight into analyzing the rock slope stability in a tropical climate than individually considering the rock mass classification system [27]. Adil et al. (2021) assessed rock fall hazard using GeoRock 2D along Swat Motorway, Pakistan. Finally, they stated that drawing a wire mesh on the slope surface and retaining wall or fence will be very useful and economical to reduce the rock falling hazards along the Swat motorway [28]. Sarfaraz et al. (2021) developed models using an artificial neural network (ANN) for stability analysis of undercut slopes. The results showed that the presented models have good accuracy [29]. Sarfaraz et al. (2021) developed numerical models for stability analysis of undercut slopes. According to these authors, determining the maximum stable undercut span is among the most important parameters in designing the undercut slopes. The numerical results of this study were evaluated through the statistical response surface methodology (RSM). Finally, a statistical relationship was proposed for computing the maximum stable undercut span [30]. Bowa et al. (2021) developed a robust analytical model for stability analysis of the rock slopes subjected to wedge slope failure induced by variable groundwater in an open pit mine. Based on the obtained results, this model was proved to be a robust analytical model for the stability analysis of rock slopes subject to wedge failure due to the presence of groundwater [31]. Hussain et al. (2021) proposed a viable stabilization method for the slope in a weak rock mass environment using numerical modeling. The results showed that this method could be used to stabilize the slope in the weakest rock mass environment [32]. Junaid et al. (2022) investigated rock mass condition quantification based on failure frequency to assess slope stability. In this study, kinematic and limit equilibrium analysis (LEM) techniques were used to evaluate the stability of rock slopes. These techniques are well established in identifying the failure type along the rock slope and calculating the factor of safety (FOS). According to the obtained results, the kinematic analysis showed that the rock slope is safe from the risk of planar failure and direct toppling. Moreover, the FOS obtained for the potential wedge using limit equilibrium analysis suggests the rock slope stability [33]. Junaid et al. (2022) proposed an expeditious approach to assess slope stability using integrated 2D electrical resistivity tomography. Eventually, the integrated approach applied in this research study proved expeditious, inexpensive, and rapid for comprehensive slope stability assessment [34]. Sarfaraz et al. (2022) developed numerical models for slide head toppling failure using FEM and DEM methods. According to the results of the distinct component method, it has acceptable accuracy compared to the FEM and can be used to examine the failure mentioned [35]. Singh and Roy (2022) studied slope stability analysis and preventive actions for a landslide location along NH-05 in Himachal Pradesh, India. Finally, they recommended some preventive measures and modifications concerning the economic and physical devastation of the considered case [36]. Walia and Roy (2022) investigated slope stability and its remedies in Palampur, Himachal Pradesh. After calculating the safety factor, they suggested some preventive steps and a few improvements [37].

According to their research on rock mass classification techniques and parameters, Qazi et al. (2023) stated that GSI has a higher efficiency than RMR for slope stability in poor rock conditions [38]. Guerrero et al. (2023) evaluated 20 years (1999-2019) of land use and applied techniques of potential environmental fragility (PEF) (natural) and emergent fragility (EF) (influenced by human activities) in a region of Brazil. The authors stated that their findings can strengthen planning and help public management. Therefore, they encourage using this method in other regions with landscape heterogeneity and land use conflicts [39]. Dilta and Sharma (2023) examined the behavior of a strip footing supported by hollow steel piles installed to stabilize a clay slope. To this end, they employed numerical modeling techniques [40]. Wagay and Suthar (2023) investigated the field of slope stability using flexible facing. They conducted an experiment to evaluate the load-bearing capacity of a soil nailing system on a slope with three different flexible materials [41]. Rezaei et al. (2023) investigated the sustainability analysis of waste dumps in Mine No. 4 of Golgohar (Sirjan, Iran). The results showed that the FOS of the waste dump with three methods, i.e., Spencer, Janbu, and Bishop, is 1.26, 1.199, and 1.226, respectively [42]. Chand and Koner (2023) studied internal mine dump slope stability and identified the failure zone through 3D modeling. To this end, they evaluated the internal dump safety using a 3D limit equilibrium and numerical methods. Subsequently, they proposed a method to evaluate and identify the potential zone of instability in the mine dumps. According to these authors, the proposed method is economical, easy to use, fast, and practical [43].

Following the above research work, the present study aims to develop a multi-factorial fuzzy classification system to identify and select the unstable slope. One of the reasons for using this hybrid approach is its adaptation to different engineering problems and its results in real conditions. Fuzzy sets were introduced in the analysis of complex systems. A fuzzy set is a set containing elements that have varying degrees of membership in the set. Therefore, this idea contrasts with the classical sets because members of a classical set would not be members unless their membership was full in that set.

2. Methodology

This study used fuzzy set theory and a multi-factorial approach to provide a classification system for evaluating the slope stability of 28 slopes from 8 mines. The first step in data analysis was to determine the degree of importance of the criteria for establishing a new classification system. The importance of each criterion was determined by referring to experts. At this stage, the questionnaire form was first sent to the experts in the field of slope wall stability. After collecting the questionnaire forms, the degree of importance of each criterion was calculated using the fuzzy Delphi analytical hierarchy Process (FDAHP). After determining the importance of the criteria, they were classified into five different quality categories, namely “high stability”, “stable”, “relatively stable”, “unstable”, and “highly unstable”. After determining the qualitative categories for each criterion, a Gaussian and sigmoidal membership function was defined for each criterion, and then five class membership functions were presented for all criteria. In the following, the research method is described in detail, and then the application of the proposed method is presented as a case study.

2.1. Fuzzy theory and fundamental principles

Fuzzy theory and fuzzy sets were first introduced by Lotfali Asgarzadeh in a treatise called "Fuzzy sets" in 1965 to analyze complex systems [44]. The fuzzy set is the generalization of the characteristic {0,1} to all numbers in the interval [0,1] [45]. Indeed, unlike classical sets, elements are not divided into two members and non-members in fuzzy sets. Instead, according to the functions defined, the degree of membership of the different elements in the fuzzy sets varies between 0 and 1. Suppose A is a fuzzy subset of the reference set X. The membership function A in the reference set X is defined as Equation (1) [46].

$$\mu_A: X \to [0,1] \quad (1)$$

where μ_A represents the degree of membership of each member of set A within the interval [0, 1].

In Equation (1), the values 0 and 1 denote non-membership and full membership, respectively, with all values between these two values used to represent the average membership rate of each member of set A. Typically, a fuzzy set with a set of regular pairs is represented as Equation (2) [46].

$$A = \{(x, \mu_A(x)), x \in U\} \quad (2)$$

where U contains a finite set of X_i. The fuzzy finite set can also be represented as Equation (3) [47].

$$A = \sum_{i=1}^{n} \frac{x_i}{\mu_{A(x_i)}} \quad (3)$$

The U set containing an infinite member is represented by Equation (4) [47].

$$A = \int_x \frac{x}{\mu_A(x)} \quad (4)$$

The membership functions represent all the information in a given fuzzy set. The membership functions of the fuzzy sets must be precisely defined concerning the type of function and its parameters. The parameters and shape of membership functions will greatly affect the accuracy of the results [48]. Triangular, trapezoidal, bell, and Gaussian functions are among the most commonly used functions. Regarding the formula's simplicity and the appropriate computational efficiency, both the triangular and trapezoidal membership functions have been widely used [49, 50]. However, as these membership functions consist of straight lines, the corner points of the lines are sharp and lack the expected smoothness. In the present study, Gaussian and sigmoidal non-linear membership functions were adopted. A Gaussian membership function is completely defined by "a" and "b". Here, "a" represents the center of the membership function, and "b" denotes the width of the membership function. The Gaussian membership function is defined by Equation (5) [51].

$$Gaussian\ (x; a, b) = \exp\left[-\frac{1}{2}\left(\frac{x-a}{b}\right)^2\right] \quad (5)$$

Although the ends of the curves of Gaussian and bell-shaped membership functions are smooth, they cannot determine asymmetric membership functions. Therefore, the sigmoidal function was used to solve this disability. A sigmoidal membership function is defined as Equation (6) [51].

$$sig\ (x; c, d) = \frac{1}{1 + \exp[-c \times (x - d)]} \quad (6)$$

where c controls the dip at the point x = d. Depending on the sign of c, the curve of a sigmoidal membership function is inherently left or right. Therefore, it is suitable for displaying concepts such as "very good" and "very poor".

