

Risk Analysis for Stabilized Earth Slope using anchors via Mamdani Fuzzy Controller in MATLAB

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Abstract: This study presents a comprehensive risk analysis of ground-anchor-reinforced slopes using a Mamdani-type fuzzy inference system implemented in MATLAB. The objective is to effectively capture the inherent uncertainties and nonlinear behaviors associated with soil properties, anchor configurations, and slope geometry parameters that traditional deterministic methods often fail to represent adequately. A systematic literature review of over 60 peer-reviewed papers was conducted, focusing on slope stabilization techniques in sandy-clayey soils. From this, a database of 150 stabilization scenarios was compiled, covering a wide range of geotechnical conditions and reinforcement schemes. Key parameters such as slope angle, internal friction angle, cohesion, anchor length and position, and initial factor of safety were extracted and normalized for use in the fuzzy model. The Mamdani fuzzy system was designed with multiple inputs and a single output (risk level), integrating expert knowledge with data-driven insights derived from the compiled database. The fuzzy rules were developed through iterative calibration and validated using sensitivity analysis and cross-validation techniques. The model was implemented and tested in MATLAB. Results demonstrate that the fuzzy-based approach can effectively identify high-risk zones and provide a more nuanced understanding of slope behavior under reinforced conditions. Compared to conventional analysis methods, the proposed system offers improved interpretability and adaptability, making it a valuable decision-support tool during preliminary design and optimization phases. The model's predictions showed strong agreement with documented outcomes from field case studies, confirming its reliability and practical relevance.

Keywords: Slope stability, Earth slopes, Fuzzy logic, MATLAB.

I. INTRODUCTION

Natural and man-made earth slopes are integral components of the terrestrial landscape and play a significant role in both environmental systems and civil infrastructure (Griffiths et

al., 2009). These slopes are commonly found in hillsides, road cuts, embankments, and excavation sites (Cousins, 1978). Depending on their origin, they can exhibit varying geometric and geomechanical characteristics that influence their stability over time. The behavior of an earth slope is governed by the interaction between gravitational forces, soil properties, groundwater conditions, and external loads. When the driving forces acting on a slope exceed the resisting forces, slope failure can occur. This phenomenon poses serious threats to life, infrastructure, and the environment, particularly in regions with complex geological settings or intense land development (Huang, 2012).

Various types of slope failures have been documented, including rotational slips, translational slides, and flow-like movements (Azadi et al., 2022). The failure mode is typically dictated by subsurface stratigraphy, moisture content, slope geometry, and loading conditions. Understanding the mechanisms behind these failures is critical for designing safe and cost-effective engineering solutions. From a geotechnical perspective, the assessment of slope stability involves evaluating the factor of safety (FoS), which represents the ratio of resisting forces to driving forces along a potential failure surface. Traditional methods such as limit equilibrium analysis, finite element modeling, and probabilistic assessments are used to estimate this ratio under different scenarios (Azarafza et al., 2021).

One of the key challenges in slope analysis lies in the inherent variability and uncertainty of soil parameters. Soil is a heterogeneous and anisotropic material whose properties may vary significantly across small distances (Wang et al., 2023). This uncertainty complicates the prediction of slope behavior and demands robust analytical frameworks that can incorporate such variability (Ji et al., 2020). Climate-related factors, such as prolonged rainfall, freeze-thaw cycles, and seismic activity, further exacerbate slope instability risks. These external influences can rapidly change the pore water pressure and shear strength of soil, making even seemingly stable slopes prone to sudden failure (Stoffel et al. 2024). As a result, slope monitoring

and predictive modeling have become crucial components of modern geotechnical risk management (Bračko et al., 2024).

Given the risks associated with earth slope failures, slope stabilization has become a fundamental aspect of geotechnical engineering practice (Shroder et al., 2005). Stabilization aims to enhance the FoS and ensure the long-term performance of slopes under varying environmental and loading conditions (Petley, 2004). The choice of stabilization method depends on several factors including soil type, slope geometry, failure mechanism, and economic considerations. Slope stabilization techniques can broadly be categorized into passive and active systems (Nanehkaran et al., 2023). Passive methods, such as toe berms, drainage systems, and vegetation; aim to improve slope stability indirectly by modifying boundary conditions or enhancing natural resistance (Huang, 2012). In contrast, active stabilization techniques directly introduce additional resisting forces into the system, often through structural reinforcements such as retaining walls, soil nails, and ground anchors (Ji et al., 2020).

Among active stabilization systems, ground anchors have proven to be particularly effective in enhancing slope stability, especially in steep or heavily loaded slopes where passive methods alone are insufficient (Hryciw, 1991). Ground anchors, also known as tiebacks or prestressed anchors, are tension-resisting elements embedded into stable strata behind the potential failure surface (Sasiharan et al., 2005). Their primary function is to transfer tensile forces from the unstable mass to deeper, more competent soil or rock layers (Koerner, 2015). Anchored slope systems are designed based on a thorough understanding of the soil-structure interaction, load transfer mechanisms, and failure modes (Blanco-Fernandez et al., 2011). Figure 1 illustrates the mechanism of an anchored slope system. The effectiveness of anchors depends on parameters such as length, inclination angle, bond length, and the mechanical properties of the grout and surrounding soil (Matos et al., 2023). Proper design ensures that the anchor's capacity exceeds the tensile demands imposed by the slope geometry and external loads (Hryciw, 1991). Designing anchor-reinforced slopes is a multi-disciplinary challenge that involves soil mechanics, structural analysis, and construction feasibility (Castro-Fresno et al., 2009). Traditional design approaches rely on deterministic calculations using fixed input parameters (He et al., 2023); however, this may overlook critical uncertainties inherent in soil behavior (Ghiassian et al., 1996), loading conditions, and installation procedures (Chen et al., 2012). This shortcoming has led to the growing interest in incorporating uncertainty modeling and risk-based methods in slope stabilization design (Zhang et al., 2019).

Recent studies have highlighted the significance of variability in geotechnical parameters such as cohesion, friction angle, and pore pressure, especially in composite soils like sandy-clayey embankments (Miao et al., 2024). These soils exhibit complex behavior due to their dual-granular and cohesive nature, often resulting in nonlinear and time-dependent responses under loading (Wang & Liu, 2024). The use of ground anchors in such soils requires careful consideration of both short-term and long-term performance criteria (Xue et al., 2024). Field applications of anchored slopes have demonstrated considerable success in infrastructure projects such as highways, dams, and urban excavations (Du et al., 2022). However, post-failure

investigations have shown that inadequate assessment of ground conditions, incorrect anchor installation, or oversimplified design assumptions can lead to system failure despite the presence of reinforcement (Zhu et al., 2005). Therefore, integrating advanced modeling techniques into the design process is essential to bridge the gap between theoretical design and field performance (Wang et al., 2024).

The use of ground anchors in slope stabilization has become increasingly important due to the growing demand for infrastructure development in topographically challenging regions (Koerner, 2015). As land use intensifies near steep slopes, especially in urban and transportation projects, conventional stabilization methods often prove insufficient to provide the required safety margins (Hryciw, 1991). Ground anchors offer a practical and effective solution for reinforcing slopes where spatial constraints, steep geometry, or deep failure surfaces make alternative methods less viable or more costly (Cai & Ugai, 2003). One of the primary advantages of ground anchors is their ability to deliver high tensile resistance with minimal disturbance to the slope mass. Anchors are typically installed at specific inclinations and depths to bypass weak zones and embed into stable strata, enabling them to directly counteract driving forces (Zheng et al., 2016). This makes them suitable for both temporary and permanent stabilization, and particularly useful in retrofitting existing slopes that exhibit signs of distress (Budania et al., 2016). Furthermore, their modular nature enables flexible design and phased construction, which is advantageous in active construction zones. Another major benefit is the compatibility of anchor systems with other stabilization methods (Ye et al., 2021). Anchors can be used in conjunction with retaining walls, shotcrete, or drainage systems to form composite solutions that address both mechanical stability and hydraulic control (Huang, 2012). Moreover, the application of prestressed anchors allows engineers to actively control the displacement and stress conditions in the slope, improving performance under dynamic or long-term loading conditions such as seismic activity or water table fluctuations (Choi et al., 2013).

