

Article

Improved Fracture Surface Analysis of Anticline Rocky Slopes Using a Modified AGA Approach: Feasibility and Effectiveness Evaluation

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Abstract: This study aims to evaluate the feasibility and effectiveness of a modified adaptive genetic algorithm (AGA) with Universal Distinct Element Code (UDEC) simulation in analyzing fracture surface feature points of an anticline rocky slope. Using coordinate data from 30 fracture surface feature points, the traditional GA and modified AGA methods were compared, with the mean value of the normalized Mahalanobis distance indicating the reliability of the results. The study found that the modified AGA approach with UDEC had a significantly smaller mean value of normalized Mahalanobis distance than the traditional GA approach, demonstrating its higher accuracy and reliability in analyzing the fracture surface feature points of the rocky slope. Additionally, the research found that the location of the fracture surface of the anticline rocky slope is closely related to the inhomogeneous bulk density caused by weathering. These findings contribute to sustainability efforts by improving our understanding of the behavior of rocky slopes, informing better land management and infrastructure planning, and reducing uncertainties in predicting the behavior of rocky slopes for more sustainable infrastructure development and land management practices.

Keywords: rocky slope; fracture surface feature points; rock mechanics; modified adaptive genetic algorithm (AGA); Universal Distinct Element Code (UDEC)



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1. Introduction

Predicting failure surfaces is a critical aspect of promoting sustainability in geological engineering projects, including houses, tunnels, and bridges. Failure surface prediction is also essential in rocky slope disaster warning systems, which can help prevent potential hazards and risks to human life and the environment. However, accurately predicting failure surfaces in natural settings can be a challenging task. Therefore, this study aims to provide a more accurate method for predicting the failure surfaces of rocky slopes in natural settings. The findings from this study can aid in the development of effective slope management and maintenance practices and contribute to promoting the sustainability of infrastructure projects. To achieve this goal, this study focuses on the diverse landscapes in southwestern China to understand how natural geography, humidity, earthquakes, and strong winds affect the overall stability of rocky slopes. A coupled approach is used to investigate the complex factors that contribute to failure surface prediction. This research aims to contribute to promoting sustainable land use practices in the region, reducing the risks of natural disasters, and protecting human lives and properties along the way. However, there are several challenges associated with analyzing and predicting fracture surfaces of materials. These challenges include obtaining a representative sample of the fracture surface, as it can be complex and contain multiple features such as secondary cracks, delaminations, and voids. Analytical methods can be destructive, making it difficult to analyze the same area multiple times. Some analytical techniques require specialized equipment

and expertise, which may not always be readily available. Finally, the interpretation of the results may be subjective and require skilled interpretation.

Goodman and Bray, as cited in Adhikary et al. and Hoek and Bray [1,2], conducted an extensive study on the formation and mechanism of damage in rocky slopes, classifying tipping damage into two categories: basic tipping types, such as bending tipping, rock mass tipping, and rock mass bending tipping, and secondary tipping types. Hocking and Huang [3,4] refined the damage mode of slopes using the kinematic principle without any slip forces. Liu and Chen [5] proposed a classification system that assessed the stability of rock slopes by considering geological, geometric, and environmental factors, which further improved the empirical method of the rock classification system (Raghuvanshi, 2019). The limit equilibrium method is widely used in slope stability analysis due to its easy calculation and simple principle, as cited in Ahmadi and Eslami, Hamza and Raghuvanshi, Huang, Janicak et al., Tang et al., and Yang and Zou [4,6–10]. However, the general research idea is to replace the natural slope's soil inhomogeneity with soil with average properties or consider the rock slope's inhomogeneity by separating different soils by depth. With the development of information technology, the combination of computationally large probabilistic methods and various specialized numerical software has inspired new ideas for exploring methods in rock slope stability analysis that are closer to real natural environments. Chowdhury et al. [11] further combined the probabilistic method to identify and evaluate the uncertainty among control parameters systematically. Tang et al. [9] used the S-curve model to define the spatially varying laminae of the shear strength parameters " c " and " ϕ " and the tensile strength of the rock mass to estimate the stability coefficients of inclined laminated rock masses and identify potential sliding surfaces. Alternatively, stability analysis considering weathering and the presence of natural pores inside rocky slopes has not been adequately concluded.

The traditional genetic algorithm (GA) is widely used for classical optimization problems that have complex solution spaces such as multimodal, multipeak, multiobjective planning, and dynamic planning (Refer to Figure 1 for a general graphical representation of the genetic algorithm's process). Although the GA has strong comprehensive solving abilities on multiobjective data features, it is not as effective as specialized solvers for optimization problems based on specific data sets [12]. Therefore, when using the GA to solve specific compound optimization problems, the computation mechanism of the GA can be adjusted appropriately to improve performance. For instance, Zhang and Tian [13] used the GA to optimize the initial weights and thresholds of the BP neural network to comprehensively evaluate the failure behavior of high-strength hydrogen transmission pipelines, residual strength, and the effects of interactions between adjacent corrosion. Shahrokhbadi et al. [14] combined the GA with the natural element method (NEM) to calculate the potential sliding surface of the slope and safety factor. In such applications [15,16], adding the GA significantly affects the computational time. However, combining multiple methods can reduce the computational cost to some extent.

There are also some better solutions to the issues of complexity, premature convergence, and stochastic roaming of the genetic operations of GA [18]. For example, the computational flow of the GA can be optimized based on graph theory [19], and Markov chain theory [20,21] can enhance the GA's ability to solve dynamic optimization problems. Additionally, Coelho [22] prevented the GA from converging to the local optimum prematurely using a new quantum behavior PSO (QPSO) with chaotic variational operators. However, despite these advancements, the GA method itself still faces issues, including the population generation pattern being too random and difficult to control, leading to suboptimal results.

Therefore, to improve the performance of predicting the fracture surface of nonhomogeneous anti-inclined rock slope, this paper optimizes the population generation mode based on the classical genetic algorithm (Figure 2 illustrates the article structure of this paper). Specifically, we enhance the initial population generation and selection mechanism of optimal individuals. The fracture model of a nonhomogeneous anti-inclined rock slope is

then constructed by considering the inhomogeneous distribution of bulk density combined with limit equilibrium theory. Finally, we use the improved adaptive genetic algorithm (AGA) to solve the failure surface.

