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Fuzzy-Based Intelligent Model for Rapid Rock Slope Stability Analysis Using Q_{slope}

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Abstract: Artificial intelligence (AI) applications have introduced transformative possibilities within geohazard analysis, particularly concerning the assessment of rock slope instabilities. This study delves into the amalgamation of AI and empirical techniques to attain highly precise outcomes in the evaluation of slope stability. Specifically, our primary objective is to propose innovative and efficient methods by investigating the integration of AI within the well-regarded Q_{slope} system, renowned for its efficacy in analyzing rock slope stability. Given the complexities inherent in rock characteristics, particularly in coastal regions, the Q_{slope} system necessitates adjustments and harmonization with other geomechanical methodologies. Uncertainties prevalent in rock engineering, compounded by water-related factors, warrant meticulous consideration during all calculations. To address these complexities, we present a novel approach through the infusion of fuzzy set theory into the Q_{slope} classification, leveraging fuzziness to effectively quantify and accommodate uncertainties. Our approach employs a sophisticated fuzzy algorithm encompassing six inputs, three outputs, and 756 fuzzy rules, thereby enabling a robust assessment of rock slope stability in coastal regions. The implementation of this method capitalizes on the high-level programming language Python, enhancing computational efficiency. To validate the potency of our AI-based approach, we conducted preliminary tests on slope instabilities within coastal zones, indicating a promising initial direction. The results underwent thorough evaluation, affirming the precision and dependability of the proposed method. However, it is crucial to emphasize that this work represents a first attempt to apply AI to the evaluation of rock slope stability. Our findings underscore a high degree of concurrence and expeditious stability assessment, vital for timely and effective hazard mitigation. Nonetheless, we acknowledge that the reliability of this innovative method must be established through broader applications across diverse scenarios. The proposed AI-based approach's effectiveness is validated through a preliminary survey on a slope instability case within a coastal region, and its potential merits must be substantiated through broader validation efforts.

Keywords: slope stability; fuzzy logic; Q_{slope}; rock slope; geomechanics

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1. Introduction

Geoengineers play a critical role in assessing slope stability for a wide range of geotechnical projects, including road and rail constructions, excavations, mines, and trench boring. Dealing with discontinuous rock conditions requires the development of effective stabilization schemes. New studies have aimed to propose innovative and efficient methods for addressing the challenges posed by such conditions and ensuring the stability of slopes in geotechnical projects [1–3]. Achieving the objective of weak rock slope stability assessment in geotechnical projects relies on the utilization of fast, efficient, and reliable methods. These methods facilitate the appropriate design and implementation of suitable support systems, enabling effective control of slope instabilities during their early stages [4]. Empirical relations have been recognized as robust solutions due to their swift analysis and minimal assumptions [5]. Leveraging the rapid quantification of rock slope features, empirical classifications facilitate prompt discussions and aid in the swift implementation of stabilization measures when slope failure is detected in its initial stages [6].

The pioneer works of Ritter [7] helped develop the most basic classification of rock mass, but Terzaghi [8] is known as the father of the modern engineering classification systems for steel frame tunnels in sedimentary rocks. Cecil [9] modified Terzaghi's approach and applied it to estimate rock mass properties. Deere and Deere [10] presented the rock quality designation index (RQD), which is considered the first computational method for evaluating rock engineering classifications. RQD is extensively used by geotechnical engineering in different projects worldwide. RQD has improved the engineering classification based on rock mass durability and engineering dimension [11]. Modern geotechnical classification systems can be traced back to rock mass classifications, which in turn are based on the rock mass rating (RMR) and Q system [12,13]. The latest version of RMR was introduced in 1989 by Bieniawski [14], and the Q system was released in 1974 by Barton [15]. For a variety of civil and mining engineering applications, RMR and Q are used for preliminary rock mass quantifications. These categories are capable of studying multiple discontinuous rock mass characteristics and offering appropriate descriptions of the conditions of the rock mass in design applications. The RMR was defined primarily for underground investigations, but with some modifications, it can also be used for discontinuous rock structures at the surface. In contrast, the Q system is only used for underground excavations [16]. The geological Strength Index (GSI) classification is introduced by Hoek et al. [17] in their study.

RMR and Q classifications have become increasingly popular and are now widely used as a result of being customized within specialized classification systems for particular goals [18,19]. Some of the most significant classification systems that developed based on RMR and Q can be categorized as following:

- Rock mass rating by Laubscher [20].
- Rock mass strength (RMS) by Stille et al. [21]
- Modified basic rock mass rating (MRMR) by Kendorski et al. [22]
- Simplified rock mass rating (SRMR) by Brook and Dharmaratne [23].
- Slope rock mass rating (SRMR) by Robertson [24].
- Natural slope methodology (NSM) by Shuk [25].
- Rock condition rating (RCR) by Goel et al. [26].
- Chinese slope mass rating (CSMR) by Chen [27].
- Rock mass number (RMN) by Goel et al. [28].
- Modified-rock mass rating (M-RMR) by Unal [29].
- Q_{TBM} by Barton [30].
- Slope mass rating (SMR) by Romana et al. [31].
- Slope stability probability classification (SSPC) by Hack et al. [32].
- Continuous slope mass rating (CSMR) by Tomás et al. [33].
- Alternative rock mass classification system (ARMCS) by Pantelidis [34].
- Fuzzy slope mass rating (FSMR) by Daftaribesheli et al. [35].
- Graphical slope mass rating (GSMR) by Tomás et al. [36].
- Slope stability rating (SSR) by Taheri [37].
- Global slope performance index (GSPI) by Sullivan [38].
- Q_{slope} by Bar and Barton [39].
- SMR-Q_{slope} [40].

The Q_{slope} system is a notable approach that utilizes an empirical method for analyzing slope stability in various regions of the world [41,42]. By incorporating slope angle (β) and the Q_{slope} number, it offers rapid stability decisions while considering elementary assumptions. However, rock engineering uncertainties can significantly impact the overall behavior of the rock mass, necessitating the correction or modification of empirical classifications. Uncertainties arise from a lack of sufficient knowledge to make informed decisions about events or targets. In the context of slope stability analysis, uncertainties primarily stem from the inherent geomechanical features. To address these uncertainties, this study proposes a novel approach that employs fuzzy logic to quantify and account for them effectively. By incorporating fuzzy logic into the Q_{slope} system, the proposed method offers a new perspective on handling uncertainties in slope stability analysis.

The presented research introduces a novel approach to rock slope stability analysis by integrating AI techniques with empirical methods, which represents a first attempt to apply the AI-based Q_{slope} method in rock slope stability evaluation. Specifically, the study focuses on the application of AI within the context of the Q_{slope} system, renowned for its effectiveness in evaluating slope stability. In coastal areas where water-induced geohazards play a crucial role, the complexities and uncertainties associated with rock characteristics demand modifications and the integration of other geomechanical methods. To address uncertainties inherent in rock engineering, further compounded by rock characterstric factors, the research proposes the incorporation of fuzzy set theory into the Q_{slope} classification. The resulting AI-based fuzzy method, featuring six inputs, three outputs, and 756 fuzzy rules, enables robust assessments of rock slope stability in coastal regions. The implementation utilizes the high-level programming language Python to enhance computational efficiency. This study significantly contributes to the field of rock engineering by offering an efficient and accurate approach to assess slope stability using AI-based methods, particularly relevant for water-induced geohazards in coastal areas.

