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An Efficient Tourism Path Approach Based on Improved Ant Colony Optimization in Hilly Areas

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Abstract: The expansion of the tourism industry has led to the development of various methods to find optimal tourism paths. However, planning tourism paths in hilly areas remains complex and has specific challenges. Different algorithms have been used to plan tourism paths in flat and hilly terrains, including the traditional Ant Colony Optimization (ACO). Although widely used, this algorithm faces a number of limitations due to its slow implementation and pheromone update rules. This paper introduces a new approach to overcome these limitations. It presents a method for efficiently optimizing tourism paths in hilly areas based on an improved version of the ACO algorithm. The limitations of the traditional ACO and the Genetic Algorithm (GA) are addressed by improving pheromone updating techniques and implementing new initialization parameters. This approach provides a comprehensive and efficient method for planning hiking trails in hilly regions, considering dynamic tourism objectives such as temperature, atmospheric pressure, and health status. The proposed method is implemented to develop tourist routes in the hilly Jebel Marra region in Western Sudan. A comparison is provided between the effectiveness of this approach and the GA and traditional ACO algorithms. The advantage of the proposed approach is illustrated by results showing an optimization time of 0 points and 27 s compared to 0 points and 45 s and 0 points and 40 s for GA and ACO, respectively.

Keywords: tourism industry; hilly areas; traveling salesman problem; dynamic tourism objectives; ant colony optimization

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1. Introduction

The tourism sector is undergoing a recent period of significant expansion. According to the World Tourism Organization (UNWTO), international tourist arrivals surged to 97% of pre-pandemic levels during the initial quarter of 2024, signaling a substantial rebound from the impacts of the pandemic. Approximately 285 million tourists made international journeys during the first quarter of 2024 [1,2]. This rapid expansion has garnered interest from businesses and governments in capitalizing on tourism opportunities. Reaching tourist destinations, especially in hilly regions, necessitates specialized transportation planning and infrastructural development. Therefore, path planning in hilly regions poses unique challenges requiring careful examination to provide visitors convenient access to scenic mountain resorts and attractions. Addressing path-planning challenges can leverage solutions like the Traveling Salesman Problem (TSP) to optimize paths between multiple destinations [3–5]. The TSP and similar algorithms can solve various path-finding issues with irregular paths, including logistics, robot navigation, military operations, and docking maneuvers. Accordingly, applying such optimization approaches through the TSP can potentially derive efficient travel routes for flat and hilly terrain areas [6–10].

The TSP allows the optimal tourism path to be found based on a single tourist objective, such as minimizing travel time, cost, or distance between multiple destinations [11,12]. Due to the requirements of tourists and the characteristics of hilly regions, dynamic tourism destinations (considering local weather and health conditions, complicated routes in hilly areas, and other planning objectives) should be considered when solving the hill areas path-planning problem. For example, temperatures in hilly regions tend to be reduced. Therefore, it is important to consider safety measures relevant to cold weather conditions, such as wearing appropriate clothing [13,14]. Because air pressure varies with altitude, it is also a crucial dynamic target in hilly terrain. Since hilly terrain can spread diseases and epidemics, health conditions should be considered when planning tourist routes [14,15]. Many algorithms have been developed to find optimal paths, particularly for identifying the best tourist paths. These include Dijkstra, Floyd, A* algorithms, heuristic search methods, GA, Neural Networks, and ACO. The Dijkstra, Floyd, and A* algorithms are specifically designed to determine the shortest path between two points. However, they are unsuitable for solving the TSP, which requires finding the optimal path that visits predefined locations and returns to the starting point. Advanced algorithms such as GA, Neural Networks, and ACO are more effective in addressing the complexity of TSP, as they can determine the optimal route that efficiently visits all designated sites [16–19]. These approaches provide methods for determining the optimal routes between several tourist attractions.

Inspired by the foraging behavior of ants, ACO has evolved into a powerful optimization technique and is particularly well suited for complex path-planning tasks such as tourism routes in hilly areas. Its effectiveness is derived from mimicking ant behavior and its sophisticated algorithmic features, including iterative search, pheromone-guided exploration, and adaptive optimization strategies [20,21]. In this study, we enhanced ACO by refining pheromone updating rules, optimizing initialization parameters, and incorporating dynamic objectives such as temperature, atmospheric pressure, and health status alongside traditional factors, including distance and elevation. These improvements enable ACO to efficiently navigate the complexities of mountainous terrain, providing optimized routes that adapt to real-time environmental and tourist-related conditions. The emphasis on technical advancements and practical applications highlights the ability of ACO to solve complex optimization problems beyond its biological origins. Furthermore, ACO demonstrates a strong aptitude for addressing challenges related to tourism path planning.

Consequently, various approaches have been developed to apply ACO or enhance its performance in path planning. For example, Cui et al. [21] used ACO to determine the global path planning of vehicles underwater and the designed rules of pheromone updating using iteration optimization and global optimal information. However, the rules of updating pheromones were updated excessively depending on the best solution in the iteration, thereby reducing the search area.

Similarly, Li et al. [22] improved the automatic detection of ACO and path planning by decreasing the system and finding energy usage. In relevant research, Gong et al. [23] designed a top-notch obstacle avoidance method to lessen research blindness. The ACO algorithm, including variants such as the MAX-MIN Ant System, is highly effective in solving the TSP, often efficiently achieving optimal or near-optimal solutions, particularly for problem sizes relevant to this approach. However, in dynamic environments such as tourism path planning in hilly regions, the traditional ACO can face challenges, including slower convergence and susceptibility to local optima, when dealing with dynamic objectives such as fluctuating weather conditions, atmospheric pressure, and health statuses.

This approach employs ACO to tackle the challenge of optimal path finding in hilly areas, where tourism-related activities occur, such as by efficient route planning. The inherent dynamic nature of ACO, which enables it to adjust to varying environmental conditions like terrain difficulty and weather, renders it particularly suitable for this application. Unlike conventional methods, ACO can provide real-time updates to ensure safe and efficient travel, offering a distinct advantage in tourism applications. These modifications make the algorithm more adaptable to hilly terrains' complex and changing conditions. By harnessing the strengths of the traditional ACO while incorporating targeted improvements, this approach extends the applicability of the algorithm to more dynamic and multi-objective optimization problems. In summary, the main contributions of this paper are as follows:

Improve the traditional ACO by enhancing the rules of updating pheromones and optimizing the initialization parameters of the algorithm.

Optimize the process of selecting the best paths for tourists in hilly areas.

Consider the dynamic tourism objectives when planning hilly paths, which helps enhance the mountain tourism experience.

Our approach has been compared with other approaches, and our approaches showed an optimal time to implement the ACO algorithm to find the optimal tourism path.

This paper is structured as follows. The introductory section provides an overview of the study. Section 2 discusses the methodology, covering the proposed dynamic objectives and the enhancements made to the ACO algorithm. Section 3 presents the research findings and includes a comprehensive discussion. Included are the concluding remarks and considerations for future work in Section 4.