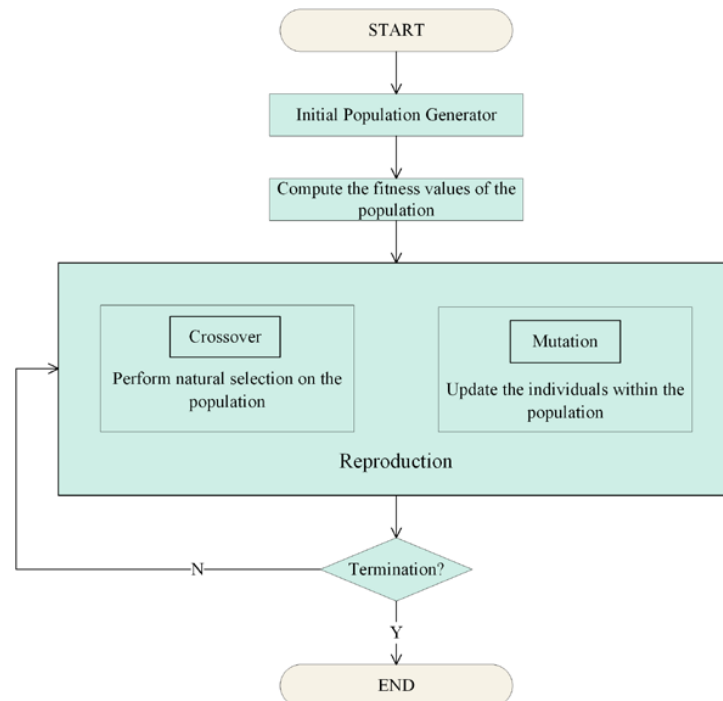


Figure 1. Standard genetic algorithm flow chart [17].

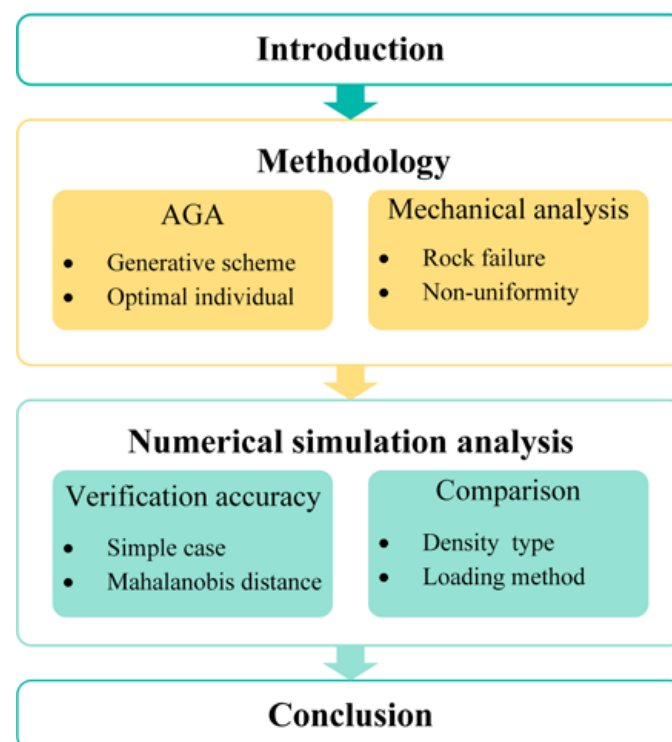


Figure 2. Structural block diagram of the proposed research.

2. Materials and Methods

Meta-heuristic algorithms have emerged as a means of improving computational efficiency and finding optimal solutions. One such algorithm, GA, is a classical meta-heuristic algorithm that has been widely used since its inception. However, when combined with the damage mechanism of the toppling rock slope, the classical GA faces two major shortcomings. Firstly, generating the initial population that satisfies multidimensional complex constraints requires multiple cycles. Secondly, the genetic operation operator of the classical GA is too simplistic, resulting in premature convergence and random roaming phenomena.

2.1. Modified AGA

Regarding the initial population cycle generation model of classical GA, a modified method can be used. First, a feasible initial solution A in the multidimensional complex constraints domain is found. In other words, an initial individual is generated that satisfies the constraints. A unit vector $d_i = (\cos d_i, \sin d_i)$ in random directions and a sufficiently large number M are defined and given so that the vector domain consisting of $|A + Md_i|$ can geometrically cover the entire feasible domain composed of constraints. For a specific direction d_i , if the numerical point of $|A + Md_i|$ is in the feasible domain, it is regarded as an individual in the initial population. If it does not satisfy the constraint, M is replaced by a random number $M_1 \in [0, M]$. If $|A + M_1d_i|$ still fails to meet the constraint, M_1 is replaced by another random number $M_2 \in [0, M_1]$ until the numerical point of $|A + M_2d_i|$ is in the feasible domain. By repeating the process n times, the initial population containing n individuals that meet the complex approximate conditions can be generated. This process can be described using Figure 3 and mathematical Equation (1) as follows:

$$\text{Feasible domain} = \sum_{i=1}^n |A + M_i d_i| \quad (1)$$

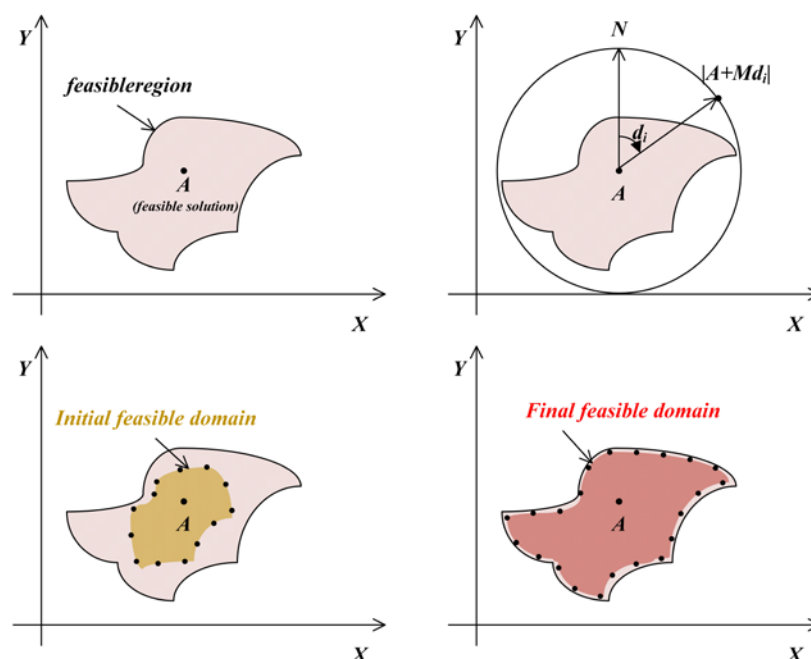


Figure 3. Schematic diagram of the initial population generation of the modified AGA algorithm.