The research further highlights the significance of rapid stability assessment for timely and effective hazard mitigation in slope stability risks. By leveraging AI with empirical methods, this approach enhances the understanding and mitigation strategies for rock slope instabilities. Moreover, the integration of fuzzy set theory in the Q_{slope} classification provides a comprehensive consideration of uncertainties inherent in rock engineering factors. As a result, the proposed AI-based approach offers a robust and adaptable solution for analyzing slope stability in coastal areas. The research findings underscore the importance of addressing slope stability challenges in coastal regions, where rock characteristics are complex. By bridging AI techniques with the Q_{slope} and validating the approach through regular slope stability check and site survey, this study contributes to the field of rock engineering and offers valuable insights into the efficient assessment of slope stability using AI-based methods. Overall, the integration of fuzzy logic into the Q_{slope} method offers several advantages for estimating rock slope stability. Fuzzy logic excels in handling uncertainties inherent in geotechnical data, providing a more flexible representation of complex geological conditions and uncertain parameters. This enhanced adaptability allows the Q_{slope} method to deliver more accurate and reliable predictions of rock mass quality (Q value) and subsequent slope stability assessments. Additionally, fuzzy logic-based systems are more interpretable, enabling geotechnical engineers to better understand and interpret the estimated Q_{slope} values. The reduced sensitivity to parameter selection and improved handling of vague or incomplete data further enhance the method's robustness and practicality. Moreover, the implementation of fuzzy logic improves computational efficiency, allowing for faster slope stability assessments and facilitating timely hazard evaluations and mitigation strategies. The incorporation of fuzzy logic into the Q_{slope} method provides a valuable tool for geotechnical engineers, offering more reliable, precise, and efficient estimates of rock slope stability.

The application of fuzzy logic in conjunction with the Q_{slope} system for rock slope stability analysis offers several notable advantages. Fuzzy logic excels in handling uncertainties inherent in rock engineering and complexities associated with water-induced factors in coastal regions. By incorporating fuzzy sets, the Q_{slope} becomes more adaptable, allowing for a comprehensive representation of different degrees of membership for rock mass quality, thus providing a more versatile approach to assess slope stability. This sophisticated approach takes into account multiple parameters and their interactions, leading to more reliable stability assessments compared to conventional methods. Additionally, the rapid stability assessment enabled by fuzzy logic accelerates the analysis process, facilitating timely and effective hazard mitigation strategies in water-affected coastal regions. However, the application of fuzzy logic in the Q_{slope} system does come with certain limitations. The development and refinement of a substantial number of fuzzy rules require considerable effort and expertise. Constructing such an extensive set of rules demands a deep understanding of both the Q_{slope} system and fuzzy logic, making rule development a complex task. Additionally, the interpretation of the decision-making process might be challenging due to the opacity of the fuzzy rules, potentially making it difficult to understand the rationale behind specific stability assessments. Furthermore, the success of fuzzy logic-based methods heavily relies on the availability and accuracy of data for defining the fuzzy sets and rules adequately. Obtaining and processing sufficient data, especially in remote or inaccessible coastal regions, could pose challenges and impact the reliability of the analysis. Moreover, the performance of fuzzy logic-based systems can be sensitive to the selection of membership functions and fuzzy rules. Inaccurate parameter choices could lead to misleading results or affect the overall reliability of slope stability assessments. While fuzzy logic enhances the adaptability of the Q_{slope} system, it may have limitations in handling certain types of complex geological conditions or geological phenomena that are not adequately represented by the current fuzzy rules. Therefore, a careful consideration of these advantages and limitations is essential when implementing fuzzy logic in the Q_{slope} system for rock slope stability analysis in coastal areas.

2. Materials and Methods

2.1. Q_{slope} Classification System

Q_{slope} is an empirical method developed for analyzing slope stability based on the Q method [39,40]. The method employs a stability chart, as depicted in Figure 1, which was modified in 2020 by Azarafza et al. [43]. According to Bar and Barton [39], the Q_{slope} number relationship, expressed in Equation (1), encompasses key elements such as the shear force element (J_r/J_a), block size (RQD/J_n), and external loading/stress factor (J_{wice}/SRF_{slope}).

$$Q_{slope} = \frac{RQD}{J_n}\left[\frac{J_r}{J_a}\right]\frac{J_{wice}}{SRF_{slope}} \quad (1)$$

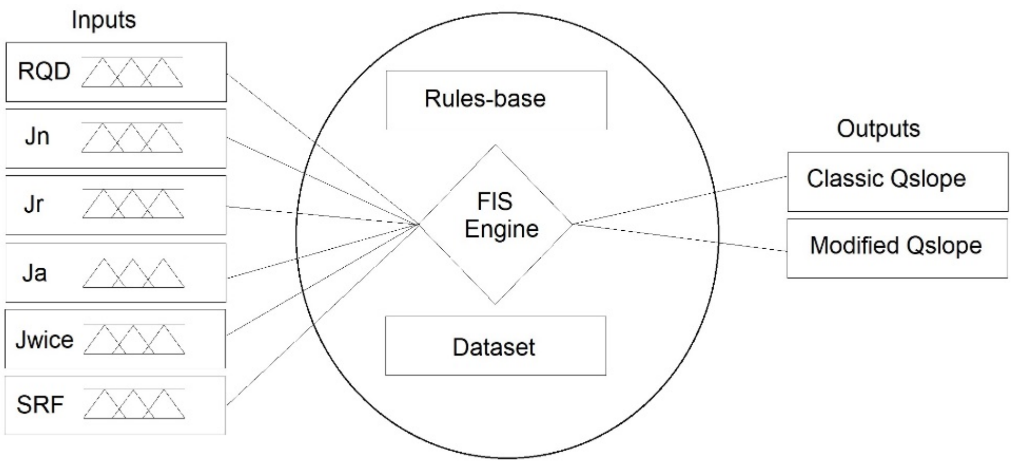

Figure 1. The process flowchart for the fuzzy-based Q_{slope} method.

In this equation, RQD represents the "rock quality designation", J_n corresponds to the "discontinuity set number", J_r denotes the "discontinuity roughness number", J_a signifies the "discontinuity alteration number", J_{wice} stands for "environmental and geological condition number", and SRF_{slope} represents the "strength reduction factor" [39–43]. RQD, commonly used worldwide by geoengineers, serves as an indicator of rock mass quality and can be estimated through direct or indirect procedures [1]. RQD signifies the degree of jointing or fracture in a rock mass measured in percentage, where RQD of 75% or more shows good-quality hard rock and less than 50% shows low-quality weathered rocks. The direct estimation procedure for RQD is a percentage of intact drill core pieces longer than 10 cm recovered during a single core run, and RQD index (%) = 100 × Σ (length of core pieces ≥ 0.10 m)/(total length of core run). As an indirect method that estimated RQD from the rock mass and jointed intensity, various methods were developed [43]. Other factors are provided based on Barton and Bar's instructions [41,42]. The presented study used the Palmstrom indirect method [43] as RQD = 115 − 3.3 J_v, where J_v is the sum of the number of joints per unit volume of the rock mass. Other variables are estimated as the original method addresses instructions.

Q_{slope} was initially developed based on Barton's Q system, which is widely used to assess the quality of rock mass [40]. While the main Q method is primarily employed for underground structures, Q_{slope} is specifically designed for evaluating slope stability through an engineering discussion-making procedure. Q_{slope} incorporates qualitative indicators derived from field observations of the slope mass conditions. Bar and Barton have provided discussion tables for grading the condition of rock slope masses [41]. By estimating the relevant parameters, Q_{slope} values are determined and plotted on the stability chart shown, as introduced by Bar and Barton [39]. To apply the stability chart, knowledge of the required support or the steepest slope angle (β) is necessary, which can be estimated using Equation (2). This equation has been modified by Azarafza et al. [43] to establish upper and lower limits, presented here as Equations (3) and (4). The obtained results utilizing the Q_{slope} stability chart allow for the estimation of the final stability condition. In this study, we adopt the foundational principles of Q_{slope} to develop a fuzzy-based method for analyzing rock mass stability:

