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Research article

Determining optimal geo-trail using genetic algorithm (Case study: Damavand Mountain, Iran)

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Abstract: Geographic locations and geo-trails are often dispersed, and their accessibility is subject to rapid changes, which can have detrimental effects on the environment, tourism, and economy. Geo-trail planning faces challenges due to geographic dispersion and varying accessibility, impacting sustainable tourism, environmental conservation, and visitor safety. This study aimed to identify the optimal geo-trail route of 12 distinct geo-sites for climbers, eco-tourists, and general tourists in the Mount Damavand region, Iran. A genetic algorithm (GA) was used to solve this multi-objective geo-trail route optimization. The GA model adhered to route connectivity and non-repetition constraints through minimizing total distance, travel time, and cost while maximizing access to services and key attractions from the perspectives of tourists and eco-tourists. The model was implemented in MATLAB (population size: 50; iterations: 100; mutation probability: 0.5) and integrated with ArcGIS for spatial analysis. The GA algorithm converged to a stable solution with an objective function value of 4.718, improved from an initial average of 8.74. The optimal route spanned 105 km and 1033 minutes, connecting key sites including Emamzadeh (S6), Glacier (S10), and Ask (S12). The performance of the GA was benchmarked against three reference approaches: the nearest neighbor (NN) heuristic, a random search baseline, and ant colony optimization (ACO). While both GA and ACO vastly outperformed simple heuristics, the choice between them may depend on specific implementation constraints or desired solution characteristics (e.g., GA's ease of parallelization vs. ACO's faster initial convergence). The GA exhibited greater robustness, with a coefficient variation of 0.9% across runs versus 2.4% for ACO. This demonstrates the effectiveness of GAs in solving complex geotourism routing problems and provides a data-driven framework for sustainable trail planning. The proposed approach enhances visitor experience, supports intelligent tourism management, and minimizes environmental impacts, offering a scalable model for mountainous and ecologically sensitive regions.

Keywords: genetic algorithm; geotourism; geo-trail; Damavand Mountain; geo-trail optimization

1. Introduction

Geo-trails are interpretive, educational, and recreational journeys of geological significance to showcase local geological features, landscapes, and natural history. A geo-trail should contain services, scenic spots, visitor attractions, and cultural heritage, allowing visitors to explore and understand the Earth's history through landscapes, rocks, and landforms. Functionally, geo-trails connect dispersed geo-sites through interpretive signs that highlight significant landscapes and landforms and serve both educational and recreational purposes [1]. Nowadays, geo-trails have evolved into a vital component of the global tourism industry, significantly influencing travel destination choices [2,3]. Furthermore, geo-trails can enhance the development of new trail systems in natural areas by supporting more informed and sustainable decision-making [4,5].

Geo-trails can be categorized as either guided or unguided [6]. For unguided geo-trails, strategic signage is crucial for visitor orientation, education, and site management, while some trails incorporate fencing for safety and preservation (Figure 1) [7]. For example, expertly placed interpretive panels increased the value of dispersed geo-sites and reduced reliance on guides by creating thematic connections in the Trail of Time in Grand Canyon National Park, USA [8]. Despite this potential, many geo-trails are inadequate to synthesize educational content and tourism research. This limits their ability to engage the public, communicate geological information effectively, and attract visitors [9]. This underscores the necessity to optimize geo-trails across multiple dimensions, including time, cost, adaptability, and environmental sustainability. An effective geo-trail should deliver a coherent narrative through thematic design, augmented by multimedia tools (e.g., brochures, maps, interactive panels) and expert guidance, while ensuring year-round accessibility via multiple transportation modes [10].

Traditional methods like Dijkstra's algorithm or the least-cost path (common in GIS tools such as ArcGIS) work well for simple shortest-path problems on raster cost surfaces [11,12]. However, real-world geo-trail problems are often complex combinatorial optimization tasks with nonlinear constraints, multiple conflicting objectives, and very large search spaces (e.g., continuous coordinates or thousands of possible waypoints) [13–17]. Designing effective geo-trails requires a holistic approach of multi-objective optimization that integrates geomorphological, technical, economic, environmental, and social factors [18]. A primary challenge lies in navigating environmental constraints, such as avoiding sensitive areas, while balancing predefined points of interest, time, and cost to establish an optimal route due to the complex interplay of different factors and constraints [18]. Heuristic methods like genetic algorithms (GA) and ant colony optimization (ACO) excel here because they efficiently explore global solutions without needing derivatives or exhaustive enumeration. Therefore, advanced computational optimization tools, such as ACO, GA, graph neural network models, and the K-means algorithm, have been successfully applied to tourism route planning [18–22]. Among these, GAs, introduced by Holland and colleagues, are particularly well-suited for complex routing problems [23–25]. Chen et al. [19] proposed a disentangled graph neural network model for travel recommendations. They used three heterogeneous graphs to learn the relationships between destination, departure, and price. Their results show that disentangled representations of three factors could be extracted via contrastive learning. Damos et al. [21] proposed an improved version of the ACO algorithm to optimize tourism paths in the Jebel Marra region. Their results show an optimization time of 0 points and 27 s using the improved ACO, compared to 0 points and 45 s using GA, and 0 points and 40 s using ACO. In geospatial planning contexts (e.g., geo-trail optimization), GA has advantages in its global search, flexibility with GIS-derived fitness, and ability to handle multi-criteria constraints that make it a go-to choice over pure ACO (when speed matters) and vastly superior to K-means (which is not suited for path/sequence optimization). Due to GAs' robust search and optimization, GAs can adapt and navigate efficiently large solution spaces when an exhaustive search may be impractical [23,24]. Despite their proven efficacy, their performance depends greatly on careful parameterization and implementation. Thus, the application of such data-driven optimization methods to geo-trail planning remains limited in the Mount Damavand region of Iran. Consequently, managing the natural and heritage resources associated with trails often lacks a scientific, optimization-based approach for determining optimal routes.

