Study of Optimization of Tourists' Travel Paths by Several Algorithms

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Abstract

The purpose of this paper is to optimize the tourism path to make the distance shorter. The article first constructed a model for tourism route planning and then used particle swarm optimization (PSO), genetic algorithm (GA), and ant colony algorithms to solve the model separately. Finally, a simulation experiment was conducted on tourist attractions in the suburbs of Taiyuan City to compare the path optimization performance of the three algorithms. The three path optimization algorithms all converged during the process of finding the optimal path. Among them, the ant colony algorithm exhibited the fastest and most stable convergence, resulting in the smallest model fitness value. The travel route obtained through the ant colony algorithm had the shortest distance, and this algorithm required minimal time for optimization. The novelty of this article lies in the enumeration and description of various algorithms used for optimizing travel paths, as well as the comparison of three different travel route optimization algorithms through simulation experiments.

Keywords: Tourism; Path Planning; Genetic Algorithm; Particle Swarm Optimization; Ant Colony Algorithm.

1. Introduction

The tourism industry has always been an important part of the global economy, attracting a large number of tourists seeking different cultural, historical, natural, and entertainment experiences worldwide [1]. However, tourists face numerous challenges during their journeys, and one of them is how to optimize their time and resources while exploring as many areas of interest as possible. Tourism path optimization is a method that utilizes computer algorithms [2] to determine travel routes with the aim of enabling visitors to see multiple attractions within a specific timeframe. It uses mathematical models and algorithms to calculate the optimal path by considering factors such as distance, transportation options, time constraints, and individual preferences and needs of tourists [3].

Tourism path optimization techniques can help tourists save time and money while enhancing their exploration and experiences at the destination. As artificial intelligence and machine learning algorithms advance, tourism path optimization techniques have become increasingly precise and personalized. Wu et al. [4] proposed a utility function for the tourism experience and established an optimization model for tourism route planning. The experimental results showed that tourist attraction preferences, attention to travel time, and travel cost significantly influenced tourism route planning. Zhang et al. [5] put forward a route planning method that comprehensively considers factors such as distance between sites, initial travel position, initial departure time, travel time, total cost, site scores, and popularity. The method was analyzed through real data experiments, and the results showed that the genetic algorithm (GA) had better performance than two benchmark algorithms in terms of running time.

Zhu et al. [6] selected route information formats for setting tourism nodes in coastal cities with natural hot springs and used a multi-objective optimization algorithm to identify key routes for tourism in these cities. The results showed that, compared with traditional models, the proposed model obtained paths with shorter travel times. Khamsing et al. [7] proposed a solution to the problem of family travel routes by considering daily time windows and utilizing an enhanced adaptive large neighborhood search method for its resolution. The findings demonstrated that this approach was beneficial for tourism organizations when devising route plans. Hirano and Yamamoto [8] developed a tourist planning support system aimed at determining lunch and dinner locations, sightseeing spots en route, as well as optimal routes. A preliminary questionnaire survey revealed that users highly appreciated the functionality provided by this system. Chen et al. [9] proposed a method that combines user clustering, an improved GA, and a rectangular region path planning algorithm to design personalized travel routes for users. Theoretical analysis and experimental evaluation showed that this method outperformed other methods in terms of route prediction and area coverage.

Xu et al. [10] introduced an adaptive 2-opt_integral non-dominated sorting GA (AONSGA) for designing museum tour routes. Computational results demonstrated that the AONSGA exhibited better convergence and diversity compared to the non-dominated sorting GA-II. Zhang et al. [11] proposed research strategies for customizing tourism e-commerce using big data algorithms such as random forest, support vector machine, and Bayesian estimation. The results showed that 79.84% of customers were willing to repurchase related products after experiencing personalized travel services through big data technology.

