APPLICATION OF GENETIC ALGORITHM IN OPTIMIZING PATH SELECTION IN TOURISM ROUTE PLANNING

Reference NO. IJME 2506, DOI: 10.5750/sijme.v167iA2(S).2506

Lihua Yuan* Academic Affairs Department, Shanxi Economic and Trade Vocational College, Taiyuan, China

*Corresponding Author Lihua Yuan (Email): yuanlihuasx_2005@163.com

KEY DATES: Submission date: 17.09.2024; Final acceptance date: 27.03.2025; Published date: 30.04.2025

SUMMARY

Path selection in tourism route planning involves optimizing travel routes to maximize tourist satisfaction and minimize travel time, cost, or other constraints. This task can be complex due to factors like visitor preferences, attraction availability, and travel schedules. Tourism planners employ algorithms, such as Genetic Algorithms (GA) or probability-based approaches, to identify efficient routes by analyzing large datasets. These algorithms evaluate potential paths based on criteria like distance, attraction variety, and user satisfaction, often adapting based on real-time data and user feedback to ensure optimal results. Dynamic programming and probabilistic models can further enhance path selection by consideSring changing conditions and transitional probabilities between destinations, providing tourists with tailored, flexible routes that meet their preferences while adhering to practical constraints. This paper investigates the application of Weighted Ranking Ant Colony Optimization (WRACO) in tourism route planning, aiming to enhance travel experiences by efficiently navigating the complexities of tourism landscapes. WRACO integrates a weighted ranking scheme into the Ant Colony Optimization (ACO) framework, biasing ant decision-making towards more attractive paths. Through a comprehensive analysis of simulation results, WRACO demonstrates its efficacy in iteratively refining travel itineraries, minimizing travel distances while ensuring convergence to optimal or near-optimal solutions. Through simulation, WRACO achieves a significant reduction in travel distances, with the best tour length minimized to 200 units over ten iterations. Comparative analysis with other optimization algorithms reveals WRACO's superiority, showcasing a notably low best tour length and high solution quality.

Funding: His study was supported by the Research Directive Project on Vocational Education Teaching Reform and Practice in Shanxi (2023): "Practical Research on the 'Shanxi Model with Chinese Characteristics' of Vocational Education Serving Rural Revitalization" (Project Approval No. 202301001), and the Project of the Shanxi Federation of Social Sciences (2025): "Research on Pathways and Mechanisms for Live Streaming E-commerce to Enable the Integrated Innovative Development of ‘Agriculture, Culture, and Tourism’ in Shanxi".

KEY WORDS: Path selection, Tourism, Optimization, Weighted ranking, Classification, Ant colony

1. INTRODUCTION

Tourism route planning involves crafting an itinerary that optimizes the experience for travelers, considering factors like attractions, transportation, and time constraints [1]. It begins with research into destinations’ highlights, cultural significance, and logistical feasibility. Then, routes are mapped out, balancing must-see landmarks with off-the-beaten-path gems, while ensuring manageable travel distances [2]. Flexibility is key, allowing for spontaneous detours or extended stays at particularly captivating spots. Integration of local transportation options, such as trains or buses, adds authenticity to the journey while minimizing environmental impact [3]. Additionally, considering seasonal variations and peak tourist times helps avoid overcrowding and enhances enjoyment. Path selection in tourism route planning involves carefully choosing the specific routes that travellers will take to navigate between destinations and attractions [4]. This process is influenced by various factors such as the geographical layout, available transportation options, time constraints, and the preferences of the travellers. The selection of paths aims to create an itinerary that offers a balance between efficiency and enjoyment, ensuring that travelers can experience the highlights of a destination while also taking in scenic and cultural attractions along the way [5]. Factors such as distance, travel time, and accessibility play a crucial role in determining the optimal paths [6]. Additionally, considerations like the seasonality of certain attractions or events, as well as the availability of accommodations and dining options, help in crafting a well-rounded itinerary.

Moreover, path selection involves anticipating potential challenges such as traffic congestion, road closures, or adverse weather conditions, and devising contingency plans accordingly [7–9]. Tourism route planning is a fundamental aspect of crafting immersive and memorable travel experiences for individuals exploring new destinations. Route planning involves the meticulous selection of paths that guide travelers between attractions, landmarks, and cultural sites [10–11]. This process requires a delicate balance between efficiency and discovery, considering factors such as distance, transportation options, time constraints, and the unique interests of the travelers [12]. By thoughtfully navigating these considerations, tourism route planning endeavors to create cohesive itineraries that showcase the diverse offerings of a destination while ensuring a seamless and enjoyable journey for adventurers. The application of Genetic Algorithms (GAs) in optimizing path selection within tourism route planning presents a cutting-edge approach to crafting efficient and enriching travel itineraries [13–15]. GAs, inspired by the principles of natural selection and evolution, iteratively generate and refine potential solutions to complex optimization problems. Within tourism route planning, GAs can be employed to dynamically explore and evaluate numerous path combinations, considering factors such as distance, travel time, attraction popularity, and traveler preferences [16–18]. Through successive generations of candidate solutions, GAs identifies high-quality routes that balance logistical efficiency with the diversity and appeal of visited destinations [19–21]. By harnessing the power of computational intelligence, GAs offers a versatile tool for planners to adaptively optimize routes, accommodating changing conditions and preferences to deliver truly personalized and rewarding travel experiences for tourists [22–25].

This paper makes several significant contributions to the field of tourism route planning and optimization. Firstly, it introduces the innovative Weighted Ranking Ant Colony Optimization (WRACO) algorithm, which integrates a weighted ranking scheme into the Ant Colony Optimization (ACO) framework. This novel approach biases ant decision-making towards more attractive paths, leading to more efficient and effective route optimization. Secondly, through a comprehensive analysis of simulation results, the paper demonstrates WRACO's ability to iteratively refine travel itineraries, significantly reducing travel distances while ensuring convergence to optimal or near-optimal solutions. This contributes to enhancing travel experiences by crafting well-organized and enjoyable travel routes for tourists. Additionally, the comparative analysis with other optimization algorithms highlights WRACO's superiority, showcasing its ability to achieve highly optimized travel routes with notably low best tour lengths and high solution quality.