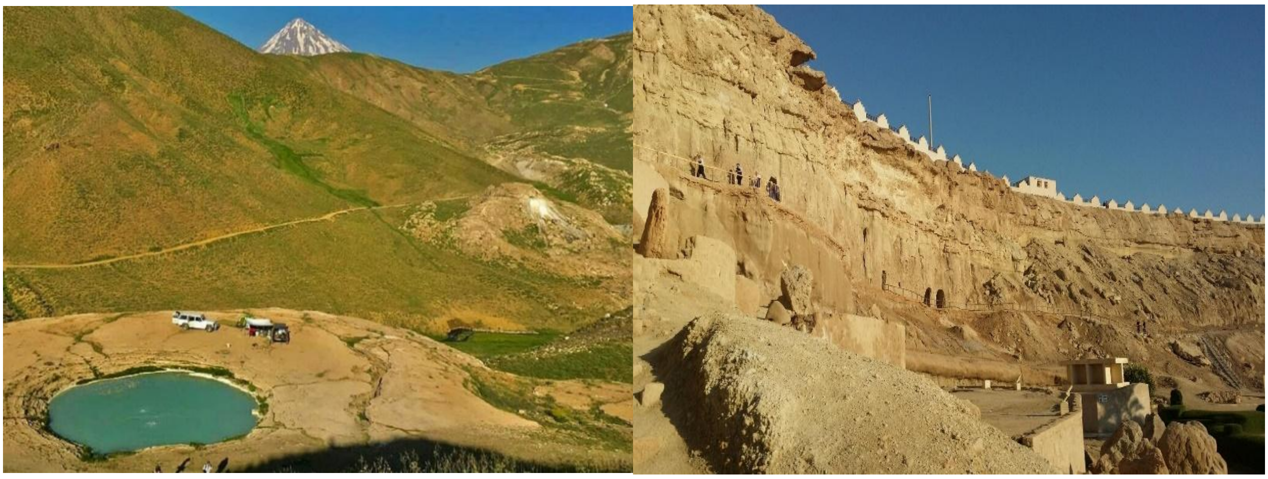


Figure 1. Two examples of geo-trails: (a) unprotected geo-trail featuring information boards on Mount Damavand, Iran (left); (b) protected geo-trail located within the Song Shan Global Geopark on Qeshm Island, Iran (right) [7].

The primary objective of this study is to develop a GA-based optimization framework to optimize the geo-trail route that links significant geological, natural, heritage, and cultural sites in the Mount Damavand region of Iran. Optimal geo-trail routes will minimize cost, distance, and travel time for diverse users while maximizing accessibility to welfare services and site attractiveness for a network of 12 key geo-sites. The second objective is to design a quantitative composite objective function that integrates conflicting economic criteria (cost, time, distance) with qualitative ones (access to services, geomorphological attractiveness) into a single model in a sensitive and complex region such as Mount Damavand. Furthermore, this study directly integrates GIS spatial analyses into the optimization process, thereby bridging the gap between theoretical modeling and real-world spatial and practical constraints. The final output is not only a theoretical optimal path but also an actionable and sustainable pathway proposal that simultaneously advances the goals of environmental conservation, tourist satisfaction, and economic efficiency. This will cater to the needs of climbers, eco-tourists, and general tourists, and support local economic development. It thus serves as a scalable and generalizable methodological template for similar mountainous regions worldwide.

2. Materials and methods

2.1. Study area

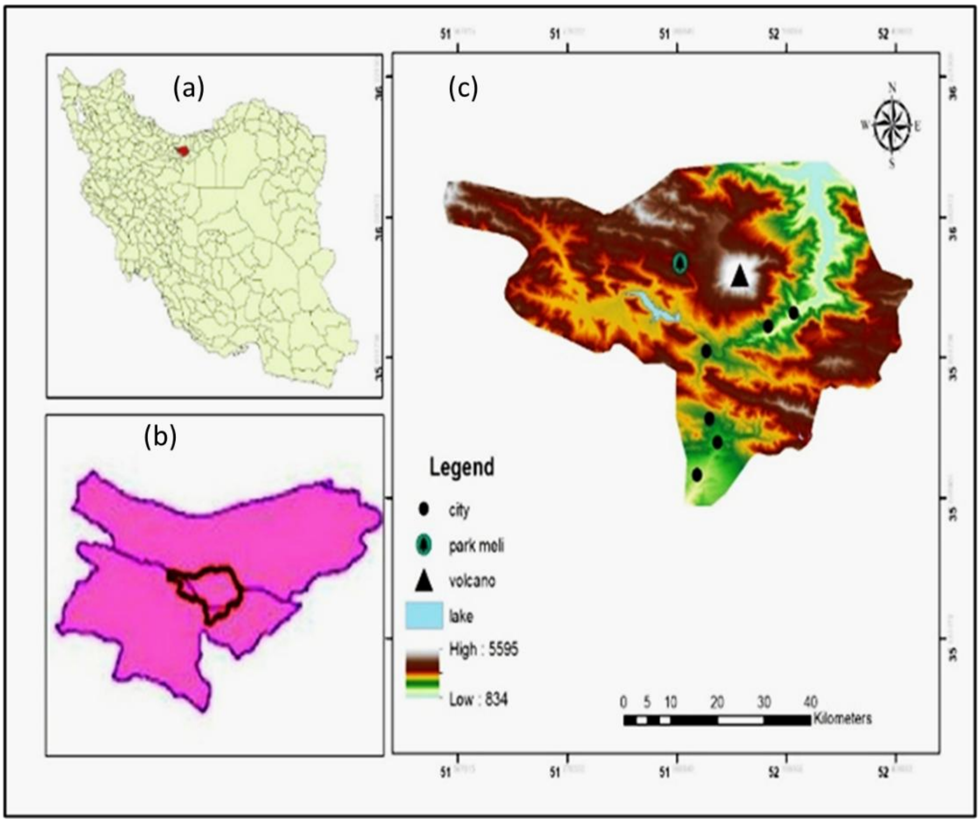


Figure 2. The study area and location: (a) Iran, (b) Mazandaran province, and (c) Damavand Geopark.