Damos et al. [12] proposed a city tourism route planning method based on a multi-objective GA that was more accurate and intuitive compared to existing methods. In previous related studies, different researchers have proposed various tourism route planning methods. However, the focus of these studies was mainly on developing tourism route planning models that can be used to measure the quality of planned routes, while this paper emphasizes the optimization algorithms for solving the route planning models. This article briefly introduces a tourism path planning model used to measure the quality of tourism planning routes and three tourism path planning algorithms based on particle swarm optimization (PSO), GA, and ant colony algorithms that could solve the model. Then, a simulation experiment was conducted using tourist attractions in the suburbs of Taiyuan City. The main difficulty of this article lies in the construction of the tourist route planning model. If all factors were fully considered, the model would become complex, and the computational difficulty would greatly increase. Therefore, when constructing the model, some conditions have been simplified. The main contribution of this article lies in the research on PSO, GA, and ant colony algorithms, providing effective references for optimizing travel routes. The structure of this article consists of an abstract, an introduction, a description of the tourism path algorithm, simulation experiments, discussion, and a conclusion.

2. Travel Path Optimization Algorithm

2.1. Path Planning Model for Travel

Before optimizing the tourism path, it is first necessary to construct a tourism path planning model, which is used to measure the goodness and feasibility of the planned path [13]. By using the total travel time, a tourism path planning model can be constructed with the aim of enhancing the tourist experience by minimizing their travel time. In this model, the target value of the tourism path plan is determined by summing up both travel time between attractions and tour time at each attraction, which can be minimized by adjusting the order of attractions in the path plan [7, 14].

The total travel time can intuitively reflect the time spent by tourists in tourism. However, in real life, due to traffic jams or congestion at attractions and other factors, the travel time becomes uncertain. The path length between attractions is usually kept constant. Therefore, this paper uses the travel distance to measure the path scheme. The mathematical expression of the path planning model [15] is:

objective function:

$$min \, s = \sum_{i=1}^{N} \sum_{j=1}^{N} r_{ij} s_{ij} \tag{1}$$

conditional function

$$\begin{cases} r_{ij} = \begin{cases} 1 & \text{tourists from point i to point j} \\ 0 & other \end{cases} \\ r_{ij} \times r_{ji} = 0 \\ \sum_{i=1}^{N} r_{i1} = \sum_{j=1}^{N} r_{1j} = 1 \\ \sum_{i=1}^{N} \sum_{j=1}^{N} r_{ij} = N \end{cases} \tag{2}$$

where s is the total distance of the path scheme, s_{ij} is the distance from attraction i to attraction j, r_{ij} is the decision variable, and N is the total number of attractions. The objective function can minimize the total distance of the path scheme, and the conditional function can ensure that the tourists in the path scheme can traverse all the attractions at once and finally return to the starting point through the decision variable [16]. The second condition in the conditional

function ensures that there are no round trips in the path, the third condition ensures that the path eventually returns to the starting point, and the fourth condition ensures that all scenic spots are visited at once.

2.2. PSO-based Path Planning Algorithm

After establishing the path planning model of the tour, the model can be solved to obtain the optimal path solution. The exhaustive method lists all feasible solutions and finds the optimal solution among them, which can be considered as the most accurate way to solve the path planning model. However, this method becomes computationally intensive when dealing with path planning for multiple attractions [17-19].

The PSO algorithm generates more than one particle in the "search space" when planning tourism paths. The number of axes in the "search space" is influenced by the number of attractions, and the sequence of coordinates of each particle represents the order of visiting attractions. By substituting the path scheme represented by each particle into the path planning model, the path length obtained after calculation is the fitness value of the particle. When the PSO algorithm searches for the optimal tourism path scheme, the fitness value represented by the objective function of the path model is used as a guiding direction to adjust particle positions in the space through an iterative formula until the desired goal is achieved. The iterative formula is:

$$\begin{cases} v_i(t+1) = \varpi v_i(t) + c_1 r_1(P_i(t) - x_i(t)) + c_2 r_2(G_g(t) - x_i(t)) \\ x_i(t+1) = x_i(t) + v_i(t+1) \end{cases} \tag{3}$$

where $v_i(t+1)$ and $x_i(t+1)$ denote the velocity and position of particle i after one iteration, $v_i(t)$ and $x_i(t)$ denote the velocity and position of particle i before the iteration, ϖ is the inertia weight of the particle, c_1 and c_2 represent learning factors, r_1 and r_2 represent random numbers between 0 and 1.