2.2. Multi-criteria evaluation method

Suppose U is a set of elements for evaluation and $\prod = \{f_1, f_2, \dots, f_m\}$ is a set of parameters that determine the quality of the evaluated elements. Also, $E = \{e_1, e_2, \dots, e_p\}$ is a set of verbal results. Here, e_k determines the quality of class k. For each parameter f_j, a fuzzy class e_k is generated for each value of k from the set {1, 2, ..., p}. Since the fuzzy class e_k is a fuzzy set controlled by f_j, the fuzzy set is designed by A_{jk} [52]. If qualitative classes are employed by the distance index, the objective function $Q^{(k)}(x)$ is defined as the membership function. $Q^{(k)}(x) = A_{jk}(x)$ is calculated by Equations (7), (8), and (9).

$$Q_j^{(1)}(x) = \frac{1}{1 + exp\left[-c_j \times \left(x - d_j\right)\right]} \quad (7)$$
$$j = 1, 2, \dots, m$$

$$Q_j^{(k)}(x) = exp\left(-\frac{1}{2}\left(\frac{x - a_j}{b_j}\right)^2\right) \quad (8)$$
$$j = 1, 2, \dots, m \quad , \quad k = 2, \dots, p - 1$$

$$Q_j^{(p)}(x) = \frac{1}{1 + exp\left[-c_j \times \left(x - d_j\right)\right]} \tag{9}$$

$j = 1, 2, \dots, m$

A multi-criteria evaluation system requires the following three key parameters:

- A set of parameters $\prod = \{f_1, f_2, \dots, f_m\}$
- A set of quality classes $E = \left\{e_1, e_2, \dots, e_p\right\}$
- For each element $u \in U$, there is a single-factor evaluation matrix.

Note that the number of quality classes for all parameters is f_j. By accepting three elements for the set $u \in U$, the evaluation results of $R^u = \left(r_{jk}(u)\right)_{mxp}$ can be obtained as in Figure 1.

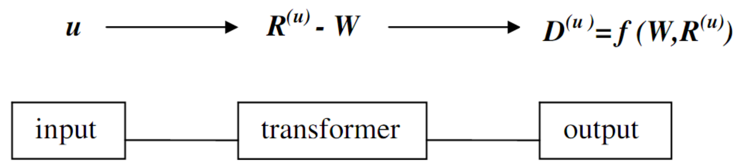

Figure 1. The process of multi-factorial evaluation model [34].

Figure 1 displays a mapping of the multi-criteria evaluation method including the weight of the parameters and the corresponding matrix combined with a decision function (Equations 10 and 11) [53].

$$\xi: U \to F(E) \tag{10}$$

$$u \to \xi(u) \quad , \quad D^{(u)} = f(W, R^{(u)}) \tag{11}$$

In the above equations, f is the decision criterion used to evaluate the option.

2.3. Aggregation

Using a suitable aggregation of fuzzy sets in multi-factorial fuzzy analyses is very important. Many transformation functions such as max (min) and min (max) have been developed for this purpose. Aggregation operators are used to evaluate different types of decision behavior. This process requires different transformations for the judgments. Accordingly, the decision-maker may choose a decision function that best reflects the goals of the decision [53]. Equation (12), as a well-known decision function, was proposed by Dubois and Prade to obtain weighted minimum (and maximum) operators that can be applied in the setting of the possibility theory [47].

$$D^W(\mu_1, \mu_2, \dots, \mu_m) = \wedge_{i=1}^{m}[(1 - w_i) \vee \mu_i] \tag{12}$$

In this study, we used the function introduced by Dubois and Prade with minimum weight.

3. Parameters Affecting Slope Stability

The most important factors affecting slope stability include two general groups of controllable parameters (e.g. slope characteristics, design, and extraction characteristics of mine) and uncontrolled parameters (e.g. environmental conditions and rock mass characteristics). Figure 2 represents the parameters affecting slope stability.

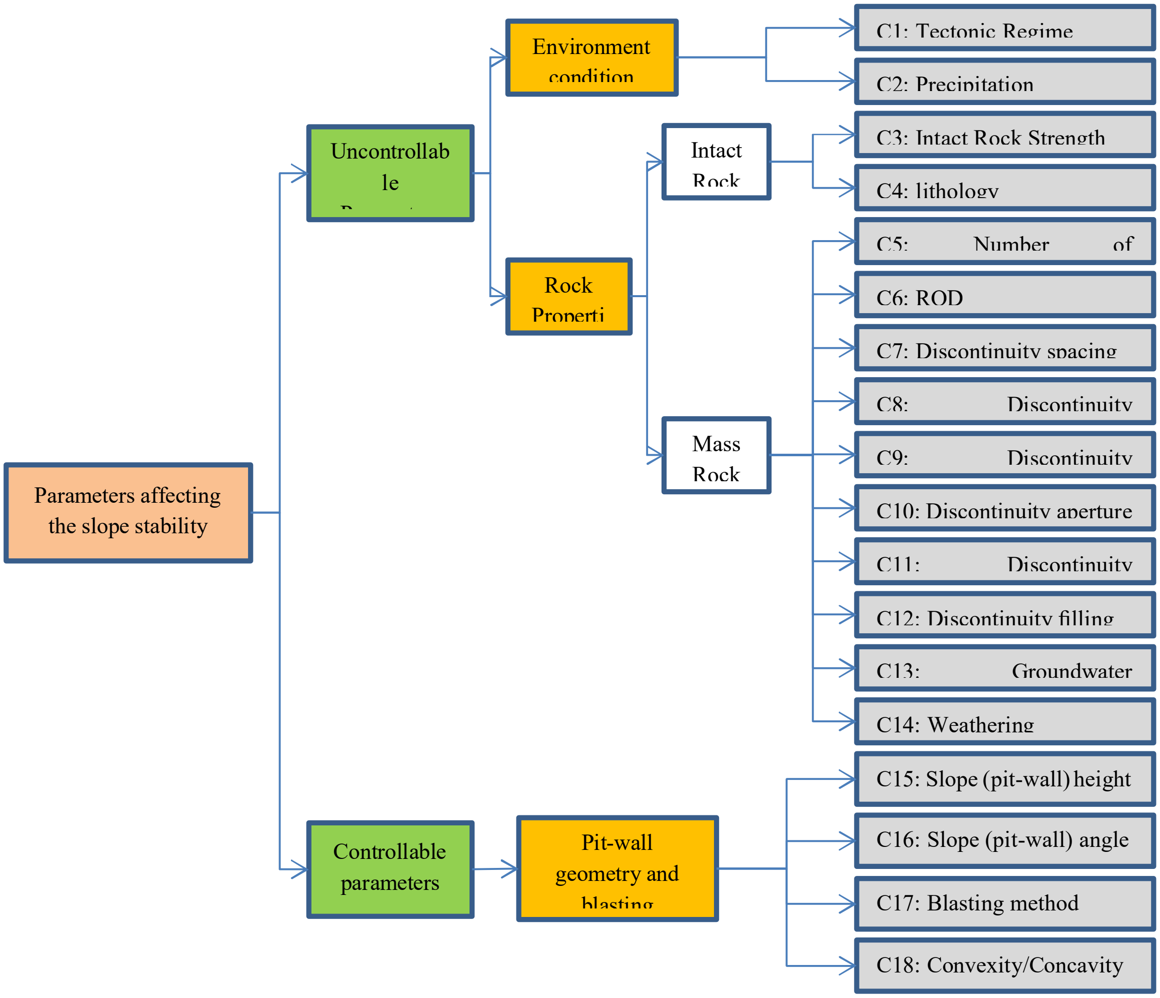

Figure 2. Parameters affecting the slope stability.

4. Development of Classic Classification

One of the most important parts of developing a classification system is determining the quality categories and classifying the criteria into specific categories. In the present study, considering the five classes of the proposed fuzzy classification system, the criteria were divided into five categories: very good, good, average, poor, and very poor. Table 1 presents the results for the criteria classification. As can be seen in this table, some criteria have small values, and some have descriptive concepts. The terms used to perform the fuzzy calculations are referred to in the following sections, with values ranging from 0 to 100.

Table 1. A quantitative and qualitative classification of criteria affecting the slope stability.