Iran exhibits exceptional biodiversity and varied landscapes. Within Iran, the Mazandaran province stands out as a region of significant geological and biological richness. The Damavand Geopark is situated within this province and represents an area of notable scientific and environmental value (Figure 2). Geographically, the study area lies between longitudes 51°59'E and 52°16'E and latitudes 35°49'N and 36°5'N. It encompasses three cities and 46 villages, with a total population of 47,102 inhabitants, of whom 8865 reside in rural areas and 38,237 in urban areas. The remarkable geological diversity and biodiversity are characterized by significantly different adjacent units. This morphological and biological diversity is influenced by climatic factors, lithological characteristics, erosion, weathering, and tectonic activity. The region is characterized by a cold, humid climate. The landforms and geomorphological processes have predominantly been influenced by Mount Damavand, the highest peak in Iran and the Middle East, with an elevation of 5610 meters. There are noteworthy mountain glaciers at this relatively arid latitude. Biogeographically, the region supports a diverse array of rare plant and animal species; specifically, 450 rare plant species and 150 animal species [7]. The proposed route encompasses 12 geo-sites, each distinguished by unique attractions and specifications (Table 1). Table 1 illustrates the characteristics of the highland region, the nature of the operations, and the considerable distances, including significant sites for tourists and geo-tourists in climbing activities. Moreover, the lithology of the significant routes pertains to the Quaternary period, providing evidence of the youth and dynamic geological processes of the region.

Table 1. Specifications of proposed routes in the study area.

No	Geomorphosite	Route type	Route duration (min)	Path length (km)	Activity	Location	Lithology/geological/ historical age
1	Polur & lar	Blacktop	60	17	Walking and mountain	Mountainous	Quaternary\Alluvial
2	Lar & vararod	Dirt-road and blacktop	30	10	Traveling in mountain	Mountainous	Jurassic/Limestone
3	Ask-polur	Dirt-road and blacktop	20	12	Walking and mountain	Mountainous	Jurassic/Limestone
4	Volcano-Ask	Stony road	1080	20	Traveling in mountain	Mountainous	Quaternary/Trachyandesitic
5	Volcano-Larijan	Dirt-road and blacktop	1200	30	Traveling in mountain	Mountainous	Quaternary/ Limestone
6	Vararod-Volcano	Dirt-road and blacktop	600	8	Traveling in mountain	Mountainous	Jurassic/Limestone
7	Polur-Emamzadeh	Blacktop	25	8	Traveling in mountain	Mountainous	Jurassic/Shale/sandstone and coal
8	Ab-Ali-Emamzadeh	Blacktop	40	6	Walking	Rural	Eocene/Shale
9	Mosha-Emamzadeh	Dirt-road	30	4	Walking	Rural	Cenozoic/Tufted Green
10	Mosha-Ab-Ali	Blacktop	20	5	Walking	Rural	Quaternary/Alluvial New Territories
11	Mosha- Ala spa	Blacktop	20	7	Walking	Rural	Carboniferous/Limestone
12	Shebli tower-Ala spa	Blacktop	30	6	Walking	Urban	Quaternary/Trachyandesites

2.2. Genetic algorithm and optimization

The lowest cost, shortest distance, shortest time, and maximum services show the greatest appeal from the perspective of tourists and ecotourists. The research adopted a seven-stage methodology. Figure 3 illustrates the performance of the genetic algorithm in terms of selection, crossover (mating), mutation, and population replacement [23–26].

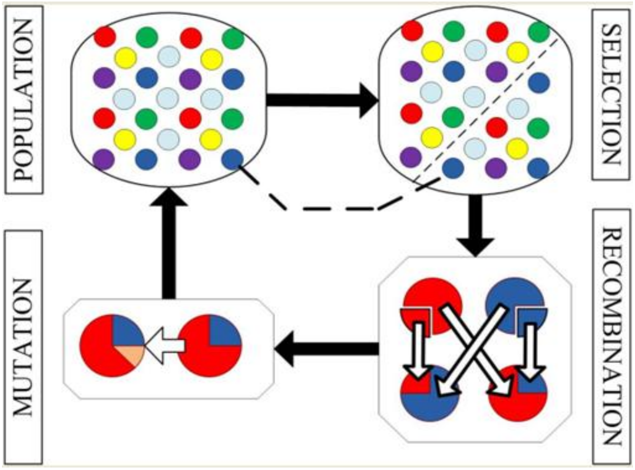


Figure 3. The genetic algorithm incorporates the primary operators Population, Selection, Crossover, and Mutation.

This study assesses an objective function aimed at minimizing the overall cost associated with the geo-trail. The objective function integrates various criteria and constraints. In instances where the objective function encompasses design constraints—an occurrence that is not uncommon—a penalty function may be employed to address violations of these constraints (e.g., connectivity and access restrictions). The objective function is subsequently multiplied by the penalty function, which assumes a value of one in cases where no constraints are violated. A principal constraint is that the same path segment cannot be traversed more than once. Additionally, direct connections between certain geo-sites (nodes) may be infeasible; for instance, traveling directly from geo-site 4 to geo-site 8 may not be possible. For the network of 12 geo-sites, the site series can be expressed by an array.

$$S_i=\{1,2,3,\ldots\ldots,12\} \tag{1}$$

The multi-objective optimization problem of geo-trail paths is scalarized into a single composite objective function using the weighted sum method as follows [23,24]:

$$F(\mathbf{x}) = Min\{W_1K_1F_1 + W_2K_2F_2 + W_3K_3F_3 - W_4K_4F_4 - W_5K_5F_5\} \tag{2}$$

Where F_1, F_2, and F_3 are the total length of the route, time, and cost, respectively. F_4 and F_5 are the total welfare services and geo-site attraction score, respectively. W_i is the weight at the i^{th} factor. K_i is the correction coefficient at the i^{th} factor.