2.3. GA-based Path Planning Algorithm

GA is also an optimization algorithm [20] that mimics the evolutionary process in nature. GA generates more than one chromosome when planning tourism paths, and each of which represents a path scheme. The genetic sequence of the chromosomes is the order of visiting the attractions. By substituting the path scheme represented by each chromosome into the path planning model, the path length obtained after calculation is the fitness value of the chromosome. GA takes the existing chromosome population as parents, selects, crosses over, and mutates them to obtain offspring. Then it calculates the fitness value of the offspring chromosomes. These iterative operations are repeated until the fitness value of the population reaches the termination condition. The iterative operation is at the core of GA. The selection operation involves reserving the best chromosome from the parent population to the offspring population, and roulette wheel selection is often used to determine which chromosome becomes an offspring. The crossover operation randomly selects two chromosomes according to the preset crossover probability and swaps the codes at the same gene position to generate offspring chromosomes. The mutation operation changes the code of a gene position in a chromosome according to the preset mutation probability. The planning of the paths in this paper needs to ensure that each attraction is passed through only once, so some adjustments are needed when performing crossover and mutation operations. The crossover operation, as shown in Figure 1, exchanges gene fragments from the same part of two chromosomes. However, duplicate fragments may appear in the exchanged offspring chromosomes, necessitating conflict adjustment. In the mutation operation, where only a single gene fragment is randomly transformed, duplicate fragments may also occur. Therefore, this paper proposes swapping two fragments in the chromosome as the mutation operation.
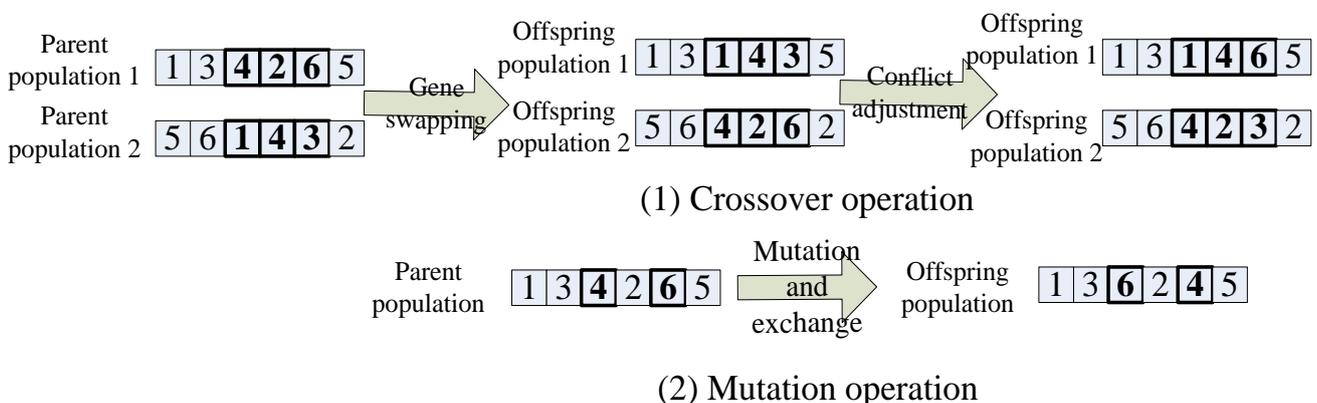

(1) Crossover operation

(2) Mutation operation

Figure 1. Schematic diagram of crossover and mutation operations

2.4. Path Planning Algorithm based on Ant Colony Algorithm

The ant colony algorithm is also a commonly used path planning algorithm for optimizing tourism paths [21]. When using the ant colony algorithm to optimize the tourist path, the size of the ant colony is first determined, and then the ants in the colony randomly select the next attraction based on a certain probability. The formula for calculating the probability is:

$$P_{ij}^r(u) = \begin{cases} \dfrac{\omega_{ij}^\theta(u)\eta_{ij}^\sigma}{\Sigma_{j\in M_j^r}\omega_{ij}^\theta(u)\eta_{ij}^\sigma} & j \notin tabu(r) \\ 0 & otherwise \end{cases} \tag{4}$$