Parameters	Classification categories				
	Very Good	Good	Medium	Weak	Very Weak
Rock type (lithology)	**Igneous:** Granite, Granodiorite, Diorite, and Gabbro **Metamorphic:** Gneiss, Quartzite, and Amphibolite	**Sedimentary:** Breccia, Greywacke, Sandstone and Conglomerate **Metamorphic:** Hornfels; **Igneous:** Dolerite, Obsidian, Andesite, Norite, and Agglomerate	**Sedimentary:** Anhydrite and Gypstone **Igneous:** Tuff, Basalt, Breccia, Dacite, and Rhyolite	**Sedimentary:** Limestone shale, Dolomite, Limestone, Chalk, and Siltstone **Metamorphic:** Slate, Phyllites, and Marble	**Metamorphic:** Schists and Mylonites **Sedimentary:** Clay shale, Mudstone, Claystone, and Marble
Precipitation (annual rainfall and snow) (mm/y)	< 150	150-300	300–450	450–600	> 600
Intact rock strength-UCS (MPa)	> 250	250-100	50-100	25-50	< 25
RQD (%)	90-100	75-90	50-75	25-50	< 25
Weathering	Fresh	Slightly weathered	Moderately weathered	Highly weathered	Highly weathered
Tectonic regime	Almost the absence of meaningful tectonic	presence of foliation, schistosity, and cleavage	Presence of folds, faults, and discontinuities	High fractured zones	Imbrications and overthrusts
Groundwater condition	Dry	Damp	Wet	Dripping	Flowing
Number of major discontinuity sets	0	2	4	5	> 5
Discontinuity persistence (m)	< 5	5-10	10-25	25-40	> 40
Discontinuity spacing (m)	> 2	0.6-2	0.2-0.6	0.06-0.2	< 0.06
Discontinuity orientation	Very favorable	Favorable	Fair	Unfavorable	Very Unfavorable
Discontinuity aperture (mm)	No separation	< 0.1	0.1-1	1-5	> 5
Discontinuity roughness	Very rough	Rough	Slightly rough	Smooth	Slickensided
Discontinuity filling	Not filled	Very hard filling	Hard filling	Soft filling	Very soft filling
Slope (pit-wall) angle	< 30	30-40	40-50	50-60	> 60
Slope (pit-wall) height (m)	< 50	50-100	100-200	200-300	> 300
Blasting method	Regular blasting/ mechanical	Modified production blast	Smooth wall/ cushion	Postsplit	Presplitting
Convexity/Concavity	Concavity	Concavity to Smooth	Smooth	Smooth to Convexity	Convexity

5. Development of Multi-factorial Fuzzy Classification

The first step for establishing a new classification system is determining the degree of importance of the criteria. The importance of each of these criteria was determined by the experts. At this stage, the experts completed the questionnaire, and the degree of importance of each criterion was calculated using the Fuzzy Delphi Analytical Hierarchical Process (FDAHP). The results of applying this method in many studies indicate the feasibility of the FDAHP method in determining the degree of importance of the criteria. Table 2 shows an example of a questionnaire sent to the experts.

Table 2. A sample of the questionnaire answered by the first expert.

Parameters affecting the slope stability	Qualitative importance				
	Very Strength	Strength	Moderate	Weak	Very Weak
Rock type (major)	✓				
Rainfall (mm/year)					✓
Intact rock strength-UCS (Mpa)	✓				
RQD (%)		✓			
Weathering			✓		
Tectonic regime				✓	
Groundwater conditions				✓	
Number of major discontinuity sets			✓		
Discontinuity persistence (m)			✓		
Discontinuity spacing (m)		✓			
Discontinuity orientation		✓			
Discontinuity aperture (mm)			✓		
Discontinuity roughness (JRC)			✓		
Discontinuity filling				✓	
Slope (pit-wall) angle (deg)	✓				
Slope (pit-wall) height (m)	✓				
Blasting method		✓			
Convexity/Concavity				✓	

Next, the pair-wise comparisons matrix was developed based on expert opinions based on Saaty (1994) [54]. At this stage, the paired comparison matrices were formed by comparing the elements of each level in pairs at higher levels than any of their existing elements. Numerical scores were assigned to pair-wise comparison of the significance of the two indices based on Table 3.

Table 3. Quantitative and qualitative classification for pair-wise comparison of criteria.

Definition	Intensity of importance
Extreme importance	9
Very strong or demonstrated importance	7
Strong importance	5
Moderate importance	3
Equal Importance	1
Weak, Moderate plus, Strong plus, andVery, very strong	2, 4, 6, and 8

The pair-wise comparison matrix is a $n \times n$ matrix, where n is the number of elements compared. For each pair comparison matrix, the elements on the diagonal are equal to 1 and do not need to be evaluated. However, in other matrix layers, they must be determined based on pair-wise comparisons. The opposite sides of the diagonal are inverse. The pair-wise comparison matrix can be computed using Equation (13).

$$A = \left[a_{ij}\right] = \begin{bmatrix} 1 & a_{12} & \cdots & a_{1n} \\ 1/a_{12} & 1 & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ 1/a_{1n} & 1/a_{2n} & \cdots & 1 \end{bmatrix} \tag{13}$$

The pair-wise comparison matrix based on the first expert's opinion is listed in Table 4.

Table 4. The pair-wise comparison matrix based on the first expert's opinion.

Criteria	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18
C1	1.00	9.00	1.00	3.00	5.00	7.00	7.00	5.00	5.00	3.00	3.00	5.00	5.00	7.00	1.00	1.00	3.00	7.00
C2	0.11	1.00	0.11	0.14	0.20	0.33	0.33	0.20	0.20	0.14	0.14	0.20	0.20	0.33	0.11	0.11	0.14	0.33
C3	1.00	9.00	1.00	3.00	5.00	7.00	7.00	5.00	5.00	3.00	3.00	5.00	5.00	7.00	1.00	1.00	3.00	7.00
C4	0.33	7.00	0.33	1.00	3.00	5.00	5.00	3.00	3.00	1.00	1.00	3.00	3.00	5.00	0.33	0.33	1.00	5.00
C5	0.20	5.00	0.20	0.33	1.00	3.00	3.00	1.00	1.00	0.33	0.33	1.00	1.00	3.00	0.20	0.20	0.33	3.00
C6	0.14	3.00	0.14	0.20	0.33	1.00	1.00	0.33	0.33	0.20	0.20	0.33	0.33	1.00	0.14	0.14	0.20	1.00
C7	0.14	3.00	0.14	0.20	0.33	1.00	1.00	0.33	0.33	0.20	0.20	0.33	0.33	1.00	0.14	0.14	0.20	1.00
C8	0.20	5.00	0.20	0.33	1.00	3.00	3.00	1.00	1.00	0.33	0.33	1.00	1.00	3.00	0.20	0.20	0.33	3.00
C9	0.20	5.00	0.20	0.33	1.00	3.00	3.00	1.00	1.00	0.33	0.33	1.00	1.00	3.00	0.20	0.20	0.33	3.00
C10	0.33	7.00	0.33	1.00	3.00	5.00	5.00	3.00	3.00	1.00	1.00	3.00	3.00	5.00	0.33	0.33	1.00	5.00
C11	0.33	7.00	0.33	1.00	3.00	5.00	5.00	3.00	3.00	1.00	1.00	3.00	3.00	5.00	0.33	0.33	1.00	5.00
C12	0.20	5.00	0.20	0.33	1.00	3.00	3.00	1.00	1.00	0.33	0.33	1.00	1.00	3.00	0.20	0.20	0.33	3.00
C13	0.20	5.00	0.20	0.33	1.00	3.00	3.00	1.00	1.00	0.33	0.33	1.00	1.00	3.00	0.20	0.20	0.33	3.00
C14	0.14	3.00	0.14	0.20	0.33	1.00	1.00	0.33	0.33	0.20	0.20	0.33	0.33	1.00	0.14	0.14	0.20	1.00
C15	1.00	9.00	1.00	3.00	5.00	7.00	7.00	5.00	5.00	3.00	3.00	5.00	5.00	7.00	1.00	1.00	3.00	7.00
C16	1.00	9.00	1.00	3.00	5.00	7.00	7.00	5.00	5.00	3.00	3.00	5.00	5.00	7.00	1.00	1.00	3.00	7.00
C17	0.33	7.00	0.33	1.00	3.00	5.00	5.00	3.00	3.00	1.00	1.00	3.00	3.00	5.00	0.33	0.33	1.00	5.00
C18	0.14	3.00	0.14	0.20	0.33	1.00	1.00	0.33	0.33	0.20	0.20	0.33	0.33	1.00	0.14	0.14	0.20	1.00

After forming pair-wise comparison matrices, the results were used to form the fuzzy pair comparison matrix. The triangular membership function and, consequently, triangular fuzzy numbers are used to form this matrix. The calculation for this method involves the following steps:

Step 1. Fuzzy number calculation:

Fuzzy numbers a_{ij} are cacluated through the direct use of expert opinion polls. In this study, fuzzy numbers were calculated based on the triangular membership function. Figure 3 indicates the calculation of fuzzy numbers by the triangular method.