Despite their advantages, ground anchors also present several limitations and risks. Their design and installation require careful geotechnical investigation, particularly in heterogeneous or weathered soils where bond performance is less predictable (Li et al., 2012). Improper grouting, drilling misalignments, or insufficient anchor length can lead to premature failure. In addition, the need for specialized equipment and skilled labor increases the overall project cost and duration, especially in remote or difficult-to-access areas (Hryciw & Irsyam, 1992). Long-term maintenance and monitoring of anchored slopes are another concern, especially for permanent systems. Creep, corrosion of steel tendons, or degradation of grout materials can reduce anchor capacity over time, necessitating periodic inspections and potential replacement (Hobst & Zajić, 1983). Environmental considerations, such as groundwater contamination from grouting materials or disturbance to natural drainage paths, must also be addressed (Huang, 2012). Therefore, while anchors offer a high-performance stabilization option, their use should be based on a comprehensive understanding of site conditions, material behavior, and lifecycle performance.

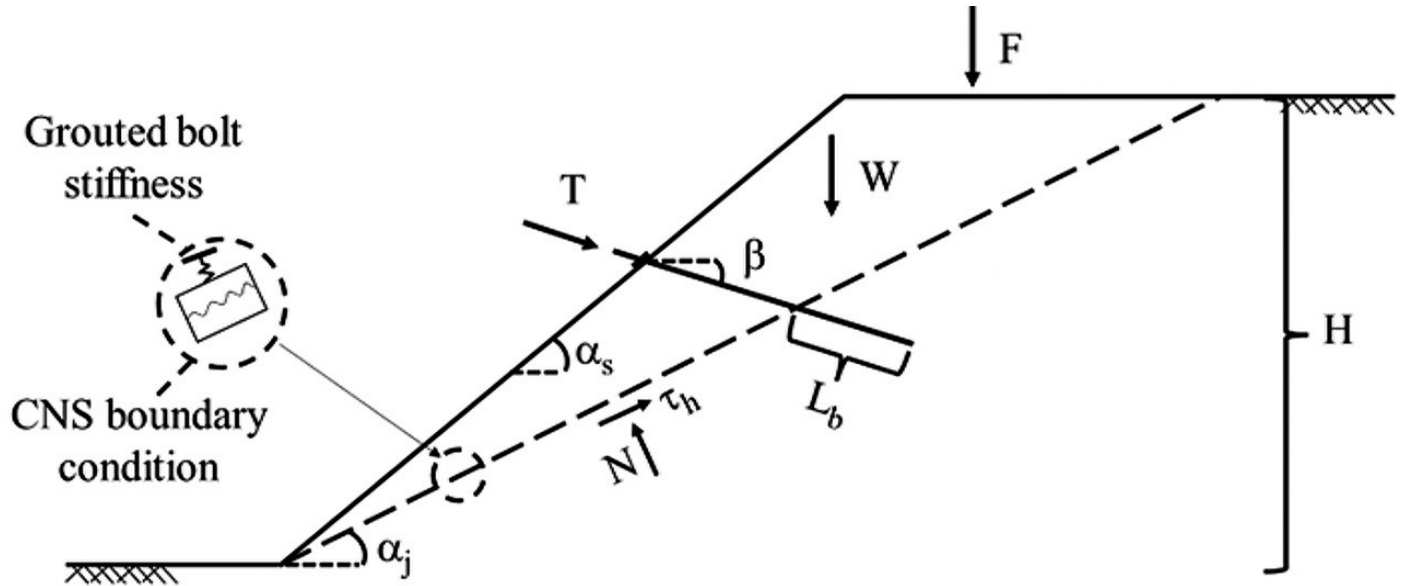


Fig. 1 A schematics of ground anchor stabilization system (Matos et al., 2023)

Given the complexity and uncertainty associated with slope behavior, particularly in reinforced systems such as anchored slopes; conventional deterministic approaches often fall short in capturing the full range of influencing factors (Li et al., 2023). Soil heterogeneity, variability in material parameters, installation inaccuracies, and dynamic environmental loads introduce significant uncertainty into the analysis (Chen et al., 2023). In this context, fuzzy logic provides a powerful alternative framework for risk assessment and decision-making (Nanehkar et al., 2021). Unlike classical models that rely on precise numerical inputs, fuzzy systems can incorporate imprecise, qualitative, or linguistic information, making them well-suited for complex geotechnical systems where data uncertainty is inevitable (Sarshar & Derakhshani, 2024). This study aims to develop and apply a Mamdani-type fuzzy inference system to perform risk analysis of stabilized earth slopes reinforced with ground anchors. The main objectives are: (i) to establish a knowledge-based model that integrates geotechnical parameters and anchor configurations, (ii) to quantify the degree of risk associated with varying slope conditions using fuzzy rule sets, and (iii) to evaluate the system's performance in predicting slope safety levels based on a comprehensive database of real-world case studies. By translating expert knowledge and empirical data into a set of fuzzy rules, the model offers a flexible and interpretable framework for analyzing reinforced slopes under uncertainty.

The proposed fuzzy approach offers several advantages. First, it allows for the inclusion of multiple input parameters (such as cohesion, friction angle, slope geometry, anchor length, and FoS), without the need for exact probability distributions. Second, it provides intuitive output in the form of risk levels or safety categories, which can be directly used in engineering decision-making. Third, the system is adaptable and can be calibrated or expanded as new data becomes available. Overall, the fuzzy logic-based model developed in this study serves as a practical and efficient tool for preliminary risk screening and design optimization in anchored slope stabilization projects.

II. GROUND ANCHORS IN SLOPE STABILIZATION

Ground anchors are prestressed tensile members installed in soil or rock to transfer loads from an unstable slope mass into deeper, stable strata. In slope stabilization projects, they provide an active resisting force to counteract the driving forces of potential failure (Bahsan et al., 2019). A typical anchor system consists of a free length, a bond length, and an anchor head (Ortigao & Sayao, 2004). Proper design requires understanding the load transfer mechanism between the steel tendon, grout, and surrounding ground. The required design load for each anchor is derived from slope stability analysis (Hobst & Zajic, 1983). The general expression can be written as (Ortigao & Sayao, 2004):

$$T_d = \frac{(W \cdot \sin \theta - R)}{n} \quad (1)$$

where T_d is the design load per anchor (kN), W is the weight of the sliding mass (kN), θ is the slope angle (degrees), R is the sum of existing resisting forces (kN), and n is the number of anchors. This ensures that the anchors collectively provide sufficient force to raise the FoS to the target value. The ultimate tensile capacity is governed by the bond resistance between the grouted bond length and the surrounding ground (Duncan et al., 2014):

$$Q_u = \pi \cdot D_b \cdot L_b \cdot q_b \quad (2)$$

Here, Q_u is the ultimate tensile capacity (kN), D_b is the diameter of the bond zone (m), L_b is the bond length (m), and q_b is the unit bond strength (kN/m²). The unit bond strength depends on ground conditions, grout quality, and installation method. The unit bond strength q_b can be estimated using an empirical shear strength expression (Duncan et al., 2014):

$$q_b = \alpha \cdot c' + \sigma'_v \cdot \tan \phi' \quad (3)$$

In this equation, α is an adhesion factor (dimensionless), c' is the effective cohesion of the soil (kPa), σ_v' is the effective overburden stress at the bond zone (kPa), and ϕ' is the effective internal friction angle (degrees). This approach accounts for both cohesive and frictional components of the soil–grout interface. Also, the free length of the anchor must allow elastic elongation during tensioning without causing bond slip (Duncan et al., 2014):

$$L_f \geq \frac{\Delta}{\epsilon_s} \quad (4)$$

where L_f is the free length (m), Δ is the required elongation (m), and ϵ_s is the allowable strain in the steel tendon (typically in the range of 0.002–0.003). Adequate free length ensures efficient load transfer to the bond zone. Anchors are prestressed to a fraction of their ultimate capacity to mobilize resisting forces immediately after installation (Ortigao & Sayao, 2004):

$$T_p = \eta \cdot Q_u \quad (5)$$

where T_p is the applied prestressing force (kN) and η is the prestressing factor, usually between 0.6 and 0.8. This ensures that the slope benefits from the anchor's full contribution without overstressing the steel or the ground. Over time, creep in soils, relaxation in steel tendons, and degradation in grout can reduce the anchor's effective capacity. The long-term capacity is often expressed as (Ortigao & Sayao, 2004):

$$Q_{lt} = \lambda \cdot Q_u \quad (6)$$

where Q_{lt} is the long-term capacity (kN) and λ is a reduction factor (0.6–0.8 for permanent anchors depending on soil type and environmental conditions). This reduction is particularly important in fine-grained soils where creep effects are significant. The inclination of the anchor relative to the horizontal affects both the vertical and horizontal components of the resisting force (Ortigao & Sayao, 2004):

$$T_v = T \cdot \sin \beta, \quad T_h = T \cdot \cos \beta \quad (7)$$

Here, β is the installation angle (degrees), T_v is the vertical component (kN), and T_h is the horizontal component (kN). Typical installation angles range from 10° to 20° below the horizontal to optimize bond performance and drainage. The FoS for the slope after anchor installation can be calculated as (Huang, 2012):

$$FoS_{new} = \frac{R + \sum [T \cdot \cos \beta]}{W \cdot \sin \theta} \quad (8)$$