The welfare services component (F_4) is quantified as the cumulative count of discrete service facilities accessible along the route. Each geo-site contributes to F_4, based on the number of distinct facility types within a 500-m buffer of the trail, including: (i) basic amenities (potable water points, restrooms, shelters), (ii) safety infrastructure (first-aid stations, ranger posts, emergency call points), and (iii) informational resources (visitor centers, interpretive signage, guide stations). For example, a geo-site equipped with a shelter, water source, and information board contributes three units to F_4. The geo-site attraction score (F_5) represents the aggregated scientific and experiential value of the selected sites. Each geo-site is pre-evaluated using a multi-attribute scoring framework (scale 0–1 per attribute) across four dimensions: geomorphological uniqueness, scenic/aesthetic quality, recreational potential, and cultural significance. The total F_5 for a route equals the sum of individual geo-site scores included in that route.

2.3. Model implementation

The stages for executing the genetic algorithm in MATLAB software can be delineated as follows:

Stage 1: Manufacturing a random initial population

The initial stage involved integer encoding utilizing a permutation-based substitution method, which was essential due to the inherent characteristics of the problem, wherein the permutation of each gene alters with each iteration. An initial population comprising 50 chromosomes, each containing 12 genes, was established (see Figure 4). The preliminary stage in implementing the genetic algorithm was the generation of this initial population. This process was executed in MATLAB through the use of the random function.

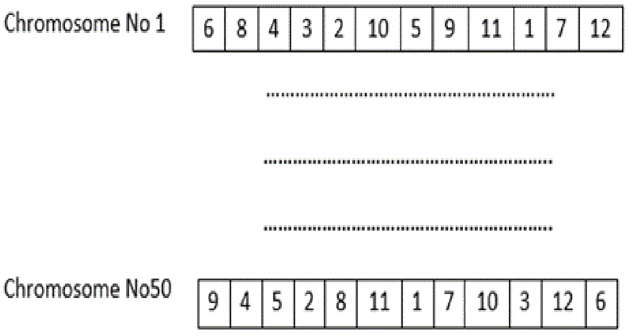


Figure 4. Primary population generation and chromosomes.

Stage 2: Competency assessment solutions (chromosomes)

Chromosomes were chosen for reproduction based on their fitness scores. The objective function was assessed for each of the 50 chromosomes. Higher-fitness chromosomes exhibited a greater likelihood of being selected multiple times for reproduction, while lower-fitness chromosomes were less likely to be chosen. The objective function, which included trail length, was fundamental in determining the fitness scores.

Stage 3: Excluding chromosomal count as a parental factor

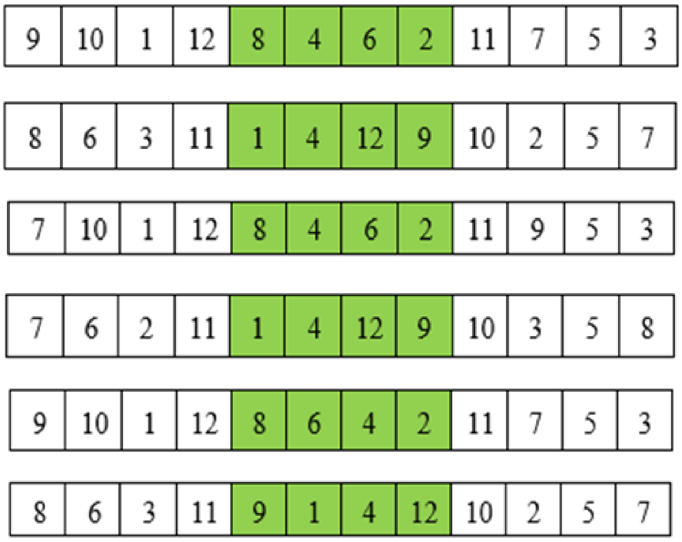
In general, it is anticipated that each successive generation will demonstrate improvements over its predecessor. Researchers must utilize chromosomes with superior present properties to enhance the probability of successful integration into the graft. Consequently, scientists are developing mechanisms to select the most promising chromosomes for merging (co-ownership) within the graft.

In this study, 50 initial populations were evaluated using this suitability function. Five chromosomes were identified as the most elite selection. These five chromosomes exhibit minimal error and effectively minimize the target function, thereby facilitating the opting-out process.

Stage 4: Executing the combination operation (crossover) and generating offspring

Merging involves the combination of two parental chromosomes to generate two new offspring chromosomes, which exhibit the genetic characteristics of the parents. To produce each offspring, two parents are initially selected randomly from the available samples. Given the nature of the research problem, which pertains to permutations, traditional methods of chromosome merging are not applicable. Instead, a technique known as sequential combination, tailored specifically for permutations, should be employed.

As illustrated in Figure 5, two random breakpoints are identified among the gene pool. Subsequently, similar to the second method, genes positioned before and after the breakpoint region (as demonstrated in offspring 1 and 2) or the genes within the broken segment (as shown in offspring 3 and 4) are transferred from the two parent chromosomes. The distinction lies in the procedure, whereby, upon copying genes from the first parent into the first offspring, the genes from the second parent must be arranged in the first offspring in the same order as they appear in the second parent [24].



9	10	1	12	8	4	6	2	11	7	5	3
8	6	3	11	1	4	12	9	10	2	5	7
7	10	1	12	8	4	6	2	11	9	5	3
7	6	2	11	1	4	12	9	10	3	5	8
9	10	1	12	8	6	4	2	11	7	5	3
8	6	3	11	9	1	4	12	10	2	5	7

Figure 5. Ordinal crossover operator

The value of P_C, or the probability of crossover, in this study, is represented by Equation 3:

$$P_c = \frac{The\ value\ of\ Choromosom\ \ in\ Crossover}{Total\ population} = \frac{45}{50} = 0.9 \tag{3}$$

Stage 5: Mutation

Following crossover, the mutation operator is applied to offspring chromosomes with a mutation probability of $P_m = 0.5$ to maintain population diversity and prevent premature convergence. Given the permutation-based encoding, each chromosome represents a unique sequence of geo-sites. The swap mutation operator is employed to randomly select two distinct positions within a chromosome and exchange the geo-site identifiers at these positions, thereby preserving the validity of the permutation. This facilitates an effective search that ensures that each geo-site is visited exactly once while introducing localized structural variations. For instance, applying a swap mutation to the chromosome [S1, S3, S12, S4] by selecting positions 2 and 4 yields the mutated chromosome [S1, S4, S12, S3].