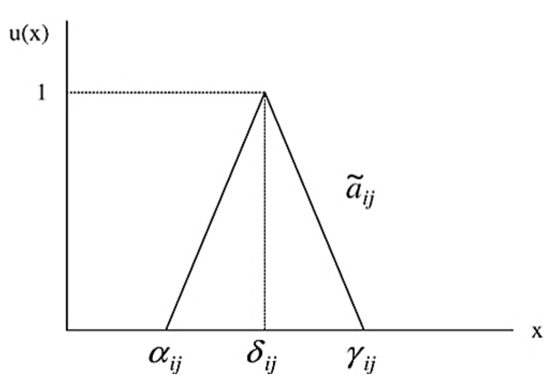

Figure 3. Triangular membership function in Delphi fuzzy method [55].

According to Figure 3 in the Delphi fuzzy method, a fuzzy number can be calculated using Equations (14) to (17).

$$a_{ij} = (\alpha_{ij}, \delta_{ij}, \gamma_{ij}) \quad (14)$$

$$a_{ij} = Min(\beta_{ijk}) \ , \ k = 1,2, \dots, n \quad (15)$$

$$\delta_{ij} = \left(\prod_{k=1}^{n} \beta_{ijk}\right)^{\frac{1}{n}} \ , \ k = 1,2, \dots, n \quad (16)$$

$$\gamma_{ij} = Max(\beta_{ijk}) \ , \ k = 1,2, \dots, n \quad (17)$$

In the above equations, γ_{ij} and α_{ij} represent the upper and lower boundaries of the experts' decisions, respectively. The β_{ijk} parameter also represents the relative importance of parameter i over parameter j based on the expert's point of view [55].

Step 2. Establish fuzzy pair-wise comparison matrix:

In this step, the fuzzy numbers matrix of fuzzy pair-wise comparison between different parameters is created using Equation (18).

$$
\begin{aligned}
&\tilde{A} = [\tilde{a}_{ij}] \\
&\tilde{a}_{ij} \times \tilde{a}_{ij} \approx 1 \quad , \quad Ai, j = 1,2, \dots, n \\
&\tilde{A} = \begin{bmatrix} (1,1,1) & (\alpha_{12}, \delta_{12}, \gamma_{12}) & (\alpha_{13}, \delta_{13}, \gamma_{13}) \\ \left(1/\gamma_{12}, 1/\delta_{12}, 1/\alpha_{12}\right) & (1,1,1) & (\alpha_{23}, \delta_{23}, \gamma_{23}) \\ \left(1/\gamma_{13}, 1/\delta_{13}, 1/\alpha_{13}\right) & \left(1/\gamma_{23}, 1/\delta_{23}, 1/\alpha_{23}\right) & (1,1,1) \end{bmatrix}
\end{aligned}
\tag{18}
$$

The fuzzy pair-wise comparison matrix is presented in Table 5.

Table 5. The fuzzy pair-wise comparison matrix.

	C1			C2			C3			C4			C5			C6		
C1	1.00	1.00	1.00	0.33	2.59	9.00	1.00	1.32	3.00	1.00	2.59	5.00	1.00	3.34	5.00	1.00	3.20	7.00
C2	0.11	0.39	3.00	1.00	1.00	1.00	0.11	0.44	3.00	0.14	0.58	7.00	0.20	0.83	7.00	0.33	0.86	5.00
C3	0.33	0.76	1.00	0.33	2.28	9.00	1.00	1.00	1.00	1.00	1.97	5.00	1.00	2.94	5.00	1.00	2.82	7.00
C4	0.20	0.39	1.00	0.14	1.73	7.00	0.20	0.51	1.00	1.00	1.00	1.00	1.00	1.73	3.00	0.33	1.50	5.00
C5	0.20	0.30	1.00	0.14	1.21	5.00	0.20	0.34	1.00	0.33	0.58	1.00	1.00	1.00	1.00	0.33	1.00	3.00
C6	0.14	0.31	1.00	0.20	1.16	3.00	0.14	0.35	1.00	0.20	0.67	3.00	0.33	1.00	3.00	1.00	1.00	1.00
C7	0.14	0.16	0.20	0.11	0.44	3.00	0.14	0.17	0.20	0.20	0.23	0.33	0.20	0.29	0.33	0.20	0.34	1.00
C8	0.14	0.17	0.20	0.11	0.50	5.00	0.14	0.18	0.20	0.20	0.26	0.33	0.20	0.39	1.00	0.20	0.45	3.00
C9	0.14	0.21	0.33	0.14	0.70	5.00	0.20	0.23	0.33	0.20	0.39	1.00	0.33	0.58	1.00	0.33	0.58	3.00
C10	0.14	0.22	0.33	0.11	0.71	7.00	0.14	0.24	0.33	0.20	0.39	1.00	0.33	0.58	3.00	0.20	0.58	5.00
C11	0.14	0.21	0.33	0.14	0.58	7.00	0.20	0.23	0.33	0.20	0.45	1.00	0.20	0.67	3.00	0.20	0.58	5.00
C12	0.20	0.23	0.33	0.20	0.76	5.00	0.20	0.26	0.33	0.20	0.51	3.00	0.20	0.88	3.00	0.20	0.88	3.00
C13	0.14	0.18	0.20	0.14	0.53	5.00	0.20	0.20	0.20	0.20	0.34	1.00	0.20	0.51	1.00	0.20	0.51	3.00
C14	0.14	0.25	1.00	0.33	0.58	3.00	0.14	0.27	1.00	0.20	0.45	5.00	0.20	0.58	5.00	0.20	0.67	3.00
C15	0.14	0.47	1.00	0.11	1.73	9.00	0.14	0.61	1.00	0.33	1.00	3.00	0.33	1.50	5.00	0.20	1.43	7.00
C16	0.20	0.51	1.00	0.14	1.84	9.00	0.20	0.67	1.00	1.00	1.32	3.00	1.00	1.97	5.00	0.33	1.63	7.00
C17	0.33	0.58	1.00	0.33	1.85	7.00	0.33	0.76	3.00	0.33	1.50	5.00	0.33	2.24	5.00	0.33	2.24	5.00
C18	0.14	0.41	3.00	1.00	1.32	3.00	0.14	0.47	3.00	0.20	0.63	7.00	0.33	0.94	7.00	0.33	1.14	5.00

Table 5. Continued.

	C7			C8			C9			C10			C11			C12		
C1	5.00	6.44	7.00	5.00	5.92	7.00	3.00	4.79	7.00	3.00	4.58	7.00	3.00	4.79	7.00	3.00	4.40	5.00
C2	0.33	2.28	9.00	0.20	2.01	9.00	0.20	1.43	7.00	0.14	1.40	9.00	0.14	1.73	7.00	0.20	1.32	5.00
C3	5.00	5.92	7.00	5.00	5.44	7.00	3.00	4.40	5.00	3.00	4.21	7.00	3.00	4.40	5.00	3.00	3.87	5.00
C4	3.00	4.40	5.00	3.00	3.87	5.00	1.00	2.59	5.00	1.00	2.59	5.00	1.00	2.24	5.00	0.33	1.97	5.00
C5	3.00	3.41	5.00	1.00	2.59	5.00	1.00	1.73	3.00	0.33	1.73	3.00	0.33	1.50	5.00	0.33	1.14	5.00
C6	1.00	2.94	5.00	0.33	2.24	5.00	0.33	1.73	3.00	0.20	1.73	5.00	0.20	1.73	5.00	0.33	1.14	5.00
C7	1.00	1.00	1.00	0.33	0.76	1.00	0.33	0.44	1.00	0.20	0.51	1.00	0.20	0.51	1.00	0.20	0.39	1.00
C8	1.00	1.32	3.00	1.00	1.00	1.00	0.33	0.58	1.00	0.33	0.58	1.00	0.33	0.58	1.00	0.20	0.51	1.00
C9	1.00	2.28	3.00	1.00	1.73	3.00	1.00	1.00	1.00	0.33	1.00	3.00	0.33	1.00	3.00	0.33	0.76	3.00
C10	1.00	1.97	5.00	1.00	1.73	3.00	0.33	1.00	3.00	1.00	1.00	1.00	0.33	1.00	3.00	0.20	0.88	3.00
C11	1.00	1.97	5.00	1.00	1.73	3.00	0.33	1.00	3.00	0.33	1.00	3.00	1.00	1.00	1.00	0.33	0.76	3.00
C12	1.00	2.59	5.00	1.00	1.97	5.00	0.33	1.32	3.00	0.33	1.14	5.00	0.33	1.32	3.00	1.00	1.00	1.00
C13	1.00	1.73	3.00	1.00	1.32	3.00	0.33	0.76	1.00	0.33	0.76	3.00	0.33	0.76	1.00	0.33	0.58	1.00
C14	1.00	1.63	7.00	0.33	1.24	7.00	0.33	0.86	5.00	0.20	0.83	7.00	0.20	1.00	5.00	0.33	0.76	3.00
C15	1.00	3.64	7.00	1.00	3.34	5.00	0.33	2.24	5.00	1.00	2.59	5.00	0.33	2.24	5.00	0.20	1.97	5.00
C16	3.00	4.79	7.00	3.00	4.40	5.00	1.00	2.94	5.00	3.00	3.41	5.00	1.00	2.94	5.00	0.33	2.24	5.00
C17	3.00	5.21	7.00	3.00	4.58	7.00	1.00	3.20	7.00	1.00	2.65	7.00	1.00	3.20	7.00	3.00	3.41	5.00
C18	1.00	3.00	9.00	0.33	2.28	9.00	0.33	1.63	7.00	0.20	1.52	9.00	0.20	1.88	7.00	0.33	1.50	5.00

Table 5. Continued.