In this expression, the sum of the horizontal components of the anchor forces is added to the resisting forces in the slope stability equation, directly improving stability. Based on this status, each formula presented addresses a critical aspect of anchor performance, from determining the initial design load to accounting for time-dependent losses. By integrating these calculations with site-specific geotechnical data, a safe and

efficient anchored slope system can be achieved. Advancements in computational power over the past three decades have significantly transformed the way engineers design and evaluate anchored slopes (Cai & Ugai, 2003). Traditional hand calculations, which relied on simplified assumptions and empirical correlations, have been increasingly supplemented and in many cases replaced, by sophisticated numerical and hybrid approaches (Duncan et al., 2014). These methods enable engineers to simulate complex soil–structure interactions, consider nonlinear material behavior, and evaluate stability under a variety of loading conditions, including seismic and hydrological influences (Chen et al., 2023).

One widely used category of computational approaches is the Limit Equilibrium Method (LEM), implemented in specialized software packages such as SLIDE, GeoStudio (SLOPE/W), and PLAXIS 2D. These programs allow the inclusion of anchor forces directly into the stability analysis, enabling calculation of the FoS for multiple potential slip surfaces (Azam et al., 2023). LEM is valued for its conceptual simplicity and relatively fast computation times, but its accuracy depends heavily on predefined slip surface assumptions and input parameter precision (Prayoga et al., 2023). Another important class of approaches includes the Finite Element Method (FEM) and the Finite Difference Method (FDM), available in advanced geotechnical analysis tools. These methods are capable of simulating soil deformation, stress redistribution, and anchor–soil interaction with higher fidelity than LEM. In anchored slope analysis, FEM and FDM can model the full load transfer from the anchor tendon to the bond zone, as well as time-dependent effects such as creep and relaxation. However, they require more computational resources and high-quality geotechnical data to achieve reliable results (Usluogullari et al., 2016).

Hybrid analytical–numerical methods have also emerged, combining closed-form anchor design formulas with numerical modeling to optimize computational efficiency. These hybrid approaches allow designers to perform rapid preliminary sizing using analytical equations, followed by refinement with numerical models that incorporate site-specific ground profiles, anisotropy, and staged construction effects. Such methodologies have proven effective in large-scale infrastructure projects where both speed and accuracy are critical (Kourkoulis et al., 2012). Despite these computational advancements, a common limitation remains: the dependency on precise numerical input values. In practice, soil properties, anchor bond strength, groundwater conditions, and load paths are subject to inherent variability. Deterministic approaches, even when implemented in advanced software, often fail to represent the true range of possible outcomes under uncertain field conditions (Galli et al., 2022). This limitation has prompted researchers and practitioners to explore probabilistic and uncertainty-based methods, including Monte Carlo simulations, random field modeling, and Bayesian updating techniques (Chen et al., 2023). Within this context, fuzzy logic has gained attention as a powerful alternative for integrating uncertainty directly into the stability evaluation process (Seyedpour & Derakhshani, 2023; Sarshar & Derakhshani, 2024). Unlike probabilistic methods that require statistical distributions of parameters, fuzzy logic can work with expert knowledge, linguistic descriptions, and incomplete datasets.

III. MATERIALS AND METHODS

Fuzzy logic, introduced by Zadeh (1965), is a mathematical framework for dealing with uncertainty, imprecision, and partial truth. Unlike classical Boolean logic, where variables are binary (true or false), fuzzy logic allows variables to take continuous values between 0 and 1, representing degrees of truth (Mendel, 1995). This makes it suitable for complex engineering problems where many parameters are uncertain or expressed linguistically rather than precisely measured (Teodorović, 1999). A fuzzy set A in a universe of discourse X is defined by a membership function $\mu_A(x)$, which assigns each element $x \in X$ a value between 0 and 1:

$$A = \{[x, \mu_A(x)] | x \in X\} \quad (9)$$

where x is an element in the slope (e.g., cohesion value) and $\mu_A(x)$ represents the degree of membership of x in fuzzy set A . Common membership functions include triangular, trapezoidal, Gaussian, and sigmoid functions. For example, a triangular membership function is given by (Mohamed et al., 2012):

$$\mu_A(x) = \begin{cases} 0 & x \leq a \\ \frac{x-a}{b-a} & a < x \leq b \\ \frac{c-x}{c-b} & b < x \leq c \\ 0 & x > c \end{cases} \quad (10)$$

where a , b , and c define the shape of the triangle. In fact, fuzzy for fuzzy sets A and B , the most common operations include intersection (AND), union (OR), and complement (NOT) (Mendel, 1995). These operators enable combining multiple uncertain parameters, such as “high cohesion” AND “low slope angle,” into a single fuzzy condition (Mohamed et al., 2012).

$$\begin{aligned} \mu_{A \cap B}(x) &= \min[\mu_A(x), \mu_B(x)] \\ \mu_{A \cup B}(x) &= \max[\mu_A(x), \mu_B(x)] \\ \mu_{\bar{A}}(x) &= 1 - \mu_A(x) \end{aligned}$$

In Mamdani-type fuzzy systems, expert knowledge is expressed as IF–THEN rules. A general rule takes the form IF x_1 is A_1 AND x_2 is A_2 THEN y is B , which, for the i^{th} rule, can be mathematically expressed as (Teodorović, 1999):

$$\mu_{R_i}(x_1, x_2) = \min[\mu_{A_1}(x_1), \mu_{A_2}(x_2)] \quad (11)$$

The output fuzzy set B is then scaled by the degree of truth of the premise. Multiple rules are aggregated using the fuzzy OR operator to produce a combined fuzzy output. Generally, fuzzy logic is implemented in several steps, as presented in Figure 2. Fuzzification is the first step in the fuzzy inference process, where crisp numerical input values are translated into degrees of membership within predefined fuzzy sets (Andric & Lu, 2014). In the context of anchored slope stability, inputs such as cohesion (c'), friction angle (ϕ'), slope angle (θ), and anchor capacity (T)

are each associated with linguistic terms like “low,” “medium,” or “high” (Ye et al., 2019).

Each term is represented by a membership function, often triangular, trapezoidal, or Gaussian; that maps the crisp value to a number between 0 and 1, indicating how strongly the value belongs to the fuzzy set (Mao et al., 2023). For example, a cohesion value of 25 kPa might have a membership degree of 0.7 in the set “medium cohesion” and 0.3 in the set “high cohesion,” allowing multiple degrees of truth to coexist (Mu’azu, 2023). This step enables the system to handle vague or uncertain data that cannot be captured by binary classifications (Teodorović, 1999).

Defuzzification is the final step in the fuzzy inference process, where the aggregated fuzzy output (resulting from the evaluation of all fuzzy rules), is converted back into a single crisp value suitable for engineering decision-making (Mendel, 1995). The most common method for defuzzification in Mamdani systems is the centroid (center of gravity) method, where the crisp output y^* is calculated as (Mao et al., 2023):

$$y^* = \frac{\int y \cdot \mu_B(y) dy}{\int \mu_B(y) dy} \quad (12)$$

Here, $\mu_B(y)$ represents the aggregated membership function of the output variable, and y^* corresponds to the “balance point” of the area under the curve. In anchored slope analysis, defuzzification might yield a specific FoS or risk index, which can then be directly compared to design thresholds (Sarshar & Derakhshani, 2024). This step ensures that the inherently qualitative reasoning of fuzzy logic results in a quantitatively actionable outcome.