$$\beta = 20\log_{10}(Q_{slope}) + 65 \quad (2)$$

$$\text{Lowerlimite}: \beta = 11.9\log_{10}(Q_{slope}) + 46.3 \quad (3)$$

$$\text{Upperlimite}: \beta = 17.2\log_{10}(Q_{slope}) + 54.1 \quad (4)$$

2.2. Fuzzy Logic and Model Implementation

Fuzzy logic or fuzzy set theory is a form of many-valued logic, which uses the used truth value of variables by any number between 0 and 1. The fuzzy set theory was developed by Zadeh [44] in the first place, has been expanding significantly in recent years, and has extensive application in different aspects of engineering fields based on address uncertainties in studies compared to classical calculations. The fuzzy set theory is a multiple-valued logic founded on mathematical intelligence for the calculation of 'degrees of truth' or 'degrees of false' rather than the Boolean logic (true or false) that is applied by fuzzy sets and membership functions. The application of the fuzzy membership function makes a difference between crisp and fuzzy descriptions. In the crisp sets, the membership function has only two values (0 or 1), but in fuzzy sets, it is classified as specific, limited, and identifiable ranges [45]. Fuzzy logic uses 'if and/or then' rules to establish the knowledge base and perform logic inference. Considering a main fuzzy set theory architecture for solving problems, the input information was converted into fuzzy data by the fuzzification process, and the fuzzified information was processed by the fuzzy inference system (FIS), which is operated based on the knowledge base. This base was defined by the user based on engineering experiences and expertise. After analysis, the processed data were fuzzified by using the defuzzification process, and the output was be reported.

In the fuzzification stage, input parameters based on the technical comments of experts are modified and associated with fuzzy memberships. After being fuzzified, the input information is entered into the FIS engine, which is responsible for making logical decisions. The FIS is operated based on knowledge-based instructions. The implication functions that are used in the knowledge base are called the fuzzy "if–and/or–then" rule. The FIS structure consists of three conceptual components: (i) the rules base, which contains the selection of rules; (ii) the database, which defines the membership functions used in the fuzzy rules; and (iii) the reasoning mechanism, which performs the inference procedure upon the rules and the given facts to derive a reasonable output. The Mamdani–Assilian, Takagi–Sugeno–Kang, Tsukamoto, and Singleton fuzzy models are the FIS systems commonly used by engineering worldwide. The differences between these FIS systems are in the consequences of their fuzzy rules, aggregation, and defuzzification procedures. Mamdani–Assilian FIS is considered in this study to calculate the fuzzy applications. FIS takes fuzzified information and analyzes the data, which leads to report results (known as consequences or conclusions). These results have to convert to crisp sets until used for assessments. The converting process was performed based on the defuzzification stage. Defuzzification is a process that converts an aggregated fuzzy set into crisp values, typically representing the most representative value within the fuzzy sets interval [35]. The centroid of area or center of gravity, mean of maximum, and smallest of maximum is the most used defuzzification function by researchers in the geo-engineering field. The centroid of area capability is that all activated membership functions of the conclusions take part in the defuzzification process, and so it is used in this research as well.

Fuzzy sets are characterized by triangular or trapezoid-shaped curves, wherein each value exhibits an increasing slope, a peak at a value of 1 (which can vary in length from 0 to greater values), and a decreasing slope. Fuzzy sets employ a sigmoid function, commonly known as the standard logistic function [35]. One notable advantage of fuzzy logic systems is their robustness in handling situations where input values are either unavailable or unreliable. This resilience stems from the fact that the output of a fuzzy system represents a consensus derived from all of the rules and inputs. Additionally, weightings can be assigned to individual rules in the rule base, enabling control over the influence of each rule on the output values. These rule weightings can be determined based on factors such as rule priority, dependability, or consistency. The weightings assigned to rules can be either fixed or dynamic, with the potential for adjustments based on the outcomes of other rules [45]. By leveraging these rules, users (typically experts) can incorporate specific terms that encompass the existing uncertainties inherent in the calculations.

As previously mentioned, the objective of this study is to develop a fuzzy-based Q_{slope} calculator for rapid decision making in the initial stage of slope stability analysis. The ability to make fast and accurate decisions is crucial for implementing appropriate stabilization measures. However, many geo-engineering processes involve linguistic variables and vague predicates, which introduce numerous uncertainties and subjective judgments into the decision-making process. Therefore, the application of fuzzy logic can provide a systematic approach to handle complex and ambiguous geo-engineering problems.

In this research, the "if-then" rules are employed to establish the core knowledge base, which is implemented using the Mamdani-Assilian Fuzzy Inference System (FIS). The fuzzy model comprises seven inputs, corresponding to the requirements of Q_{slope}, and three outputs, resulting in a total of 756 rules. To obtain crisp outputs from the fuzzy model, the centroid of the area defuzzifier is utilized for defuzzification, ensuring accurate and reliable results. The process flowchart of the fuzzy-based applied method is depicted in Figure 1. This fuzzy inference system (FIS) is designed to calculate the Q_{slope} values and provide the stability status of the slope as the output. Each input parameter is estimated on-site following the instructions provided by Bar and Barton, relying on observation methods and the expertise of geoengineers. The output classes of the models are classified as 'stable' and 'uncertain' and 'unstable' categories, which are obtained based on Q_{slope} values. The input parameters are the main Q_{slope} requirements, which contain RQD, J_n, J_r, J_a, J_{wice}, and

SRF_{slope}. Figures 2 and 3 present the inputs and output membership functions used in this article. So, the program is operated based on entering the inputs and calculating the outputs. The output parameters directly provide the slope stability status based on both main and modified relationships. The entire modeling was implemented in Python programming language. As seems to be the case in Figure 2, six different decision functions are defined for fuzzy sets responsible for Q_{slope} requirements that must be estimated during the ground survey. These parameters are mainly measured based on geo-engineer experiences and available necessities dictated in the original Q_{slope} paper published by Bar and Barton [39]. These parameters are identified in Section 2.1. These parameters are converted into fuzzy parameters using fuzzy membership functions presented in Figure 1. We also expected to model categories of the results of the Q_{slope} value in three different stability classes shown in Figure 3. The stability classes are categorized in 'stable,' 'uncertain,' and 'unstable,' representing the main stability classification areas from the Q_{slope} stability chart [39]. These areas show the stability condition of slopes. All membership functions are defined by the expert system based on the rule base. As seen in this figure, as the stability index increases, the stability conditions in the slope also change from unstable to stable. Now, returning to Figure 1, it can be stated that the process of implementing the fuzzy model is first, and the input parameters are converted into fuzzy values and then analyzed by the processing core and the fuzzy inference system. Finally, they are reported as fuzzy outputs. The point of interest in Figure 1 is related to the output, which is a stability value for Q_{slope}. This value is used to calculate the classic Q_{slope} [39] and modified Q_{slope} [43]. These values are used to estimate the primary stability condition in the slope.

Regarding the FIS analysis core, which is operated by Mamdani–Assilian, trapezoidal membership functions are employed in the calculations. It is necessary to assign corresponding values to the fuzzy system's input and output components to construct a fuzzy system. Output values are defined in the Gaussian membership function and added to the fuzzy system.

The visualization process is structured into three main steps:

1. Data Input: This step involves providing the input data gathered from the field survey and correctly placing the imported values in the system.
2. Rules-Based Database: In the second step, a rules-based database is prepared using expert opinions. These rules establish the connection between the input parameters and the stability categories, leveraging the expertise of professionals in the field of slope stability assessment.
3. Output Export: The final step involves exporting the output value, which represents the stability index and ranges from 0 to 1.0. For instance, an output value of 0.7 indicates that the slope's stability condition is mostly stable, whereas a value of 0.2 suggests primarily unstable conditions. Professionals should consider necessary precautions during the design stage for slopes with an output value of 0.2. Conversely, for slopes with an output value of 0.7, a less solid support system may be considered.

By following these three steps, our visualization process allows geotechnical professionals to efficiently and effectively assess the stability of rock slopes in coastal regions, guiding them in making informed decisions for appropriate design and support strategies.