Related Work

Planning tourist routes is a path-planning problem relevant to robotics, logistics, navigation, and industry. Scholars have recently solved the path-planning problem in various ways. For instance, Liang et al. [24] suggested that the ACO algorithm was improved based on the context feedback and developed a strategy for solving the problem of the tourism path. Pasandi et al. [25] proposed a new approach to adaptive ACO for the agricultural robots' path in hilly fields. Their paper aimed to solve the convergence speed inefficiency problem, quickly slipping into the standard ACO algorithm's local optimal values. However, they ignored the dynamic objectives. In another study, Sidi et al. [26] proposed an improved ACO algorithm that considered the context information of tourism areas, such as the comfort level of the tourism site, when finding the best tourism path. In other research, Dahan et al. [27] enhanced the ACO algorithm by incorporating concepts inspired by hypothetical flying ants. The novelty of this approach lies in the achievement of higher-quality solutions and a reduction in execution time. Cong et al. [28] demonstrated a model to use the ACO to obtain the optimal path under multiple objectives, such as time, speed, and tourist expense. The above paper handled static objectives but ignored dynamic objectives. Y et al. [29] presented a hybrid approach of ACO-PSO to obtain the optimal route for tourists, avoiding obstacles during the path.

Yong et al. [30] proposed a mathematical approach to maximize revenue, minimizing costs, travel time, and CO_2 emissions. Their model was based on the multi-depot vehicle routing problem (MDVRP), a variant of the classic vehicle routing problem (VRP) that deals with the optimal allocation of vehicles in a fleet to the desired destinations. They also developed an improved ACO based on ant behavior when finding food sources. Similarly, Ren et al. [31] presented improved ACO to solve the path problem, and an initial solution was generated with vehicle pheromones, enhancing the initial population's quality. Popovi et al. [32] proposed the "Ant Colony Optimization Algorithm for Traveling Car Renter Problem" (ACOCaRS), a novel approach designed to solve the Traveling Car Renter Salesman (CaRS) problem. This problem involves identifying the optimal closed tour while allowing for the possibility of switching cars at various points along the route. The algorithm is based on ACO and demonstrated superior performance for more minor problem instances when compared to other published algorithms. However, for larger instances, it was outperformed by the Transgenetic Algorithm. The results were statistically significant, and the study introduced new, best-known solutions for certain CaRS instances. Despite its contributions, the study had limitations, as it focused solely on cost as a single objective and did not consider multiple objectives and dynamic objectives.

Nikola Ivković et al. [33] investigated various strategies to enhance the performance of ACO algorithms. By modifying pheromone reinforcement strategies, this paper aimed to improve the adaptability and efficiency of ACO in addressing NP-hard problems, such as the TSP and the Asymmetric Traveling Salesman Problem (ATSP). Through empirical analysis, the authors demonstrated that adaptive strategies can achieve significantly better performance compared to traditional methods. However, the study did not provide a clear explanation of the rules governing pheromone updates, leaving a gap in the methodology.

Finally, Zhang et al. [34] presented a hybrid approach termed EACSPGO for mobile robot route planning that combined the improved ACO with a local optimization algorithm based on path geometry aspects. The traditional ACO was enhanced with a simplified model of pheromone diffusion, the unequal allocation pheromone initialization method. As a result, the computation efficiency and quality of the solutions significantly increased. However, the articles mentioned above have overlooked several dynamic parameters, including temperature, atmospheric pressure, and terrain. Additionally, there are shortcomings in the execution time of the ACO algorithm in determining the optimal path.

2. Methodology

Tourism path planning in hilly areas is crucial for developing tourism in these regions. This approach introduces a dynamic objective approach to enhance tourism in hilly areas. The implementation of this approach unfolded through several stages:

In the initial stage, the selection of objectives is crucial. Three dynamic objectives, temperature, atmospheric pressure, and health status, are chosen, as they directly impact the overall tourism experience. Additionally, two static objectives, distance and altitude, were included to provide essential information about the geographical aspects of the tourist destinations. These enhancements mainly concentrated on optimizing the pheromone implementation guidelines, leading to a faster and more effective algorithmic implementation. The enhanced ACO algorithm can efficiently identify the route that optimizes visitor satisfaction and experience in hilly areas by considering distance, altitude, and static and dynamic objectives. With careful planning and adaptation to the unique qualities and difficulties of hilly terrain, this last phase guarantees that the tourism path offers guests a delightful and unforgettable experience amidst the breathtaking natural scenery of these regions. Figure 1 shows how to create the optimal path for tourism under dynamic objectives. After collecting the dynamic objectives from their above resources, they are converted into quantitative data by arranging them in the form of data matrices, as shown in Figure 2. These dynamic objectives are then combined, as illustrated in Equation (7). Finally, the optimal paths are calculated by applying the improved algorithm.

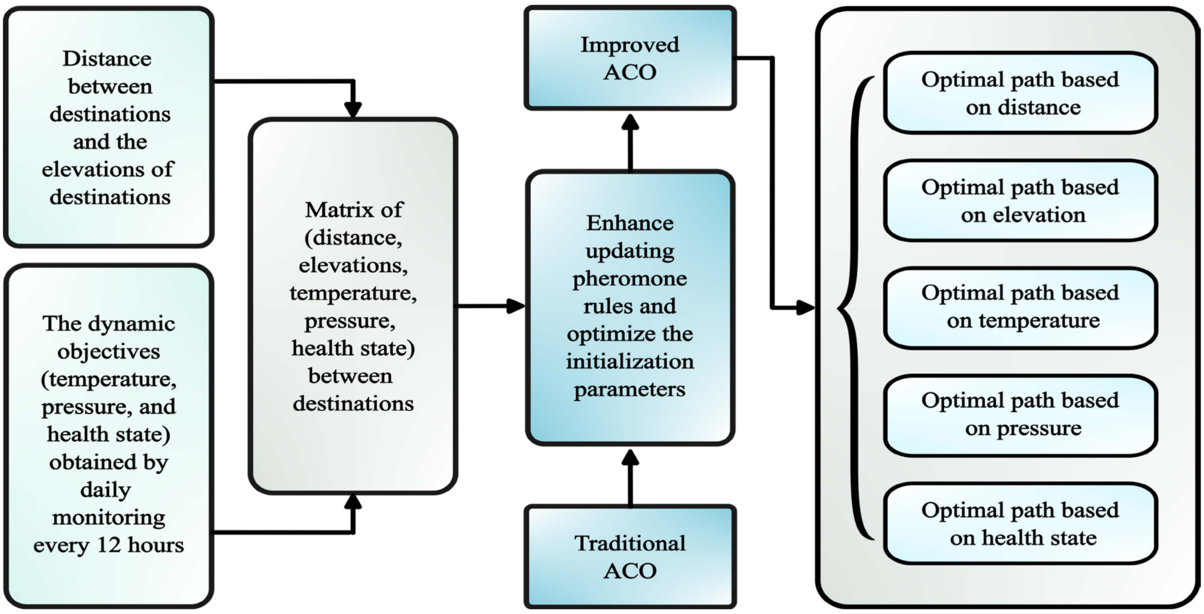

Figure 1. Process of finding the best path-based dynamic objectives in hilly area.