	C13			C14			C15			C16			C17			C18		
C1	5.00	5.44	7.00	1.00	3.96	7.00	1.00	2.14	7.00	1.00	1.97	5.00	1.00	1.73	3.00	7.00	2.43	7.00
C2	0.20	1.88	7.00	0.33	1.73	3.00	0.11	0.58	9.00	0.11	0.54	7.00	0.14	0.54	3.00	1.00	0.76	1.00
C3	5.00	5.00	5.00	1.00	3.64	7.00	1.00	1.63	7.00	1.00	1.50	5.00	0.33	1.32	3.00	7.00	2.14	7.00
C4	1.00	2.94	5.00	0.20	2.24	5.00	0.33	1.00	3.00	0.33	0.76	1.00	0.20	0.67	3.00	5.00	1.59	5.00
C5	1.00	1.97	5.00	0.20	1.73	5.00	0.20	0.67	3.00	0.20	0.51	1.00	0.20	0.45	3.00	3.00	1.06	3.00
C6	0.33	1.97	5.00	0.33	1.50	5.00	0.14	0.70	5.00	0.14	0.61	3.00	0.20	0.45	3.00	3.00	0.88	3.00
C7	0.33	0.58	1.00	0.14	0.61	1.00	0.14	0.27	1.00	0.14	0.21	0.33	0.14	0.19	0.33	1.00	0.33	1.00
C8	0.33	0.76	1.00	0.14	0.81	3.00	0.20	0.30	1.00	0.20	0.23	0.33	0.14	0.22	0.33	3.00	0.44	3.00
C9	1.00	1.32	3.00	0.20	1.16	3.00	0.20	0.45	3.00	0.20	0.34	1.00	0.14	0.31	1.00	3.00	0.61	3.00
C10	0.33	1.32	3.00	0.14	1.21	5.00	0.20	0.39	1.00	0.20	0.29	0.33	0.14	0.38	1.00	5.00	0.66	5.00
C11	1.00	1.32	3.00	0.20	1.00	5.00	0.20	0.45	3.00	0.20	0.34	1.00	0.14	0.31	1.00	5.00	0.53	5.00
C12	1.00	1.73	3.00	0.33	1.32	3.00	0.20	0.51	5.00	0.20	0.45	3.00	0.20	0.29	0.33	3.00	0.67	3.00
C13	1.00	1.00	1.00	0.20	0.88	3.00	0.20	0.39	3.00	0.20	0.30	1.00	0.14	0.24	0.33	3.00	0.47	3.00
C14	0.33	1.14	5.00	1.00	1.00	1.00	0.14	0.45	7.00	0.14	0.41	5.00	0.14	0.31	1.00	1.00	0.44	1.00
C15	0.33	2.54	5.00	0.14	2.24	7.00	1.00	1.00	1.00	0.33	0.76	1.00	0.14	0.81	3.00	7.00	1.63	7.00
C16	1.00	3.34	5.00	0.20	2.43	7.00	1.00	1.32	3.00	1.00	1.00	1.00	0.20	0.88	3.00	7.00	1.73	7.00
C17	3.00	4.21	7.00	1.00	3.20	7.00	0.33	1.24	7.00	0.33	1.14	5.00	1.00	1.00	1.00	5.00	1.70	5.00
C18	0.33	2.14	7.00	1.00	2.28	3.00	0.14	0.61	9.00	0.14	0.58	7.00	0.20	0.59	3.00	1.00	1.00	1.00

The fuzzy weight of each parameter can be determined using Equations (19) and (20) [55].

$$\tilde{Z}_i = \left[\tilde{a}_{ij} \otimes \dots \otimes \tilde{a}_{in}\right]^{\frac{1}{n}} \tag{19}$$

$$\widetilde{W}_i = \tilde{Z}_i \otimes (\tilde{Z}_i \oplus \dots \oplus \tilde{Z}_n) \tag{20}$$

where $\widetilde{W}_i$ is a row vector representing the fuzzy weight of the i[th] parameter. Table 6 reports the fuzzy Z and W weight vectors.

Table 6. The fuzzy Z and W weight vectors.

Z1	1.75	3.08	5.38	**W1**	0.18	0.14	0.10
Z2	0.21	0.97	4.76	**W2**	0.02	0.05	0.09
Z3	1.55	2.63	4.79	**W3**	0.1	0.12	0.09
Z4	0.61	1.54	3.27	**W4**	0.06	0.07	0.06
Z5	0.44	1.03	2.70	**W5**	0.05	0.05	0.05
Z6	0.31	1.03	3.13	**W6**	0.03	0.05	0.06
Z7	0.23	0.36	0.70	**W7**	0.02	0.02	0.01
Z8	0.28	0.44	0.97	**W8**	0.03	0.02	0.02
Z9	0.36	0.66	1.78	**W9**	0.04	0.03	0.03
Z10	0.31	0.66	1.91	**W10**	0.03	0.03	0.03
Z11	0.35	0.65	2.16	**W11**	0.04	0.03	0.04
Z12	0.37	0.80	2.26	**W12**	0.04	0.04	0.04
Z13	0.32	0.53	1.32	**W13**	0.03	0.02	0.02
Z14	0.27	0.63	3.16	**W14**	0.03	0.03	0.06
Z15	0.37	1.52	3.68	**W15**	0.04	0.07	0.07
Z16	0.74	1.84	3.91	**W16**	0.08	0.09	0.07
Z17	0.86	2.06	4.81	**W17**	0.09	0.10	0.09
Z18	0.31	1.12	5.06	**W18**	0.03	0.05	0.09

Step 3. Defuzzification

After finding the fuzzy weights of each parameter, all the fuzzy numbers are defuzzied using Equation (21) [55].

$$\widetilde{W}_i = \left(\prod_{i=1}^{3} \omega_j\right)^{\frac{1}{3}} \tag{21}$$

Table 7 reports the degree of importance of the parameters affecting slope stability using the FDAHP method.

Table 7. The degree of importance of the parameters affecting the slope stability.

Criteria	Final weight	Criteria	Final weight
Rock type	0.140	Discontinuity spacing	0.033
Rainfall	0.051	Discontinuity orientation	0.035
Intact rock strength-UCS	0.123	Discontinuity aperture	0.039
RQD	0.064	Discontinuity roughness	0.027
Weathering	0.047	Discontinuity filling	0.038
Tectonic regime	0.045	Slope (pit-wall) angle	0.058
Groundwater conditions	0.018	Slope (pit-wall) height	0.078
Number of major discontinuity sets	0.022	Blasting method	0.090
Discontinuity persistence	0.033	Convexity/Concavity	0.059

In the next step, according to the classes corresponding to each criterion, a Gaussian or sigmoidal membership function is defined for each criterion. Table 8 and Figure 4 present the Gaussian and sigmoidal membership functions defined for all criteria.

Table 8. The Gaussian and sigmoidal membership functions defined for all criteria.