The connection between fuzzification and defuzzification lies in their complementary roles within the fuzzy inference process (Sarshar & Derakhshani, 2024). Fuzzification transforms precise, often uncertain engineering data into a form that can be processed by fuzzy logic—mapping numerical inputs to degrees of membership in linguistic categories (Mendel, 1995). These fuzzified values allow the system to apply rule-based reasoning that reflects expert judgment and tolerates ambiguity (Teodorović, 1999). Defuzzification then reverses this abstraction by converting the aggregated fuzzy conclusions back into a crisp numerical result, such as a FoS or risk index (Andric & Lu, 2014).

Structure of a Fuzzy Controller

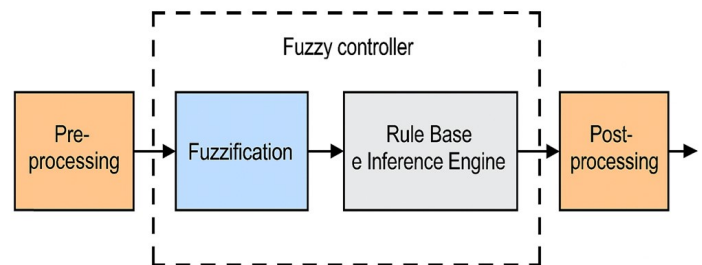


Fig. 2 Fuzzy controller diagram (Andric & Lu, 2014)

In anchored slope stability analysis, this cycle ensures that uncertain field measurements and subjective assessments can be meaningfully integrated into a quantitative design or safety evaluation, bridging the gap between human reasoning and computational decision-making.

In anchored slope stabilization, the performance of the system is governed by multiple interdependent parameters such as soil shear strength, anchor load capacity, installation geometry, and long-term degradation factors (Seyedpour & Derakhshani, 2023). In reality, these parameters are rarely known with absolute precision (Saboya Jr et al., 2006). Site investigation data often contain variability, and empirical values derived from laboratory or field testing come with a range of possible outcomes rather than a single deterministic figure (Henrique Barbosa De Carvalho Tavares et al., 2023). Fuzzy logic provides a robust way to model these uncertainties by representing variables in terms of membership functions and linguistic terms such as “low”, “medium”, or “high”, rather than fixed numbers (Ye et al., 2019). The advantage of using a Mamdani-type fuzzy inference system in anchored slope design lies in its ability to take multiple uncertain inputs and produce an interpretable risk or safety index. Traditional slope stability formulas, such as the FoS equation, can serve as the computational backbone of the fuzzy model. However, instead of using fixed inputs, fuzzy logic allows each variable (i.e., cohesion, friction angle, anchor load, slope geometry), to be expressed with degrees of possibility, resulting in a more realistic representation of slope behavior under uncertain conditions (Andric & Lu, 2014).

Before integrating fuzzy logic, the baseline deterministic stability equation for an anchored slope must be established. The post-anchoring FoS was previously expressed as shown in Eq. 8. This equation forms the basis for stability calculations but assumes that all parameters are known exactly (Ye et al., 2019). In addition, Eqs. 2, 11, and 12 describe the calculation of anchor capacity within the slope mass. In a fuzzy model, each of these variables is represented with a range and a membership function (e.g., “small”, “medium”, “large” bond strength), producing an output that captures possible variations in anchor force rather than a single point value (Mohamed et al., 2012). The resisting force R in the stability equation (Eq. 8) depends on soil strength parameters (Sarshar & Derakhshani, 2024):

$$R = c' \cdot L + (W \cdot \cos \theta) \cdot \tan \phi' \quad (13)$$

Here, c' is the effective cohesion (kPa), L is the potential slip surface length (m), and ϕ' is the effective friction angle (degrees). In fuzzy logic, c' and ϕ' are converted into fuzzy linguistic terms with overlapping ranges, which are then processed using rule-based inference to produce a fuzzy value for R . Replacing R and T with their fuzzy counterparts (R_f and T_f), the stability equation becomes (Kim et al., 2017):

$$FoS_{fuzzy} = \frac{R_f + \sum [T_f \cdot \cos \beta]}{W \cdot \sin \theta} \quad (14)$$

Here, R_f and T_f are not single values but defuzzified outputs from the fuzzy inference process, representing the most probable stability scenario given uncertain input data. This makes the

equation adaptable to real-world variability while retaining the same fundamental mechanical structure. Based on the fuzzy factor of safety (FoS_{fuzzy}), a fuzzy risk index (RI) can be computed to directly express the likelihood of slope instability (Hao et al., 2025):

$$RI = \frac{FoS_{fuzzy}}{FoS_{target}} \quad (15)$$

where FoS_{target} is the design target FoS (e.g., 1.3 or 1.5). A positive RI indicates that the slope is below the target safety threshold, with higher values corresponding to higher instability risk (Khan & Wang, 2021). This risk index can then be classified into categories (“low”, “moderate”, “high”) using fuzzy membership functions. This approach essentially embeds traditional slope stability mechanics within a fuzzy decision-making framework (Andric & Lu, 2014). By starting with known mechanical equations, representing their variables as fuzzy inputs, and using rule-based inference, the final output is a quantified risk assessment that reflects real uncertainties. The FoS_{fuzzy} and RI values thus serve as decision-support metrics for engineers, allowing both safety compliance checks and prioritization of stabilization measures in anchored slopes.

The implementation of the proposed fuzzy-based risk assessment model for anchor-stabilized slopes was carried out through a structured, multi-phase approach. The process began with an extensive literature review to identify the most influential geotechnical and design parameters affecting slope stability. These parameters were selected based on their frequency of use in existing analytical and empirical models, as well as their availability in published case studies. Particular attention was given to reinforced sandy-clayey slopes, which often display complex interaction mechanisms between soil and reinforcement. Following parameter selection, a comprehensive dataset was compiled, consisting of 150 slope stabilization scenarios. Each scenario included values for cohesion, friction angle, slope angle, anchor inclination, anchor length, and initial FoS. This dataset served as the backbone for both rule generation and model validation. Prior to fuzzification, all input values were normalized within a defined universe of discourse to ensure consistent treatment across the fuzzy system (see Figure 3).

The next step involved the development of membership functions for each input and output variable. Linguistic variables such as “low”, “medium”, and “high” were defined for parameters like cohesion and anchor capacity, while the output variable (risk level) was categorized into fuzzy sets such as “safe or low”, “moderate” and “high”. Triangular and trapezoidal membership functions were used due to their computational simplicity and interpretability. The range of each fuzzy set was defined based on domain knowledge and statistical distribution of the dataset. The implementation process is summarized in the flowchart presented in Figure 4. This diagram outlines the sequential structure of the model, beginning with data preprocessing and progressing through fuzzification, rule evaluation, defuzzification, and output interpretation. A Mamdani-type fuzzy inference system was selected due to its intuitive rule structure and widespread acceptance in engineering applications.