Regarding the optimization strategy of the genetic operator, in addition to defining the crossover probability P_c and variation probability P_m , the partial taboo search algorithm's core idea is incorporated to optimize the optimal individual selection strategy, speeding up

the search. The relationship between changing values of P_c and P_m can be found in Figure 4.

$$\text{Crossover} : \begin{cases} V'_i = \alpha_c V_i + (1 - \alpha_c) V_j \\ V'_j = (1 - \alpha_c) V_i + \alpha_c V_j \end{cases} \quad (2)$$

$$\text{Variance} : \begin{cases} V_i = [x_{i,1}, x_{i,2}, \dots, x_{i,j}, \dots, x_{i,n}] \\ x'_{i,j} = x_{i,j} + \alpha_m (x_{i,jmax} - x_{i,jmin}) \\ V'_i = [x_{i,1}, x_{i,2}, \dots, x'_{i,j}, \dots, x_{i,n}] \end{cases} \quad (3)$$

where $x_{i,1}, x_{i,2}, \dots, x_{i,j}, \dots, x_{i,n}$ represents all of the genes of an individual; $x'_{i,j}$ represents a gene after mutation; and V'_i represents the new individual after mutation.

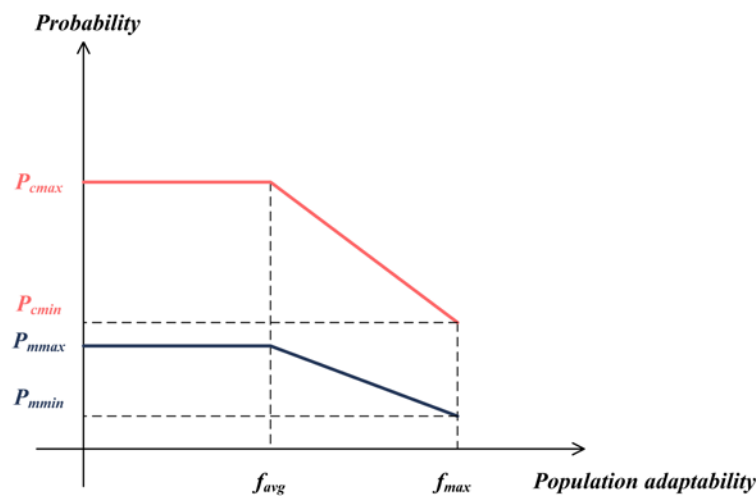


Figure 4. Variation and crossover probability of the AGA algorithm.

Defining the crossover probability P_c has the advantage of providing better control over the crossover rate of the population, thereby preventing premature convergence and stagnation. Additionally, the minimum crossover probability allows certain local optimal solutions to escape their domain interval and accelerate the global search process. The variance probability P_m is important in determining the behavior and performance of the genetic algorithm [23] as it directly impacts the convergence rate of the algorithm. If P_m is too large, the GA will resemble a random search algorithm, resulting in reduced search efficiency and a lower probability of finding the global optimal solution. Conversely, if P_m is too small, the genetic diversity of the population decreases, and the GA loses its fundamental characteristics. A visualization of this process can be found in Figure 5.

The optimal individual selection mechanism incorporates elements of the forbidden search algorithm strategy. First, a specific initial solution is identified to optimize the objective function. Second, the solution vector corresponding to the optimal value is used as the center of a circle, with the minimum distance value of each direction to the boundary of the solution space serving as the maximum radius. This circle represents the neighborhood of the solution $A(X_{1A}, Y_{1A})$. Third, when the current solution leaps from A to point B within the neighborhood, the direction value $dir(^{\circ})$ of the leap is recorded in the taboo table, and the interval of this direction is defined as the forbidden direction interval. Therefore, during the next iteration at point B , no further leaps along this direction interval are permitted.

Finally, the above improvement scheme is summarized, and the algorithm flow depicted in Figure 6 is used to code the program.

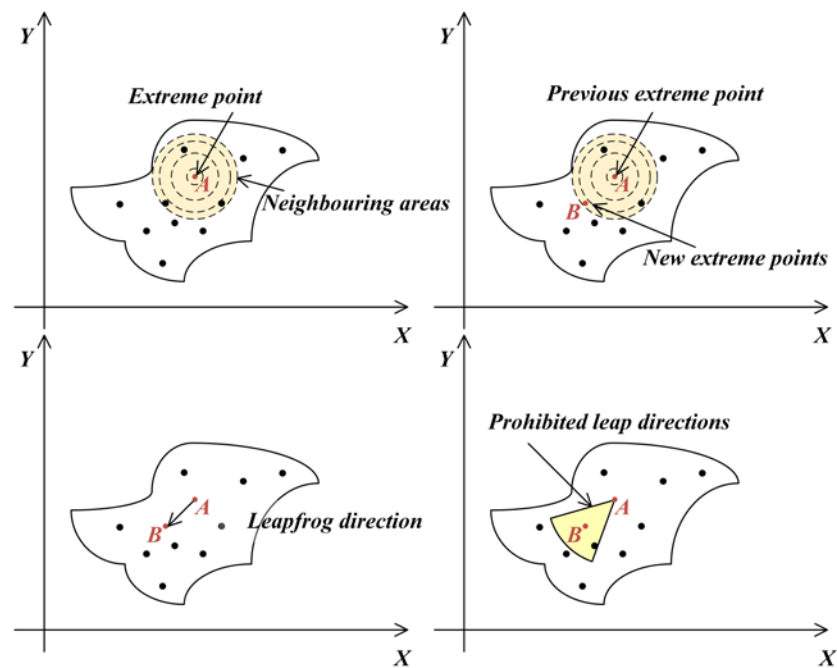


Figure 5. Schematic diagram of the optimal population generation model of the modified AGA.