The algorithm's parameters were selected, based on established practices, for combinatorial routing problems and preliminary computational experiments. The population size of $N = 50$ balances genetic diversity and computational efficiency for the 12-node solution space. The relatively high mutation rate ($P_m = 0.5$) was deliberately adopted after sensitivity analysis confirmed its effectiveness in sustaining search diversity throughout the optimization process for this compact problem instance, without compromising convergence stability. This value aligns with documented practices for swap mutation in permutation-based encodings requiring robust exploration pressure. The result of the mutation is demonstrated in Table 2.

Table 2. Results of the mutation operator.

Based on changes P_m	Value of the target function
0.01	9.845
0.02	8.712
0.05	6.683
0.1	5.432
0.2	5.023
0.5	4.718
0.01	9.845

Stage 6: Placement

A. Generational replacement: The entire next generation is comprised exclusively of the offspring.

B. Steady-state replacement: The population size in the subsequent generation is maintained at the same level as that of the previous generation. The remaining individuals are selected from the newly generated offspring.

Stage 7: An examination of stop conditions

A. Predefined runtime: The algorithm operates for a predetermined duration.

B. Fitness threshold: The algorithm terminates when the fitness of the best solution in a generation surpasses a predefined threshold.

C. Fitness stagnation: The algorithm ceases operation when the average fitness of the population demonstrates no significant improvement over a specified number of generations.

In this study, we employ the third method for the termination of the genetic algorithm, as it is observed that the average fitness of the population reached a state of stagnation, indicating that no further improvement was achievable over a series of generations. Numerous parameters within genetic algorithms are grounded in mathematical principles and have been adapted from solutions to computer network routing issues. The fundamental concept of genetic algorithms is derived from Darwin's theory of evolution and operates according to the principles of natural genetics [23].

2.4. Model parameters and sensitivity analysis

The goal is to minimize distance, time, and cost and maximize welfare services and geomorphological site value. To address a problem, the genetic algorithm is utilized to establish two key recommendations. The first recommendation pertains to formulating a problem statement that articulates a feasible solution, while the second recommendation involves the development of criteria for assessment. To achieve the desired objective function, all stages of the genetic algorithm's implementation in MATLAB had to be completed. Ultimately, multiple parameters were attained as a result of this process. The implementation of a penalty function ensures that infeasible solutions are systematically penalized, guiding the search process toward practical and implementable routes. The objective function is designed to accumulate various data properties that effectively demonstrate the measurement trajectory.

Whereas the objective of the geo-trail was to minimize the impact of various factors, it is essential to define existing parameters that are incorporated into the objective function, as presented in Table 3. The mathematical formulas provided in Table 3 describe how these values were theoretically computed from raw data. In the objective function, F_1, F_2, and F_3 have a positive sign, while F_4 and F_5 have a negative sign. All weight coefficients (W_i) in this model are set to 1. This indicates that the relative importance of each criterion is solely controlled by its correction factor (K_i).

Role of correction coefficient (K_i): The coefficient K_i is a dimensional normalization and scale adjustment. The constituent criteria are measured in inherently different units (kilometers, minutes, monetary units, counts, and dimensionless scores). Normalized K_i enables their direct summation and prevents any single criterion from dominating the objective function. For minimization criteria (F_1, F_2, F_3), the coefficient K_i is defined as the inverse of a plausible maximum value for that criterion within the network (e.g., K_1 = 1/max estimated route distance). For maximization criteria (F_4, F_5), the coefficients K_4 and K_5 are similarly set to normalize the welfare service count and site attraction score to a commensurable scale, often by dividing by their maximum attainable values in the network. This process renders all terms dimensionless and is numerically comparable on a commensurate scale.

Rationale for initial weight assignment (W_i): In this foundational model, all priority weights (W_1 to W_5) are initially set to 1.0. This establishes a neutral "non-preference" baseline, assigning equal relative importance to each of the five normalized criteria. This approach is a standard practice in preliminary multi-objective optimization, as it avoids introducing a priori bias without empirical justification from stakeholder surveys (e.g., using methods like the analytic hierarchy process). It allows the model to reveal the inherent trade-offs and synergies between the objectives based solely on the network's structure and site attributes.

All GA parameters were calibrated through preliminary experiments and aligned with established practices for combinatorial routing optimization. Population size (50) and iteration count (100) were determined via convergence analysis to balance solution quality and computational efficiency. Elitism selection with five preserved parents (10% of the population) maintains solution stability while encouraging diversity. The two-point sequential crossover operator was selected for its compatibility with permutation encoding of routes, and a high crossover probability (0.9) promotes exploration. Dual mutation operators (swap and shift) with probability 0.5 provide complementary local and structural search capabilities, critical for navigating the complex solution space of multi-objective geo-trail routing. Table 4 presents the final parameters and their respective quantities utilized in this algorithm.

Table 3. Objective function parameters and factors.

F	Effective factors in choosing the path	The value of the function	Weight coefficients (W)	Value	Correction factor (K)	value
F_1	Total length of the route	$\sum_{i=1}^{11} L_i , i+1$	W_1	1	K_1	0.01
F_2	Total route time	$\sum_{i=1}^{11} T_{i,i+1}$	W_2	1	K_2	0.001
F_3	Total route cost	$\sum_{i=1}^{11} C_{i,i+1}$	W_3	1	K_3	0.000005
F_4	Total welfare services	$\sum_{i=1}^{11}(Max\ F - F_{i,i+1})$	W_4	1	K_4	0.02
F_5	Geomorphosite total path	$\sum_{i=1}^{11}(Max\ G - G_{i,i+1})$	W_5	1	K_5	0.2

Table 4. Final parameters of the genetic algorithm control.