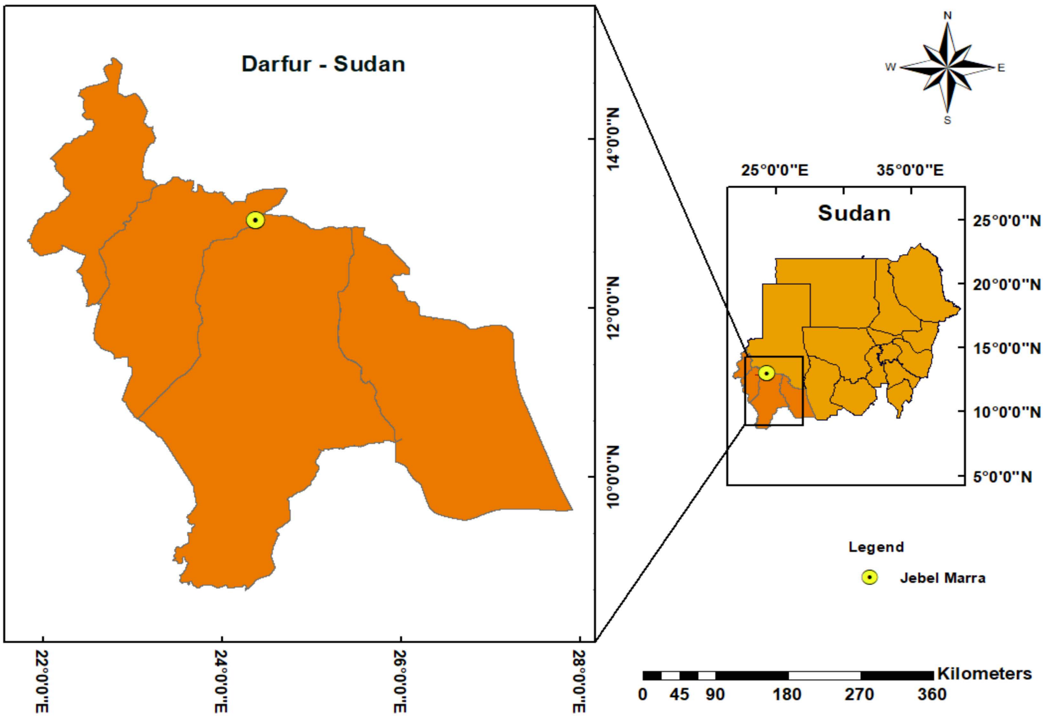

Figure 2. Location of Jebel Marra in Sudan.

2.1. Study Area

Jebel Marra is a cluster of volcanic peaks that rise to 3000 m. Situated in the central region of Darfur in Sudan, it spans an area of 12,800 km^2 and extends over several hundred kilometers from the southern city of Kass to the outskirts of El Fasher in the north. This mountainous expanse is characterized by its Mediterranean-like climate, offering moderate temperatures and experiencing rain throughout various seasons. It boasts a diverse range of plant life, including citrus fruits, apples, and forest trees, thanks to the regular rainfall. Jebel Marra is home to unique plant species found internationally and hosts a significant population of rare animals and wildlife. With its stunning natural landscapes, pleasant climate, and pristine environment, Jebel Marra attracts numerous visitors who seek to appreciate its beauty and serene surroundings. It is the second-highest peak in Sudan, reaching an elevation of 10,000 feet above sea level, and its mountain range spans approximately 240 km in length and 80 km in width. Jebel Mara Mountain is shown in Figure 2. We chose to work with an 11-point distribution in the mountainous region to implement this approach. The distribution of points is illustrated in Table 1 and Figure 3.

Table 1. Jebel Marra point's distribution.

POI	X	Y	H	Name	Description
P1	12.96	24.05	3125.0	Nirti Falls (NF)	Ever-flowing waterfalls.
P2	12.91	23.48	3120.1	Arebo Valley (AV)	The valley has green and beautiful areas.
P3	12.94	24.26	3075.7	Sonny Lake (SL)	A freshwater lake with rare fish.
P4	12.96	24.28	3050.3	Dereah Lake (DL)	A lake at the highest part of the mountain.
P5	12.06	24.25	2960.5	Keeling (K)	A tourist village with a resort.
P6	12.08	24.31	3200.0	Mount Arrow (MA)	Mount in the shape of an arrow.
P7	12.96	24.07	3189.2	Kaliy (KV)	Tourist village.
P8	12.96	24.05	3300.7	Nirti Hotel (MH)	A hotel with rest areas and restaurants.
P9	13.16	24.50	3105.9	Morning (MM)	Tourist village.
P10	13.08	24.51	2890.6	Darbat market (DM)	A large market for heritage items.
P11	13.10	24.53	3177.3	Mishi (M)	Tourist village.

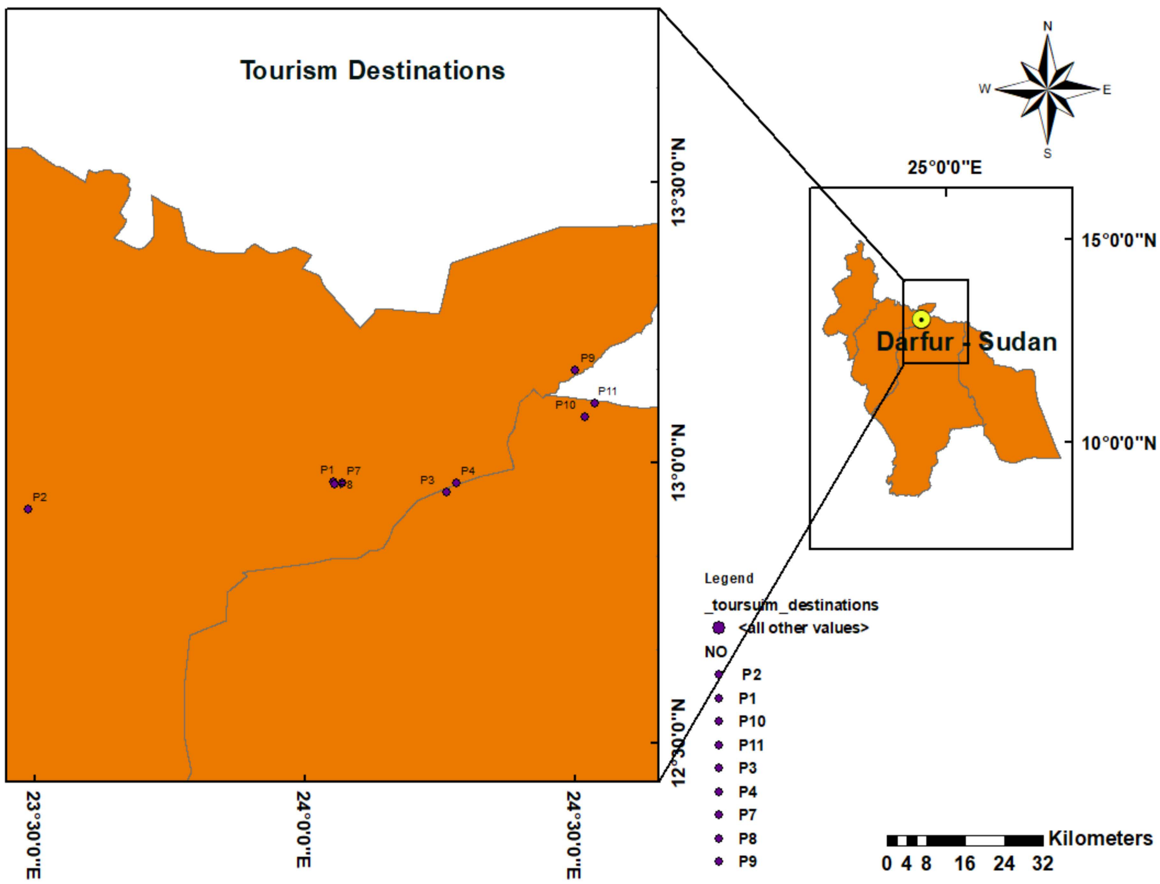

Figure 3. Tourist sites distributed within Jebel Marra.

