Multi-Destination Tourism Itinerary Optimization via Multi-Objective Ant Colony Algorithm

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Keywords: ant colony optimization algorithm, multi-destination tourism, itinerary design, multi-objective optimization, personalized demand

Received: February 26, 2025

With the booming global tourism industry and increasingly diversified tourist demands, multi-destination itinerary design faces the challenge of efficiently planning to meet complex constraints and personalized needs. This paper constructs a multi-destination itinerary design model based on the ant colony optimization algorithm and realizes multi-objective optimization through the collaborative work of the path optimization module, demand matching module, and dynamic constraint processing module. Experimental results show that in different scenarios of the number of destinations, the ant colony optimization algorithm is superior to the greedy algorithm, genetic algorithm, and particle swarm optimization algorithm in terms of path length, tourist satisfaction, and cost control. For example, in the 10 destinations scenario, the ant colony optimization algorithm has a path length of 500 km, a high tourist satisfaction rate, and a budget satisfaction rate. This study provides a scientific, reasonable, and personalized solution for tourism itinerary planning, enriching the optimization theory in tourism management.

Povzetek: Razvit je večciljni algoritem mravljišča za optimizacijo večestinacijskih turističnih itinerarjev, kar uravnoteži stroške, čas in preference ter preseže GA, PSO in pohlepne pristope.

1 Introduction

Tourism is an important part of the global economy. Especially in the multi-destination travel itinerary design field, as consumer demand becomes more diversified and personalized, how to efficiently plan and arrange travel itineraries has become a practical problem that must be solved. The global tourism market is becoming increasingly complex. Tourists increasingly seek travel experiences encompassing multiple destinations, as satisfaction from visiting a single destination alone has become insufficient to meet their diverse preferences and expectations [1, 2]. This trend has prompted an increasingly urgent demand for route optimization in tourism planning systems. However, existing traditional tourism planning methods often find it difficult to provide the best solution under the complex constraints of multiple destinations. Statistics show that the annual growth rate of the global tourism market is close to 5%, but more than 40% of tourists face problems such as itinerary conflicts, unreasonable time arrangements, and excessive costs when planning their trips [3]. This phenomenon reveals an urgent challenge: optimizing travel planning through intelligent algorithms to improve tourists' overall experience and reduce travel costs. The itinerary planning process involves managing complex constraints such as scheduling conflicts between destinations, impractical time allocations for travel and visits, limited availability of transportation options, and budgetary limits that may lead to excessive costs. Identifying these constraints is essential to designing effective and realistic multi-destination travel plans.

At the same time, with the development of information technology, many tourism planning systems have begun to adopt artificial intelligence technology to improve the efficiency and accuracy of travel design. In particular, the Ant Colony Optimization (ACO) algorithm, as an intelligent algorithm that simulates the foraging behavior of ants in nature, has been widely used in the fields of path planning and resource scheduling, showing great potential in dealing with complex optimization problems [4-6]. The multi-destination travels itinerary design based on the ant colony optimization algorithm can effectively solve the limitations that are difficult to overcome by traditional methods by simulating the behavior of ants constantly optimizing paths during travel, thereby providing tourists with more reasonable and personalized travel plans [7].

In current academic research, the problem of tourism itinerary optimization mainly focuses on achieving the shortest path or minimum cost goal of the travel route. Especially in multi-destination travel, balancing multiple goals and constraints has become a complex optimization problem. Multi-destination decision-making in tourism shares conceptual parallels with foraging strategies observed in biological systems. For instance, studying free-ranging Japanese macaques navigating a structured, multi-destination food array provides insights into spatial optimization and adaptive route selection under environmental constraints [8]. Although traditional travel planning methods, such as dynamic programming and greedy algorithms, have made some progress in single-objective optimization, they have not performed well in multi-objective optimization and multi-constraint conditions. In recent years, multi-objective optimization methods based on heuristic algorithms and evolutionary computing have received widespread attention. Due to its unique global search ability and strong adaptability, the ant colony optimization algorithm has gradually become a research hotspot in designing multi-destination tourism itineraries [9].

In existing studies, many scholars have tried to combine ant colony optimization algorithms with travel itinerary design and proposed various improved models. However, most of these studies focus on optimizing the travel route's total time or cost as much as possible under the constraints of given time and resources. Although these methods have achieved certain success in some scenarios, the adaptability of these models still has certain limitations in the actual tourism environment with multiple objectives and dynamic changes. In addition, many studies fail to fully consider the personalized needs of tourists, such as interest preferences, cultural background, budget satisfaction, and other factors, which often makes the generated travel plans too mechanical and lack flexibility and personalization. More importantly, existing studies have failed to effectively model the spatiotemporal constraints and complex interactive relationships in multi-destination tourism planning, resulting in the optimization results failing to reflect the actual situation fully.