Qualitative classification	Slope (pit-wall) angle	Number of major discontinuity sets
Very Weak	$Q_1^{(1)}(x)=\frac{1}{1+\exp((-0.4)\times(x-55))}$	$Q_1^{(1)}(x)=\frac{1}{1+\exp((-7)\times(x-3.5))}$
Weak	$Q_1^{(2)}(x)=exp\left(-\frac{1}{2}\left(\frac{x-50}{4}\right)^2\right)$	$Q_1^{(2)}(x)=exp\left(-\frac{1}{2}\left(\frac{x-3}{0.3}\right)^2\right)$
Medium	$Q_1^{(3)}(x)=exp\left(-\frac{1}{2}\left(\frac{x-43}{4}\right)^2\right)$	$Q_1^{(3)}(x)=exp\left(-\frac{1}{2}\left(\frac{x-2.1}{0.3}\right)^2\right)$
Good	$Q_1^{(4)}(x)=exp\left(-\frac{1}{2}\left(\frac{x-35}{4}\right)^2\right)$	$Q_1^{(4)}(x)=exp\left(-\frac{1}{2}\left(\frac{x-1.2}{0.3}\right)^2\right)$
Very Good	$Q_1^{(5)}(x)=\frac{1}{1+\exp((-0.3)\times(x-15))}$	$Q_1^{(5)}(x)=\frac{1}{1+\exp((8)\times(x-0.7))}$
	Intact rock strength	**Discontinuity persistence**
Very Weak	$Q_1^{(1)}(x)=\frac{1}{1+\exp((0.25)\times(x-25))}$	$Q_1^{(5)}(x)=\frac{1}{1+\exp((-0.7)\times(x-40))}$
Weak	$Q_1^{(2)}(x)=exp\left(-\frac{1}{2}\left(\frac{x-45}{18}\right)^2\right)$	$Q_1^{(4)}(x)=exp\left(-\frac{1}{2}\left(\frac{x-32}{3.5}\right)^2\right)$
Medium	$Q_1^{(3)}(x)=exp\left(-\frac{1}{2}\left(\frac{x-85}{23}\right)^2\right)$	$Q_1^{(3)}(x)=exp\left(-\frac{1}{2}\left(\frac{x-20}{3.5}\right)^2\right)$
Good	$Q_1^{(4)}(x)=exp\left(-\frac{1}{2}\left(\frac{x-160}{27}\right)^2\right)$	$Q_1^{(2)}(x)=exp\left(-\frac{1}{2}\left(\frac{x-8}{3.5}\right)^2\right)$
Very Good	$Q_1^{(5)}(x)=\frac{1}{1+\exp((-0.1)\times(x-230))}$	$Q_1^{(1)}(x)=\frac{1}{1+\exp((1.5)\times(x-3))}$
	RQD	**Discontinuity spacing**
Very Weak	$Q_1^{(1)}(x)=\frac{1}{1+\exp((0.4)\times(x-15))}$	$Q_1^{(1)}(x)=\frac{1}{1+\exp((1.5)\times(x-5))}$
Weak	$Q_1^{(2)}(x)=exp\left(-\frac{1}{2}\left(\frac{x-35}{8}\right)^2\right)$	$Q_1^{(2)}(x)=exp\left(-\frac{1}{2}\left(\frac{x-17}{6}\right)^2\right)$
Medium	$Q_1^{(3)}(x)=exp\left(-\frac{1}{2}\left(\frac{x-60}{8}\right)^2\right)$	$Q_1^{(3)}(x)=exp\left(-\frac{1}{2}\left(\frac{x-50}{11}\right)^2\right)$
Good	$Q_1^{(4)}(x)=exp\left(-\frac{1}{2}\left(\frac{x-78}{7}\right)^2\right)$	$Q_1^{(4)}(x)=exp\left(-\frac{1}{2}\left(\frac{x-110}{18}\right)^2\right)$
Very Good	$Q_1^{(5)}(x)=\frac{1}{1+\exp((-0.4)\times(x-85))}$	$Q_1^{(5)}(x)=\frac{1}{1+\exp((-0.2)\times(x-155))}$
	Discontinuity aperture	**Slope (pit-wall) height**
Very Weak	$Q_1^{(1)}(x)=\frac{1}{1+\exp((-5)\times(x-4))}$	$Q_1^{(1)}(x)=\frac{1}{1+\exp((-0.1)\times(x-340))}$
Weak	$Q_1^{(2)}(x)=exp\left(-\frac{1}{2}\left(\frac{x-2.5}{0.6}\right)^2\right)$	$Q_1^{(2)}(x)=exp\left(-\frac{1}{2}\left(\frac{x-270}{37}\right)^2\right)$
Medium	$Q_1^{(3)}(x)=exp\left(-\frac{1}{2}\left(\frac{x-0.8}{0.2}\right)^2\right)$	$Q_1^{(3)}(x)=exp\left(-\frac{1}{2}\left(\frac{x-130}{35}\right)^2\right)$

Good	$Q_1^{(4)}(x) = exp\left(-\frac{1}{2}\left(\frac{x-0.4}{0.15}\right)^2\right)$	$Q_1^{(4)}(x) = exp\left(-\frac{1}{2}\left(\frac{x-48}{20}\right)^2\right)$
Very Good	$Q_1^{(5)}(x) = \frac{1}{1+\exp((15)\times(x-0.3))}$	$Q_1^{(5)}(x) = \frac{1}{1+\exp((0.25)\times(x-25))}$
	Rainfall	**Qualitative parameters**
Very Weak	$Q_1^{(1)}(x) = \frac{1}{1+\exp((-0.1)\times(x-370))}$	$Q_1^{(1)}(x) = \frac{1}{1+\exp((0.4)\times(x-15))}$
Weak	$Q_1^{(2)}(x) = exp\left(-\frac{1}{2}\left(\frac{x-330}{35}\right)^2\right)$	$Q_1^{(2)}(x) = exp\left(-\frac{1}{2}\left(\frac{x-40}{8}\right)^2\right)$
Medium	$Q_1^{(3)}(x) = exp\left(-\frac{1}{2}\left(\frac{x-225}{35}\right)^2\right)$	$Q_1^{(3)}(x) = exp\left(-\frac{1}{2}\left(\frac{x-60}{8}\right)^2\right)$
Good	$Q_1^{(4)}(x) = exp\left(-\frac{1}{2}\left(\frac{x-100}{30}\right)^2\right)$	$Q_1^{(4)}(x) = exp\left(-\frac{1}{2}\left(\frac{x-80}{7}\right)^2\right)$
Very Good	$Q_1^{(5)}(x) = \frac{1}{1+\exp((0.15)\times(x-40))}$	$Q_1^{(5)}(x) = \frac{1}{1+\exp((-0.7)\times(x-92))}$

6. Case Study

In this study, sustainability analysis was performed by investigating different slopes of 8 open pit mines. Table 9 reports the studied slopes in this study. The information on each slope was completed either through field study or based on published reports. Table 10 shows an example of field data collected from the southwest wall of the Sungun copper mine.

Table 9. The list of studied slopes in the database.

Case number	Name	Case number	Name
A1	Sarcheshmeh-Iran-East wall	A15	Aznalcollar-Spain-South wall
A2	Sarcheshmeh-Iran-North wall	A16	Aznalcollar-Spain-West wall
A3	Sarcheshmeh-Iran-South wall	A17	Aznalcollar-Spain-North wall
A4	Sarcheshmeh-Iran-West wall	A18	Cadia Hill-Australia-Northeast wall
A5	Angoran-Iran-Southeast wall	A19	Cadia Hill-Australia-East wall
A6	Sangan-Iran-Baghak wall	A20	Cadia Hill-Australia-West wall
A7	Sangan-Iran-Anomaly A	A21	Cadia Hill-Australia-North wall
A8	Chuquicamata-Chile-Northwest wall	A22	Cadia Hill-Australia-South wall
A9	Chuquicamata-Chile-South wall	A23	Aitik-Sweden-East wall
A10	Chuquicamata-Chile-West wall	A24	Aitik-Sweden-Northeast wall
A11	Chuquicamata-Chile-North wall	A25	Aitik-Sweden-Northwest wall
A12	Chuquicamata-Chile-East wall	A26	Aitik-Sweden-Southeast wall
A13	Aznalcollar-Spain-Southeast wall	A27	Aitik-Sweden-Southwest wall
A14	Aznalcollar-Spain-Southwest wall	A28	Sungon-Iran-Southwest wall

Table 10. An example of field data collected from the Sungun copper mine.