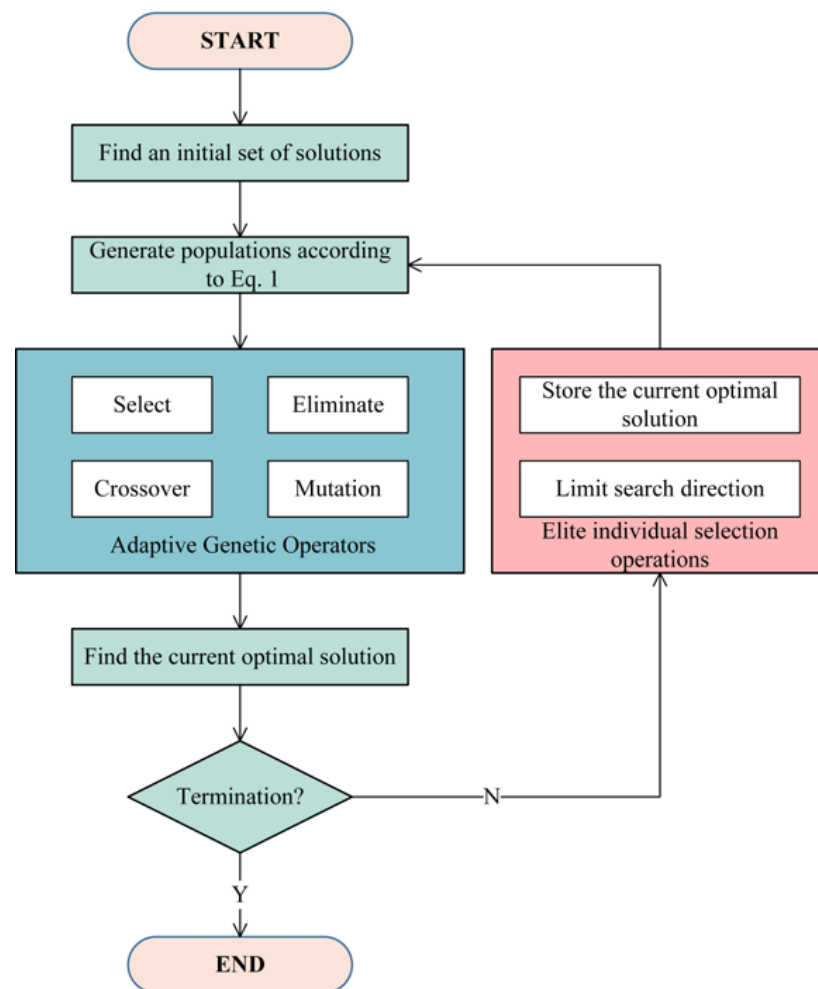


Figure 6. Schematic diagram of the adaptive genetic algorithm process.

2.2. Mechanical Analysis

Neglecting the influences of physical factors, such as groundwater and temperature, the overturning of the rock slope can be modeled as a series of elongated rock columns arranged discretely [2]. According to experimentally derived equilibrium theory [24–27], when a rock formation experiences bending or tipping, equilibrium is achieved at the interface between adjacent rock layers. From this, the normal force N_i and moment M_i between adjacent rock columns on the base, as well as the shear force Q_i in the direction perpendicular to the base, can be derived [28]. The force distribution of this can be found in Figure 7.

$$N_i = W_i \cos \beta + Q_i^l - Q_i^r \cong W_i \cos \beta \quad (4)$$

$$M_i = l_i P_i^l - r_i P_i^r - \frac{t_i}{2} (Q_i^l + Q_i^r) + \frac{h_i}{2} W_i \sin \beta \quad (5)$$

$$Q_i = P_i \tan \varphi_d \quad (6)$$

where φ_d denotes the friction angle of the rock mass.

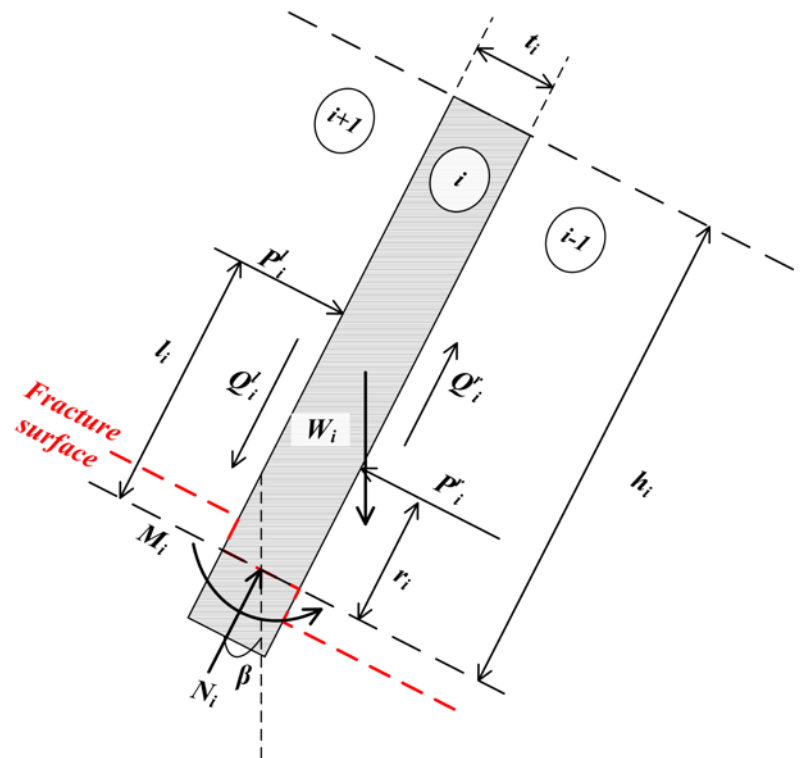


Figure 7. Schematic diagram of the force analysis of the rock column in layer i .