where ω_{ii} is the residual pheromone, θ is the importance of the pheromone [22], η_{ii} is the heuristic factor of the path, σ is the importance of the heuristic factor, $tabu(r)$ is the tabu table, and $P_{ii}^r(u)$ is the probability of selecting the next node. The ants in the colony traverse all attractions for one iteration, and then the pheromone on the path is updated according to the path taken by the ants. The update formula is:

$$\begin{cases} \omega_{ij}(u+1) = \rho\omega_{ij}(u) + \Delta\omega_{ij}(u+1) \\ \Delta\omega_{ij}(u+1) = \sum_{k=1}^m \Delta\omega_{ij}^r(u+1) \\ \Delta\omega_{ij}^r(u+1) = \begin{cases} \dfrac{Q}{s_r} & \text{The path of ant r contains edge (i, j) in this iteration} \\ 0 & else \end{cases} \end{cases} \tag{5}$$

where ρ is the pheromone residual coefficient, $\Delta\omega_{ii}(u+1)$ is the pheromone increment on the path from attraction i to attraction j [23], m is the number of ants in the colony, $\Delta\omega_{ii}^r(u+1)$ is the pheromone increment of ant r on the path from attraction i to attraction j, Q is the amount of pheromone that ants can release, and s_r is the length of the path searched by ant r, i.e., the objective function.

3. Simulation Experiments

3.1. Experimental environment

The experiments in this paper were carried out on a laboratory server with configurations of Windows 7 system, 16 G memory, and I7 processor. The Matlab simulation platform was used to implement the model algorithm.

3.2. Experimental Setup

The three path planning algorithms were preliminarily tested using the Benchmark27 problem, followed by simulation experiments conducted at tourist attractions in the suburbs of Taiyuan city. The geographical location of Taiyuan City is illustrated in Figure 2. The map of the suburbs around Taiyuan city and the topology of the target attractions are shown in Figure 3. The feasible paths between the attractions in the simulation experiments are simplified to line segments connecting the nodes in the topology diagram, which facilitates their calculation. Table 1 shows the node numbers corresponding to the attraction names, where node 0 represents both the starting and ending point of the self-driving tour, while the remaining ten nodes represent target attractions. The distances between the nodes are shown in Table 2.
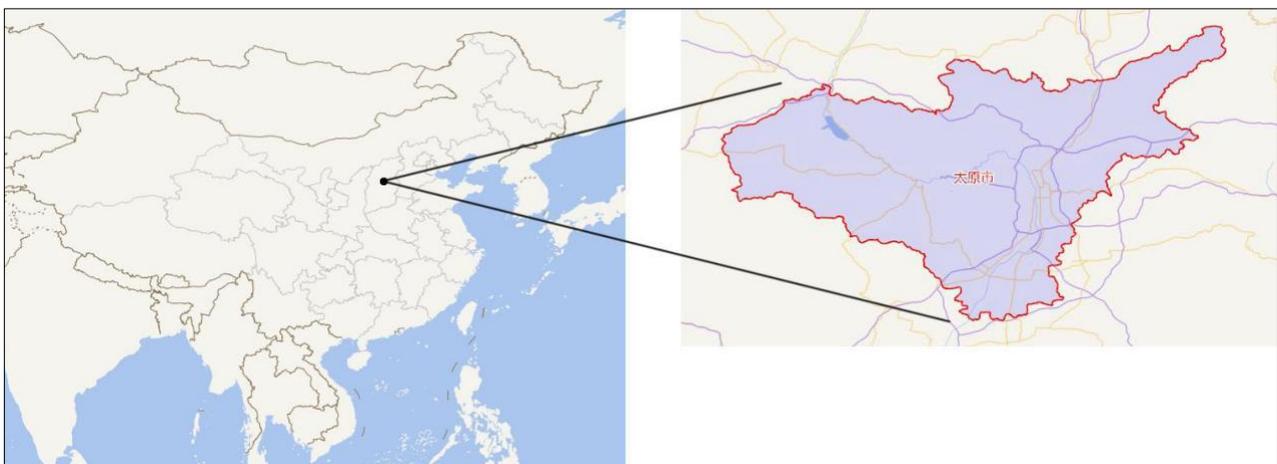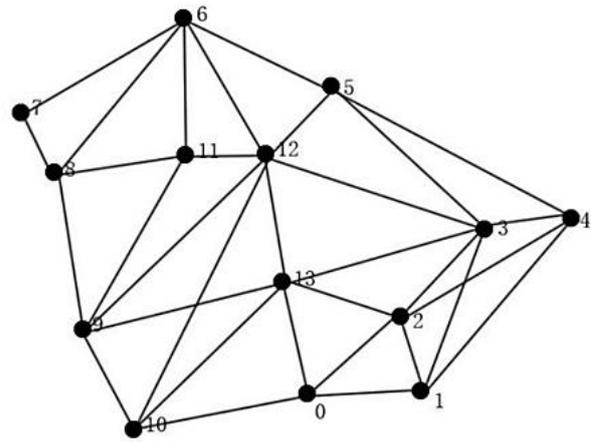