NO	Parameters	SW Sungun
C1	Rock type (major)	Quartz monzonite (SP) & Diorite (Dk-1)
C2	Rainfall (mm/year)	300-450
C3	Intact rock strength-UCS (Mpa)	30-80
C4	RQD (%)	50-75
C5	Weathering	W3
C6	Tectonic regime	Strong
C7	Groundwater conditions	Damp
C8	Number of major discontinuity sets	1
C9	Discontinuity persistence (m)	10-30
C10	Discontinuity spacing (m)	0.06-2
C11	Discontinuity orientation	Favorable
C12	Discontinuity aperture (mm)	0.5-1
C13	Discontinuity roughness (JRC)	Smooth
C14	Discontinuity filling	Hard filling
C15	Slope (pit-wall) angle (deg)	30-40
C16	Slope (pit-wall) height (m)	450
C17	Blasting method	Modified production
C18	Convexity/Concavity	Concave

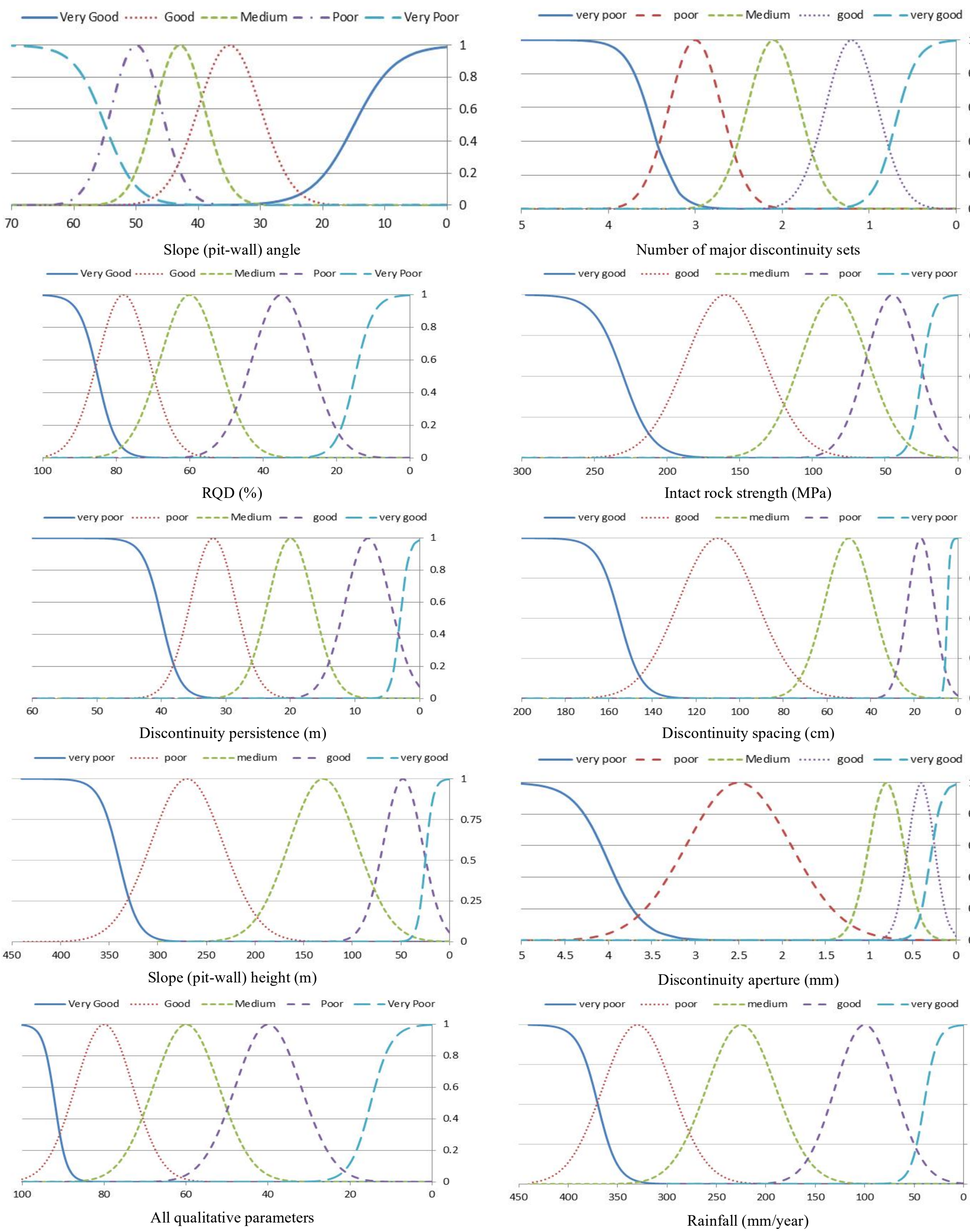

Figure 4. Diagram of criteria membership functions.

The present study attempted to quantitatively or qualitatively evaluate all the characteristics affecting sustainability. The qualitative values in collected forms were scored in 5 classes from 10 to 100. Table 11 represents the quantitative characteristics of the 28 studied slopes.

Table 11. The quantitative characteristics of the 28 studied slopes.

Name	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18
A1	80	135	60	45	90	60	100	3	12.5	5.3	40	3	90	60	35	390	40	60
A2	80	135	70	55	90	60	100	3	6.5	350	90	3	90	60	35	420	40	60
A3	80	135	55	45	90	60	60	4	10	350	60	3	80	40	35	620	40	60
A4	80	135	55	45	90	60	60	4	10	300	40	3	80	50	35	800	40	60
A5	40	497	73	41	90	60	100	4	20	75	40	3	40	50	30	170	40	60
A6	60	155	105	45	85	75	100	1	7.5	125	40	0.55	90	50	41	50	40	60
A7	60	155	90	40	60	75	60	3	15	85	40	0.55	40	50	45	65	40	60
A8	80	35	59	48	60	60	100	3	5	200	40	0.55	40	60	32	210	40	60
A9	80	35	52	59	40	60	100	4	2.75	325	60	0.55	90	60	31	700	40	60
A10	80	35	48	23	60	60	60	5	5.75	325	15	3	60	50	32	750	40	60
A11	80	35	67	44	40	60	100	5	5.75	400	60	0.55	60	60	31	750	40	60
A12	60	35	85	46	60	60	100	6	7.75	240	10	3	80	50	42	780	40	60
A13	80	650	55	60	100	40	100	3	3	225	80	0.1	80	60	34	240	40	60
A14	40	650	24	25	100	40	60	4	10	165	15	3	60	60	34	210	40	60
A15	40	650	20	25	60	40	60	4	10	90	40	3	60	40	34	210	40	60
A16	40	650	35	40	60	40	60	5	15	115	40	3	40	40	32	210	40	60
A17	60	650	35	40	100	40	60	3	7.5	60	60	0.55	60	60	32	240	40	60
A18	95	800	87	60	100	60	100	3	6.5	415	60	0.55	90	40	58	500	80	90
A19	95	800	53	56	100	60	100	2	4.5	375	60	3	90	40	58	500	80	60
A20	95	800	50	60	100	60	100	3	4.5	105	40	0.55	90	40	46	500	80	60
A21	95	800	89	68	100	60	100	3	3	175	80	3	100	40	58	500	80	60
A22	60	800	46	65	90	60	60	4	5.5	75	40	3	80	40	52	500	80	90
A23	95	680	133	78	60	60	60	4	2.25	350	80	0.55	80	80	42	125	60	90
A24	60	680	75	80	60	60	60	5	9.5	150	40	3	80	80	47	230	60	90
A25	95	680	138	82	100	60	100	5	3	325	60	0.55	90	40	51	250	60	90
A26	95	680	124	78	60	60	100	4	2.5	325	80	0.1	90	40	49	325	60	60
A27	95	680	138	85	60	60	100	4	3.5	150	60	0.55	90	40	53	325	60	90
A28	95	375	75	30	60	60	100	1	20	100	90	0.75	40	80	35	475	60	90

6. Discussion

The ability of the new fuzzy classification system was evaluated according to the results of assessing the stability of the studied slopes. To achieve this goal, a fuzzy matrix was created for each slope. Table 12 provides an example of a fuzzy matrix belonging to the southwestern slope of the Sungun copper mine.

Table 12. Fuzzy matrix for the southwestern slope of the Sungun copper mine.

Criterion	Evaluation matrix component				
	Very Poor (VP)	Poor (P)	Medium (M)	Good (G)	Very Good (VG)
C1	0.89	0.1007	0	0	0
C2	0	0	0	0.44	0.62
C3	0	0	0.91	0.25	0
C4	0	0	0	0	0
C5	0	0.02	1	0.04	0
C6	0	0.02	1	0.04	0
C7	1	0.02	0	0	0
C8	0.08	0.8	0	0	0
C9	0	0	1	0	0
C10	0	0.86	0	0	0
C11	0.2	0.36	0	0	0
C12	0	0.066	1	0.01	0
C13	0	0	0.04	1	0
C14	0	1	0.04	0	0
C15	0	1	0.14	0	0
C16	0	0	0	0	1
C17	0	0.02	1	0.04	0
C18	0.2	0.36	0	0	0

In the last stage of the evaluation, the evaluation vectors summarized using the Dubois-Prade decision operator are shown as follows:

$$d_1(u) = ((1 - w_1)\vee r_{11}(u))\wedge \dots \wedge((1 - w_7)\vee r_{181}(u)) = 0.86$$

$$d_2(u) = ((1 - w_1)\vee r_{12}(u))\wedge \dots \wedge((1 - w_7)\vee r_{182}(u)) = 0.86$$

$$d_3(u) = ((1 - w_1)\vee r_{13}(u))\wedge \dots \wedge((1 - w_7)\vee r_{183}(u)) = 0.86$$

$$d_4(u) = ((1 - w_1)\vee r_{14}(u))\wedge \dots \wedge((1 - w_7)\vee r_{184}(u)) = 0.86$$

$$d_5(u) = ((1 - w_1)\vee r_{15}(u))\wedge \dots \wedge((1 - w_7)\vee r_{185}(u)) = \mathbf{0.88}$$

$$D = f(W, R) = (0.86, 0.86, 0.86, 0.86, \mathbf{0.88})$$

Overall, the stability class of the southwestern slope of the Sungun copper mine is rated as “Very good”. The results obtained for all studied slopes are shown in Table 13.