2.2. Selection Objectives

Destinations that cater to tourists thrive when static and dynamic objectives are carefully balanced. The foundation of a destination's appeal is its static objectives, which focus on protecting and enhancing its natural attractions. However, dynamic objectives provide flexibility and adaptability in planning for tourism. These objectives, subject to change depending on the circumstance or period, become especially intricate and crucial in places with diverse topographies and environmental elements, such as hilly regions. Objectives such as safety, weather conditions, accessibility, and the availability of specific activities or events are all considerations under dynamic objectives [34]. Planning a tourism path requires these considerations, especially in hilly areas where these variables differ significantly based on elevation [35]. The dynamic objectives are chosen based on their critical impact on the safety, comfort, and overall experience of travelers in hilly regions. Temperature is included as it directly affects the physical safety and comfort of tourists, especially in high-altitude or cold regions. Air pressure is considered because it varies significantly with elevation, influencing both physiological factors (e.g., altitude sickness) and weather-related planning. Health status reflects real-time risks, such as disease outbreaks or environmental hazards, that could influence the desirability or safety of specific destinations. These dynamic objectives are updated periodically (e.g., every 12 h) using reliable sources, such as meteorological services for temperature and air pressure and local health reports for health-related data [36]. The objectives were arranged in matrix form, and the three matrices refer to the difference in temperature, pressure, and health statuses, respectively, among the destinations. In addition to the dynamic objectives in this approach, two static objectives, distance, and elevation, were included because of their importance in planning hilly tourism paths. Table 2 presents the distances between tourist attraction points in kilometers, which is sufficient to present how to calculate the distance between POI.

Table 2. Total distance matrix (km).

POI	NF	AV	SL	DL	K	MA	KV	NH	MM	DM	M
NF	0	25.8	39	15.8	21	17.6	29.3	12	30	31.8	27
AV	25.8	0	11.5	31.6	15.9	15	22.5	18.9	21	39	21.4
SL	39	11.5	0	8.5	23.6	7.4	22.9	21	29	16.1	21.6
DL	15.8	31.6	8.5	0	13.2	16	20.9	22.5	32.5	19	10.5
K	29.3	15.9	23.6	13.2	0	18.3	13.5	18.9	33.6	18	29
MA	17.6	15	7.4	16	18.3	0	7.8	11.8	11.6	12.9	24.5
KV	29.3	22.5	22.9	20.9	13.5	7.8	0	16.9	15.6	14.4	13.8
NH	12	18.9	21	22.5	18.9	11.8	16.9	0	21.9	23.9	18.5
MM	30	21	29	32.5	33.6	11.6	15.6	21.9	0	11.7	27.1
DM	31.8	39	16.1	19	18	12.9	14.4	23.9	11.7	0	24.6
M	27	21.4	21.6	10.5	29	24.5	13.8	18.5	27.1	24.6	0

2.3. Proposed Algorithm

ACO is a computer search algorithm for nearly optimal searches and discrete function optimization. ACO, inspired by the cooperative behavior of ants, utilizes swarm intelligence. One intriguing aspect of ant behavior is finding the shortest paths between their nests and food sources by following pheromone trails left by other ants. This process is illustrated in Figure 4.

Biologists have observed that ants communicate and collaborate using pheromones. When searching for new routes, ants assign probabilities based on the concentration of pheromones. Initially, when ants explore new food sources, their search is completely random since no pheromone trails exist to guide them. The Ant System (AS), the first ACO algorithm, can tackle TSP. Numerous ant colony algorithms have since been developed based on AS for various applications. The fundamental ant colony algorithm is implemented in two main steps: (1) designing the path for solving the actual problem and (2) updating the pheromones along the path.

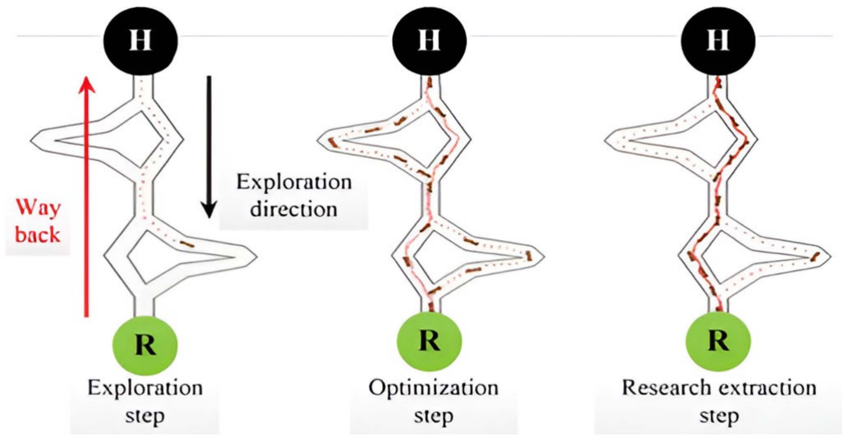

Figure 4. Ant colony optimization algorithm process [37].

2.4. Mathematical Description of ACO

Selection Function: Depending on the pheromone concentration, the ants will choose the next node, and ants find it simpler to choose the node with a higher pheromone concentration.

$$P_{mn}^{k} = \left\{ \frac{[\tau(m,n)]^{\alpha}[\rho(m,n)]^{\beta}}{\sum_{s\in nk}^{n}[\tau(m,s)]^{\alpha}[\rho(m,s)]^{\beta}} \right\} \quad n \in A \tag{1}$$

P_{mn}^{k} represents the probability that an ant k will move from node m to node n. $\tau(m,n)$ refers to the pheromone concentration on the edge between nodes m and n, which influences the ant's decision to select that path. $\rho(m,n)$ refers to the heuristic information, typically the inverse of the Euclidean distance between nodes m and n, indicating the desirability of the path based on proximity. Parameter α is an exponent that controls the influence of pheromone concentration in the decision-making process, indicating the relative importance of pheromone levels. Parameter β is an exponent that controls the influence of heuristic information, signifying how much the distance between nodes affects the ant's choice. n_k represents the set of nodes that ant k can still visit.

In the ACO algorithm, the updates of pheromones are pivotal in directing ants toward the most favorable paths. As ants move through nodes, each visited node is recorded in a taboo list to prevent revisits within the same iteration, forming a complete path. Pheromone updates occur through local and global mechanisms. The local update involves a slight reduction in pheromone levels on visited paths, encouraging exploration and preventing premature convergence. In contrast, the global update involves a significant increase in pheromone levels on the top-performing paths discovered by ants, making them more appealing for future iterations. The process of pheromone evaporation, regulated by the evaporation rate, helps maintain a balance between exploration and exploitation by gradually decreasing pheromone concentrations on all paths. This dynamic updating process ensures that ants adjust their search continuously, refining their paths toward the optimal solution while avoiding excessive commitment to any single path too early in the exploration phase.

$$\tau_{mn}(t+1) = (1-\rho)\tau_{mn}(t) + \Delta\tau_{mn}(t), \tag{2}$$

$$\Delta\tau_{mn}(t) = \sum_{k=1}^{m} \Delta\tau_{mn}^{k}(t) \tag{3}$$

where $\tau_{mn}(t+1)$: updated pheromone concentration between nodes m and n at time $(t+1)$. ρ is the evaporation rate of the pheromone, controlling how quickly pheromone levels decay. $\Delta\tau_{mn}t$ is the pheromone deposited on the path based on the quality of the solution found. $\Delta\tau^k_{mn}(t)$ is the pheromone contribution from ant k at time t. m: the total number of ants contributing to the pheromone update.