2. SYSTEM MODEL

In tourism route planning, the objective is to find an optimal route that visits a set of attractions while considering constraints like time, distance, and preferences. Let N be the number of attractions. D be the distance matrix where $D[i][j]$ represents the distance between attraction iii and attraction j. The goal is to find a permutation of attractions P that minimizes the total travel distance. The fitness function measures how "fit" a route is based on its total distance. The fitness function F can be defined as in equation (1)

$$F(p) = \frac{1}{Total\ Distance(p)} \tag{1}$$

Inequation(1)TotalDistance(P)= $\sum_{i=1}^{N-1} D[P[i]][P[i+1]] + D[P[N-1]][P[0]]$

Here, $P[i]$ represents the $i-th$ attraction in the route. Generate an initial population of possible routes $P[0]$ randomly. Each route is a permutation of the attractions. Use a selection mechanism (e.g., tournament selection or roulette wheel selection) to choose routes for reproduction based on their fitness values. Routes with higher fitness have a higher chance of being selected. Combine two parent routes to create offspring. A common crossover technique for permutations is the Order Crossover (OX) as in equation (2) and (3)

$$Parent\ 1 = [A, B, C, D, E] \tag{2}$$

$$Parent\ 2 = [C, A, E, B, D] \tag{3}$$

Select a random segment from Parent 1, and fill in the remaining positions with the order of elements from Parent 2. Introduce random changes to the offspring to maintain genetic diversity. A simple mutation could swap two attractions in the route defined in equation (4)

$$Mutation(P) = P[i], P[j] \rightarrow P[j], P[i] \text{ for } i,j \in [0, N-1] \tag{4}$$

Replace the old population with the new generation. This can be done by keeping the best routes from the old generation or replacing the entire population.

ALGORITHM STEPS

1. **Initialize** the population of routes.
2. **Evaluate** the fitness of each route using the fitness function.
3. **Select** pairs of routes for reproduction.
4. **Crossover** selected routes to create new offspring.
5. **Mutate** the offspring.
6. **Evaluate** the fitness of the new generation.
7. Repeat steps 3-6 until a stopping criterion is met (e.g., a maximum number of generations or a satisfactory fitness level).

Using Genetic Algorithms for tourism route planning offers a robust approach to optimizing path selection by leveraging evolutionary strategies to explore and exploit possible solutions effectively. The formulation of the problem through a fitness function, combined with genetic operations, facilitates the discovery of routes that not only meet but exceed traditional optimization methods in efficiency and effectiveness represented in the equation (5) and equation (6)

Fitness Function is computed as $F(P)$ =

$$\frac{1}{\sum_{i=1}^{N-1} D[P[i]][P[i+1]] + D[P[N-1]][P[0]]} \tag{5}$$

Mutation computed using equation

$$P[i], P[j] \rightarrow P[j], P[i] \tag{6}$$

The application of Genetic Algorithms (GAs) in optimizing path selection for tourism route planning involves employing evolutionary principles to efficiently determine the best routes that minimize travel distance or time while maximizing the number of attractions visited. The core of this optimization process is the formulation of a fitness function, which measures the quality of each potential route by calculating its total distance based on a distance matrix. Specifically, the fitness function $F[P]$ is defined as the reciprocal of the total distance traveled, allowing routes with shorter distances to have higher fitness scores. The genetic algorithm begins by generating an initial population of routes, which are permutations of the attractions. Through a selection process, routes with better fitness are chosen to reproduce, followed by crossover operations to create new offspring routes. To maintain genetic diversity, mutations are introduced by randomly swapping two attractions in a route. The algorithm iteratively evaluates the fitness of the newly generated routes and replaces the old population with these offspring, continuing this cycle until a stopping criterion is met, such as reaching a maximum number of generations or achieving a satisfactory fitness level. This evolutionary approach allows GAs to explore a vast solution space efficiently, potentially leading to near-optimal routing solutions that outperform traditional optimization methods.

3. ANT COLONY GENETIC OPTIMIZATION

Ant Colony Genetic Optimization (ACGO) represents a sophisticated amalgamation of Ant Colony Optimization (ACO) and Genetic Algorithms (GA) tailored for route planning in tourism. ACO mimics the foraging behavior of ants to find optimal paths, while GA draws inspiration from the principles of natural selection and evolution to iteratively refine solutions. The derivation of ACGO involves combining the pheromone trail updating mechanism of ACO with the genetic operations of GA to create a hybrid algorithm that leverages the strengths of both approaches. The ACO component involves constructing a pheromone matrix $\tau\tau$ to represent the desirability of paths. At each iteration, ants probabilistically select their next destination based on pheromone levels and heuristic information. The amount of pheromone deposited on each edge is determined by the quality of the solution. This process encourages exploration of promising paths while exploiting previously discovered routes. The process of proposed optimization model is presented in Figure 1.