According to the results in Table 13, 9 slopes from 3 studied mines in Iran, Sweden, and Australia were classified in very good stability conditions. Also 9 slopes from 3 mines in Iran, Chile, and Spain were classified in the category of suitable quality. Six mines from 4 studied mines in Iran, Sweden, Spain, and Chile were classified as medium or susceptible to instability. Finally, 4 slopes from two mines in Iran and Spain were classified as unstable conditions. The validity and reliability of the results were evaluated by analyzing the field study reports collected from all the mines studied, followed by comparing their actual behavior and predicted quality grades. The results of these surveys are presented in Table 14.

Table 13. Slope stability classes for studied mine.

Case	Class	Case	Class
A1	Good	A15	Poor
A2	Good	A16	Poor
A3	Good	A17	Medium
A4	Good	A18	Very Good
A5	Poor	A19	Very Good
A6	Medium	A20	Very Good
A7	Medium	A21	Very Good
A8	Good	A22	Medium
A9	Good	A23	Very Good
A10	Good	A24	Medium
A11	Good	A25	Very Good
A12	Medium	A26	Very Good
A13	Good	A27	Very Good
A14	Poor	A28	Very Good

Table 14. Actual behavior of studied slopes.

Case	Slope behavior (actual)	Class	Case	Slope behavior (actual)	Class
A1	Stable	Good	A15	Overall failure	Poor
A2	Stable	Good	A16	Overall failure	Poor
A3	Stable	Good	A17	Failure in the set of benches	Medium
A4	Stable	Good	A18	Stable	Very Good
A5	Overall failure	Poor	A19	Stable	Very Good
A6	Failure in the set of benches	Medium	A20	Stable	Very Good
A7	Failure in the set of benches	Medium	A21	Stable	Very Good
A8	Stable	Good	A22	Failure in the set of benches	Medium
A9	Stable	Good	A23	Stable	Very Good
A10	Stable	Good	A24	Failure in the set of benches	Medium
A11	Stable	Good	A25	Stable	Very Good
A12	Failure in the set of benches	Medium	A26	Stable	Very Good
A13	Stable	Good	A27	Stable	Very Good
A14	Overall failure	Poor	A28	Stable	Very Good

The results of this study and its comparison with the actual behavior of slopes in all the studied mines suggest the proper performance of the non-linear multi-factorial fuzzy classification system. All stable slopes were distinguished from unstable or unstable slopes by good and very good quality. The slopes were classified as poor and medium quality, with a general and partial collapse in several slopes, respectively.

7. Conclusions

The slope stability is a highly technical and economically important concept, especially in surface mines. The stability conditions required for a rock slope depend on the project type and the failure outcomes. In this respect, any slight changes in the depth of the slopes and, thus, the final slope deep of the mine will have a significant impact on the economic parameters of mining operations. In the design sector, the slope reduces the tailing ratio, lowers the return on capital, and increases the extractable mineral reserve. At the extraction stage, the slopes’ stability will allow numerous arbitrary explosions to crush the rocks completely. Regarding safety both in the design and the extraction phase, the slope stability enables better control of the mine walls, better control of surface and groundwater, and designing and constructing safety walls in the final wall of the mine. The present results offer a non-linear multi-factor fuzzy classification system. This system is applied to evaluate the stability of sloping walls using the data obtained from 28 sloping walls through fuzzy matrix formation through Dubois and Pride fuzzy operators in five classes. The accuracy of the results was validated by preparing field reports for eight surface mines and comparing them with the results of the classification system. The results of the investigations and their comparison with the recorded actual observations revealed that the non-linear multi-factor fuzzy classification system with the applied operator was able to evaluate and rank the slope stability in five classes of very good (high stability), very good (stable), moderate (relatively stable), weak (unstable), and very weak (highly unstable). Overall, the research results suggest the ability of the developed non-linear multi-factorial fuzzy classification system to classify the studied slopes. Also, the results revealed that the slope stability could be evaluated with high precision using the new fuzzy classification system according to information such as rock mass characteristics, intact rock properties, rainfall, tectonic regime, groundwater conditions, slope information, and blasting method.

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ارزیابی پایداری دیواره شیبدار در شرایط زمین‌شناسی با استفاده از سیستم طبقه‌بندی فازی چند فاکتوره

مرتضی نیرومند[۱]، رضا میکائیل[۲*]، مهران ادوای[۱] و مسعود زارع نقده‌ای[۳]

۱. گروه مهندسی معدن، واحد اهر، دانشگاه آزاد اسلامی، اهر، ایران
۲. دانشکده محیط زیست، دانشگاه صنعتی ارومیه، ارومیه، ایران
۳. دانشکده علوم و مهندسی زمین ماکای، دانشگاه نوادا، رنو، ایالات متحده آمریکا

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* نویسنده مسئول مکاتبات: Reza.mikaeil@gmail.com

چکیده:

ناپایداری شیب می‌تواند در اثر بارهای خارجی مانند زلزله، انفجار و فشار آب منفذی رخ دهد.علاوه بر این، در شرایط طبیعی، ناپایداری دیواره‌های شیبدار می‌تواند ناشی از عواملی مانند فرسایش بخش‌های از دیواره در اثر جریان آب یا باد و افزایش تدریجی سطح آب‌های زیرزمینی باشد. عامل دیگری که منجر بـه ناپایـداری دیواره شیبدار می شود، فعالیت‌های انسانی است که شامل انواع مختلف بارگیری و تخلیه در دیواره شیبدار می شود. ناپایداری شیب‌ها ممکن است با جابجایی‌های محدود یا بزرگ همراه باشد که می‌تواند باعث ایجاد مشکل یا آسیب به سازه‌ها در دیواره شود. بنابراین این پدیده در تمامی مراحل طراحی و اجرای دیواره شیبدار نیاز به تمهیدات و مراقبت لازم دارد. به طور کلی، پایداری دیواره شیبدار تحت تأثیر عوامل طبیعی مانند نوع سنگ (لیتولوژی)، شـرایط زمـین سـاختی منطقـه، شرایط ناپیوستگی توده سنگ و شرایط آب و هوایی منطقه است. علاوه بر این، تابعی از عوامل طراحی مانند شیب، ارتفاع، الگوی انفجـاری و روش انفجـار اسـت. مطالعه حاضر یک سیستم طبقه بندی فازی چند فاکتوره را با استفاده از رویکرد فازی چند معیاره برای ارزیابی پایداری دیواره شیبدار ارائه مـی‌دهـد. ارزیـابی در پنج کلاس شامل «پایداری بالا»، «پایدار»، «نسبتاً پایدار»، «ناپایدار» و «بسیار ناپایدار» انجام می‌شود. در ادامه، قابلیت پایـداری ۲۸ دیـواره شـیبدار از ۸ معـدن روباز بزرگ در نقاط مختلف جهان مورد ارزیابی قرار گرفت. با توجه به نتایج طبقه‌بندی فازی، ۴ و ۶ شیب به ترتیب در شرایط نسبتاً پایدار و ناپایدار ارزیابی شدند و سایر شیب‌ها به عنوان کلاس پایدار طبقه‌بندی شدند. پس از آن، سیستم طبقه بندی فازی توسعه یافته بر اساس رفتار واقعی دیواره‌ها ارزیابی شد. نتایج نشـان داد که در اکثر دیواره‌ها در شرایط ناپایدار و نسبتاً پایدار، یک شکست عمومی بزرگ و موضعی وجود دارد. از این رو می‌توان از یک سیستم طبقه بندی فازی چند فاکتوره غیرخطی با قابلیت اطمینان خوب برای ارزیابی پایداری دیواره‌های شیبدار استفاده کرد.

کلمات کلیدی: پایداری دیواره شیبدار، نظریه فازی، سیستم طبقه بندی فازی چند فاکتوره.