To assess the stability of a rock formation subject to bending or tipping damage, the safety factor F_s can be introduced. Utilizing the bending theory of cantilever beams, the maximum tensile stress σ_i^{max} at the bottom of the rock formation can be determined.

$$\sigma_i^{max} = \frac{M_i}{I_i} \frac{t_i}{2} - \frac{N_i}{t_i} = \frac{\sigma_t}{F_s} \left(I_i = \frac{t_i^3}{12} \right) \quad (7)$$

where I_i denotes the inertia modulus of the i^{th} layer and σ_t is the ultimate tensile stress of the rock material.

By combining Equations (4)–(7), we can determine the normal force $P_{i,w}^r$ acting on the right side of the rock formation when it undergoes bending and overturning.

$$P_{i,w}^r = \frac{P_i^l \left(l_i - \frac{t_i}{2} \tan \varphi_d \right) + W_i \left(\frac{h_i}{2} \sin \beta - \frac{t_i}{6} \cos \beta \right) - \frac{\sigma_i t_i^2}{6F_s}}{r_i + \frac{t_i}{2} \tan \varphi_d} \quad (8)$$

The shear force S_i acting parallel to the base on the rock formation can be calculated through force analysis when it is subjected to shear damage.

$$S_i = W_i \sin \beta + P_i^l - P_i^r \quad (9)$$

The principal stress $\sigma_{i,n}$ and tangential stress τ_i in the cross section can be calculated using the shear force S_i parallel to the base on the rock formation, as well as other relevant parameters.

$$\sigma_{i,n} = \frac{W_i \cos \beta}{t_i} \quad (10)$$

$$\tau_i = \frac{P_i^l - P_i^r + W_i \sin \beta}{t_i} \quad (11)$$

The instability of the rock formation occurs when the value of τ_i reaches the shear strength of the intact rock. By introducing the safety factor F_s , the critical value of τ_i can be obtained.

$$\tau_i = \sigma_{i,n} \frac{\tan \varphi_d}{F_s} + \frac{c}{F_s} \quad (12)$$

where c denotes the cohesion of the rock mass.

The normal force acting on the right side of the rock formation can be determined through relevant calculations and equations.

$$P_{i,s}^r = P_i^l + \left[W_i \sin \beta \left(1 - \frac{\tan \varphi_d}{F_s \tan \beta} \right) - \frac{ct_i}{F_s} \right] \quad (13)$$

Considering the thrust associated with the two damage modes, we use the expression $P_i^r = \max(P_{i,w}^r, P_{i,s}^r, 0)$ and make the following definition:

$$\begin{cases} P_i^r < 0 & \text{the slope is stable,} \\ P_i^r = 0 & \text{the slope is in limiting equilibrium,} \\ P_i^r > 0 & \text{the slope is unstable.} \end{cases}$$

The force acting on the next layer is $P_{i-1}^l = P_i^r$.

2.3. Introduction of Non-Uniformity

When considering the effects of weathering and erosion in a natural environment, the surface rock mass is vulnerable to damage and cracking, resulting in a lower bulk density compared to the deeply buried rock mass. Additionally, natural rock masses are typically characterized by the presence of pores, and the inhomogeneity of bulk density can be described through analogy with random field theory [10,27,29–33], where the spatial coordinate h represents the depth of the rock mass and the regionalization variable φ is defined as a function of $\varphi(h)$. Due to the impossibility of sampling and measuring everywhere in space, finite samples are used to generate regionalized variables. To characterize the inhomogeneity of bulk density at different depths of the rock formation, a model based on the exponential autocorrelation function in random fields [29,30] can be fitted to the data. A schematic of the heterogeneous rocks can be seen in Figure 8.

$$W_i = \int A_i h_i \varphi(h_i) dh_i \quad (14)$$

where $\varphi(h_i) = C_0 / (C_1 \ln h_i + C_2)$, C_0, C_1, C_2 can be fitted by experimental data, and A_i is the cross-sectional area of the rock column.

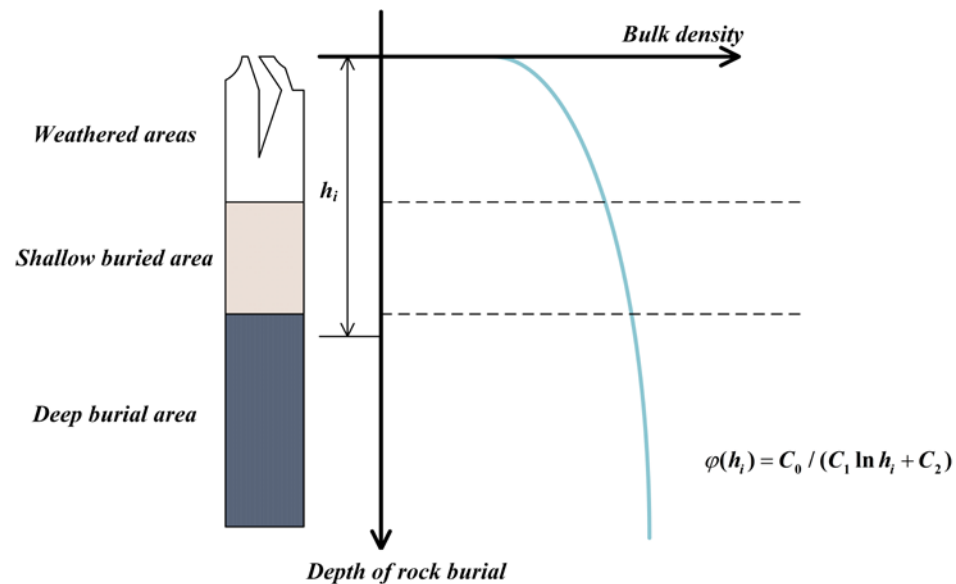


Figure 8. Consider a rocking body with an inhomogeneous bulk density.

In a two-dimensional plane, the rock body is treated as a unit area, and its gravity can be calculated using relevant equations and parameters:

$$W_i = \int t_i h_i \varphi(h_i) dh_i \quad (15)$$

where t_i is the width of the rock column.