Figure 2. The geographical location of Taiyuan City

Figure 3. Topology of the tourist attractions

**Table 1. Names of attractions corresponding to node numbers**

Node number	Name of the attraction	Node number	Name of the attraction
0	Taiyuan South Station	7	Gengyang Suburban Forest Park
1	Jiulong International Cultural and Ecological Tourism Park	8	Yuquanshan Suburban Forest Park
2	Dongshan Wulong Suburban Forest Park	9	Xishan Changfeng Suburban Forest Park
3	Taitai Mountain Scenic Area	10	Jinyang Lake Park
4	Wujinshan Carnival Valley	11	Taiyuan Forest Park
5	Caiwei Manor	12	Taiyuan Zoo
6	Nanzhai Park	13	Double-tower Park

Table 2. Distance between tourist attractions (unit: km)

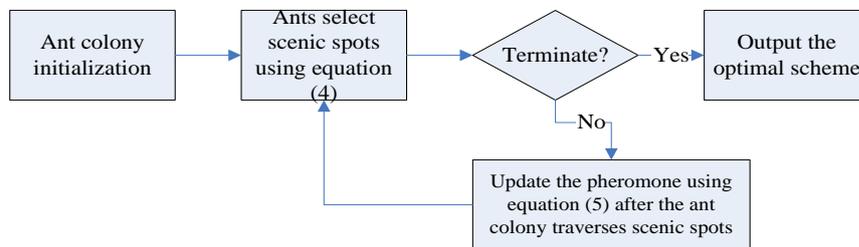| Number	0	1	2	3	4	5	6	7	8	9	10	11	12	13
0	0													
1	6	0												
2	6.7	4.3	0											
3	/	9.7	6.7	0										
4	/	10.4	10.2	6.5	0									
5	/	/	/	11.4	18.0	0								
6	/	/	/	/	/	8.7	0							
7	/	/	/	/	/	/	10.4	0						
8	/	/	/	/	/	/	11.2	3.7	0					
9	/	/	/	/	/	/	/	/	8.6	0				
10	9.7	/	/	/	/	/	/	/	/	6.3	0			
11	/	/	/	/	/	/	7.7	9.1	7.2	11.0	/	0		
12	/	/	/	12.6	/	5.3	8.7	/	/	13.8	16.9	4.2	0	
13	6.2	/	6.7	11.6	/	/	/	/	/	11.3	11.5	/	7.2	0