The Q_{slope} fuzzy model is a classification system used to determine the stability of slopes by incorporating fuzzy logic principles. It utilizes fuzzy sets and membership functions to handle uncertainty and imprecise information in slope stability assessments. The judging criteria and the determination of slope stability using the fuzzy Q_{slope} model involve the following steps:

- Input Parameters: The model considers various input parameters that characterize the geological and geomechanical properties of the slope. These parameters typically include factors such as rock mass quality, joint spacing, groundwater conditions, slope geometry, and more. Each input parameter is assigned a linguistic variable or descriptor, such as "low", "medium", or "high", to represent qualitative descriptions.

- Membership Functions: For each input parameter, membership functions are defined to specify the degree of membership to different fuzzy sets. These fuzzy sets represent different stability categories, such as "unstable", "uncertain", or "stable". The membership functions assign a value between 0 and 1 to each linguistic variable, representing the degree of membership to a particular fuzzy set.
- Fuzzy Inference System: The fuzzy inference system combines the linguistic variables and membership functions of the input parameters using fuzzy logic operations, such as fuzzy AND and fuzzy OR. It applies a set of predefined rules that define the relationship between the input parameters and the stability categories. These rules are typically based on expert knowledge and experience in slope stability assessment.
- Fuzzy Output: The fuzzy inference system generates a fuzzy output, which represents the degree of membership of the slope to each stability category. This fuzzy output is typically a fuzzy set with membership values assigned to different stability categories, such as "unstable", "uncertain", or "stable". The membership values indicate the likelihood or confidence of the slope belonging to each category.
- Defuzzification: To obtain a crisp or numerical value for the slope stability, defuzzification is performed. Various defuzzification methods can be used, such as centroid, mean of maximum, or weighted average, to convert the fuzzy output into a single numerical value or score that represents the overall stability of the slope.
- Stability Classification: Based on the defuzzified value or score, the slope is classified into a specific stability category, such as "unstable", "uncertain", or "stable". The classification depends on predefined thresholds or ranges associated with each stability category.

In accordance with the fuzzy Q_{slope}, the translation of numerical values (Q-value) into "ambiguous" linguistic variables using the fuzzy-based Q_{slope} method presents notable advantages in the domain of slope stability analysis. Fuzzy logic serves as a suitable tool to represent uncertain or imprecise data through linguistic variables, accommodating the inherent uncertainties associated with complex geological conditions and limited data availability. An essential advantage lies in its ability to integrate expert knowledge and experience into the analysis, enabling the capture of intricate relationships through linguistic rules and membership functions. Moreover, the flexibility of fuzzy logic proves advantageous in handling complex non-linear and non-monotonic behavior, which traditional numerical methods may struggle to represent effectively. By incorporating fuzzy logic, the Q_{slope} method gains robustness against data outliers and variations, leading to more reliable results. The interpretability of the fuzzy-based model is enhanced, as linguistic variables allow for a clear understanding of the output and the implications for engineers and stakeholders. Furthermore, the approach facilitates the integration of diverse geological, geotechnical, and environmental factors into a unified framework, contributing to a more comprehensive slope stability assessment. The utilization of fuzzy logic and linguistic variables in the Q_{slope} method contributes to a more flexible, interpretable, and robust approach, especially when dealing with uncertain data, thereby providing valuable insights and informed engineering decisions.

The fuzzy Q_{slope} model allows for a more flexible and interpretable approach to slope stability assessment by incorporating linguistic variables and membership functions. It captures the inherent uncertainty and vagueness in slope stability evaluations, providing a quantitative measure of stability and aiding in decision making regarding slope stabilization measures, design considerations, and risk management strategies.

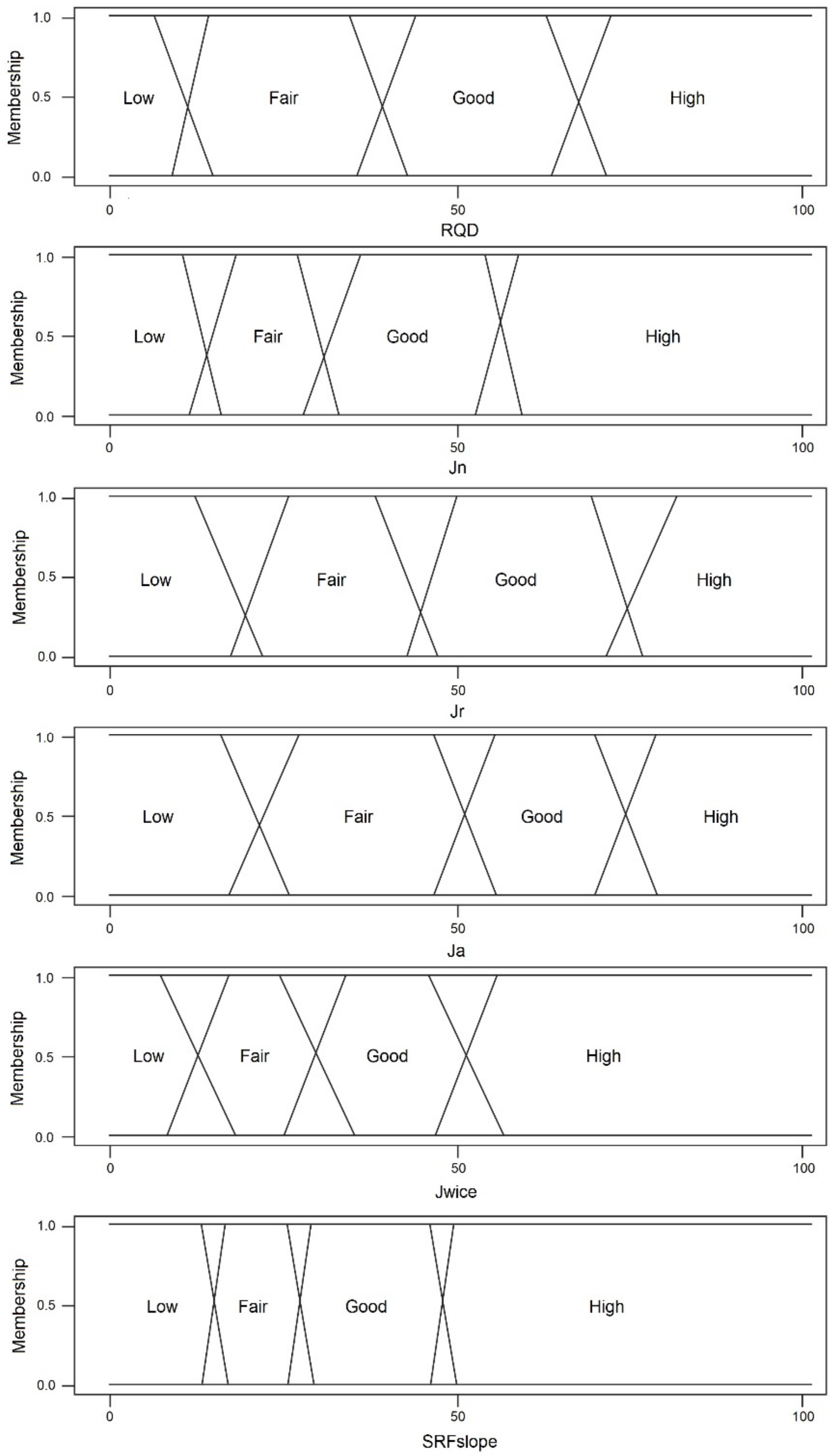

Figure 2. Membership functions for input parameters.