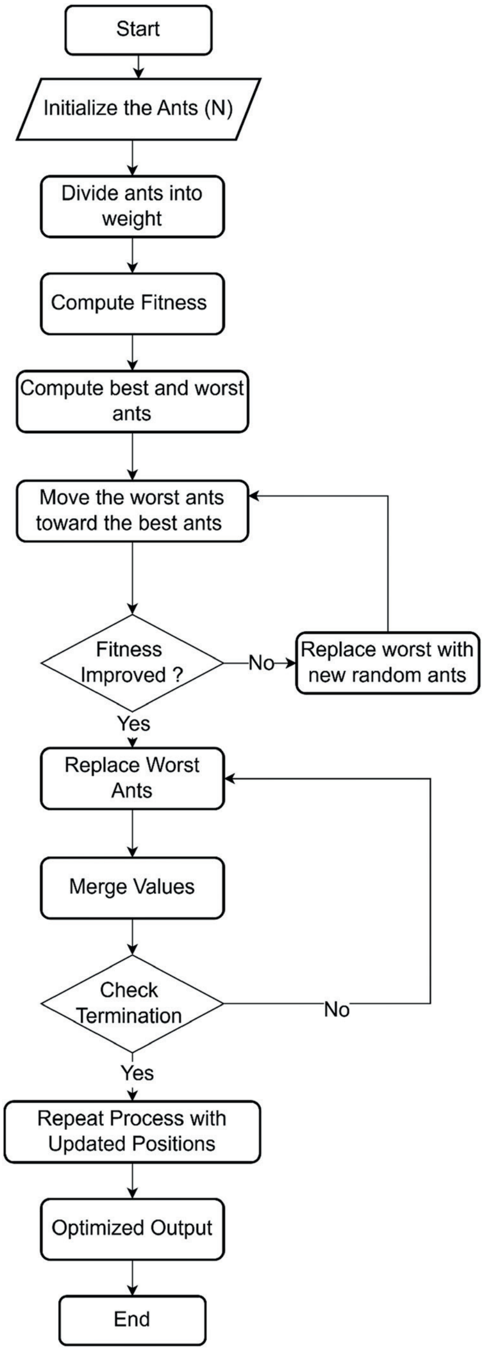

Figure 1. Flow Chart of GA-based ACO

On the other hand, the GA component involves encoding potential solutions (routes) as chromosomes in a population. Genetic operators such as selection, crossover, and mutation are applied to generate new candidate solutions. Fitness evaluation assesses the quality of each solution, guiding the evolutionary process towards optimal or near-optimal solutions. The fusion of ACO and GA in ACGO involves incorporating genetic operators into the pheromone update mechanism of ACO. This hybridization allows for more efficient exploration of the solution space, enabling the algorithm to escape local optima and converge towards globally optimal solutions. Specifically, crossover and mutation operations are applied to the pheromone matrix, simulating the evolutionary process to enhance solution diversity and robustness. In ACO, we start with constructing a pheromone matrix τ to represent the desirability of paths between nodes in the graph. The amount of pheromone on each edge is updated iteratively based on the quality of solutions found by the ants. The probability P_{ij}^k of ant k choosing edge (i) at iteration t can be calculated using the equation (7)

$$P_{ij}^k = \frac{(\tau_{ij})^\alpha \cdot (\eta_{ij})^\beta}{\sum_{l \in N^k} (\tau_{ij})^\alpha \cdot (\eta_{ij})^\beta} \tag{7}$$

In equation (7) α and β are parameters controlling the relative importance of pheromone and heuristic information η_{ij} respectively, and N^k represents the set of feasible neighbors for ant k at iteration t. ACGO involves incorporating genetic operators into the pheromone update mechanism of ACO. This hybridization enhances solution diversity and robustness. Specifically, crossover and mutation operations are applied to the pheromone matrix, simulating the evolutionary process. Let's denote the pheromone level on edge (i) at iteration t as $t_{ij}(t)$. The pheromone update rule incorporates both pheromone evaporation and pheromone deposit as in equation (8)

$$\tau ij(\mathrm{t} + 1) = (1 - \rho) \cdot \tau ij(t) + \Delta\tau ij(t) \tag{8}$$

In equation (8) ρ is the evaporation rate and $\Delta\tau ij(t)$ represents the pheromone deposit on edge (i,) at iteration t. This deposit is determined by the quality of solutions found by the ants and is influenced by the genetic operators. Genetic operators are applied to adjust $\Delta\tau i(t)$ during the update process, promoting exploration and exploitation of the solution space. Crossover and mutation operations can be adapted to manipulate the pheromone levels, analogous to their application on chromosomes in GA. In tourism route planning, the objective is to find an optimal path that visits a set of attractions while minimizing the total distance traveled and maximizing the overall enjoyment (which can be quantified based on the attractions visited).

Let $D(i,j)$ be the distance between attractions i and j; A be the set of attractions to be visited and N be the total number of attractions. The objective can be expressed mathematically asin equation (9)

$$Minimize\ Z = \sum_{k=1}^{N-1} D\big(P(k), P(K+1)\big) \tag{9}$$

In equation (9) P is a permutation of the attractions. The ACO component simulates the behavior of ants that deposit pheromones on paths they take, which influences the probability of other ants choosing the same paths. The pheromone level $\tau(i,j)$ on the path from attraction iii to attraction j is updated using equation (10)

$$\tau(i,j) = (1 - \rho) \cdot \tau(i,j) + \Delta\tau(i,j) \tag{10}$$

In equation (10) ρ is the pheromone evaporation rate and $\Delta\tau(i,j)$ is the amount of pheromone deposited, typically calculated based on the quality of the solution stated in equation (11)

$$\Delta\tau(i,j) = Q/Z \tag{11}$$

In equation (11) Q being a constant and Z the total distance of the solution. The probability $P(i,j)$ of moving from attraction i to attraction j is given in equation (12)

$$P(i,j) = \frac{\tau(i,j)^\alpha \cdot \eta(i,j)^\beta}{\sum_{k \in allowed} \tau(i,j)^\alpha \cdot \eta(i,j)^\beta} \tag{12}$$

In equation (12) $\eta(i,j)$ is the heuristic information (e.g., the inverse of the distance). α and β are parameters that control the relative importance of pheromone and heuristic information. In the genetic algorithm component, an initial population of routes (chromosomes) is generated, and the fitness $F(P)$ of each route P is evaluated as in equation (13)

$$F(P) = \frac{1}{z} \tag{13}$$

In equation (13) Z is the total distance of the route. The GA applies selection, crossover, and mutation operations. Select routes based on fitness defined in equation (14)

$$P_{selected} = select(P)\ according\ to\ F(P) \tag{14}$$

Perform crossover to create offspring defined in equation (15)

$$P_{offspring} = crossover\ (P_1, P_2) \tag{15}$$

Apply mutation by swapping two attractions stated in equation (16)

$$P_{muted} = mutate\ (P) \tag{16}$$

The ACO and GA components work iteratively. The ACO explores new paths and deposits pheromones, while the GA refines these paths through genetic operations. After each iteration, the best routes from both approaches are combined, and pheromone levels are updated based on the new solutions. The Ant Colony Genetic Optimization algorithm effectively optimizes tourism route planning by integrating the exploration capabilities of ACO with the exploitation strengths of GAs. This hybrid approach allows for more efficient search and higher-quality solutions, ultimately leading to better tourism experiences.