2.5. The Improved ACO

This approach proposes several key improvements to the traditional ACO algorithm to enhance performance in dynamic and complex environments, such as tourism path planning in hilly areas. These improvements focus on refining the pheromone updating process, optimizing the initialization parameters, and incorporating dynamic objectives to make the algorithm more adaptable and efficient. We will explain these improvements in detail:

Enhanced Pheromone Updating Rules: In traditional ACO, the pheromone updating process can lead to premature convergence and local optima, especially in complex terrains with dynamic factors. Our approach introduces an adaptive pheromone update mechanism that adjusts the pheromone intensity based on real-time environmental data, such as weather conditions and atmospheric pressure. This enhancement improves the balance between exploration and exploitation, ensuring that the algorithm does not overly reinforce suboptimal paths. The following equations reinforce the rules for pheromone updating:

In traditional ACO, we modified the pheromone update by Equation (3) to adjust the pheromone update rule dynamically. $\Delta\tau_{mn}(t)$ on environmental conditions, introducing a scaling factor F_w that accounts for dynamic objectives such as temperature and atmospheric pressure:

$$\tau_{mn}(t+1) = (1-\rho)\tau_{mn}(t) + F_w \cdot \Delta\tau_{mn}(t) \tag{4}$$

where $F_w = |C_L - C_{L-1}|\ e^{|\tau_{cd} - \tau_{cd-1}|}$ adjusts the pheromone contribution based on environmental changes. τ_{cd} represents the current pheromone concentration associated with the dynamic objective (e.g., temperature, pressure, or health status) at a given tourism destination c and tourism destination d. τ_{cd-1} represents the pheromone concentration from the previous iteration for the same node c and destination. The difference $|\tau_{cd} - \tau_{cd-1}|$ captures the change in the pheromone trail due to variations in the dynamic objective over time. $|C_L - C_{L-1}|$ represent the current and previous values of the dynamic objective (e.g., temperature, pressure).

The exponential function $e^{|\tau_{cd} - \tau_{cd-1}|}$ amplifies the impact of changes in pheromone concentration τ_{cd} based on the magnitude of their difference. This exponential functions to give more weight to significant environmental changes, such as sharp variations in temperature or pressure, which are critical in dynamic objectives such as those used in this approach. The absolute value ensures that the amplification applies to the magnitude of the difference, regardless of its direction. This is particularly relevant when the changes are bidirectional (e.g., increase or decrease in temperature or pressure) and should uniformly influence the pheromone update.

Dynamic Objective Integration: Unlike ACO, which primarily focuses on static objectives such as distance, our modified algorithm incorporates dynamic objectives such as temperature, atmospheric pressure, and the health status of the paths. These additional factors are updated regularly to reflect real-time conditions, allowing the algorithm to adjust its search strategy dynamically. This integration ensures that the selected paths are not only optimal in terms of distance but also align with the varying conditions of the terrain, enhancing the safety and experience of tourists. The dynamic objectives (temperature, pressure, health status) are integrated into the heuristic function η_{mn}, which traditionally only considers the inverse of distance. The modified heuristic function is

$$\eta_{mn} = \frac{1}{d_{mn}\left(1 + |T_{mn} + T_{\text{opt}}| + |P_{mn} + P_{\text{opt}}| + \frac{1}{H_{mn}+\varepsilon}\right)} \quad (5)$$

where d_{mn} is the distance between nodes m and n. T_{opt} is the optimal temperature for the region. P_{opt} is the desired atmospheric pressure. H_{mn} is the health status at the destination (lower values indicate better health). ϵ is a small constant to avoid division by zero. T_{mn} is the temperature at the destination. P_{mn} is the atmospheric pressure.

Normalization is a crucial step in the algorithm to ensure that all dynamic objectives including temperature (T), atmospheric pressure (P), and health status (H) are scaled to a comparable range. This prevents any single objective from dominating the optimization process due to differences in scale or units. The denominator (lower part) of Equation No. 5 represents the process of normalization and the summation of dynamic objectives to obtain compatible results under a multi-objective approach.

Optimization of Initialization Parameters: To further improve convergence speed, we optimized the initialization parameters of the ACO algorithm, including the number of ants, pheromone evaporation rate, and the influence of heuristic factors. These adjustments reduce the algorithm's dependency on random initialization and help guide the search more effectively from the outset, speeding up the convergence to the optimal solution. The initialization parameters, such as the number of ants (k), influence the pheromone update and exploration–exploitation balance. Our improvements involve optimizing the initialization settings:

$$K = \alpha * N \quad (6)$$

where α is a pheromone importance (α). N is the number of nodes.

The selection and setting of key parameters in the improved ACO algorithm were carefully determined to balance exploration and exploitation while considering the specific context of hilly terrain path planning with dynamic objectives. For α (pheromone importance) and β (heuristic importance), commonly used values in the literature served as starting points. α = 1.0 and β = 2.0 based on the literature studies [38]. The pheromone evaporation rate (ρ = 0.5) was chosen to maintain a balance between exploration and exploitation. Other key parameters were also optimized to improve algorithm performance. The number of ants (k = 200) was proportional to the problem size, providing sufficient exploration without excessive computational overhead. The initial pheromone level (τ = 1.0) ensured a balanced initial influence, and the maximum number of iterations was set at 500 with an additional stopping criterion based on solution stagnation over 50 consecutive iterations. The improvement of the traditional ACO algorithm depends on the above equations and uses the optimal number of ants, which helps reduce the number of iterations and improves the time to find the best path in Table 3. Displaying the optimization parameters is used to improve the algorithm. In Figure 5, a flowchart of improved ACO is shown.

Table 3. Parameter settings of improved ACO.

Parameters	Description	Values
Number of Ants (k)	Population size of ants	200
Pheromone Evaporation Rate ρ	Controls how quickly pheromones evaporate	0.5
Pheromone Importance (α)	Importance of pheromone trail in decision-making	1.0
Heuristic Importance (β)	Importance of heuristic information	2.0
Maximum Iterations	Number of iterations before termination	500