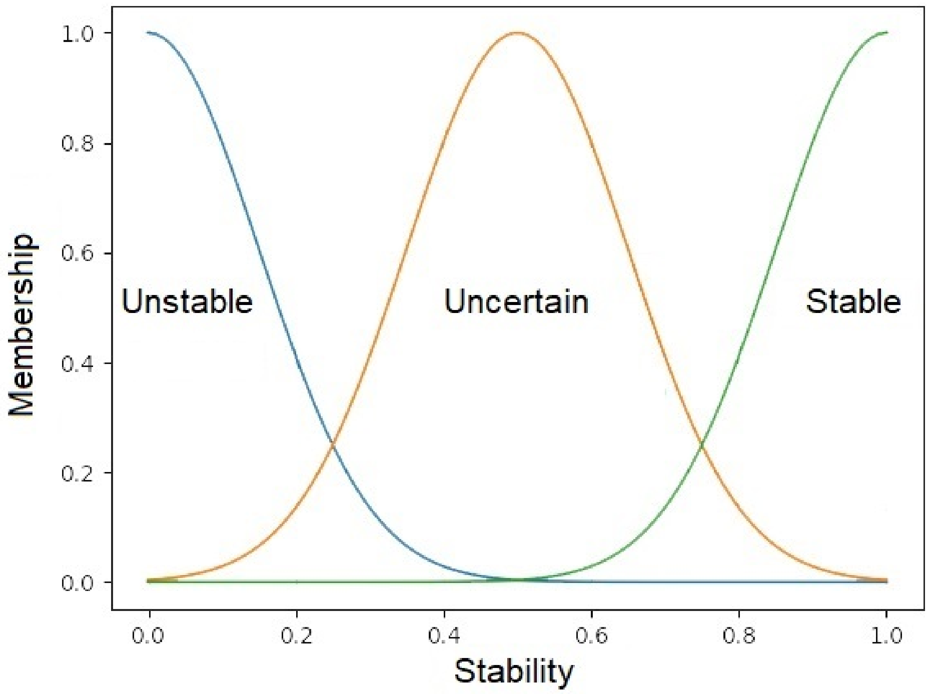

Figure 3. Membership functions for output parameters.

2.3. Data Preparations

To assess the stability of slopes, several essential factors need to be considered, which can be obtained through field surveys and laboratory tests. The uniaxial compressive strength (UCS) of the rock [46] is a key parameter that is determined by conducting tests on rock samples obtained from the slope. Additionally, a geomechanical survey based on the Geological Strength Index (GSI) classification system [17] is performed to evaluate the slope's characteristics. The GSI is a tool for rock mass characterization developed by Hoek and his colleagues for geotechnical designs that are used for rock mass strength and deformation modulus estimations. GSI provides a description of rock mass based on the Hoek–Brown criterion and rock mass quality, which involves rock blocks, UCS, joint intensity, block size, etc. [47] The results utilize Hoek–Brown criterion parameter calculations with spreadsheets or the Rocklab program. The GSI index is estimated based on several standard charts presented by the Hoek team [17]. Based on field rock mass investigations, which range from blocky to disintegrated rock structures (poorly interlocked and heavily fractured rock mass), the GSI system divides the rock mass environment into five categories from very good to very poor [47]. The GSI value has an interval of 5 and ranges from 10 to 80. There are four charts considered for rock mass structures and five categories of rock mass quality [48]. In this study, the GSI value is utilized to estimate the geomechanical properties of the target slope, enabling a comprehensive understanding of its stability characteristics.

2.4. Model Validation

To model validation, geoengineering researchers used two paths for model verification. The first uses modeling and computer programs; the second uses back-analysis validation based on actual results from a case study. The presented study used a back-analysis validation path. In this case, the model was implemented in real conditions, and estimated results were compared with field data and stability assessments. The agreements and differences between the results and the real conditions are investigated to verify the modeling performance. The model was placed for conducting a back-analysis for a slope located in Assalouyeh, which belongs to the Bushehr province, southwest of Iran. A slope was selected in the South Pars region (Assalouyeh) to demonstrate the presented methodology's performance as a slope stability estimator.

South Assalouyeh is located in the southwest of Iran, and shown in Figure 4. Geologically, the studied region is related to discontinuous sedimentary rock masses from the Aghajari and Mishan formations. These formations mainly consist of grey to cream marlstone, shale, marly limestone, layered limestone, and some sandstone. Geo-structurally, the slopes have three or four discontinuity sets and several unsystematic discontinuity sets oriented favorably to different scale instabilities. The selected slope belongs to the Aghajari formation and comprises marly limestone with sandstone geo-units. A view of the studied slope is presented in Figure 5. Table 1 provides a detailed description of the studied slope. After consideration of the target slope for stability analysis, the slope was investigated regarding geotechnical sampling and slope characteristics. This information was used to provide a stability evaluation with the limit equilibrium method. The limit equilibrium method is a verification procedure used to verify the fuzzy model's results. SLIDE program from Rocscience Inc. (Toronto, ON, Canada) [49] was used for the limit equilibrium method. SLIDE is a well-known program that provides the safety factor for slopes using 2D limit equilibrium stability analysis to evaluate the safety factor or probability of failure of circular or noncircular failure surfaces in soil or rock slopes [50].

Figure 4. The location of the South Pars region (Assalouyeh) in Iran.

Table 1. The geometrical properties of the studied slope.

No.	Parameter	Unit	Value
1	Slope height, H	m	17
2	Slope angle, β	degree	63
3	Slope surface	-	Natural
4	Seepage	-	Dry
5	Weathering	-	Low to medium
6	GSI	-	52
7	Geology	-	Marlstone

Figure 5. A view of the selected slope.

SLIDE (known as Slide2) is a piece of geotechnical software developed by Rocscience [49], specifically designed for two-dimensional slope stability analysis. With SLIDE, users can create detailed models of slope geometries and define material properties for different layers. The software supports cohesive and non-cohesive soils, groundwater conditions, and seismic effects. It employs limit equilibrium and finite element methods for comprehensive slope stability analysis using various established methods, such as Bishop, Janbu, Spencer, and Morgenstern-Price. SLIDE offers powerful modeling capabilities, allowing users to create accurate representations of slope configurations, including layered slopes, embankments, and benches. Material models can be chosen from a predefined library or customized, considering factors such as cohesion, friction angle, and unit weight.

The software incorporates groundwater analysis, enabling the simulation of steady-state or transient seepage conditions and the consideration of pore pressure effects on slope stability. Sensitivity analysis and parametric studies can be performed to evaluate the influence of different factors on stability, while optimization tools help refine slope designs. SLIDE provides visualization tools, including safety factor contours, displacement vectors, and stress distributions, to aid in the interpretation of results. Users can generate comprehensive reports containing input data, analysis results, and visualizations for documentation purposes. Overall, SLIDE is a versatile software package that assists engineers and geotechnical professionals in analyzing slope stability, optimizing designs, and making informed decisions about slope stabilization measures. It combines advanced analysis methods, comprehensive modeling capabilities, and visualization tools to ensure accurate and efficient slope stability assessments.

In addition to the SLIDE model, the fuzzy model was validated by comparing the results with expert opinions and the empirical regulations of Q_{slope}. The stability analysis based on Q_{slope} is determined by utilizing the empirical relationship presented in Equation (1), along with Equations (2)–(4). To further validate the fuzzy model, 10 rock engineering experts' opinions were collected regarding the selected slope's stability. These expert opinions were considered as an additional means of validation, with the majority of responses considered as the primary determinant.

These verification procedures, including the comparison with expert opinions and the application of the fuzzy model, were performed to assess the capability and performance of the proposed model, ensuring its reliability and effectiveness in slope stability analysis.

2.5. Practical Example for Model Implementation

The practical benefits of incorporating fuzzy logic into the Q_{slope} method for rock slope stability analysis are significant and diverse. Firstly, fuzzy logic enhances the accuracy and reliability of slope stability assessments by effectively handling uncertainties and complex geological data. This practical advantage allows geotechnical engineers to make well-informed decisions regarding potential hazards and necessary stabilization measures with increased confidence in the results. Moreover, the adaptability of fuzzy logic enables the Q_{slope} method to handle real-world data scenarios, including incomplete or uncertain information, making it a valuable tool for assessing slope stability in challenging geological conditions. This flexibility in data representation ensures that the method remains applicable and practical in various geotechnical settings. The advantages of the fuzzy logic Q_{slope} method are further underscored by its computational efficiency, leading to time and cost savings. The faster computational speed enables geotechnical engineers to analyze multiple slopes efficiently, facilitating timely hazard mitigation strategies. Additionally, the interpretable results provided by fuzzy logic-based models allow engineers and stakeholders to gain deeper insights into the factors influencing slope stability, enabling effective communication and collaboration during decision-making processes.