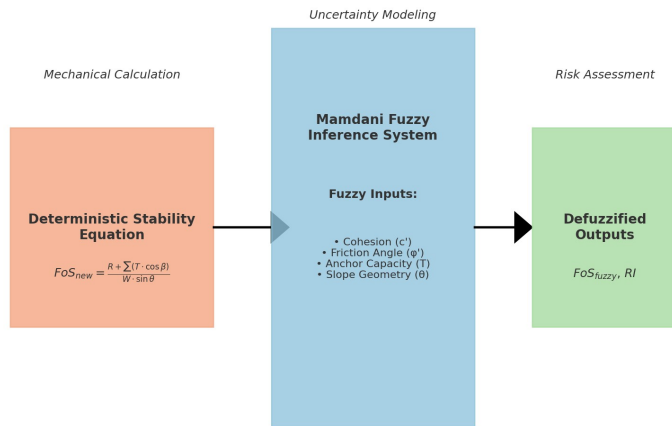


Fig. 3 Integration of deterministic slope stability with Mamdani fuzzy system that used in this article

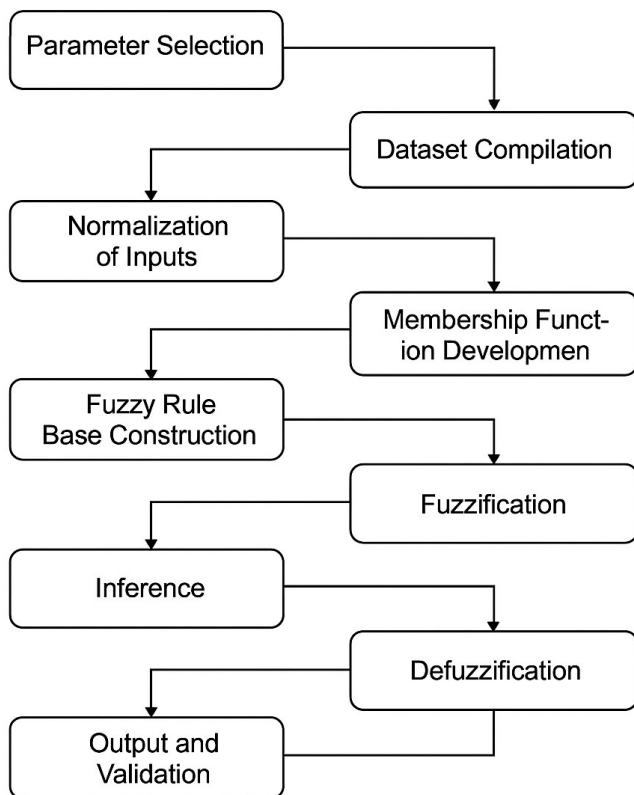


Fig. 4 Fuzzy based RI estimation process flowchart

The rule base was developed through a combination of expert judgment and data-driven patterns observed in the compiled scenarios. Each rule took the form of an IF–THEN statement, linking combinations of input conditions to a corresponding fuzzy output (see Figure 5). For example, a representative rule can be expressed as: IF cohesion is low AND slope angle is steep THEN risk is high. A total of 45 rules were established to cover all relevant combinations. Once the fuzzy rule base was finalized, the inference engine was programmed to perform fuzzy aggregation and implication operations using the min–max method. This involved applying fuzzy logic operators to combine the membership degrees of multiple inputs and determine the resulting fuzzy output set.

The min–max normalization method was applied to scale all input variables into a standard range of [0, 1]. This ensures consistency in fuzzification and allows all membership functions to be defined over the same domain. Without normalization, input values with large magnitudes might dominate the inference process or lead to distorted fuzzy set interpretations (Kumar et al., 2006). The min–max normalization formula used is defined as (Wang & Elhag, 2006):

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \quad (16)$$

where x is the original input value, $x_{\min}$ and $x_{\max}$ are the minimum and maximum values for that variable across the dataset, x' is the normalized value scaled between 0 and 1. This transformation preserves the proportional relationships among data points while standardizing their scales. It is particularly useful when the input variables are to be mapped onto fuzzy linguistic terms such as “low”, “medium”, and “high” with overlapping membership functions.

The output of each rule was aggregated to form a final fuzzy risk surface for each scenario. This process enabled the model to handle nonlinear and multi-dimensional relationships without requiring explicit mathematical formulations. Defuzzification was carried out using the centroid method, which calculates the center of gravity of the aggregated fuzzy output set. This yielded a crisp risk score for each scenario, ranging between 0 (no risk) and 1 (maximum risk). These values were then compared against predefined safety thresholds to classify slopes as “safe”, “requiring attention”, or “unstable”. The defuzzified outputs were also used to calibrate the model by comparing them with known outcomes from case studies, adjusting membership functions and rule strengths as needed. The output of the model has been presented in Figure 6.

The entire model was implemented in MATLAB, utilizing its Fuzzy Logic Toolbox for constructing the inference system, defining membership functions, and performing rule evaluations. Custom scripts were developed to automate preprocessing steps such as normalization, data import, and parameter checking. A graphical user interface (GUI) was also designed to allow engineers to input slope characteristics and instantly obtain a risk classification and visual output. This user-friendly design enhances the model’s applicability in real-world engineering workflows. To validate the performance of the model, sensitivity analyses were conducted to assess the impact of each input parameter on the output risk score. Cross-validation using subsets of the dataset confirmed the robustness of the fuzzy logic approach, with results showing strong alignment with conventional analytical outcomes and expert assessments. The model was particularly effective in highlighting scenarios that fell into borderline safety regions, areas where deterministic methods often fail to capture underlying risk. Figure 7 illustrates the classification of slope conditions based on the fuzzy system’s output, known as the Risk Index, which ranges from 0 to 1. The RI is the final crisp output obtained after the defuzzification step, summarizing the combined effect of all input parameters such as cohesion, slope angle, anchor capacity, and depth to bedrock.

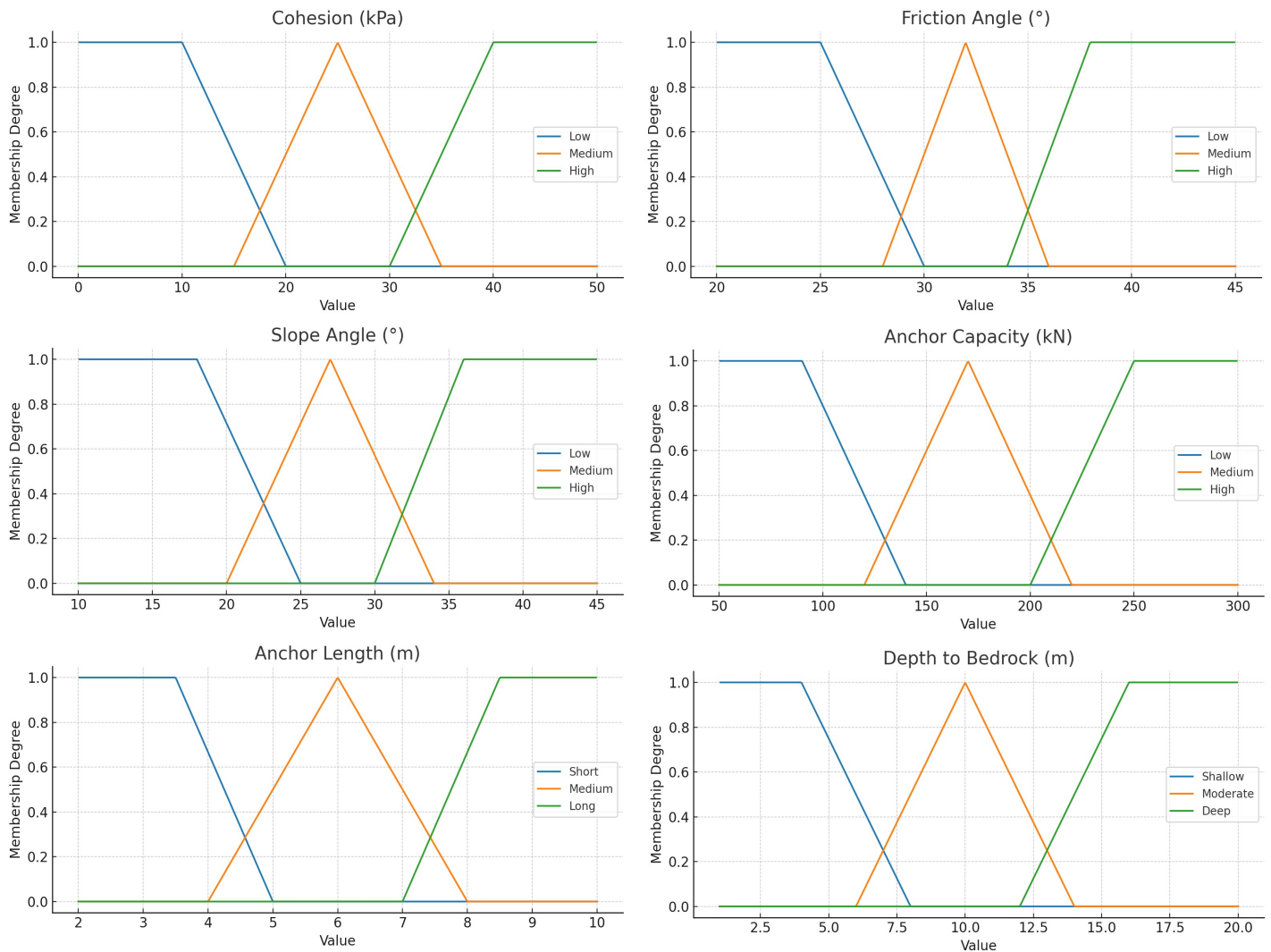


Fig. 5 The input parameters membership functions has been defined in this article