The basic flow of the three algorithms is shown in Figure 4.
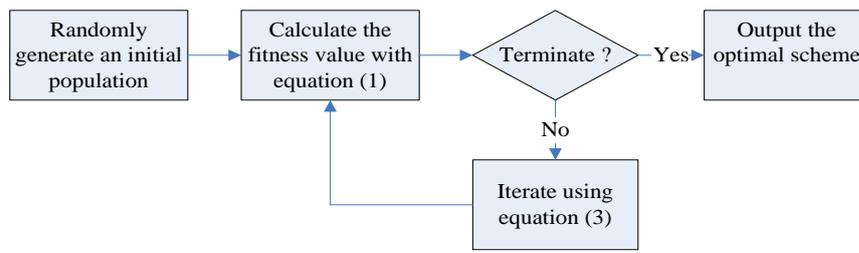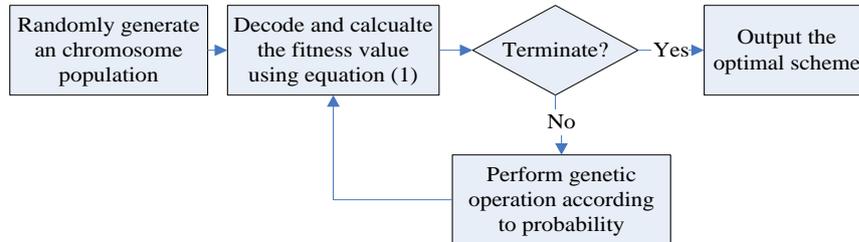
Figure 4. The basic flow of three algorithms

The relevant parameters of the PSO-based path planning algorithm are shown below. The population size was set to 20, learning factors c_1 and c_2 were 1.5 and 1.0, respectively, the inertia weight was 0.6, and the maximum number of iterations was 300.

The relevant parameters of the GA-based path planning algorithm were set as follows. The population size was 20. The crossover probability was 0.6. The mutation probability was 0.1. The maximum number of iterations was 300.

The relevant parameters of the ant colony algorithm were set as follows. The colony size was set to 20. The pheromone residual coefficient was 0.5. The pheromone that the ants can release was set to 600. θ and σ were set to 3. The maximum number of iterations was 300. The above parameters were obtained by orthogonal experiments.

3.3. Experimental Results

The Benchmark27 problem was used to preliminarily test three path planning algorithms. The planning results of the three path planning algorithms are shown in Figure 5. The PSO-based path planning algorithm obtained a path scheme with a distance of 14,603, the GA-based path planning algorithm obtained a path scheme with a distance of 14,512, and the path planning algorithm based on the ant colony algorithm obtained a path scheme with a distance of 14,397. It was observed from Figure 5 that the shortest path distance was obtained by using the ant colony algorithm, and the longest path distance was obtained by using the PSO algorithm.

The iterative convergence curves of the three path planning algorithms in the optimization process are shown in Figure 6. The fitness values of the path schemes derived by the three path planning algorithms converged as the number of iterations grew. The ACO-based path planning algorithm had the fastest decrease in fitness value during convergence and reached a stable state after approximately 30 iterations. The fitness value of the GA-based path planning algorithm decreased the second fastest and converged to a stable state after about 100 iterations and stabilized after about 120 iterations. The fitness value of the PSO-based path planning algorithm decreased the slowest and converged to a stable state after about 170 iterations and stabilized after 200 iterations. The PSO-based path planning algorithm had the slowest decrease in fitness value, converging to a stable state after approximately 170 iterations and stabilizing around 200 iterations. In addition, it was observed from Figure 4 that the scheme obtained by the PSO algorithm had the highest fitness value, the scheme obtained by the GA had the second highest fitness value, and the scheme obtained by the ant colony algorithm had the lowest fitness value once all the algorithms reached stability.
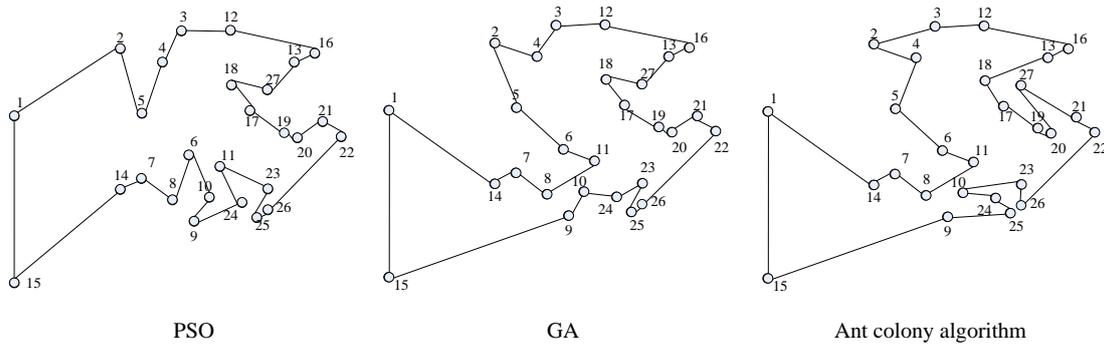
Figure 5. Planning results of three path planning algorithms for Benchmark27 problem
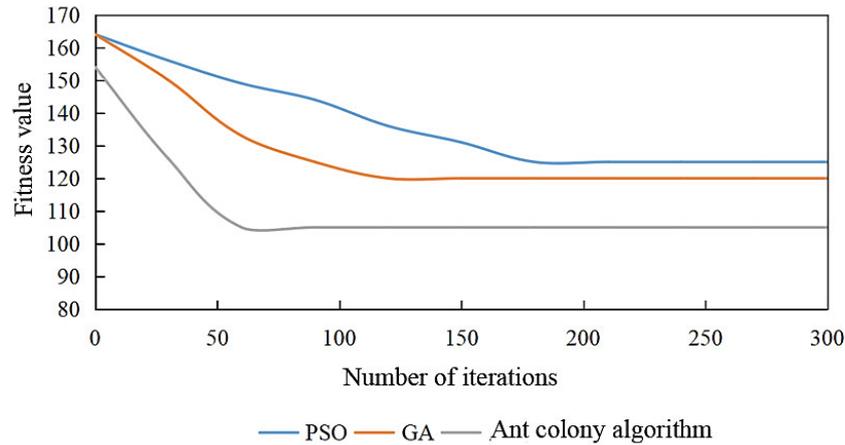