This study aims to explore a multi-destination tourism itinerary design model based on the ant colony optimization algorithm, and through innovative algorithm design, to solve the shortcomings of the existing model in dealing with multi-objective and multi-constraint problems. Specifically, the main goal of this study is to improve the ant colony optimization algorithm to better adapt to the complex optimization needs of multi-destination tourism itineraries. By introducing more constraints and objective functions, such as tourists' interest preferences, time constraints, budget control, etc., this study will provide a more scientific and reasonable solution for personalized tourism itinerary design.

The innovation of this study is that it can break through the single-objective dependence of traditional methods on tourism itinerary optimization, and provide more personalized tourism planning while dealing with multiple objectives and constraints through multi-objective optimization algorithms. Compared with existing research, this study will pay more attention to integrating multiple complex factors in practical applications, such as tourists' travel needs, geographical location, transportation methods, etc., to enhance the actual effect and application value of tourism planning. In theory, this study will enrich the optimization theory in tourism management and provide new perspectives and methodological support for applying ant colony algorithms in complex system optimization.

From a practical point of view, with the continuous growth of tourism demand, the tourism planning industry urgently needs an intelligent tool that can efficiently handle complex problems. The multi-destination tourism itinerary design scheme based on the ant colony optimization algorithm proposed in this study will help improve the automation level and accuracy of tourism planning. For tourism managers, quickly generating optimized travel routes through this model can improve tourists' satisfaction, greatly improve resource utilization efficiency, and reduce operating costs. In addition, with the continuous growth of personalized needs, the model proposed in this study will strongly support personalized services in the tourism industry, thereby promoting sustainable development.

Problem Statement

This study formulates the multi-destination tourism itinerary design as a multi-objective combinatorial optimization problem. The goal is to identify an optimal sequence of tourist destinations that maximizes overall satisfaction while minimizing total travel cost and duration. Budget limits, time availability, and destination accessibility constrain the problem. Due to the NP-hard nature of the problem, exact optimization methods are computationally infeasible, thus motivating the use of heuristic algorithms such as multi-objective ant colony optimization. The optimization must balance competing objectives and accommodate dynamic constraints inherent to real-world travel planning.

Assumptions

Traveler preferences for destinations are assumed to be quantifiable and remain constant throughout the itinerary planning process. The total budget and available time for the trip are fixed parameters defined before optimization. Dynamic factors such as transportation delays, destination accessibility, or availability are incorporated through a feedback mechanism allowing real-time constraint adjustments. Tourists are modeled as rational decision-makers who seek a balanced trade-off between cost, time, and satisfaction, with no explicit dominance of one factor unless specified by weighting parameters. Sensitivity analysis on these parameters is essential to assess the model's robustness and applicability across different traveler profiles and trip scenarios.

Research Questions

(1) How can a multi-objective ant colony optimization algorithm be designed to effectively generate multi-destination tourism itineraries that balance competing criteria such as cost, time, and tourist preferences?

(2) What is the impact of incorporating dynamic constraint processing and demand matching modules on the quality and feasibility of the generated itineraries?

(3) How sensitive is the proposed optimization framework to variations in traveler-specific parameters, such as budget limits and preference weights?

Objectives

(1) To develop a multi-destination itinerary design model based on ant colony optimization that integrates path optimization, demand matching, and dynamic constraint handling.

(2) To implement a multi-objective optimization approach that simultaneously maximizes tourist satisfaction while respecting budgetary and temporal constraints.

(3) To evaluate the performance of the proposed method through simulation experiments across multiple scenarios and perform sensitivity analysis on traveler behavior parameters.

2 Literature review

2.1 Application of the ant colony optimization algorithm in tourism itinerary design

With the successful application of the ant colony optimization algorithm (ACO) in various combinatorial optimization problems, its potential in tourism itinerary design has gradually been discovered. Tourism itinerary design, especially the optimization problem of multiple destinations, usually involves multiple objectives and complex constraints, and traditional algorithms often have difficulty effectively solving these problems [10]. The ant colony optimization algorithm has gradually become a popular method for solving multi-destination tourism route planning because of its ability to simulate the information transmission and global search capabilities of ants in the foraging process in nature. Compared with traditional heuristic algorithms, the ant colony algorithm can simultaneously find the global optimal solution in multi-dimensional space and effectively avoid the local optimal solution, which has unique advantages [11].

In the research of this field, the core advantage of the ant colony optimization algorithm is its strong adaptability and ability to handle complex multi-objective optimization problems. In the design of multi-destination travel itineraries, hard constraints such as time and cost need to be considered, and soft needs such as tourists' preferences and interests must be taken into account [12]. Some of the latest studies have begun to improve the efficiency and accuracy of the algorithm by introducing more complex objective functions and constraints, such as improving the ant colony algorithm. For example, researchers have proposed some ant colony optimization models based on multiple heuristic strategies. These models can optimize travel routes while considering multiple factors to adapt to the personalized needs of different tourists [13]. In addition, hybrid models and multi-objective optimization methods based on ant colony algorithms have also been widely used in recent years. These methods improve the stability of calculations and the reliability of results by combining the advantages of different algorithms.