It is essential to consider the limitations of the fuzzy logic Q_{slope} method. Developing a comprehensive set of fuzzy rules and membership functions can be complex and requires expertise, which may be a practical challenge in some applications. Adequate and accurate data is crucial for the method's performance, and the reliance on such data may pose limitations in data-scarce or remote regions. Furthermore, the interpretation of linguistic rules in fuzzy logic may still involve some subjectivity, potentially introducing biases in the analysis. Careful calibration of membership functions and fuzzy rules is necessary to ensure the method's sensitivity to parameter selection does not adversely impact the model's performance and reliability. The calibration plays a key role in reducing and controlling the errors that appear during calculation and assumptions. In conclusion, the fuzzy logic Q_{slope} method brings practical benefits, including improved accuracy, adaptability to real-world data, time and cost efficiency, and enhanced interpretability. Its advantages in handling uncertainties, adaptability, and interpretable results make it a valuable tool for slope stability analysis. Nonetheless, considering the complexity of rule development, data requirements, interpretation subjectivity, and sensitivity to parameter selection are all crucial for its successful implementation and reliable slope stability assessments.

Regarding the results in Tables 2 and 3, it can be stated that the fuzzy logic Q_{slope} is capable of providing reliable results with low uncertainties. We can point out the practical benefit of the proposed method based on the explicit step-by-step development of the example presented as follows (and, for simplicity, we will consider three input parameters: Q-value, joint roughness coefficient (JRC), and groundwater condition (GW)):

- Step 1: Linguistic Variables and Membership Functions: Define linguistic variables for each input parameter. For instance, the Q-value can be categorized as the different parameters that are presented in Figures 1–3.

Table 2. Result of Roclab software for studied slope.

Evaluation Criteria	Results
Hoek–Brown	mb = 1.261; s = 0.0048; a = 0.505
Mohr–Coulomb	C = 1.102 MPa; phi = 28.93°

Table 3. The calculated result of stability analysis with different applied methods.

Analysis Method	Estimated sValue	Representative Factor of Safety	Description	Decision
Limit equilibrium method	1.035	1.035	Stable with a low safety factor	Critical state
Expert opinion	Failure	~1.00	Slope need attention	Unstable
Q_{slope}	0.094	<1.00	Unstable	Local unstable
Fuzzy $Q_{slope\_classic}$	44.49 (<50%)	1.047	Unstable	Local unstable
Fuzzy $Q_{slope\_modified}$	36.45 (<50%) 34.12 (<50%)	1.057 (Upper) 1.059 (Lower)	Unstable	Local unstable

Assign membership functions to each linguistic variable, determining the degree of membership for each value within the categories. Membership functions can take various shapes, such as triangular or trapezoidal (see Figures 1–3).

- Step 2: Fuzzy Rule Base: Create a set of fuzzy rules that relate the input variables to the output (slope stability assessment). For example:

IF Q-value is poor AND JRC is low AND GW is high, THEN Stability is Low.
IF Q-value is moderate AND JRC is medium AND GW is medium THEN Stability is Medium.
IF Q-value is good AND JRC is high AND GW is low THEN Stability is High.

- Step 3: Fuzzification: Given specific input values for Q-value, JRC, and GW, apply the membership functions to determine the degree of membership for each input in their respective linguistic categories.
- Step 4: Rule Evaluation: Evaluate each fuzzy rule based on the degree of membership of the inputs. Combine the fuzzy rules using fuzzy logic operators (e.g., AND, OR) to obtain the overall fuzzy output for each stability category.
- Step 5: Defuzzification: Convert the fuzzy output obtained from Step 4 into a crisp output value for slope stability. Defuzzification methods, such as the Center of Gravity or Weighted Average, can be employed for this purpose.
- Step 6: Interpretation: Interpret the crisp output value to determine the final slope stability assessment. For example, if the defuzzified value falls into the "Stable" category, the slope stability is assessed as "Stable" (See Figure 3).
- Step 7: Validation and Fine-Tuning: Validate the fuzzy logic Q_{slope} model by comparing its stability assessments to real-world slope stability data or expert knowledge (verification stage). Fine-tune the model by adjusting the membership functions and fuzzy rules based on validation results to improve accuracy.

This step-by-step development process showcases how fuzzy logic can be integrated into the Q_{slope} method to assess slope stability more comprehensively, considering uncertainties and complex data. The example provided is simplified for illustrative purposes, and in practice, the model would involve multiple input parameters and more intricate fuzzy rule bases. Nonetheless, this example highlights the practical application of fuzzy logic in enhancing the Q_{slope} method for slope stability analysis.

3. Results and Discussions

In rock structure studies, the uncertainties are related to geometrical properties that originate from the rock mass features. In this regard, employing the fuzzy method proves to be highly advantageous as it does not require much information about the environment and focuses on proper approximation of environmental elements to obtain accurate results. Hence, the application of fuzzy approaches in various analyses that face uncertainties is an advantage. Using fuzzy logic to estimate the stability condition of the slopes with appropriate accuracy can help in rapid stabilizations. The proposed method used fuzzy and Q_{slope} principles to investigate the slope stability status. The representation of input-output parameter variations leads to a fast decision on the stability of slopes. The selected slope in the South Pars region was analyzed regarding stability by the proposed method in the same way as the limit equilibrium method and expert opinion, which were compared with the algorithm results. To conduct the limit equilibrium evaluations, several geotechnical tests, such as uniaxial compressive strength, which was the same as the GSI index, were performed. The GSI index was estimated based on a field geomechanics survey to determine the Hoek–Brown criteria. Rocklab program [51] was used to provide the index geotechnical properties of the slope. Figures 6 and 7 present the view and limit equilibrium analysis results for the selected slope. Table 2 provides the geomechanical properties of the rock materials by using Roclab software. Table 3 illustrates the stability analysis results for the verification slope based on different assessment methods. As can be seen in Table 2, the fuzzy description prepared by the applied method is in good agreement with the expert opinion, and it limits equilibrium analyses. So, using the proposed fuzzy-based Q_{slope} method is capable of providing proper results in stability assessments. In this regard, the fuzzy model provides appropriate results that could be used as alternative or complementary solutions for primary stability analyses of slopes.