The expression for the damage thrust of an inhomogeneous rock formation can be determined through relevant calculations and equations.

$$P_i^r = \begin{cases} \frac{P_i^l \left(l_i - \frac{t_i}{2} \tan \varphi_d \right) + \left(\frac{h_i}{2} \sin \beta - \frac{t_i}{6} \cos \beta \right) \int t_i h_i \varphi(h_i) dh_i - \frac{\sigma_t t_i^2}{6 F_s}}{P_i^l + \left[\sin \beta \left(1 - \frac{r_i + \frac{t_i}{2} \tan \varphi_d}{F_s \tan \beta} \right) \int t_i h_i \varphi(h_i) dh_i - \frac{c t_i}{F_s} \right]} \end{cases} \quad (16)$$

3. Results and Discussion

3.1. Verification of the Validity of the AGA Algorithm

In order to verify the accuracy of the algorithm, this paper conducted a verification using the rock slope data from the literature [28], as illustrated in Figure 9 and Table 1. To simplify the calculation process and focus solely on the correctness and robustness of the algorithm, this paper neglected physical factors such as temperature, groundwater effects, etc.

The Mahalanobis distance, which was proposed by the Indian statistician P. C. Mahalanobis [34], represents the covariance distance of the data and is an effective method for calculating the similarity of two unknown sample sets. In our study, we utilized this method to evaluate the accuracy of the AGA algorithm in predicting the fracture surface of a slope model. Specifically, we recorded the location coordinates of the experimental fracture surface and the fracture surface generated by the AGA algorithm and UDEC software using a right-angle coordinate system with the leftmost point at the bottom of the slope model as the origin. We then calculated the Mahalanobis distance between the experimental sample set and the numerical simulation sample set and subsequently normalized the results to analyze the approximation between the numerical simulation and experiment. Based on our numerical experiments, our results demonstrate that the AGA algorithm is able to accurately

predict the fracture surface of the slope model, thus highlighting its value and effectiveness for engineering applications. A detailed representation of the results can be found in Figure 10.

Table 1. Model parameters used in the verification cases.

Parameters	Values
Height of the slope, H (mm)	300
Angle of the slope, $\beta(^{\circ})$	61
Angle between the normal to the joints and the horizontal direction	10
Spacing of the joints, t_i (mm)	10
Cohesion of the intact rock, c (MPa)	1.4
Friction angle of the intact rock, $\varphi(^{\circ})$	37
Tensile strength of the intact rock, σ_t (MPa)	1.4
Unit weight of the intact rock, γ (kN/m ³)	2380
Cohesion of the joints, c_d (MPa)	0
Friction angle of the joints, $\varphi_d(^{\circ})$	26

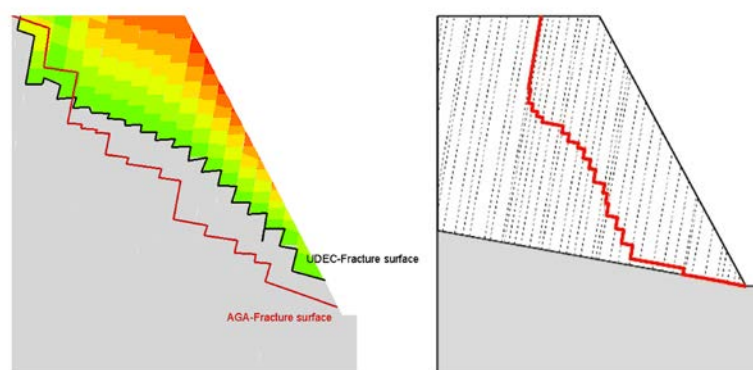


Figure 9. The comparison between the fracture surface results obtained from the Universal Distinct Element Code (UDEC) with the modified adaptive genetic algorithm (AGA) (**left**) and the genetic algorithm (GA) proposed by Zheng et al. [28] (**right**) highlights the superior performance and reliability of the modified AGA approach in analyzing fracture surface feature points of an anticline rocky slope.

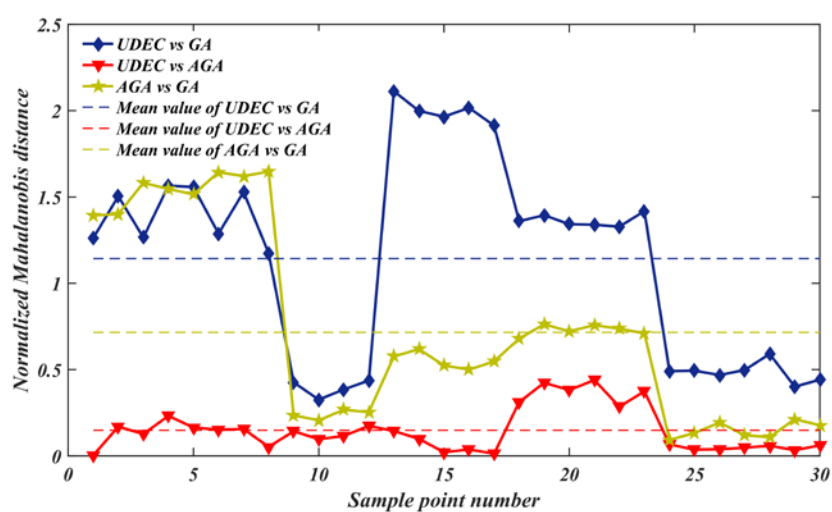


Figure 10. The Mahalanobis distance judgment of AGA, UDEC, and GA calculation results.

To evaluate the accuracy of the AGA algorithm in predicting the fracture surface of a slope model, we utilized a unified coordinate system to record the coordinate sets of fracture surface locations obtained by both the UDEC simulation and the AGA algorithm. We then compared these coordinate sets with the experimental data and calculated the results, as

shown in the figure above. The maximal normalized Mahalanobis distance between the modified AGA algorithm and UDEC simulation results was 0.47, while the minimum was 0.01. For the same 30 fracture surface feature point coordinates, the mean value of Mahalanobis distance between the modified AGA and UDEC simulation results was 6.68 times smaller than that between the traditional GA and UDEC. Moreover, compared with the simulation results of UDEC, the overall Mahalanobis distance fluctuation of the modified AGA was smaller than that of the traditional GA. The figure clearly indicates that the fracture surface solved by the modified AGA is more similar to that of the numerical simulation software, and the fluctuation of the difference value in each characteristic point is smaller, which verifies the effectiveness of the modified AGA algorithm. Overall, these results demonstrate the value and effectiveness of our algorithm in predicting the fracture surface of slope models, thereby providing a useful tool for engineering applications.