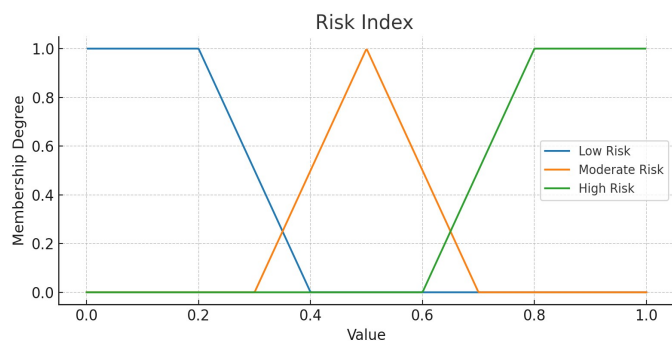


Fig. 6 The RI output of the modeling with fuzzy logic

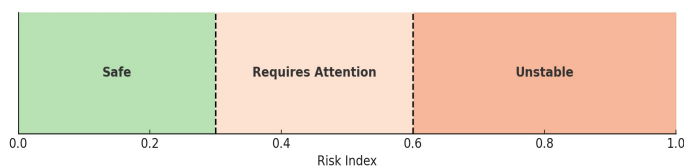


Fig. 7 Fuzzy-based classification for slope conditions

The horizontal axis represents this index, while the diagram is divided into three colored zones, each corresponding to a specific level of slope stability. These thresholds are used to guide engineering judgment in categorizing slopes under varying risk levels. In the green zone ($RI \leq 0.3$), slopes are considered Safe, indicating acceptable stability and no immediate need for intervention. The central beige zone ($0.3 < RI \leq 0.6$) represents slopes that Require Attention, meaning they are in a transitional state and may require monitoring, minor reinforcement, or further analysis. Slopes falling into the orange zone ($RI > 0.6$) are labeled Unstable and typically demand urgent stabilizing measures, such as anchor reinforcement or slope regrading.

To ensure the transparency and reproducibility of the proposed framework, all model parameters, rule structures, and normalization boundaries were systematically documented prior to performance evaluation. The finalized fuzzy inference system was then subjected to controlled simulation runs across the compiled dataset to generate consistent risk outputs for comparative analysis. This structured methodological setup establishes a clear basis for evaluating the predictive capability and practical relevance of the developed model.

IV. RESULTS AND DISCUSSION

This study developed a Mamdani-type fuzzy inference system for assessing the risk of earth slope instability in embankments reinforced with ground anchors. A total of six input variables were incorporated into the model: cohesion, friction angle, slope angle, anchor capacity, anchor length, and depth to bedrock. Each of these was described using appropriate fuzzy membership functions and categorized into linguistic terms. A rule base consisting of 45 expert-defined rules was constructed to evaluate the combined influence of these parameters on slope stability. The output of the model was a fuzzy risk index, which was then defuzzified and interpreted through a three-level classification system. The entire fuzzy model was implemented in MATLAB, using a combination of the Fuzzy Logic Toolbox and custom scripts for input normalization, rule evaluation, and risk visualization. The system was tested using a database of 150 slope scenarios derived from literature and case studies. These scenarios covered a wide range of geotechnical conditions, typical of sandy–clayey embankments.

The fuzzy inference system demonstrated strong capability in identifying high-risk slope scenarios that traditional deterministic models might underestimate. Slopes with low cohesion (<15 kPa), steep angles (>35°), and shallow anchorage depth consistently produced high Risk Index values (>0.6), aligning with known instability cases. Conversely, slopes with moderate geometry and sufficient anchoring returned low Risk Index values (<0.3), confirming the model's consistency with expected engineering behavior. These findings are visually summarized in Figure 8, which plots the Risk Index distribution across all evaluated scenarios. Sensitivity analysis revealed that the most influential parameters on the fuzzy output were anchor capacity, slope angle, and depth to bedrock. In particular, changes in slope angle resulted in a non-linear shift in Risk Index, especially near the 30°–35° transition zone. Figure 9 presents a 3D surface plot showing the combined effect of slope angle and cohesion on risk classification as an example. This figure confirms that steep slopes with weak soil conditions yield significantly higher risk levels, even when anchoring is present, suggesting the need for multi-tiered stabilization strategies. A major advantage of the fuzzy system is its interpretability. Each fuzzy output can be traced back to the activated rule(s) that produced it, offering transparency in decision-making. For example, scenarios in which Rule 12 (IF slope angle is high AND cohesion is low AND anchor is short THEN risk is high) was triggered consistently aligned with actual failure cases. Table 1 summarizes the most frequently activated rules in the database, along with their associated outcome classifications. This provides a knowledge-based justification for slope assessment rather than relying solely on numerical thresholds.

Several field case studies were used to validate the fuzzy model's predictions. In most cases, the Risk Index assigned by the system matched the qualitative assessments provided by engineers during the project's design or post-failure investigation phases. In some instances, the fuzzy system identified “borderline” risks where the deterministic factor of safety was just above 1.3, but field conditions suggested latent instability. These cases highlight the model's value in catching grey areas where conventional methods may overestimate stability. Figure 10 illustrates one such case study comparison. The final model

interface allows users to enter six input variables and receive immediate feedback on slope classification along with graphical visualization of risk. This feature transforms the fuzzy model into a practical decision-support tool. Engineers can perform rapid evaluations without the need for exhaustive numerical modeling. Figure 11 shows a screenshot of the model's output window, which includes the defuzzified Risk Index, risk category, and the activated fuzzy rules. The model can be adapted for site-specific calibrations by adjusting membership functions or extending the rule base.