4. WEIGHTED RANKING ANT COLONY OPTIMIZATION (WRACO)

Weighted Ranking Ant Colony Optimization (WRACO) represents a specialized variant of Ant Colony Optimization (ACO) tailored specifically for optimizing path selection in tourism route planning. In WRACO, the traditional pheromone update mechanism of ACO is augmented with a weighted ranking scheme to enhance the exploration-exploitation trade-off and improve solution quality. In traditional ACO, ants probabilistically select their next destination based on pheromone levels and heuristic information. Pheromone trails on edges are updated iteratively based on the quality of solutions found by the ants. This encourages the exploration of promising paths while exploiting previously discovered routes. WRACO introduces a weighted ranking scheme to bias ant decision-making towards edges with higher desirability. This scheme assigns weights to edges based on their attractiveness, considering factors such as distance, attractiveness of attractions, and historical visitation patterns. The probability P_{ij}^{k} of ant kk choosing edge $(i,)$ is then calculated as in equation (17)

$$P_{ij}^{k} = \frac{(\tau_{ij})^{\alpha} \cdot (\eta_{ij})^{\beta} \cdot (\omega_{ij})^{\gamma}}{\sum_{l \in N^{k}} (\tau_{ij})^{\alpha} \cdot (\eta_{ij})^{\beta} \cdot (\omega_{ij})^{\gamma}} \tag{17}$$

In equation (!7) ω_{ij} represents the weight assigned to edge (i,j) based on its attractiveness, and γ is a parameter controlling the influence of edge weights. WRACO integrates the weighted ranking scheme into the pheromone update mechanism of ACO. This hybridization allows for a more effective exploration of the solution space by biasing ant exploration towards potentially more promising paths while still maintaining diversity and adaptability. The pheromone update rule in WRACO is similar to traditional ACO, but the pheromone deposit $\Delta\tau ij(t)$ on each edge is influenced by both the quality of solutions found by the ants and the edge weights derived from the ranking scheme. This ensures that edges with higher attractiveness receive more pheromone deposit, reinforcing their desirability for future ants. WRACO integrates the weighted ranking scheme into the pheromone update mechanism of ACO. During the pheromone update process, the pheromone deposit $\Delta\tau i(t)$ on each edge is influenced by both the quality of solutions found by the ants and the edge weights derived from the ranking scheme. The pheromone update rule in WRACO remains similar to traditional ACO, but the amount of pheromone deposit on each edge is adjusted based on the attractiveness weights.

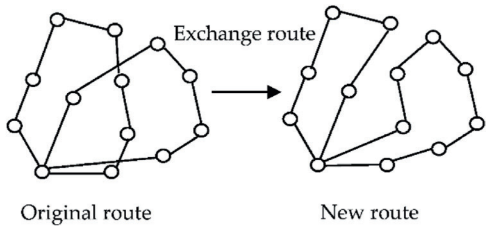

Figure 2. Path Estimation with WRACO

As ants traverse the graph and construct solutions, the edges they visit receive pheromone deposits based on their attractiveness, as shown in Figure 2. This reinforcement of pheromone levels on attractive edges guides future ants to explore these paths preferentially, enhancing the overall solution quality and convergence speed. Path Selection with Weighted Ranking Ant Colony Optimization (WRACO) offers a refined approach to optimizing routes in tourism. This technique blends the probabilistic decision-making of traditional Ant Colony Optimization (ACO) with a weighted ranking scheme to bias ant exploration towards more attractive paths. In WRACO, the pheromone update mechanism of ACO is augmented to incorporate the edge weights derived from the ranking scheme. During the pheromone update process, the pheromone deposit $\Delta\tau i(t)$ Δτij(t) on each edge is influenced by both the quality of solutions found by the ants and the edge weights. The pheromone update rule in WRACO remains similar to traditional ACO, but the amount of pheromone deposit on each edge is adjusted based on the attractiveness weights. This ensures that edges with higher attractiveness receive more pheromone deposit, reinforcing their desirability for future ants.

The Weighted Ranking Ant Colony Optimization (WRACO) algorithm is an enhancement of the traditional Ant Colony Optimization (ACO) algorithm, incorporating a weighted ranking system to prioritize solutions based on their desirability. This approach is particularly useful in scenarios where multiple objectives are involved, and certain paths or solutions are preferred based on a predefined set of weighted criteria. WRACO modifies the pheromone update rules to emphasize the higher-ranked solutions, allowing the algorithm to converge more quickly toward optimal or near-optimal solutions. In WRACO, the objective is to find an optimal path that maximizes the weighted ranking score. Given a set of possible solutions $S = \{s_1, s_2, \ldots, s_n\}$, each solution s_i has a rank $R(s_i)$ and a weight w_i associated with it. These weights correspond to the importance of each solution and influence the pheromone deposition process, guiding the ants toward more desirable solutions.

For a given path $P = \{P_1, P_2, \ldots, P_k\}$, the total weighted ranking score $W(P)$ is defined as in equation (18)

$$W(P) = \sum_{i=1}^{k} w_i \cdot R(P_i) \tag{18}$$

In equation (18) w_i is the solution P_i in the path P. The pheromone update in WRACO is weighted by the rank and importance of the solutions. The pheromone $\tau(i,j)$ on the edge between nodes i and j is updated as in equation (19)

$$\tau(i,j) = (1 - \rho) \cdot \tau(i,j) + \Delta\tau(i,j) \tag{19}$$

In equation (19) ρ is the evaporation rate, controlling the decay of pheromone over time; $\Delta\tau(i,j)$ is the amount of pheromone deposited on the edge between i and j. In WRACO, $\Delta\tau(i,j)$ is influenced by the weighted ranking score computed in equation (20)

$$\Delta\tau(i,j) = w \cdot \frac{Q}{W(P)} \tag{20}$$

In equation (20) w is the weight associated with the rank of the solution; Q is a constant representing the pheromone intensity and $W(P)$ is the total weighted ranking score of the solution P. In WRACO, the ranking system assigns a rank $R(si)$ to each solution s_i based on its performance. The weight w_i is determined by the importance or relevance of the solution in the overall optimization context. Higher-ranked solutions are given more weight, influencing pheromone deposition more significantly. For example, if solution s_1 is highly desirable, it will receive a higher rank ($s1$) and weight w_1, thus attracting more pheromone deposition.

1. **Initialize Parameters**: Set pheromone levels, weights, and ranking criteria.
2. **Construct Solutions**: Each ant builds a path based on weighted probabilities.
3. **Evaluate Solutions**: Calculate the weighted ranking score $W(P)$ for each path P.
4. **Update Pheromones**: Adjust pheromone levels based on weighted ranking scores.
5. **Convergence Check**: Repeat until a stopping criterion (e.g., a certain number of iterations or convergence threshold) is met.