3.2. Multi-Dimensional Comparison of AGA and UDEC

The dynamic loading is modeled as a sinusoidal velocity with a frequency of 10 Hz, an amplitude of 2 m/s, and a duration of 0.1 s. To evaluate the response of the slope model to this dynamic loading, the velocities at the bottom and top boundaries were measured. The results, shown in the Figure 11 below, indicate that no waveform distortion occurred during propagation, suggesting that the cell size used was sufficiently small to accurately simulate wave dynamics at that frequency. Overall, these findings provide critical insight into the response of the slope model under dynamic loading conditions and highlight the importance of establishing appropriate numerical parameters to accurately capture the relevant physical phenomena.

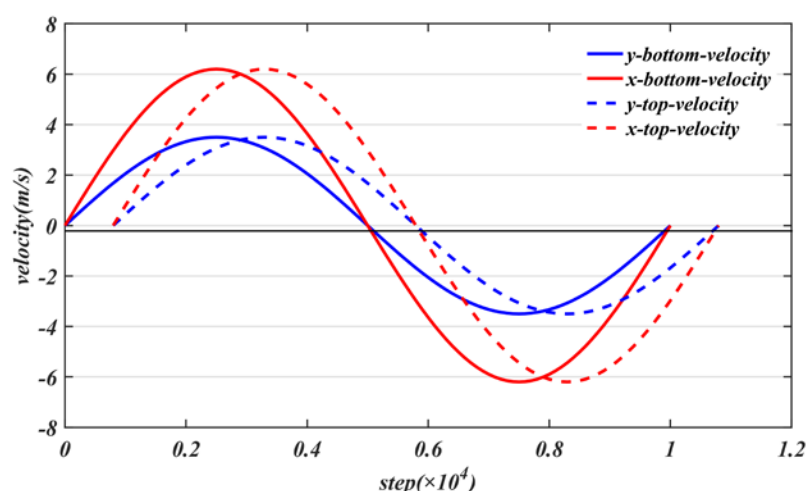


Figure 11. Velocity waveforms at the bottom and top boundaries of the slope.

The data analysis revealed a logarithmic bulk density random distribution chart, suggesting the presence of inhomogeneous bulk density and its relationship with the location of fracture surface feature points on the anticline rocky slope. Additionally, a logarithmic-type failure surface prediction diagram was developed using the modified adaptive genetic algorithm with Universal Distinct Element Code (UDEC) simulation as a reliable tool to predict potential failure surfaces of the slope. Furthermore, a random-type volume density distribution chart was analyzed, indicating the uneven distribution of volume density, which raises implications for slope stability and emphasizes the importance of accurate volume density measurement and analysis. Another random-type failure surface prediction diagram was developed using the modified adaptive genetic algorithm and UDEC simulation, providing a novel tool to predict and analyze potential failure surfaces of the slope. Moreover, in a comparison between the fracture surface calculations performed using the modified AGA and UDEC software under vibrational conditions for rock mass with nonuniform bulk density caused by pore presence, it was observed that the inhomogeneity of bulk density affects the shape of the fracture surface, highlighting

the importance of considering this factor in numerical simulations. Overall, the results underscore the effectiveness of the modified AGA algorithm in predicting fracture surfaces of rock formations under complex loading conditions and offer important insights into the internal mechanisms governing fracture propagation in porous rock masses.

Under vibration conditions, the fracture surface calculation results in the modified AGA and UDEC shown in Figure 12. The effects of the nonhomogeneous type of bulk density on the prediction of failure surface of rocky slopes are compared. For the case of exponential inhomogeneous distribution of volume density, the displacement calculated by UDEC presents obvious layering, and its fracture surface is approximately linear. In contrast, the fracture surface calculated by AGA closely fits the rock mass region with nearly constant density, exhibiting strong nonlinearity. Moreover, the development trend of the failure surface from the middle to the top of the slope is almost identical for both methods; however, the starting fracture position at the bottom of the slope is different. This is primarily due to the AGA algorithm being optimized by assigning equal weight to every individual in each iteration, resulting in conservative calculations of the fracture location for each rock column, thereby ensuring its stability even during individual stress analysis. As a result, the depth of the rock mass fracture position causing the slope stability tends to be deeper overall, closer to the rock mass region with nearly constant density.