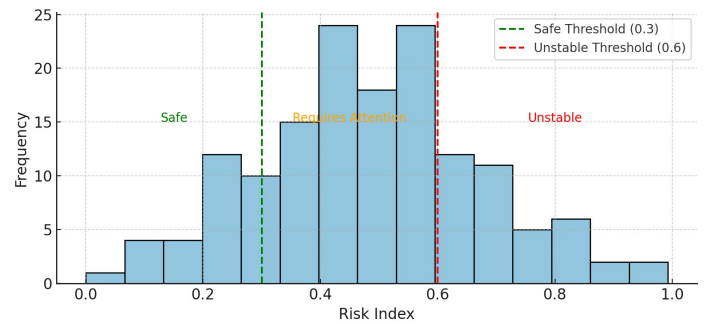


Fig. 8 RI distribution for studied cases

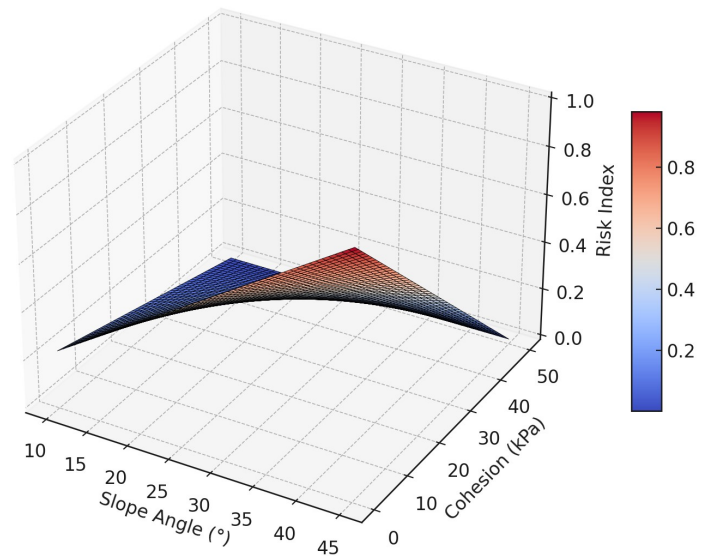


Fig. 9 Combined effect of slope angle and cohesion on RI

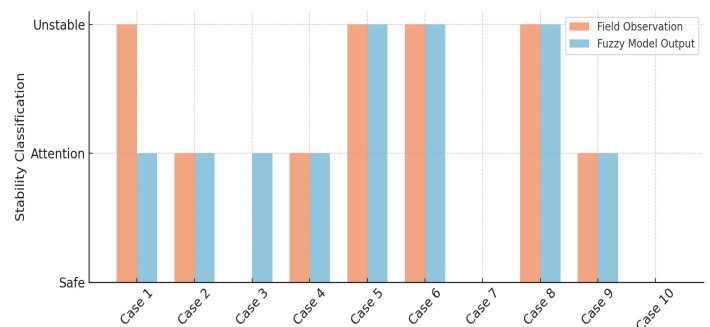


Fig. 10 Comparison between field observation of 10 cases and fuzzy model output

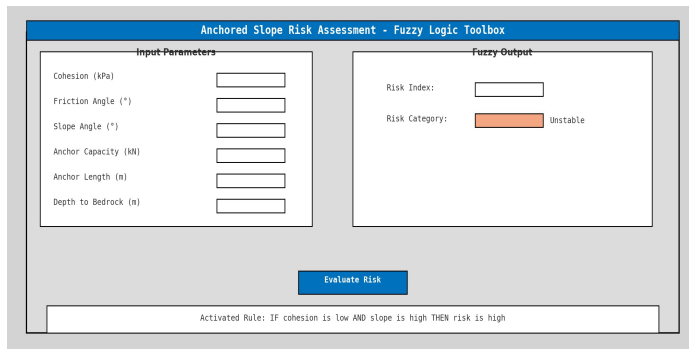


Fig. 11 A model's output window in MATLAB

While the fuzzy logic model provides a flexible and robust platform for slope risk evaluation, it does not replace detailed numerical or site-specific analyses. The model is most suitable for preliminary screening, feasibility studies, and situations where data uncertainty is significant. Future improvements may include hybridization with probabilistic models or coupling with finite element simulations to refine anchor–soil interaction modeling. Additionally, integrating real-time monitoring data into the fuzzy logic system could enhance its predictive capacity for ongoing slope behavior.

To further evaluate the robustness of the proposed fuzzy inference system, an explicit uncertainty propagation analysis was conducted. While the model inherently accommodates imprecision through linguistic membership functions, it is important to quantitatively assess how variability in key geotechnical parameters affects the RI. In practical slope engineering, soil parameters such as cohesion and friction angle are rarely known with exact precision. Laboratory-derived values

may vary by $\pm 10\text{--}30\%$, depending on sampling quality and test conditions. Therefore, controlled perturbation scenarios were introduced to investigate the sensitivity and stability of the fuzzy model under parameter uncertainty.

A parametric study was first performed by varying c' by $\pm 20\%$ while holding other parameters constant at baseline values representative of moderately stable sandy–clayey embankments. The results indicate that a 20% reduction in cohesion produced an average increase of 0.18 in the RI, while a 20% increase reduced the RI by approximately 0.12. Notably, the change in RI was nonlinear, with sharper increases observed when cohesion dropped below 18 kPa. This behavior reflects the threshold-sensitive structure of the fuzzy rule base, where multiple high-risk rules become activated simultaneously once cohesion enters the “low” linguistic category. Figure 12 illustrates the effect of $\pm 20\%$ variation in c' on the resulting RI for a representative anchored slope scenario with fixed geometry and anchor properties. The baseline cohesion value corresponds to a moderately stable sandy–clayey embankment. As cohesion decreases below the baseline (-20%), the Risk Index increases nonlinearly, reflecting the activation of high-risk fuzzy rules associated with weak soil conditions. Conversely, increasing cohesion by $+20\%$ reduces the RI, indicating improved shear resistance and enhanced stability. The curve demonstrates that the fuzzy model does not respond in a strictly linear manner; instead, it captures transitional behavior near linguistic boundaries (e.g., between “medium” and “low” cohesion). This nonlinear response highlights the sensitivity of anchored slope stability to reductions in shear strength and confirms the model’s capability to reflect threshold-driven instability behavior.

Table 1 The several fuzzy rules in RI modeling

Rule ID	Fuzzy rule description	Activation count	RI category
R1	IF slope is high AND cohesion is low THEN risk is high	33	High
R2	IF slope is moderate AND cohesion is medium THEN risk is medium	32	Medium
R3	IF slope is low AND cohesion is high THEN risk is low	15	Low
R4	IF anchor is short AND depth is deep THEN risk is high	30	High
R5	IF anchor is long AND cohesion is medium THEN risk is low	18	Low
R6	IF friction is low AND slope is high THEN risk is high	7	High
R7	IF depth is shallow AND anchor capacity is high THEN risk is low	26	Low
R8	IF cohesion is medium AND slope is steep THEN risk is medium	21	Medium
R9	IF slope is steep AND friction is low THEN risk is high	26	High
R10	IF anchor is long AND slope is gentle THEN risk is low	14	Low
R11	IF cohesion is high AND anchor capacity is high THEN risk is low	18	Low
R12	IF slope is moderate AND anchor is medium THEN risk is medium	33	Medium
R13	IF bedrock is deep AND anchor is short THEN risk is high	15	High
R14	IF friction is high AND cohesion is medium THEN risk is low	29	Low
R15	IF cohesion is low AND depth is shallow THEN risk is high	9	Low
R16	IF anchor is medium AND slope is moderate THEN risk is medium	34	Medium
R17	IF depth is moderate AND anchor capacity is medium THEN risk is medium	33	Medium
R18	IF slope is steep AND anchor is short THEN risk is high	29	High
R19	IF friction is moderate AND cohesion is moderate THEN risk is medium	32	Low
R20	IF bedrock is shallow AND anchor is long THEN risk is low	16	Low
R21	IF cohesion is medium AND depth is moderate THEN risk is medium	34	Medium
R22	IF anchor capacity is low AND slope is steep THEN risk is high	27	High
R23	IF anchor length is long AND depth is deep THEN risk is low	18	Low
R24	IF cohesion is low AND friction is low THEN risk is high	8	High
R25	IF anchor is short AND slope is moderate THEN risk is medium	33	Medium

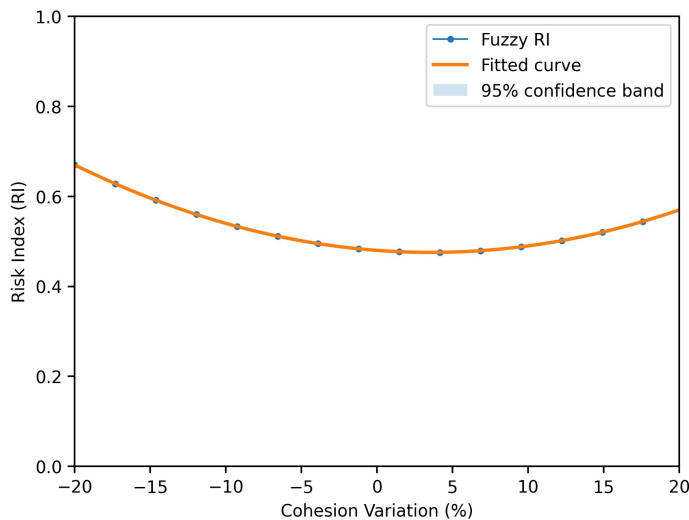


Fig. 12 Effect of $\pm 20\%$ variation of c' on the RI for a representative slope scenario