Parameter	Range	Value/specification	Rationale
Iterations (generations)	50–200	100	Ensures convergence without computational waste [27]
Population size	30–100	50	Balances diversity and efficiency [28]
Elite parents		5	Maintain top solutions (10% of population) [29]
Selection strategy		Elitism	Preserves best solutions across generations [30]
Crossover operator		Two-point sequential	Maintain route continuity in permutations [31]
Crossover probability	0.7–0.95	0.90	Promotes exploration [32]
Swap mutation		Swap	Enables local and structural search [33]
Mutation probability	0.3–0.7	0.50	Sustains diversity in discrete search space [34]

3. Results and discussion

3.1. GA benchmark against other optimization methods

To rigorously assess the efficacy of the proposed GA, its performance was benchmarked against three reference approaches: (i) the nearest neighbor (NN) heuristic, a greedy constructive method that sequentially visits the closest unvisited geo-site; (ii) a random search baseline, represented by the average objective value across 10,000 randomly generated valid routes; and (iii) ACO, implemented with standard parameters ($\alpha = 1$, $\beta = 2$, $\rho = 0.5$) as a representative bio-inspired metaheuristic. These algorithms are recognized for their capabilities in solving complex problems, particularly in the context of planning tourist routes. While GA and ACO are not directly classified under AI, they are employed as computational optimization techniques and can be effectively combined with AI methods to address routing challenges. Through the application of these approaches, this study aims to analyze and identify optimal tourist routes around Mount Damavand, striving to reduce costs, distance, and time while simultaneously enhancing the attractiveness and services of tourism.

All methods were evaluated on the same 12 geo-sites in Damavand using five metrics: (1) final objective function value $F(x)$, (2) total distance (F_1), (3) total time (F_2), (4) total cost (F_3), and (5) composite service and attraction score ($F_4 + F_5$). Each algorithm was executed independently 30 times to ensure statistical robustness. All values for stochastic methods represent mean ± standard deviation over 30 independent runs. The composite objective function $F(\mathrm{x})$ integrates normalized and weighted components F_1 to F_5 as defined in Equation (4).

Table 5. Comparative performance of optimization methods for the Damavand geo-trail routing problem (minimization objective; lower values indicate better performance).

Method	Final\(F(x)\)	Distance (km)\(F_1\)	Time (min)\(F_2\)	Cost (USD) \(F_3\)	Services \(F_4\)	Attraction \(F_5\)	Iterations to 5% convergence	Std. Dev. of \(F(x)\)
GA (proposed)	4.718	105.2 ± 2.1	1033 ± 18	842 ± 15	35	4.0	47.3 ± 3.2	0.041
ACO	5.212	112.6 ± 3.8	1105 ± 29	897 ± 24	33	4.0	61.1 ± 5.7	0.124
Nearest neighbor†	7.841	128.0	1250	1025	28	3.0	—	—
Random (avg. of 10,000)	10.554 ± 1.87	152.3 ± 14.9	1482 ± 118	1248 ± 96	22.1 ± 3.8	2.3 ± 0.7	—	1.87

† Nearest neighbor is a deterministic constructive heuristic and does not involve an iterative convergence process.

Results demonstrate that the GA consistently outperformed all benchmarks with the smallest $F(\mathrm{x})$ of 4.718 (Table 5). It achieved a 22.7% improvement in $F(x)$ over the NN heuristic, and a 38.4% improvement over the random baseline. Compared to ACO, the GA yielded a marginally superior solution [1.8% higher $F(x)$] while converging 23% faster to a solution within 5% of the final optimum (mean of 47 vs. 61 iterations). Furthermore, the GA exhibited greater robustness, with a coefficient of variation of 0.9% across runs versus 2.4% for ACO. While both GA and ACO vastly outperform simple heuristics, the choice between them may depend on specific implementation constraints or desired solution characteristics (e.g., GA's ease of parallelization vs. ACO's faster initial convergence). These findings confirm that the GA delivers high-quality routes, computational efficiency, and solution stability for this geo-trail routing problem. Damos et al. [21] compared GA and ACO and showed that ACO is slightly better than GA. Therefore, more comparisons should be performed between the two algorithms.

3.2. Optimal geo-trail

The genetic algorithm was implemented in MATLAB with a population size of 50; after 100 iterations, the function converged to a stable solution. Figure 6 shows the convergence curve that confirms algorithmic stability, with the objective function plateauing after ~50 iterations when P_m = 0.5. This validated the chosen termination criteria.

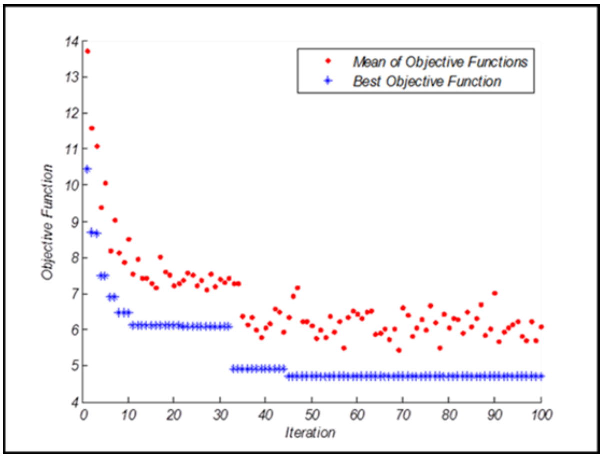


Figure 6. The final target objective function and convergence with a population size of 50 and a repetition count of 100 at $P_m = 0.5$.

Table 6. Suggested approach for implementing the genetic algorithm.

Geomorphosite	Path	Categorizes trails	Geomorphosite	Path	Categorizes trails
Lar	S8	Class3	Emamzadeh	S6	Class1
Vararod	S9	Class1	Ab-Ali	S5	Class3
Glacier	S10	Class1	Mosha	S4	Class2
Larijan	S11	Class3	Ala	S3	Class2
Polur	S7	Class4	Shebli tower	S1	Class2
Ask	S12	Class4	mosque	S2	Class2

Table 7. Algorithm population based on varying repetitions.