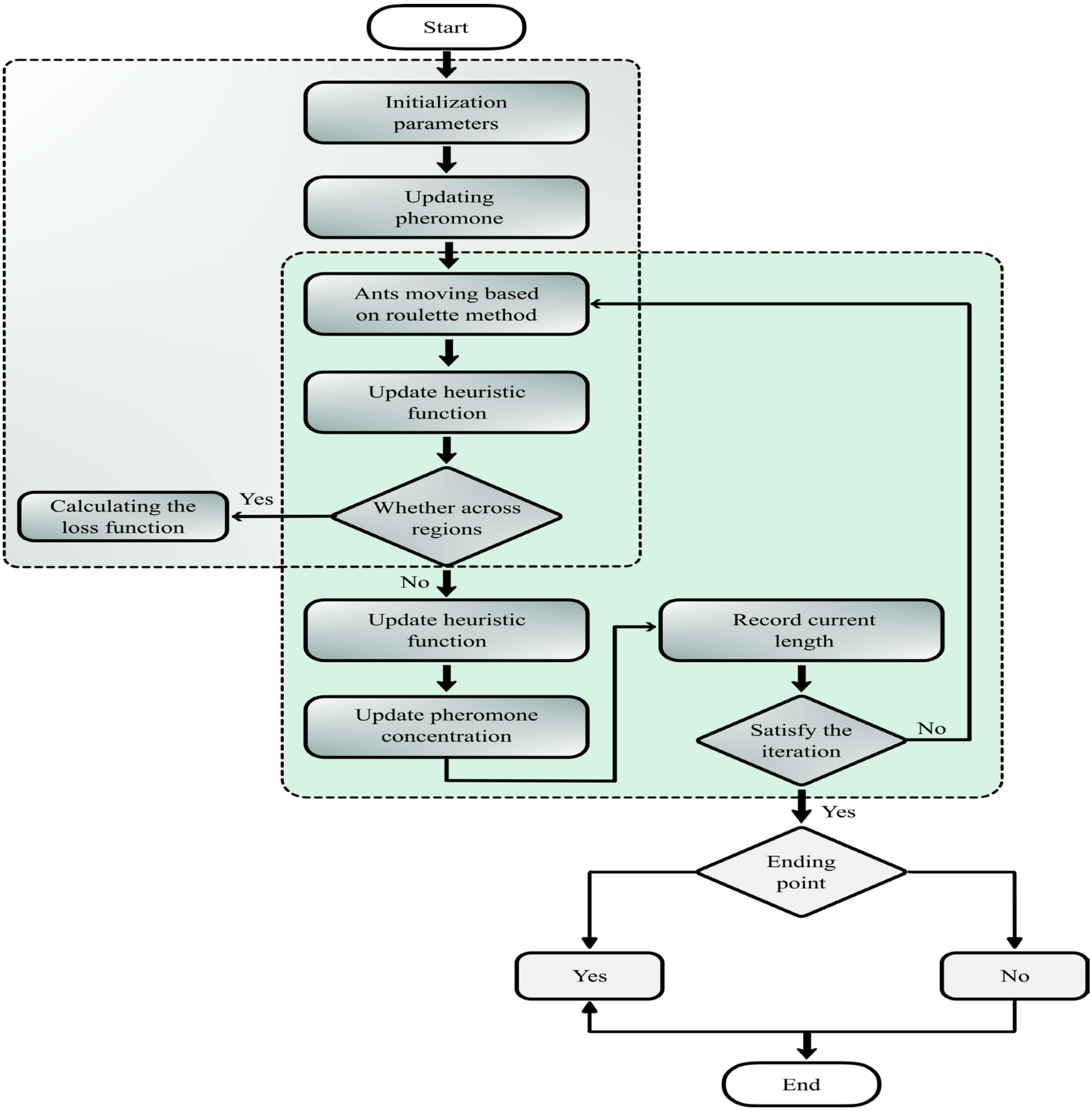

Figure 5. Flowchart of improved ACO [37].

The ACO algorithm incorporates multiple objectives—weather, atmospheric pressure, and health status—by adjusting the fitness/quality of solutions based on these factors. The fitness of a solution is calculated as the total path distance adjusted by penalties derived from the dynamic objectives. Specifically, the fitness is given by

$$F_{total} = \sum_{i}^{N} d_i \cdot (1 + \lambda_1 T_i + \lambda_2 P_i + \lambda_3 H_i) \tag{7}$$

where F_{total} is fitness function. d_i is the distance between nodes i and $i+1$. $\lambda_1, \lambda_2, \lambda_3$ are the weighting coefficients that reflect the relative importance of each objective. T_i is the weather factor for the path segment between nodes i and $i+1$. P_i is the atmospheric pressure factor for the same path segment. H_i is the health risk factor for the same path segment.

3. System Implementation and Experimental Analysis

3.1. Results

The enhanced ACO algorithm is suggested to determine the optimal routes for travelers. Two things are crucial to this success. The first factor is the separation between popular tourist spots and altitudes. Routes that reflect the varied terrain and improve the visitor experience are designed with this in mind. Second, the addition of dynamic tourism objectives improved the conventional ACO method. These objectives cover things such as tourist density, weather, and cultural events, all of which have a big impact on the overall tourist experience. The enhanced algorithm performs better than both the GA and the conventional ACO, according to the results. These outcomes highlight the usefulness and efficiency of this improved ACO method in determining the optimal travel paths. To account for the stochastic nature of ACO and ensure statistical robustness, the algorithm was independently repeated 30 times for each configuration. Each repetition began with a unique random initialization of pheromones and ants to explore diverse solutions. The stopping criteria were set at a maximum of 500 iterations or termination if no improvement in the global best solution was observed over 50 consecutive iterations.

The total distances covered by the enhanced ACO are 265.85 km, compared to 406.98 km and 400.45 km for the GA and traditional ACO, respectively. The destination elevations were 315 km for the enhanced ACO and 366 km and 377 km for the traditional ACO and GA, respectively. The best paths are determined by taking into account dynamic variables, including weather, atmospheric pressure, and health concerns. Table 4 shows the optimal path planning. Figure 6 illustrates the optimal path maps, showcasing the effectiveness of both the improved and conventional algorithms in achieving optimal routes for dynamic and distance objectives. Authors should discuss the results and how they can be interpreted from the perspective of previous studies and the working hypotheses. The findings and their implications should be discussed in the broadest context possible. Future research directions may also be highlighted.

Table 4. Tourist path based on dynamic objectives.

NO	The Objectives	The Paths
1	Optimal distance path by ACO	P5-P11-P4-P8-P7-P10-P9-P1-P3-P2-P6-P5
2	Optimal distance path by improved ACO	P10-P11-P9-P7-P8-P1-P2-P5-P6-P4-P3-P10
3	Optimal elevation path by improved ACO	P4-P1-P3-P7-P6-P2-P10-P8-P5-P9-P11-P4
4	Optimal weather path	P5-P9-P8-P7-P3-P10-P1-P11-P4-P2-P6-P5
5	Optimal atmospheric pressure path	P11-P2-P9-P5-P8-P7-P4-P1-P3-P6-P10- P11
6	Optimal health situation path	P3-P4-P6-P7-P8-P5-P2-P10-P11-P9-P1-P3

A comparison of these maps offers insights into the performance and outcomes of the improved algorithm relative to the conventional one. Finally, by taking into account the elevation differences and travel times between tourism destinations, as well as the inclusion of dynamic tourism objectives, this approach employed an enhanced version of the ACO algorithm to determine the optimal travel routes. Results are better than those obtained with GA or traditional ACO.