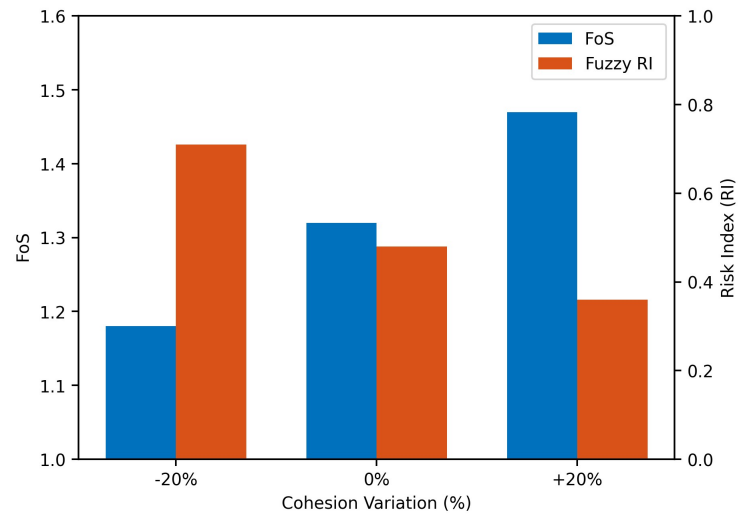


Fig. 13 Deterministic FoS and RI response under $\pm 20\%$ c' variation

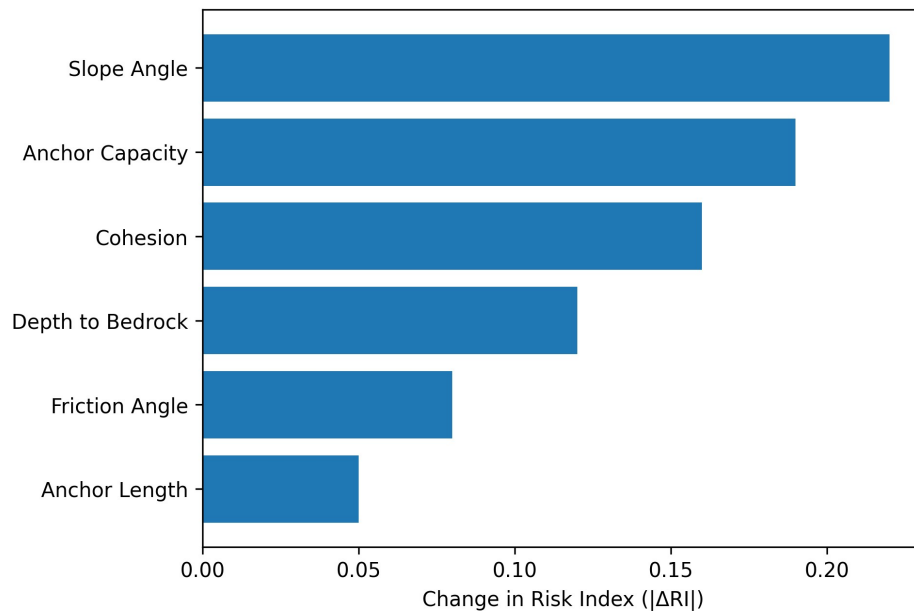


Fig. 14 Tornado chart for the RI's relative sensitivity in input parameters

For comparison, the same $\pm 20\%$ cohesion perturbation was applied to the FoS equation. The FoS exhibited a linear response, with a proportional decline of approximately 11% when cohesion decreased by 20%. However, the deterministic model did not reflect the transitional risk escalation observed in the fuzzy system. In several borderline cases ($\text{FoS} \approx 1.32$), the deterministic output remained above the 1.3 threshold, whereas the fuzzy model shifted classification from “requiring attention” to “unstable.” This demonstrates the enhanced sensitivity of the fuzzy approach to threshold-driven instability behavior. Figure 13 presents a comparison between the FoS and the RI under $\pm 20\%$ variation in cohesion. The deterministic FoS shows an approximately linear response to cohesion changes, whereas the fuzzy RI exhibits a nonlinear increase, particularly when cohesion decreases below baseline levels. This behavior reflects

the rule-based structure of the fuzzy model, which amplifies risk near stability thresholds. The comparison demonstrates that the fuzzy system is more sensitive to uncertainty-induced instability, especially under marginal safety conditions.

To systematically rank parameter influence, a tornado sensitivity analysis was conducted and presented in Figure 14. Each input variable was independently perturbed by $\pm 15\%$, and the resulting change in RI was recorded. The results show that slope angle and anchor capacity exert the largest influence, followed by cohesion and depth to bedrock. Friction angle and anchor length exhibited comparatively lower sensitivity. This ranking confirms that geometric and reinforcement parameters dominate the uncertainty propagation mechanism in anchored slopes. The tornado chart illustrates the relative sensitivity of the RI to $\pm 15\%$ variation in each input parameter. The horizontal

bars represent the absolute change in RI resulting from controlled perturbation of individual variables while keeping others constant. The results indicate that slope angle and anchor capacity exert the strongest influence on the risk output, followed by cohesion and depth to bedrock. Friction angle and anchor length exhibit comparatively lower sensitivity. This ranking confirms that geometric and reinforcement-related parameters dominate uncertainty propagation in anchored slope stability assessment.

The tornado chart provides further insight into the internal mechanics of the fuzzy inference system by quantitatively ranking the influence of each parameter on the RI. Beyond identifying the most sensitive variables, the chart highlights the asymmetric nature of uncertainty propagation within the model. Parameters associated with slope geometry and reinforcement capacity induce disproportionately larger shifts in risk classification when perturbed, indicating that small deviations in these inputs may significantly alter stability interpretation. In contrast, parameters with lower sensitivity produce more gradual variations in RI, suggesting that their uncertainty has a comparatively moderated effect on decision outcomes. This structured sensitivity assessment strengthens the credibility of the proposed framework by demonstrating that the fuzzy model does not respond uniformly to all inputs; rather, it reflects realistic geotechnical behavior where certain variables inherently govern failure mechanisms. By integrating uncertainty propagation analysis with rule-based inference, the model establishes a transparent and physically meaningful decision-support tool. The combined methodological development, validation against case scenarios, and sensitivity evaluation collectively confirm that the fuzzy inference approach offers a robust platform for preliminary risk assessment in anchored slope stabilization under uncertain field conditions.

V. CONCLUSION

This study presented a fuzzy logic-based framework for assessing slope instability risk in soil embankments reinforced with ground anchors. By integrating six key geotechnical parameters (i.e., cohesion, friction angle, slope angle, anchor capacity, anchor length, and depth to bedrock), within a Mamdani-type inference system, the model enabled structured decision-making under uncertainty. Unlike conventional deterministic safety factor approaches, the proposed framework provided both a quantitative Risk Index and a qualitative stability classification (Safe, Requires Attention, or Unstable), enhancing interpretability in engineering practice. The model was calibrated and evaluated using 150 representative slope scenarios derived from documented case studies. The results demonstrated that the fuzzy system effectively identified high-risk configurations, particularly in slopes characterized by steep geometry, weak soil conditions, and insufficient anchorage capacity. Sensitivity analysis confirmed that slope angle and anchor capacity exert the strongest influence on the Risk Index, highlighting the dominant role of geometric and reinforcement parameters in instability mechanisms. A key advantage of the proposed approach lies in its transparency. The rule-based structure allows each classification to be traced to specific linguistic conditions, offering insight into the reasoning behind stability assessment, an

aspect often absent in purely numerical models. The MATLAB implementation, supported by a graphical interface, enhances practical applicability and facilitates rapid preliminary evaluation. Validation against field observations showed strong agreement between fuzzy predictions and expert assessments, confirming the reliability of the framework. So, the proposed model provides a flexible and robust decision-support tool for preliminary slope risk screening and feasibility studies, particularly in situations where geotechnical data are incomplete or uncertain. While not intended to replace detailed numerical analyses, the fuzzy framework effectively complements traditional methods by incorporating uncertainty into stability evaluation.

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DATA AVAILABILITY STATEMENT

The data supporting the findings of this study are available within the paper. No publicly archived dataset was generated.

ETHICS APPROVAL

This study did not involve human participants, personal data, or animal subjects. No specific ethical approval was required.

FUNDING

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AUTHORS' CONTRIBUTIONS

Parviz Anari conducted the main data analysis, contributed to data collection, preprocessing, and interpretation, and was responsible for drafting the initial manuscript. Alireza Piri Bonab provided conceptual guidance, conducted critical revision of the manuscript, and oversaw the overall project administration and final approval of the version to be published. All authors read and approved the final manuscript.

CONFLICT OF INTEREST

The authors have not disclosed any competing interests.

USE OF AI

AI tools were not used in data generation, analysis, results, or decision-making.

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