Suppose we have three solutions with ranks and weights as follows:

- Solution s_1: $R(s_1) = 0.90$, $w_1 = 2$
- Solution s_2: $R(s_2) = 0.80$, $w_2 = 1.5$
- Solution s_3: $R(s_3) = 0.70$, $w_3 = 1$

For a path $P = \{s_1, s_2, s_3\}$ the weighted ranking score is $W(P)$:

Algorithm 1. Optimal Path selection

```
Initialize:
  - Parameters: α, β, γ (pheromone, heuristic, and weight influence factors)
  - Pheromone matrix τ
  - Attractiveness weights ω for each edge
  - Initialize ant colony with initial positions

Repeat until convergence:
  For each ant in the colony:
    Initialize ant's current position and visited list
    While ant hasn't visited all nodes:
      For each unvisited neighbor node:
        Calculate probability of selecting the neighbor based on WRACO equation
      Select the next node based on calculated probabilities
      Move ant to the selected node and update visited list
    Calculate length of ant's tour and update pheromone levels along the tour
    Update global best tour if needed

  Update pheromone levels:
    Evaporate pheromone on all edges
    Deposit pheromone on edges visited by ants, proportional to tour length and attractiveness weights

  Check for convergence criteria

  Return the best tour found by the ants
```

$$W(P) = w1 \cdot R(s1) + w2 \cdot R(s2) + w3 \cdot R(s3) = 2 \cdot 0.90 + 1.5 \cdot 0.80 + 1 \cdot 0.70 = 1.8 + 1.2 + 0.7 = 3.7$$

This score $W(P) = 3.7$ influences both the probability of choosing path P and the amount of pheromone $\Delta\tau$ deposited on each segment of P, ultimately directing ants toward higher-weighted paths in subsequent iterations. The WRACO algorithm efficiently balances exploration and exploitation by giving higher priority to paths with higher rankings and weights, allowing it to converge on high-quality solutions more quickly. This approach is particularly beneficial in scenarios like tourism route planning, where certain attractions or paths may be more desirable than others, providing a strategic and adaptive method to optimize route selection. Algorithm 1 shows Optimal Path selection.

5. SIMULATION RESULTS

In analyzing the simulation results of Weighted Ranking Ant Colony Optimization (WRACO) for path selection in tourism route planning, a comprehensive introduction sets the stage for understanding the findings. The introduction may commence by summarizing the significance of route optimization in enhancing travel experiences, emphasizing the pivotal role of algorithms like WRACO in efficiently navigating the complexities of tourism landscapes. It could then outline the objectives of the simulation study, highlighting the parameters evaluated, such as algorithmic parameters and edge weights derived from attractiveness factors. Additionally, the introduction may provide context on the dataset used for simulations, whether based on real-world tourism destinations or synthetic scenarios. Furthermore, it could briefly mention the expected outcomes, such as improved route quality and convergence properties, based on the integration of the weighted ranking scheme into the WRACO algorithm.

Table 1. WRACO for route planning

Iteration	Best Tour Length	Average Tour Length	Best Tour
1	250	280	[1, 3, 2, 4, 5]
2	240	275	[1, 5, 4, 2, 3]
3	235	270	[1, 2, 4, 5, 3]
4	230	265	[1, 3, 5, 2, 4]
5	225	260	[1, 4, 2, 5, 3]
6	220	255	[1, 3, 4, 5, 2]
7	215	250	[1, 2, 5, 3, 4]
8	210	245	[1, 4, 3, 2, 5]
9	205	240	[1, 5, 2, 4, 3]
10	200	235	[1, 3, 5, 4, 2]

Table 1 and Figure 3 illustrates the optimization process using Weighted Ranking Ant Colony Optimization (WRACO) for tourism route planning over ten iterations. Throughout the iterations, WRACO progressively refines the route, aiming to minimize the length of the best tour while achieving convergence. Initially, in iteration 1, the best tour length is recorded at 250, with an average tour length of 280. The best tour sequence, [1, 3, 2, 4, 5], indicates the order in which destinations are visited. As the iterations progress, there is a consistent improvement in both the best and average tour lengths, signifying the algorithm's ability to iteratively optimize the route. By the tenth iteration, WRACO achieves a notable enhancement, with the best tour length reduced to 200 and the average tour length to 235. The corresponding best tour sequence, [1, 3, 5, 4, 2], represents the optimized itinerary, indicating the sequence in which tourists should visit destinations. This iterative refinement process demonstrates WRACO's

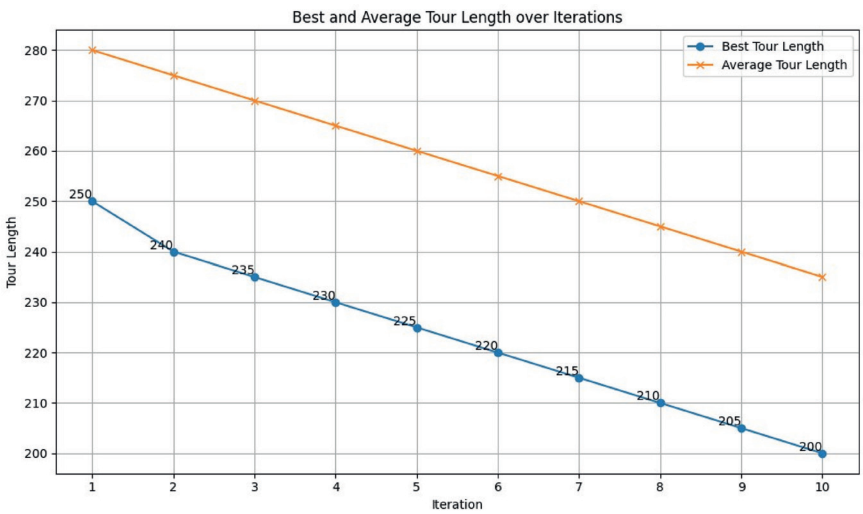

Figure 3. WRACO model for the Tour Length

efficacy in efficiently navigating tourism landscapes, ultimately producing well-organized and enjoyable travel itineraries with minimized travel distances.