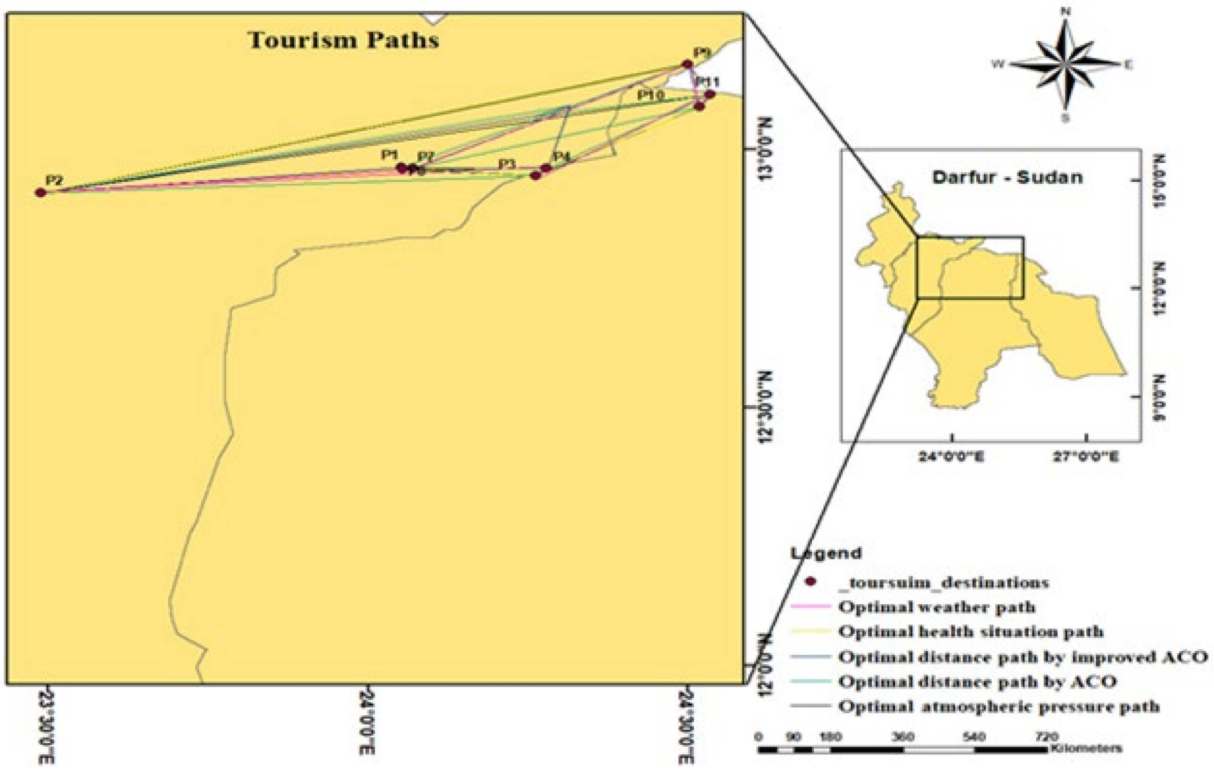

Figure 6. Optimal tourism paths by improved ACO.

3.2. Discussion

In this approach, basic ideas are introduced to improve the performance of ACO algorithms with dynamic objectives, which, especially in hilly terrain, create challenges for tourism route planning that require customized solutions. A more thorough and flexible method of route optimization is provided by the enhanced ACO algorithm, which takes into account factors such as crowd density, meteorological conditions, and cultural events. This improvement produces route maps that more closely align with travelers' preferences and real-time considerations. The outcomes of this method offer strong proof of the advantages of the modified ACO algorithm over both GA and the conventional ACO algorithm. In terms of path optimality, the modified ACO algorithm performs better than other methods and offers more reliable customized solutions that can be adjusted to meet shifting tourism objectives. By adding dynamic objectives and improving the method to fit the intricacies of tourism path planning more accurately, the limitations of conventional ACO algorithms have been addressed. This method invites users to interact with the issues raised while promoting further research and discussion in this area.

Through the incorporation of dynamic objectives, we have enhanced and refined the ACO algorithm to be more compatible with the intricacies of tourism paths in hilly terrains. The results presented in this article underscore the superiority of the modified ACO when compared to both GA and the traditional ACO. In crafting travel routes within hilly regions, dynamic objectives play a pivotal role. While prior scholars have primarily focused on static objectives, as exemplified by Li et al. [30], who proposes that network route enhancements often overlook the dynamic facets. Another approach pursued by Zhang et al. [34] involves the alteration of the final phase of the ant colony algorithm to facilitate partial point traversal within the interconnected graph by eliminating certain constraints. Although this contribution advances tourism development through the utilization of ACO, it falls short in addressing dynamic objectives.

The enhanced ACO algorithm outlined herein addresses significant challenges facing tourism path planning, especially in rugged terrains where the application of traditional methods is limited. By refining the rules for updating pheromones and incorporating dynamic parameters such as temperature, atmospheric pressure, and health conditions, our approach effectively surpasses the constraints of both the conventional ACO and GA. These enhancements enable the algorithm to account for practical environmental factors influencing tourism journeys, resulting in more effective and context-sensitive path-finding strategies. Our findings show that the enhanced ACO outperforms existing approaches in terms of path efficiency and processing time, particularly in the intricate landscapes of mountainous areas, such as Jebel Marra. This tailored adjustment renders the algorithm particularly appropriate for dynamic and intricate tourism scenarios, enriching the visitor experience by factoring in elements that are crucial for safety and convenience.

In comparison to alternative bioinspired models such as the *Physarum polycephalum* (slime mold) algorithms, which are recognized for their adaptable, decentralized nature, the improved ACO brings unique benefits in structured optimization tasks [37,39,40]. Although slime mold models excel in adapting to evolving conditions by virtue of their self-regulating characteristics, they lack the precision in multi-faceted optimization offered by our method. The advanced ACO adeptly harmonizes computational effectiveness with adaptability, reducing processing times and refining route planning accuracy by directly addressing the variable conditions prevalent in mountainous landscapes. This juxtaposition underscores the efficacy of our approach in providing robust and dependable path optimization tailored explicitly for tourism applications, presenting it as a practical and sophisticated solution for managing intricate travel paths in challenging terrains. To include dynamic objectives such as temperature, atmospheric pressure, and health conditions, we updated the objectives every 12 h.

Our approach demonstrates significant improvements in path-finding optimization when applied to mountainous regions, where tourism is a key economic driver. The use of ACO not only enhances route efficiency but also provides economic advantages by reducing infrastructure development and maintenance costs. By identifying the most efficient paths, ACO minimizes the need for extensive trail construction and reduces the associated expenses. The optimal values for temperature, atmospheric pressure, and health conditions in the region have been obtained and are shown in Table 5. Furthermore, optimized routes lead to greater tourist satisfaction, potentially increasing visitor numbers and generating more revenue for local economies. These benefits position ACO as a superior method for tourism-focused path finding when compared to traditional algorithms. The comparative experimental results are presented in Table 6, Figures 7 and 8. Table 6 quantifies the distances between tourist destinations in kilometers, corresponding to the routes identified in Table 4.

Table 5. Comparisons results of optimal dynamic objective values.

Algorithm	Optimal Weather (C)	Optimal Atmospheric (mmHg)	Optimal Health Status (Number of Persons)
Improved ACO	23	532.0	15
Traditional ACO	28	545.0	17
GA [3]	31	560.0	20

Table 6. Comparisons results of length of optimal path based on dynamic objectives.

Algorithm	Optimized Time (s)	Length of Optimal Path Based on Weather (km)	Length of Optimal Path Based on Atmospheric (km)	Length of Optimal Path Based on Health Status (km)
Improved ACO	0.27	461.95	396.9	365.9
Traditional ACO	0.4	707.75	711	704.5
GA [3]	0.45	706.98	616.6	615.6