Objective function	Algorithm population based on different repetitions
8.74	5
6.72	10
5.14	15
4.92	25
4.778	50
4.718	100

The optimal trial is presented in Table 6. The initial trial consists of the 12 geographical sites. The routes were categorized into four distinct classes: 1) mountain trails; 2) trails suitable for both pedestrian and vehicular use; 3) rocky and hiking trails; and 4) trails that encompass both carriageways and mountainous pathways. The completion of the trial involves the selection of a second geographical site without repetition. This selection adheres to the conditions established at the outset of the objective function. To enhance this outcome, the algorithm was executed for a total of 100 iterations (see Table 7). The initial five iterations produced a relatively high average objective function value of approximately 8.74. Table 7 provides a detailed account of the algorithm's population size for each iteration. The plateauing of the objective function in subsequent iterations suggests that the algorithm converged to a stable solution of 4.718, thereby confirming the appropriateness of the termination condition. The effectiveness of the genetic algorithm is demonstrated through its ability to handle a complex, nonlinear, and constrained optimization problem efficiently.

Figure 7 illustrates the spatial distribution of geo-sites and the proposed geo-trail network in the Mount Damavand region. The color gradient of a digital elevation model (DEM) represents terrain elevation, ranging from low (green) to high (red). Twelve key geomorphosite locations (S1–S12) are marked as black dots, including the notable sites S10 (Glacier), S8 (Lake), and S9 (Park Meli). Blue triangles indicate information centers, while the black triangle denotes a volcanic feature. Dashed lines represent existing or proposed trail segments connecting the geo-sites. The figure illustrates a clear and logical relationship between the number of iterations and the objective function value, indicating a systematic reduction in the objective function. Red dots represent the average objective function value, while blue dots signify the best objective function value recorded across each iteration. The final path sequence starts from S6 (Emamzadeh), progressing through key nodes such as S4 (Mosha), S10 (Glacier), and S11 (Larijan), and ending at S12 (Ask). The spatial arrangement of the geo-sites reveals a diverse distribution across varying elevations and landforms, enabling the design of routes that balance scientific value, accessibility, and visitor experience. The proposed trail network connects high-value sites with essential services and natural features, facilitating sustainable and educational tourism in this ecologically sensitive region. This represents a balanced and diverse trail that caters to both scientific and recreational interests.

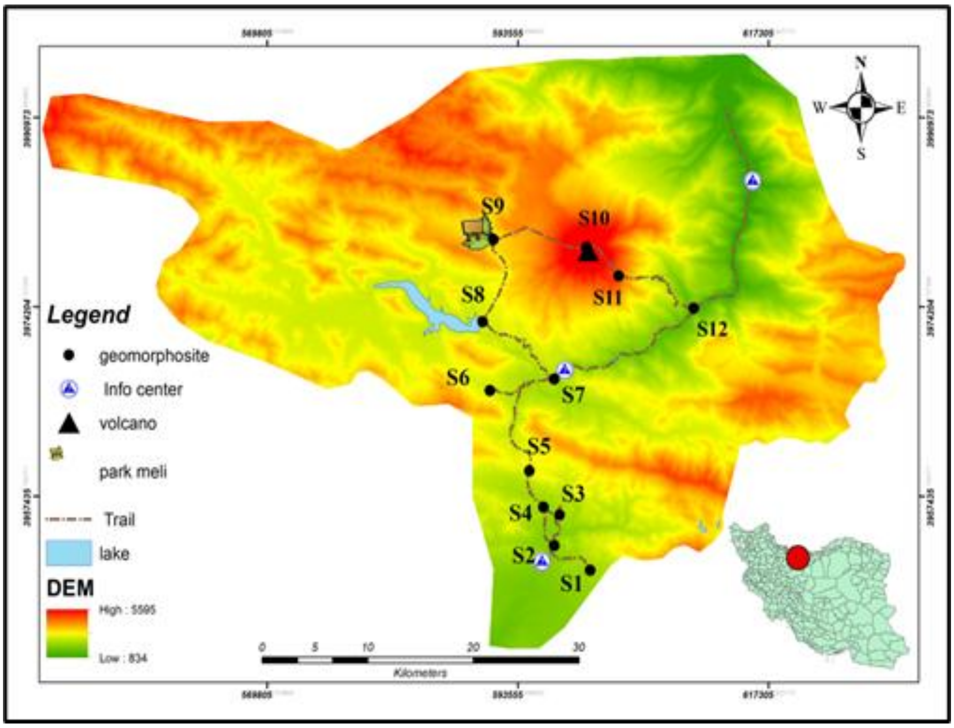


Figure 7. Geo-trail map and route.

Table 8 shows the final calculated results for the optimal route. A final objective function was improved significantly to the value of 4.718 from the initial average of 8.74 (Table 8). The values for F_4 and F_5 were 35 and 4, respectively. The optimal route identified spans 12 geo-sites, covering a total distance of 105 km and requiring approximately 1033 minutes (17.2 hours) of travel time, with a total cost of 227,000 monetary units. Crucially, this route maximizes access to high-value geo-tourism sites (e.g., glaciers, rock formations, historical landmarks) and welfare facilities (e.g., rest areas, information centers), while avoiding redundant or inaccessible connections. The optimal geo-trail achieves a total welfare services count (F_4) of 35. This value signifies that the 105-km route provides access to 35 distinct service points—equivalent to a service density of approximately one facility every 3 km. This high value indicates that the path successfully integrates a robust support infrastructure, directly enhancing tourist safety and comfort. Such density substantially enhances tourist safety and comfort by ensuring that visitors are rarely distant from essential amenities (water, shelter) or emergency support, a critical consideration for mountainous ecotourism corridors. The route also attains a cumulative attraction score (F_4) of 35. A cumulative attraction score of 4.0 represents the highest possible aggregate attraction value achievable under the given multi-objective constraints (distance, cost, time, services). This confirms that the route is not only efficient but also maximizes the quality of the geotourism experience. This score reflects the sum of pre-evaluated attraction values for the six geo-sites composing the optimal sequence (*S6*, *S4*, *S10*, *S11*, *S12*, *S2*). Achieving the maximum feasible F_5 under the multi-objective constraints confirms that the algorithm prioritized not only route efficiency but also the curation of a geotourism experience with maximal scientific and aesthetic value.