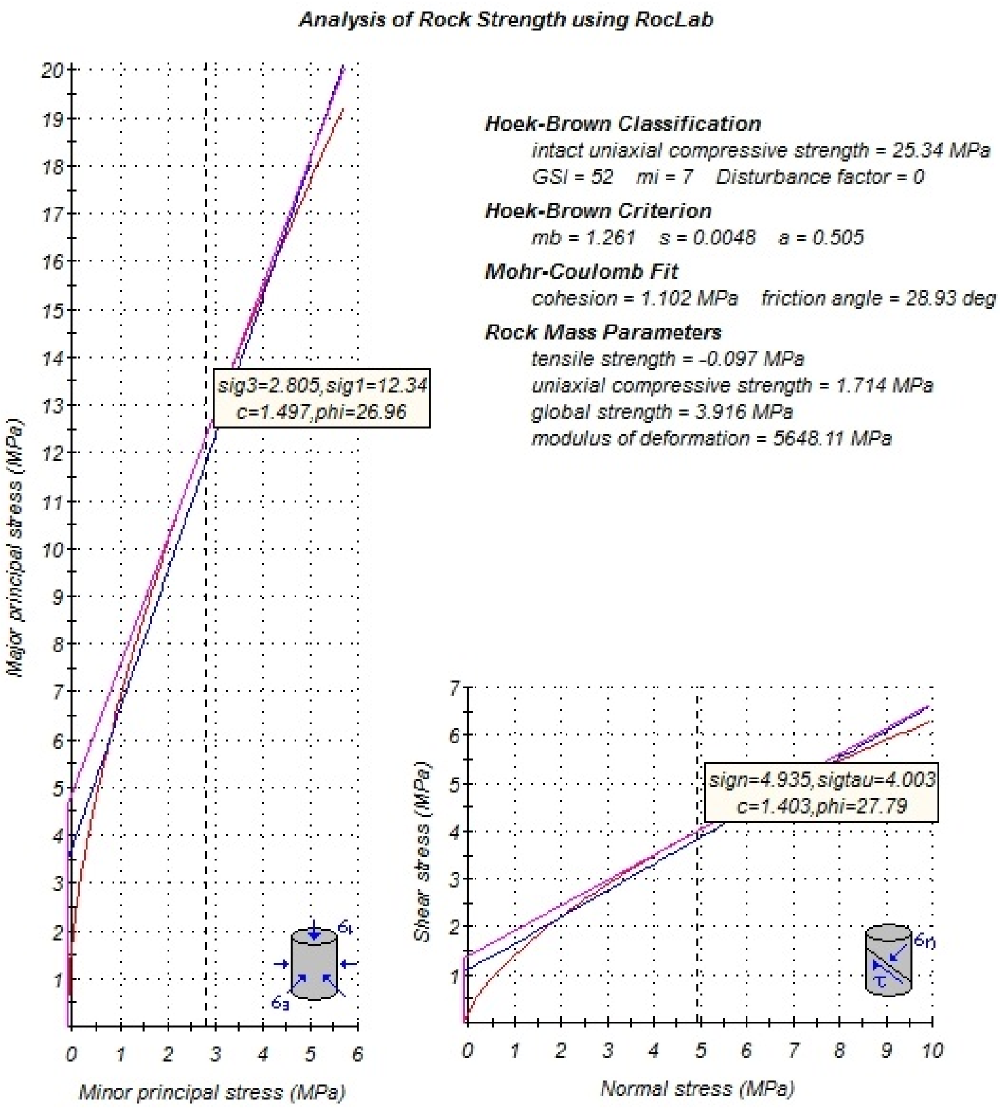

Figure 6. The geomechanics properties determination by Hoek–Brown criteria and Rocklab software.

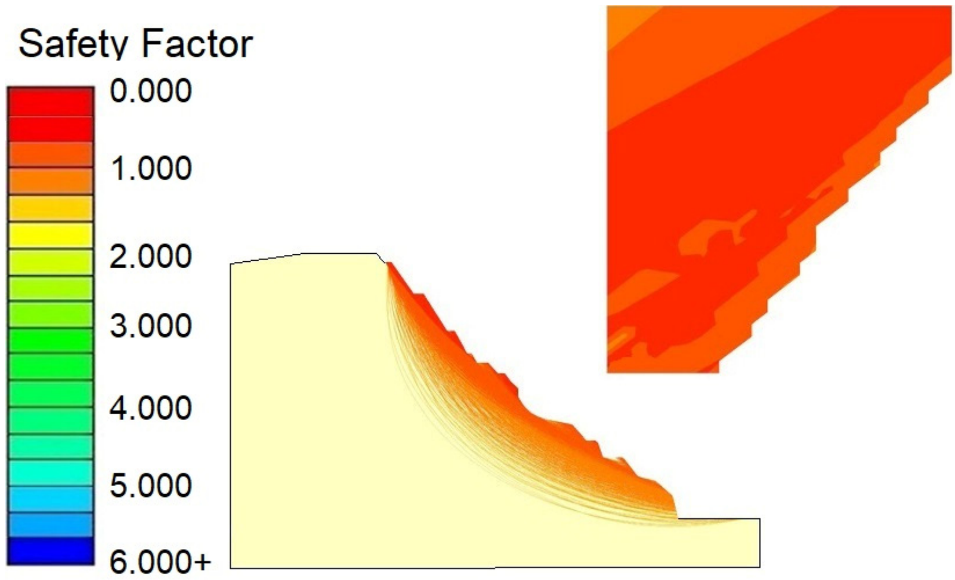

Figure 7. Stability analysis and safety factor estimation by limit equilibrium method via SLIDE.

In Table 2, the expert opinions were established for geotechnical experts who used their knowledge of geology, rock mechanics, and slope behavior to evaluate factors such as rock mass quality, jointing patterns, weathering, groundwater conditions, and other relevant parameters to provide an approximation with basic (limited) data to predict the slope stability condition on the studied slope.

Table 2 presents two values for Q_{slope} derived from different methods. The first value, referred to as '$Q_{slope\_classifc}$,' is based on the original Barton method [39]. The second value, named '$Q_{slope\_modified}$,' is derived from a modified method developed by Azarafza et al. [43]. The first value is estimated based ordinary procedure of Barton and the second value is estimated based on the modified method. Upon examining these two outcomes, it is apparent that there is minimal disparity between them. However, it is worth noting that the improved method exhibits a less conservative approach compared to the conventional method. The conventional ordinary method ($Q_{slope\_classifc}$) relies on the utilization of the relationship illustrated in Figure 1 and the corresponding Equation (1). In contrast, the second method employs Equations (3) and (4) to derive its results. On the contrary, the Q_{slope} value obtained from Equation (1) in this table indicates that the slope falls within the "Uncertain" zone when plotted on Figure 1. The findings presented in this table suggest that further investigation is warranted for the studied area due to cross-sectional instability. The presence of localized instabilities within the domain indicates its classification as low stability. Consequently, it is crucial to implement maintenance techniques to stabilize the area and ensure its stability. In the Q_{slope} fuzzy model, these input parameters are defined as linguistic variables, which represent qualitative descriptions rather than precise numerical values. Examples of input parameters can include rock quality, joint spacing, water pressure, and slope geometry. Each input parameter is assigned membership functions that describe the degree of membership to different fuzzy sets, such as "low", "medium", or "high" stability. The model combines these linguistic variables and membership functions using fuzzy logic operations, such as fuzzy AND and fuzzy OR, to calculate a fuzzy output that represents the slope stability. The output is typically represented by fuzzy sets, such as "safe", "uncertain", or "unstable". According to Figure 6, an output parameter <0.25 means "unstable", 0.25–0.50 means uncertain with tendency to unstable side, 0.50–0.75 means uncertain with tendency to stable side, >0.75 means "stable". The Q_{slope} fuzzy model allows for the incorporation of expert knowledge and linguistic descriptions, providing a more flexible and interpretable approach to slope stability assessment. It helps capture the inherent uncertainty and vagueness associated with rock slope stability evaluations. The model's outputs can be further analyzed and used to make informed decisions regarding slope stabilization measures and risk management strategies.

The Q_{slope} fuzzy model utilizes an output parameter that is modified based on specific ranges to classify the slope stability. The modified classification criteria are as follows (see Figure 6):

- If the output parameter is less than 0.25, it is categorized as "unstable".
- If the output parameter falls within the range of 0.25 to 0.50, it is classified as "uncertain with a tendency towards the unstable side".
- If the output parameter is between 0.50 and 0.75, it is considered "uncertain with a tendency towards the stable side".
- If the output parameter is greater than 0.75, it is designated as "stable".