Figure 6. Iteration curves of three path planning algorithms

The travel path schemes and computation times provided by the three path planning algorithms are shown in Figure 7 and Table 3. The path given by the PSO-based path planning algorithm had a distance of 125.7 km and a computation time of 203.5 s. The path given by the GA-based path planning algorithm had a distance of 120.3 km and a computation time of 175.3 s. The path solution given by the ant colony algorithm-based path planning algorithm had a distance of 105.4 km and a computation time of 55.6 s. The comparison of Figure 7 and Table 3 revealed that the path provided by the PSO-based path planning algorithm had the longest distance and highest computation time, followed by the path provided by the GA-based path planning algorithm, and the path provided by the ant colony algorithm-based algorithm had the shortest distance and computation time.
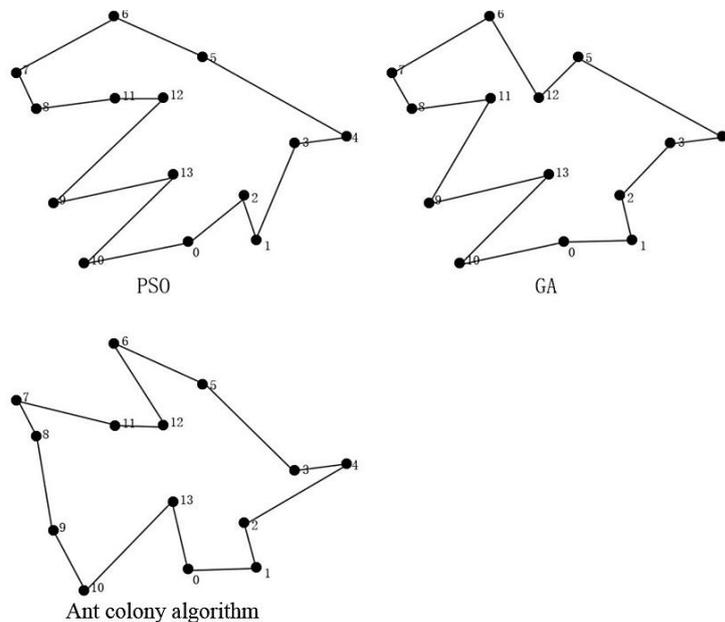

Figure 7. Travel path schemes given by the three path planning algorithms

Table 3. Path schemes given by the three path planning algorithms and the computational time consumed