Table 8. Results of the genetic algorithm.

Value	Genetic algorithm parameters
50	Population
100	Repeat
105(km)	The total length of the route F_1
1033 min	Total route time F_2
35	Total services' whole path F_4
227000	Total travel cost F_3
4	F_5 geomorphosite
1	Penalty function
4.718	Final function

The optimal 105 km route provides access to 35 discrete welfare service points. This is a high density of services for a mountain trail, indicating that the GA successfully prioritized a corridor with robust infrastructure. The route is engineered for progressive engagement. It starts from a culturally significant and accessible site (S6, Emamzadeh), moves to a scenic geological feature (S4), culminates in the high-altitude natural wonders (S10, Glacier and S11), and concludes at a terminal service hub (S12, Ask). This creates a narrative arc, enhancing satisfaction. The route minimizes operational costs and time (F_1-F_3), enabling efficient resource allocation and reliable scheduling. Its structure offers a logical progression from cultural heritage (S6) to peak natural attractions (S10, S11), facilitating compelling tour packaging. In practical terms, this quantifies the route's capacity to deliver a "premium" geological itinerary where each visited site contributes meaningfully to visitor education and experiential satisfaction.

3.3. Discussion

Unlike traditional methods, the genetic algorithm integrated geological, geographical, and infrastructural data to support geo-tourism planning. The design of a quantitative composite objective function integrated conflicting economic criteria (cost, time, distance) with qualitative ones (access to services, geomorphological attractiveness) into a single model. This allows us to explore a vast solution space through mechanisms such as elitism selection, two-point crossover, and swap/shift mutation, enabling it to escape local optima and converge toward a globally competitive solution. Compared to an ad-hoc or intuitively planned route connecting the same five geo-sites, the GA-optimized path is not only the shortest in pure distance but is also demonstrably superior in its balanced integration of economic, experiential, and safety criteria. For example, the GA explicitly found that the proposed sequence S6→S4→S10→S11→S12 yields the lowest possible value for the composite objective function ($F(x) = 4.718$). The $F(x)$ value of 4.718 is an optimal solution of various combinations of minimizing the total length of the route (F_1), time (F_2), and cost (F_3), and maximizing the total welfare services (F_4) and geo-site attraction score (F_5). Any other permutation, including intuitive ones, would result in a higher $F(x)$, meaning a worse trade-off between distance, time, cost, services, and attraction. Unlike GIS-based methods [35], this GA process often outperforms pure GIS least-cost path methods in complex, multi-objective geo-trail scenarios by finding globally better alignments that balance competing factors (e.g., shorter but fewer services). This underscores the value of a systematic, multi-objective approach over heuristic planning for sustainable geo-tourism development since it reduces time and cost but increases welfare services and attraction sites.

However, this study is limited to a static optimization framework, while real-world tourism paths should be dynamic. For example, some dynamic factors, such as weather, seasonality, traffic, or user preferences (e.g., difficulty level, interest in specific geological features), can influence tourist selections. Therefore, future work should explore real-time optimization of a geo-trail through adaptive routing. Also, dynamic variables, such as seasonal path closures, weather-dependent accessibility, and time-variant tourist density, should be integrated, akin to approaches used in advanced spatial-temporal routing models [19]. This will transform the model from a planning tool into an adaptive management system for geo-tourism.

4. Conclusions

This study presents a comprehensive optimization framework for designing an optimal geo-trail route by leveraging genetic algorithms within a multi-criteria decision-making context. The proposed model successfully integrates five key factors, including total distance, travel time, cost, welfare services, and geological significance, into a unified objective function, while enforcing critical constraints such as non-repetition of path segments and infeasible direct connections between nodes. The GA optimization of geo-trails converges on a stable solution with a final objective function value of 4.718, indicating significant improvement from the initial value of 8.74. Furthermore, the performance of GA is benchmarked against three reference approaches: the nearest neighbor (NN) heuristic, a random search baseline, and ant colony optimization (ACO). While both GA and ACO vastly outperform simple heuristics, the choice between them may depend on specific implementation constraints or desired solution characteristics (e.g., GA's ease of parallelization vs. ACO's faster initial convergence). The GA exhibited greater robustness, with a coefficient variation of 0.9% across runs versus 2.4% for ACO. Therefore, from a practical standpoint, the outcomes of this study offer tangible benefits for tourists, tour operators, regional planners, and environmental managers. Tourists benefit from a well-structured, time- and cost-effective route that enhances their experience by including high-value geo-sites and essential services. For tourism planners, the model provides a data-driven decision-support tool for designing sustainable geo-trails that balance visitor satisfaction with environmental preservation. Municipalities and conservation agencies can use this approach to optimize infrastructure investment, prioritize site development, and manage visitor flows to prevent overcrowding and ecological degradation. In conclusion, this study not only validates the effectiveness of GAs in solving complex geo-tourism routing problems but also demonstrates their practical relevance and stakeholder value. By transforming abstract optimization into actionable, real-world trail design, the research contributes to the advancement of intelligent, sustainable, and experience-oriented geo-tourism planning.

Author contributions

Conceptualization (F.S.), Methodology (F.S., A.R.K.), Analysis (F.S.), Visualization (F.S.), Writing-original draft preparation (F.S., A.R.K., J.W.), Writing-reviewing and editing (F.S., A.R.K., J.W.). All authors approved the final version of the article and accepted accountability.

Use of AI tools declaration

The authors declare they have not used Artificial Intelligence (AI) tools in the creation of this article.

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Conflict of interest

The authors declare no conflicts of interest.

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