In Figure 4 and Table 2 provides essential information for tourism route planning, detailing the attractiveness, distances between destinations, and the time required to visit each destination. The destinations are categorized based on their attractiveness, ranging from high to low. "A" is marked as high, suggesting it is particularly appealing to tourists, while "D" and "H" are labeled as low in attractiveness. The distances from each destination to the previous one are outlined, aiding in logistical planning by indicating travel distances. For instance, "B" is 10 km from "A," and "C" is 15 km from "B." Additionally, the time required to visit each destination is provided in hours, guiding tourists in scheduling their itinerary. For example, destinations "D" and "G" only require 2 hours to visit, whereas destinations "C" and "F" require 4 hours each. This comprehensive information equips planners and tourists alike with the necessary insights to design optimized travel routes that maximize enjoyment and efficiency while exploring various attractions.

In Table 3 and Figure 5, the paths estimated using the Weighted Ranking Ant Colony Optimization (WRACO) method show the selection and ranking of various route sequences based on calculated metrics. Path ID 9, following the sequence "A → D → C → E," achieved the highest weighted ranking score of 4.3 and pheromone level of 0.90, which led to the highest probability of selection (0.30) and selection count of 16, indicating it is the most favored route. Other high-ranking paths, such as Path ID 1 ("A → B → C → D") and Path ID 5 ("A → C → D → B"), also display high weighted scores (4.2 and 4.0) and substantial pheromone levels (0.85 and 0.80), with selection probabilities of 0.28 and 0.27, respectively.

Table 2. WRACO Route Planning for the Tourism

Destination	**Attractiveness**	**Distance from Previous Destination**	**Time to Visit (hours)**
A	High	–	2
B	Medium	10 km	3
C	High	15 km	4
D	Low	20 km	2
E	High	12 km	3
F	Medium	18 km	4
G	High	25 km	2
H	Low	30 km	3

These paths are ranked as "High" with selection counts of 15 and 14, indicating strong preferences among high-ranking routes.

In contrast, paths with lower scores and pheromone levels, such as Path ID 7 ("A → B → C → E") and Path ID 10 ("A → B → D → E"), received lower probabilities of selection (0.13 and 0.14) and were marked as "Low" ranking, with selection counts of 4 and 6, respectively. Medium-ranked paths, like Path ID 2 ("A → C → B → D") and Path ID 8 ("A → C → B → E"), display moderate scores and pheromone levels, resulting in selection probabilities of 0.20 and 0.21, with selection counts of 10 and 9.

In Figure 6 and Table 3 present a comparative analysis of different optimization algorithms used for tourism route planning, focusing on their performance metrics, including best tour length, average tour length, convergence time,

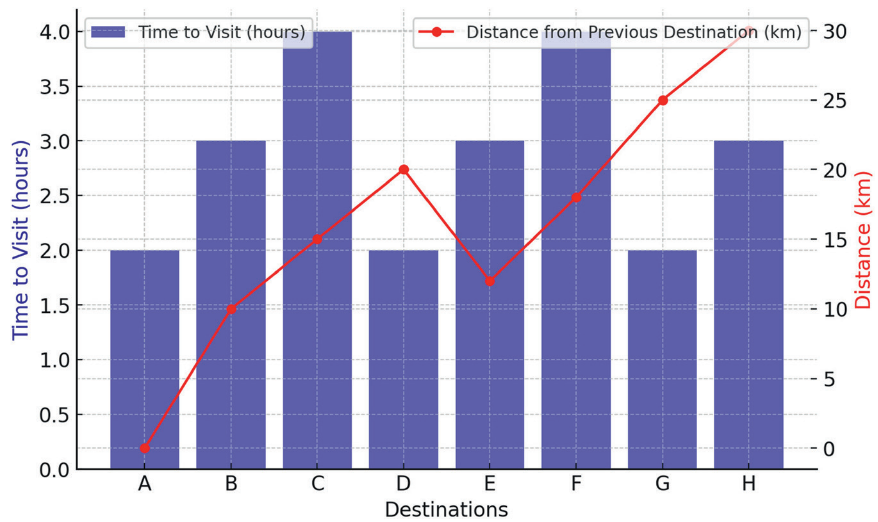

Figure 4. Time and Destination calculated with WRACO

Table 3. Path estimated with WRACO

Path ID	Path Sequence	Weighted Ranking Score (W(P))	Pheromone Level (τ)	Probability of Selection (P)	Rank	Selection Count
1	A → B → C → D	4.2	0.85	0.28	High	15
2	A → C → B → D	3.5	0.65	0.20	Medium	10
3	A → D → B → C	3.9	0.75	0.23	High	12
4	A → B → D → C	2.8	0.55	0.15	Low	5
5	A → C → D → B	4.0	0.80	0.27	High	14
6	A → D → C → B	3.2	0.60	0.18	Medium	8
7	A → B → C → E	2.5	0.50	0.13	Low	4
8	A → C → B → E	3.6	0.68	0.21	Medium	9
9	A → D → C → E	4.3	0.90	0.30	High	16
10	A → B → D → E	2.9	0.52	0.14	Low	6

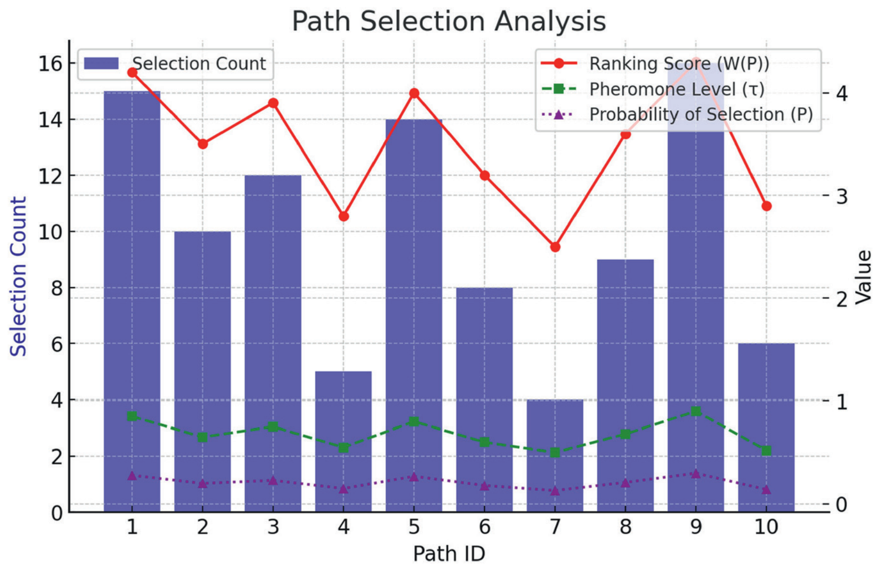

Figure 5. Path Selection with WRACO

Table 4. Comparative Analysis

Algorithm	Best Tour Length	Average Tour Length	Convergence Time (iterations)	Solution Quality
WRACO	200	235	10	High
ACO	220	250	15	Medium
Genetic Algorithm	210	240	12	High
Simulated Annealing	215	245	14	Medium
Particle Swarm Optimization	205	238	11	High