These classifications help provide a clearer understanding of the slope stability assessment by assigning linguistic categories to the fuzzy output parameter. By incorporating these ranges and interpretations, the Q_{slope} fuzzy model offers a more nuanced representation of the slope stability condition, accounting for varying degrees of uncertainty and tendencies towards stability or instability. In the Q_{slope} fuzzy model, the output parameter represents the fuzzy classification of slope stability. However, to further analyze and interpret the results, the fuzzy output can be transformed into more traditional engineering parameters, such as beta (β) and safety factor. Beta (β in Equations (2)–(4)) is a numerical index that quantifies the level of uncertainty associated with the slope stability classification (see Figure 1). It provides a measure of the degree to which the slope is either stable or unstable. The fuzzy output parameter can be mapped to a corresponding beta value using the membership functions defined in the fuzzy model. This mapping allows for a more quantitative representation of uncertainty and provides a basis for comparison and decision making. On the other hand, the safety factor is a well-established engineering parameter used to assess slope stability. It represents the ratio of resisting forces (such as shear strength) to driving forces (such as gravitational forces) acting on the slope. The fuzzy output parameter can be converted to a safety factor value based on predefined rules or relationships that link the fuzzy classification to safety factor values. These rules can be derived through expert knowledge or empirical correlations.

By transforming the fuzzy output parameter to beta and safety factor (F.S) values, the Q_{slope} fuzzy model provides a more familiar and interpretable representation of slope stability. Beta offers a numerical measure of uncertainty, while the safety factor provides an engineering parameter commonly used in slope stability analysis. This allows engineers and geotechnical professionals to better understand and utilize the results for decision making, design, and risk management purposes.

Based on the provided values of F.S = 1.035 and Fuzzy Output (Beta) = 0. 4449 (classic Q_{slope}), we can use the relationship between beta and the factor of safety to determine the fuzzy Q_{slope} model's classification.

First, we calculate the fuzzy output parameter using the relationship:

$$FS \approx |(1 + \mathrm{Beta})/(1 - \mathrm{Beta})|$$

Plugging in the given value of Fuzzy Output = 0.4449 into the equation, where FS ≈ 1.047. Next, we can classify the fuzzy output parameter based on the previously defined ranges:

- If the fuzzy output parameter is less than 0.25, it is categorized as "unstable".
- If the fuzzy output parameter falls within the range of 0.25 to 0.50, it is classified as "uncertain with a tendency towards the unstable side".
- If the fuzzy output parameter is between 0.50 and 0.75, it is considered "uncertain with a tendency towards the stable side".
- If the fuzzy output parameter is greater than 0.75, it is designated as "stable".
- In this case, the fuzzy output parameter of approximately 0.0175 would fall into the "unstable" category according to the given ranges.

Therefore, based on the F.S value of 1.035 (SLIDE) and Fuzzy Output value (Beta), the fuzzy Q_{slope} model would classify the slope as " uncertain with a tendency towards the unstable side". Based on the findings of the comparative verification, it can be concluded that the fuzzy Q_{slope} model yields dependable and precise results in a more time-efficient manner compared to traditional methods. The fuzzy Q_{slope} model offers several advantages over traditional methods in slope stability assessment:

- Handling Uncertainty: The fuzzy logic principles employed in the Q_{slope} model allow for the effective handling of uncertainty and imprecise information. It accommodates the inherent vagueness and variability associated with geological and geotechnical parameters, providing a more robust framework for slope stability analysis.
- Flexibility and Interpretability: The fuzzy Q_{slope} model uses linguistic variables and membership functions, making it a flexible and interpretable approach. It enables the incorporation of expert knowledge and allows for the integration of qualitative and quantitative data, providing a comprehensive understanding of slope stability conditions.
- Faster Analysis: The fuzzy Q_{slope} model can expedite the analysis process compared to traditional methods. By leveraging fuzzy logic techniques, it simplifies and automates complex calculations, reducing the time required for manual assessments. This time efficiency can be particularly advantageous when dealing with large-scale slope stability evaluations.
- Risk Evaluation: The fuzzy Q_{slope} model facilitates a more nuanced evaluation of slope stability risks. By providing fuzzy output values, it offers a range of stability categories (such as "unstable", "uncertain", or "stable") with corresponding membership degrees. This enables a more detailed understanding of the potential risks and assists in prioritizing mitigation measures.
- Improved Decision Making: The fuzzy Q_{slope} model assists in making informed decisions regarding slope stabilization techniques and risk management strategies. By providing quantifiable measures of stability and a clear classification system, it helps engineers and geologists evaluate the effectiveness of different interventions and select the most appropriate solutions for slope stability challenges.

4. Conclusions

The presented study aimed to develop a fuzzy-based model for estimating slope stability conditions using the principles of Q_{slope}. The model utilized fuzzy logic set theory in conjunction with the Q_{slope} empirical classification system to assess the stability of slopes. The model incorporated six input parameters, namely, RQD, J_n, J_r, J_a, J_{wice}, and SRF_{slope}, which are essential requirements for the Q_{slope} classification system in rock slopes. These input parameters were fuzzified using trapezoidal membership functions, and entered into the fuzzy inference system (FIS) for evaluations. The outputs were classified into "stable", "uncertain", and "unstable" classes, which were fuzzified using Gaussian membership functions and incorporated into the fuzzy system.

The fuzzy-based Q_{slope} model was implemented using the Python programming language. The input and output parameters were ordered according to the Q_{slope} stability procedure, providing a fast and reliable perspective on slope stability. To validate the proposed model, a real case study was conducted on a selected slope in the South Pars region (Assalouyeh), located in southwest Iran. Various verification procedures, including limit equilibrium analysis, expert opinions, and classic/modified Q_{slope} assessments, were performed on the selected slope and compared with the results obtained from the fuzzy-based Q_{slope} model. The stability of the slope was evaluated using the SLIDE 2D limit equilibrium software, with required data obtained from geotechnical tests and the GIS index.

The results of the study demonstrated good agreement between the applied fuzzy-based Q_{slope} model and the comparative options. The SLIDE analysis yielded a safety factor of 1.035, while experts suggested a safety factor of approximately 1.00. The Q_{slope}

classification determined the slope condition as "uncertain" (based on Figure 1). The fuzzy model, for both the classic and modified procedures, also classified the slope condition as "uncertain", which aligned with the original Q_{slope} method. Additionally, the stability index value of 43.82 fell within the "uncertain" class. These findings confirm the capability of the proposed model to provide accurate results in stability assessments. The fuzzy model offers a viable alternative or a complementary solution for primary stability analyses of slopes, as demonstrated by its satisfactory performance in this study. Considering the limitations of the fuzzy logic Q_{slope} method is imperative. The process of developing a comprehensive set of fuzzy rules and membership functions can be intricate, demanding specialized expertise, thereby posing practical challenges in certain applications. The method's performance heavily relies on adequate and accurate data, which may present limitations in regions with scarce or remote data availability. Additionally, the interpretation of linguistic rules in fuzzy logic might entail some subjectivity, potentially introducing biases in the analysis. Hence, meticulous calibration of membership functions and fuzzy rules becomes indispensable to mitigate the method's sensitivity to parameter selection, ensuring the optimal performance and enhanced reliability of the model.

In the realm of slope stability analysis, future research on the fuzzy-based Q_{slope} method should focus on several key aspects to enhance its applicability and reliability. Firstly, efforts should be made to expand the existing fuzzy rule base, incorporating a comprehensive range of geological, geotechnical, and environmental parameters relevant to slope stability. The optimization of membership functions using data-driven techniques or optimization algorithms is warranted to refine the model's accuracy. Furthermore, the integration of uncertainty analysis is essential to quantify the model's reliability and to assess the associated risks. Comparative studies should be conducted to contrast the performance of the fuzzy-based Q_{slope} method with conventional slope stability analysis methods. The approach should be validated through rigorous case studies and field investigations to ascertain its suitability for real-world slope stability scenarios. Additionally, exploring the potential integration of fuzzy logic with data-driven approaches could lead to more adaptive and robust models. The development of user-friendly software to implement the fuzzy Q_{slope} method can facilitate its widespread use by practitioners and engineers. Further exploration into multi-hazard consideration and sensitivity analysis will contribute to a more comprehensive understanding of the method's limitations and strengths. Lastly, investigations into the applicability of the fuzzy Q_{slope} method in diverse geological settings and rock formations would offer valuable insights into its practicality and versatility.

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