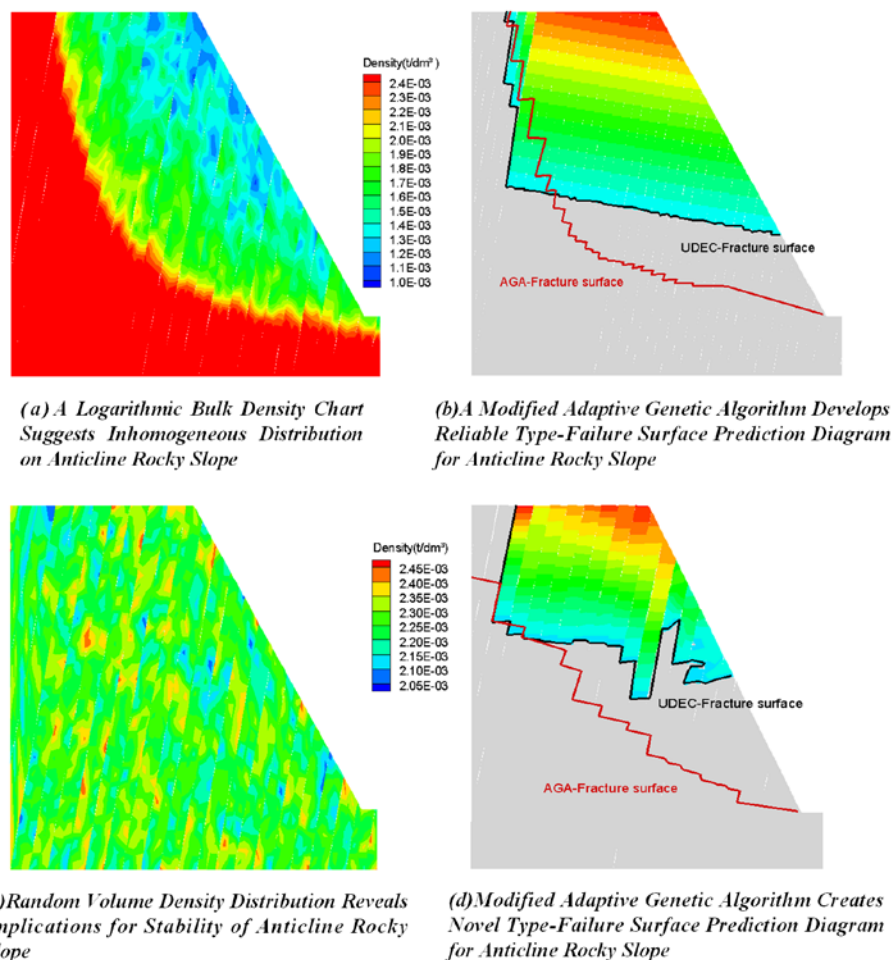


Figure 12. The effect of nonhomogeneous bulk density on the prediction of failure surfaces of rocky slopes.

Under the condition of random volume density distribution, irregular fracture surface shapes appear in the calculation results of UDEC. These mutations occur mainly in the areas where the volume density transitions are most uneven. Compared with the results of UDEC, the fracture surface calculated by AGA in this situation gradually extends in a

roughly linear trend, showing low similarity to the failure surface calculated by UDEC. The reason for this phenomenon is that the AGA algorithm uses the mean value theorem to replace this kind of local nonlinear mutation in the integral, while UDEC uses the method of discrete elements to solve the interaction between each element.

Based on the results obtained from the two scenarios, it can be inferred that the inhomogeneity of volume density resulting from the existence of pores in rock masses will affect the shape of the fracture surface. Meanwhile, the AGA algorithm exhibits stable results when calculating the fracture surface of the overturned rock slope and can provide a predictive result for the fracture surface incorporating the inhomogeneous distribution of volume density.

4. Conclusions

- The modified AGA-based scheme proposed in this study contributes to sustainability in geological engineering by providing a more reliable and accurate method of predicting fracture surface feature points of rocky slopes, which can lead to more effective and sustainable slope management and maintenance practices.
- Through a simple case study, the modified AGA approach with UDEC simulation was found to be 6.68 times more reliable than traditional GA methods, demonstrating the reliability of the calculation results and the feasibility of the modified AGA-based scheme, which can contribute to sustainable geological engineering practices.
- Through our study, we found that natural environmental factors such as weathering play a critical role in shaping the behavior of rocky slopes. Our findings provide valuable insights for understanding the behavior of rocky slopes that are significant in promoting sustainable land use practices and ensuring the safety of both human lives and infrastructure projects.
- We propose that the higher accuracy and reliability of the modified AGA approach can be widely applied to more complex rock structures, further advancing sustainable engineering practices. Future studies could explore the applicability of this approach to other types of rock structures and investigate its potential use in practical engineering scenarios, contributing further to sustainability in geological engineering.
- In conclusion, the study's findings and approach contribute significantly to promoting sustainability in geological engineering by enhancing our understanding of the behavior of rocky slopes and providing a reliable and accurate method of predicting fracture surface feature points. The application of this approach will play an essential role in designing sustainable and stable infrastructure projects, protecting human lives and properties, and preserving the environment for future generations.

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Conflicts of Interest: The authors declare no conflict of interest.

Nomenclature

Table of Letter Symbols used in the paper

$P F_i^r$	The custom right resultant force on rock failure (kN)	Q_i^l, Q_i^r	Shear force perpendicular to the fracture surface on both sides of the rock column (kN)
A	Initial solution vector of genetic algorithm	S_i	Shear force in the direction parallel to the rupture surface (kN)
A_i	Vertical profile area of the rock column (m ²)	t_i	The thickness of the rock pillars (m)
C_0, C_1, C_2	Parameters for the variation in bulk density of rocks with depth	V_i, V_j	Individuals without prior genetic manipulation
d_i	Unit direction vector	V_i', V_j'	An individual after genetic manipulation
dir	Vector azimuth from the current solution to the optimal solution (°)	W_i	The gravity of the rock column (kN)
f_{avg}	The average population adaptability	$x_{i,n}$	The inherited genes carried by an individual
f_{max}	The maximum population adaptability		Greek letters
h_i	Height of rock column above the fracture surface (m)	α_c, α_m	A random number between 0 and 1
i	Rock pillars numbered	β	The angle of slope of rock column (°)
I_i	Denotes the inertia modulus of the i^{th} layer (mm ⁴)	c	The cohesion of the rock mass (kPa)
l_i, r_i	Distance from the fracture face of the point of combined action of the left and right sides of the rock pillars (m)	σ_i^{max}	The maximum tensile stress of rock (MPa)
M_i	A random number used to control the variation in the solution vector	σ_t	The tensile strength of the intact rock (MPa)
M_i	The torque provided by the support	$\sigma_{i,n}$	The normal acting on the base of the layer (MPa)
N_i	The support provides a vertical bearing reaction	τ_i	The shear stresses acting on the base of the layer (MPa)
P_c	Crossover probability	φ_d	Friction Angle of rock (°)
P_{cmin}	The minimum crossover probability		Coordinate systems
P_{cmax}	The maximum crossover probability	$A(X_{1A}, Y_{1A})$	The two-dimensional coordinate representation of the current optimal solution
P_m	Variation probability	XOY	The global coordinate system in the outer ring center
P_{mmin}	The minimum variation probability		Abbreviations
P_{mmax}	The maximum variation probability	GA	Genetic algorithm
P_i^l, P_i^r	Combined forces on the left and right sides of the rock column (kN)	AGA	Adaptive genetic algorithm
$P_{i,w}^r$	The combined force acting on the right side of a rock formation when it bends and overturns (kN)	UDEC	Universal Distinct Element Code
$P_{i,s}^r$	The resultant force acting on the right side of the rock layer when a shear failure occurs (kN)		

Bolded letter symbols within the table signify vector quantities

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