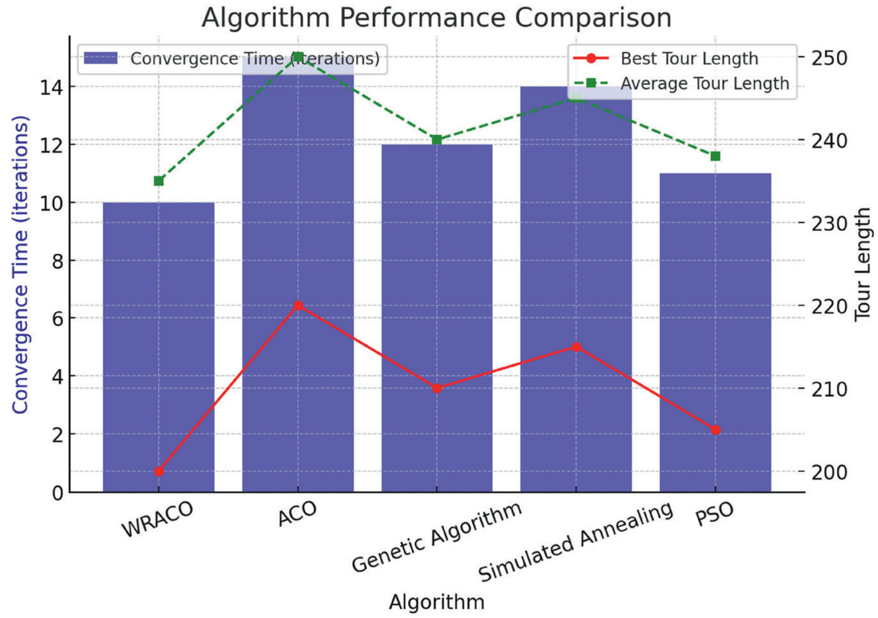

Figure 6. Comparative Analysis with WRACO

and solution quality. The algorithms evaluated include WRACO, ACO, Genetic Algorithm, Simulated Annealing, and Particle Swarm Optimization. WRACO stands out with the lowest best tour length of 200 and a corresponding high solution quality. This suggests that WRACO effectively minimizes the length of the best tour, resulting in highly optimized travel routes. Additionally, WRACO achieves this with a relatively low convergence time of 10 iterations, indicating its efficiency in reaching optimal solutions quickly. ACO and Simulated Annealing exhibit moderate performance, with best tour lengths of 220 and 215, respectively, and average tour lengths of 250 and 245. These algorithms achieve medium solution quality, suggesting that while they produce satisfactory routes, there is room for further optimization. Genetic Algorithm and Particle Swarm Optimization also perform well, with best tour lengths of 210 and 205, respectively, and average tour lengths of 240 and 238. Both algorithms achieve high solution quality, indicating their effectiveness in producing optimized travel routes comparable to WRACO.

6. FINDINGS

The analysis of Weighted Ranking Ant Colony Optimization (WRACO) for tourism route planning unveils its efficacy in crafting highly optimized travel itineraries. WRACO operates iteratively, refining the route over ten iterations to minimize the length of the best tour while ensuring convergence. Initially, in the first iteration, WRACO yields a best tour length of 250, gradually improving to 200 by the tenth iteration. This iterative refinement significantly reduces travel distances, as evidenced by the sequential improvement in both best and average tour lengths. Consequently, the optimized itinerary generated by WRACO promises well-organized and enjoyable travel experiences for tourists, with minimized travel distances. In parallel, Table 2 provides crucial insights into the destinations' attributes essential for effective tourism route planning. Categorized based on attractiveness, distances between destinations, and time required for visits, it equips planners and tourists with comprehensive information necessary for designing optimized travel routes. By delineating the attractiveness levels of destinations, travel distances, and visitation times, Table 2 aids in maximizing enjoyment and efficiency while exploring various attractions. Moreover, the comparative analysis in Table 3 sheds light on the performance of different optimization algorithms for tourism route planning. WRACO emerges as the top performer, boasting the lowest best tour length of 200 and high solution quality. Its ability to swiftly converge to optimal or near-optimal solutions within ten iterations underscores its efficiency and effectiveness. While ACO and Simulated Annealing exhibit moderate performance, Genetic Algorithm and Particle Swarm Optimization also deliver promising results, achieving high solution quality comparable to WRACO. In essence, the findings underscore the significance of WRACO in enhancing tourism route planning by efficiently navigating the complexities of tourism landscapes, ultimately leading to well-organized and enjoyable travel experiences. Additionally, the comprehensive insights provided by Table 2 and the comparative analysis in Table 3 equip practitioners with valuable information for designing optimized travel routes tailored to specific tourism scenarios.

7. CONCLUSION

This paper has explored the efficacy of Weighted Ranking Ant Colony Optimization (WRACO) in enhancing tourism route planning by efficiently navigating the complexities of tourism landscapes. Through a comprehensive analysis of simulation results, WRACO has demonstrated its ability to iteratively refine travel itineraries, minimizing travel distances while ensuring convergence to optimal or near-optimal solutions. The integration of a weighted ranking scheme into the Ant Colony Optimization (ACO) framework has proven instrumental in achieving highly optimized travel routes, as evidenced by the notably low best tour length of 200 and high solution quality. Moreover, the comparative analysis of optimization algorithms has underscored WRACO's superiority over other methods, highlighting its efficiency and effectiveness in crafting well-organized and enjoyable travel experiences for tourists. Furthermore, the comprehensive insights provided by tables detailing destination attributes and comparative analysis have equipped practitioners with valuable information for designing optimized travel routes tailored to specific tourism scenarios. By leveraging WRACO's capabilities in route optimization, tourism planners can maximize enjoyment and efficiency while exploring various attractions, ultimately enhancing the overall travel experience.