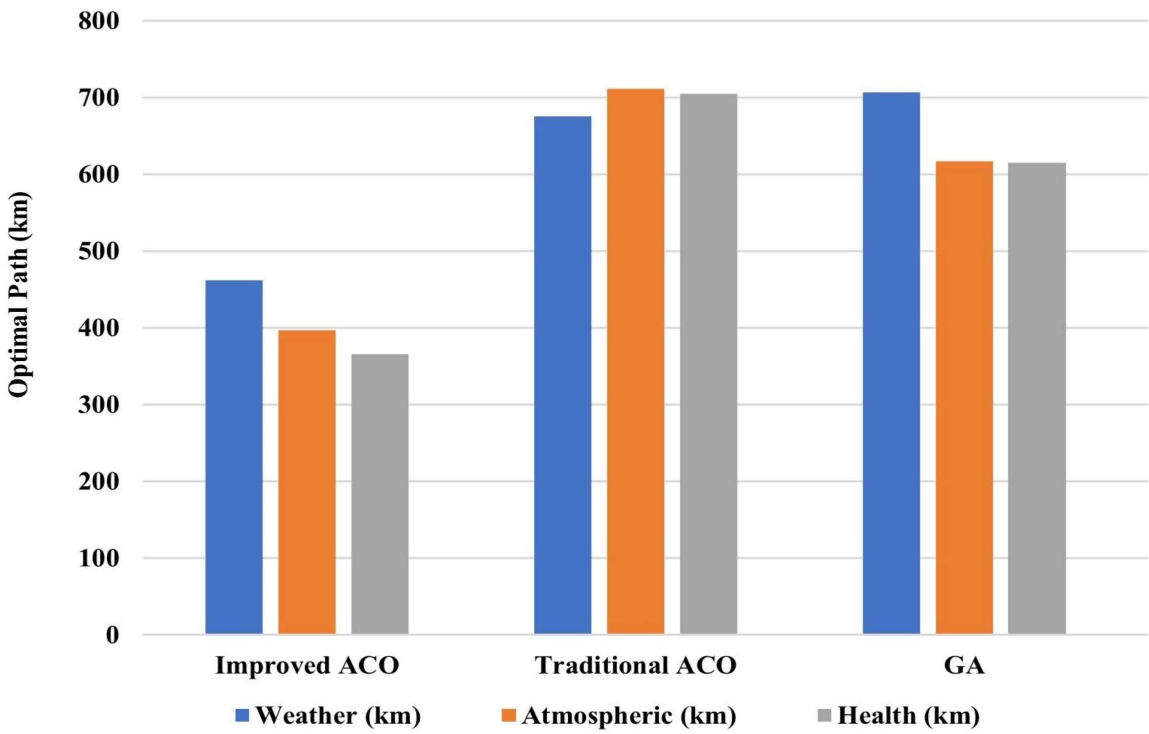

Figure 7. The optimal path is based on improved and traditional ACO and GA.

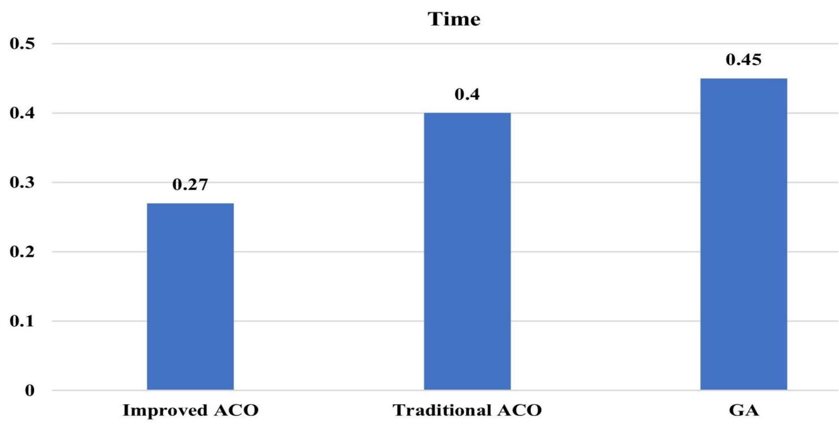

Figure 8. The optimized time based on improved and traditional ACO and GA.

The optimal paths were calculated in kilometers due to the difficulty of representing temperatures, atmospheric pressure, and health conditions on maps using different units of measurement. This makes it challenging to compare these goals without standardizing the unit of measurement. To obtain the optimal length of tourist paths based on these values, as well as based on Table 6, the distances between tourist destinations were calculated based on the dynamic objectives, which are shown in Table 6 and Figures 7 and 8.

To rigorously evaluate the algorithm's performance, the median and first quartile (25th percentile) solutions were analyzed across 30 independent runs for each configuration [21,41]. The median solutions, representing the central tendency of performance for the improved ACO were 461.5 km, 396.0 km, and 365.0 km for the weather-based, atmospheric-based, and health-based paths, respectively. In contrast, the traditional ACO achieved medians of 707.5 km, 710.0 km, and 705.0 km, while the GA produced 706.5 km, 616.5 km, and 616.0 km for the same paths. The first quartile solutions, indicative of performance under less favorable conditions for the improved ACO were 460.0 km, 395.0 km, and 364.0 km, demonstrating its robustness and reliability. Comparatively, the traditional ACO and GA exhibited significantly higher variability, with their first quartile solutions notably worse than their medians.

This analysis highlights the advantages of the improved ACO in delivering reliable and high-quality solutions for dynamic objectives. The smaller gap between the median and first quartile solutions reflects its superior stability and consistency compared to the other methods. Additionally, the best solutions achieved by the improved ACO is 459.0 km, 394.5 km, and 363.0 km consistently outperformed those of the traditional ACO and GA, showcasing its superior adaptability to dynamic environments and its ability to achieve optimal results. Table 7 shows the beast path based on median, first quartile, and best solutions for weather-based, atmospheric-based, and health-based paths across 30 runs.

Table 7. Optimal paths based on median, first quartile, and best solutions.

Algorithm	Metric	Weather-Based Path (km)	Atmospheric-Based Path (km)	Health-Based Path (km)
Improved ACO	Median	461.5	396.0	365.0
	First Quartile	460.0	395.0	364.0
	Best Solution	459.0	394.5	363.0
Traditional ACO	Median	707.5	710.0	705.0
	First Quartile	706.5	709.0	704.5
	Best Solution	705.0	708.5	704.0
GA	Median	706.5	616.5	616.0
	First Quartile	706.0	615.5	615.0
	Best Solution	705.0	615.0	614.5

4. Conclusions and Future Work

Tourism potential continues to increase due to the effective planning of tourism paths in both flat and hilly regions; however, the methods for planning tourism paths still have room for improvement. This paper has introduced a novel approach to developing tourism paths, specifically in hilly areas. The approach employed developed an enhanced ACO algorithm to optimize tourism paths in hilly areas by improving pheromone rules and initialization parameters, focusing on dynamic objectives such as temperature, atmospheric pressure, and health conditions. When applied in the Jebel Marra region, the enhanced ACO demonstrated superior performance relative to traditional ACO and GA approaches, achieving a shorter optimal route of 265.85 km and a faster execution time of 0.27 s. These results highlight the ability of the algorithm to adapt to real-time factors, offering a more efficient and tailored path-planning solution for mountainous regions. Geographical Information Systems (GIS) were employed to visualize this approach. The primary contributions of our study are as follows:

An enhanced ACO was obtained by updating pheromone-producing parameter optimization, which also increased the speed of algorithm execution, yielding improved tourism path-planning outcomes.

The utilization of the developed approach for dynamic tourism objectives in hilly regions.

Future work should focus on expanding the applicability of the enhanced ACO algorithm to diverse geographic regions with various topographies, building on the work performed for Jebel Marra. This will involve refining the algorithm by integrating additional dynamic factors such as real-time crowd density, esthetic appeal, and environmental sustainability indicators to optimize routes further. Incorporating advanced data sources such as real-time weather forecasts, IoT sensor data, and social media analytics will enhance the algorithm's decision-making and adaptability. Additionally, exploring hybrid approaches that combine the enhanced ACO with machine learning models could improve its predictive accuracy under changing conditions. Developing a user-friendly interface or mobile application to provide real-time, customized route suggestions will also further enhance the practical applications and user experience of this approach.

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