Path planning algorithm	Path schemes	Program distance/km	Computational time/s
PSO algorithm	0-2-1-3-4-5-6-7-8-11-12-9-13-10-0	125.7	203.5
GA	0-1-2-3-4-5-12-6-7-8-11-9-13-10-0	120.3	175.3
Ant colony algorithm	0-1-2-4-3-5-6-12-11-7-8-9-10-13-0	105.4	55.6

4. Discussion

With the booming development of the tourism industry, an increasing number of tourists are choosing to enjoy their holidays through self-guided tours and self-driving trips. During the travel process, how to plan a cost-effective and time-saving route becomes a concern for travelers. Travel route planning can be seen as a form of path optimization problem, where path optimization is essentially a combinatorial optimization problem with the goal of finding an optimal path given the starting point and destination. In the optimization of travel routes, the optimal path usually refers to the route that reaches the destination in the shortest time or requires the minimum cost within a given time. Algorithms used to solve this problem include Dijkstra's algorithm, the genetic algorithm, etc. This article first constructs a tourism path planning model for evaluating the quality of travel routes. Then, the PSO, GA, and ant colony algorithms were proposed to solve the path planning model.

A case study was conducted using tourist attractions around Taiyuan City, and the final results are shown as mentioned above. In the basic Benchmark 27 problems, the ant colony algorithm obtained the shortest path; when selecting actual tourist attractions, it converged the fastest and had a small fitness value after convergence to stability. The final path-planning solution obtained was also superior using the ant colony algorithm. The reasons are as follows: The PSO algorithm relies on the current best particle and the historical best position of particles during the optimization iteration process. Once these two positions fall into a local optimum, it will cause the entire particle swarm to converge towards a local optimal solution. During the process of optimization iteration, the GA relies on chromosome crossover and mutation operations, which are influenced by the probabilities of crossover and mutation. The settings of these two probabilities directly impact the effectiveness and efficiency of convergence for the entire population. If these probabilities are set too high, it becomes challenging to stabilize excellent planning solutions; if they are set too low, it reduces the optimization efficiency of chromosomes. However, determining these probabilities typically depends on experience, which means that they may not be suitable. The ant colony algorithm uses the 'ant colony' to navigate between tourist attractions, finding feasible paths and utilizing residual pheromones left by ants on the path to guide subsequent iterations of the ant colony in selecting a path. In the optimization process, the concentration of pheromones plays a crucial role in guiding the ant colony and depends on the length of the path, which is not influenced by local optima. Therefore, this algorithm exhibits better optimization performance compared to the other two algorithms.

5. Conclusion

This article briefly introduces a tourism path planning model used to measure the quality of tourism planning routes. It also discussed three tourism path planning algorithms based on PSO, GA, and the ant colony algorithm and used them to solve the model. Then, a simulation experiment was conducted using tourist attractions in the suburbs of Taiyuan City. The results are as follows: As the number of iterations increased, all three path-planning algorithms converged. The ant colony algorithm-based planning algorithm converged to a stable state after about 30 iterations, the GA-based planning algorithm converged to a stable state after about 100 iterations, and the PSO-based planning algorithm converged to a stable state after about 170 iterations. After convergence to a stable state, the PSO-based planning algorithm had the highest fitness value, followed by the GA-based planning algorithm, while the ant colony algorithm-based planning algorithm had the lowest fitness value. The path scheme provided by the PSO-based planning algorithm was "0-2-1-3-4-5-6-7-8-11-12-9-13-10-0" with a distance of 125.7 km and a computation time of 203.5 s. The path scheme provided by the GA-based planning algorithm was "0-1-2-3-4-5-12-6-7-8-11-9-13-10-0" with a distance of 120.3 km and a computation time of 175.3 s. The path scheme provided by the ant colony algorithm-based planning algorithm was "0-1-2-4-3-5-6-12-11-7-8-9-10-13-0" with a distance of 105.4 km and a computation time of 55.6 s.

6. Declarations

6.1. Data Availability Statement

The data presented in this study are available in the article.

6.2. Funding

6.3. Institutional Review Board Statement

Not applicable.

6.4. Informed Consent Statement

Not applicable.

6.5. Declaration of Competing Interest

The author declares that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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