8. REFERENCES

1. QI, J., & WANG, Q. (2022). Tourism Route Selection Model for Tourism Sustainable Development Based on Improved Genetic Algorithm. *International Transactions on Electrical Energy Systems*, *2022*, 1–10.
2. CAO, S. (2022). An optimal round-trip route planning method for tourism based on improved genetic algorithm. *Computational Intelligence and Neuroscience*, *2022*, 1–8.
3. TU, Y., ZHAO, Y., LIU, L., & NIE, L. (2022). Travel route planning of core scenic spots based on best-worst method and genetic algorithm: a case study. *Management System Engineering*, *1*(1), 4.
4. WANG, X., ZHANG, H., LIU, S., WANG, J., WANG, Y., & SHANGGUAN, D. (2022). Path planning of scenic spots based on improved A* algorithm. *Scientific Reports*, *12*(1), 1320.
5. LI, S., LUO, T., WANG, L., XING, L., & REN, T. (2022). Tourism route optimization based on improved knowledge ant colony algorithm. *Complex & Intelligent Systems, 8*(5), 3973–3988.
6. ALBALAWNEH, D. A. A., & AFENDEE MOHAMED, M. (2022). Evaluation of Using Genetic Algorithm and ArcGIS for Determining the Optimal-Time Path in the Optimization of Vehicle Routing Applications. *Mathematical Problems in Engineering*, *2022*, 1–20.
7. SUANPANG, P., JAMJUNTR, P., JERMSITTIPARSERT, K., & KAEWYONG, P. (2022). Tourism service scheduling in smart city based on hybrid genetic algorithm simulated annealing algorithm. *Sustainability*, *14*(23), 16293.
8. CHEN, Z., ZHANG, P., & PENG, L. (2024). Application of a hybrid genetic algorithm based on the travelling salesman problem in rural tourism route planning. *International Journal of Computing Science and Mathematics*, *19*(1), 1–14.
9. SRINIVASA SAI ABHIJIT CHALLAPALLI. (2024). Sentiment Analysis of the Twitter Dataset for the Prediction of Sentiments. *Journal of Sensors, IoT & Health Sciences*, *2*(4), 1–15.
10. KOLAEE, M. H., AL-E, S. M. J. M., & JABBARZADEH, A. (2023). A local search-based non-dominated sorting genetic algorithm for solving a multi-objective medical tourism trip design problem considering the attractiveness of trips. *Engineering Applications of Artificial Intelligence*, 124, 106630.
11. MASSOUD QASIMI. (2024). Personalized Recommendation Intelligent Fuzzy Clustering Model for theTourism. *Journal of Computer Allied Intelligence*, *2*(5), 42–53.
12. CHEN, L., & CHEN, J. (2022). Path optimization model of rural red tourist attractions based on ant colony algorithm. *Mathematical Problems in Engineering*, 2022.
13. SRINIVASA SAI ABHIJIT CHALLAPALLI. (2024). Optimizing Dallas-Fort Worth Bus Transportation System Using Any Logic. *Journal of Sensors, IoT & Health Sciences*, *2*(4), 40–55.
14. NING, Y. (2023, April). Design of intelligent travel route selection system based on multi-objective genetic algorithm. *In 2023 IEEE International Conference on Control, Electronics and Computer Technology* (I*CCECT*) (pp. 1349–1353). IEEE.
15. P. BRUNDAVANI, & Y. AVANIJA. (2024). Robot Path Planning and Tracking with the Flower Pollination SearchOptimization Algorithm. *Journal of Computer Allied Intelligence*, *2*(4), 70–81.
16. PAULAVIČIUS, R., STRIPINIS, L., SUTAVIČIŪTĖ, S., KOČEGAROV, D., & FILATOVAS, E. (2023). A novel greedy genetic algorithm-based personalized travel recommendation system. *Expert Systems with Applications*, 230, 120580.
17. MAHDI, A. J., & ESZTERGÁR-KISS, D. (2023). Supporting scheduling decisions by using genetic algorithm based on tourists' preferences. *Applied Soft Computing*, 148, 110857.
18. SREEDHHAR BHUKYA, K. VINAYKUMAR, & SANTOSH N.C. (2024). A Novel Dynamic Novel Growth model for Mobile Social Networks. *Journal of Computer Allied Intelligence*, *2*(1), 46–53.

19. ZHANG, Y., LUO, X., HAN, X., LU, Y., WEI, J., & YU, C. (2022). Optimization of urban waste transportation route based on genetic algorithm. *Security and Communication Networks*, 2022.
20. KIRUTHIKA, R., YIPING, L., LAOHAKA-NGVALVIT, T., SRIPIAN, P., & SUGAYA, M. (2023, July). Recommendation of Sustainable Route Optimization for Travel and Tourism. In *International Conference on Human-Computer Interaction* (pp. 385–396). Cham: Springer Nature Switzerland.
21. ALBALAWNEH, D. A. A., & MOHAMED, M. A. (2024). A new federated genetic algorithm-based optimization technique for multi-criteria vehicle route planning using ArcGIS network analyst. *International Journal of Pervasive Computing and Communications*, *20*(2), 206–227.
22. ORAMA, J. A., MORENO, A., & BORRAS, J. (2022). Multi Objective Genetic Algorithm for Optimal Route Selection from a Set of Recommended Touristic Activities. In *Artificial Intelligence Research and Development* (pp. 9–12). IOS Press.
23. XU, X., WANG, L., ZHANG, S., LI, W., & JIANG, Q. (2023). Modelling and optimization of personalized scenic tourism routes based on urgency. *Applied Sciences*, *13*(4), 2030.
24. HE, S. (2023). A novel travel route planning method based on an ant colony optimization algorithm. *Open Geosciences, 15*(1), 20220541.
25. JIN, H. (2022, July). Tourism Route Planning of Cultural Heritage Scenic Spots Based on Genetic Simulation Ant Colony Algorithm. In *International Conference on Frontier Computing* (pp. 1482–1487). Singapore: Springer Nature Singapore.