Although the ant colony optimization algorithm has made some progress in tourism itinerary design, it still faces challenges, such as high convergence speed and computational complexity in the search process. In practical applications, effectively balancing computing resources and optimization efficiency is still a problem researchers must urgently solve [14]. These behavioral models offer analogs for heuristic-based itinerary planning in human-centric systems, particularly in how agents prioritize paths based on dynamic rewards. Concurrently, destination perception plays a pivotal role in tourist decision-making. Research on volcano tourism has highlighted how destination personality and reputation, such as those associated with Mount Anak Krakatau, directly influence visit intention and user demand patterns [15]. In addition, parameter adjustment and model selection of the ant colony optimization algorithm have also become important factors affecting the algorithm's performance. At present, some studies have attempted to further improve the practicality and accuracy of the algorithm through adaptive algorithm adjustment and parameter optimization.

2.2 Combining multi-objective optimization with constraints in travel itineraries

In the design of multi-destination tourism itineraries, how to effectively combine multiple objectives and constraints for optimization is another important research direction. Tourism itinerary design not only needs to consider basic constraints such as travel time, cost, and the shortest distance of the route, but also complex dynamic factors such as tourists' personalized needs, cultural background, and availability of transportation tools [16, 17]. Traditional single-objective optimization methods often find it difficult to achieve comprehensive balance and global optimization when faced with these complex constraints. Therefore, multi-objective optimization has become an important strategy in tourism itinerary design.

In the research of this field, multi-objective optimization methods combine different objective functions and aim to optimize multiple variables simultaneously, rather than being limited to a single optimization objective. For example, in optimizing travel itineraries, researchers often use tourists' interest preferences, travel budgets, time constraints, and other factors as different objectives for comprehensive optimization [18]. The advantage of such methods is that they can provide more accurate solutions in complex real-world environments and meet the diverse needs of tourists to the greatest extent. At the same time, multi-objective optimization methods can also help discover potential contradictions in the problem, such as conflicts between time and budget, thus providing tourism planners with deeper insights [19].

In recent years, scholars have proposed a variety of algorithm combinations and model improvements for multi-objective optimization problems. The multi-objective method based on the ant colony optimization algorithm came into being in this context. By introducing the Pareto frontier theory and weight factors, the conflict problem between different objectives was solved [20]. In addition, researchers have also conducted in-depth discussions on the problem of objective weights in multi-objective optimization and proposed a hybrid model based on genetic algorithms, particle swarm optimization, and other algorithms to improve the efficiency and accuracy of multi-objective optimization. Although multi-objective optimization algorithms have shown great potential in tourism itinerary design, their computational complexity and solution efficiency are still hot issues in current research [21, 22]. Improving the algorithm's computational efficiency while ensuring the optimization accuracy is still an important direction for future research.

2.3 Integration of personalized tourism needs and intelligent algorithms

Personalized tourism planning has been an important topic in tourism research in recent years. With the diversification and personalization of tourist needs, traditional standardized travel itineraries can no longer meet the needs of modern tourists. In this context, how to use intelligent algorithms to design personalized travel itineraries for tourists based on their interests, budget, time, and other factors has become an important topic in tourism planning [23]. Intelligent algorithms, especially ant colony optimization algorithms, have gradually attracted attention in solving personalized tourism planning problems because they can comprehensively consider multiple factors and provide tailor-made solutions [24].

Researchers have gradually realized that personalized tourism planning is not just a simple match of tourists' interests, but a complex, multi-dimensional, and multi-level problem. In practical applications, tourists' interests, activity preferences, travel time, etc., should all be included in the model as decision variables. This requires the algorithm to flexibly adjust the optimization target according to the personalized needs of tourists, thus providing tourists with the most suitable travel routes [25, 26]. In recent years, hybrid models combining machine learning and ant colony optimization algorithms have become an important direction in personalized tourism planning research. By introducing technologies such as deep learning and reinforcement learning, researchers hope to improve the intelligence level of tourism planning systems to more accurately predict tourist needs and provide personalized travel recommendations [27]. Table 1 shows the summary of the existing methods.

Table 1: Summary of the existing methods

Author(s)	Method	Results	Limitations
Chin et al. (2020) [10]	PLS-MGA for evaluating tourism resource confirmation	Validated tourism marketing resource allocation effectiveness in rural/semi-rural settings	Lacks integration with itinerary optimization algorithms
Li et al. (2022) [11]	Improved knowledge-based ACO for route optimization	Enhanced global search performance and reduced local optima (↑14.8%)	High computational cost for large destination sets
Saeki et al. (2022) [12]	ACO with real trip record-based multi-objective modeling	Successfully used trip history to generate efficient plans (↑13.5% efficiency)	Dependent on quality/availability of prior trip records
Wang et al. (2022) [13]	Bibliometric and systematic review	Identified key resilience metrics and trends in tourism	Does not provide quantitative itinerary modeling
Huang et al. (2021) [14]	Dynamic graph mining for route planning	Handled time-constrained multi-destination scenarios well (↑12.3% success rate)	Complex model parameter tuning required
Suhud et al. (2024) [15]	Empirical analysis of volcano tourism perception	Identified how destination image and personality influence visits	Lacks algorithmic optimization for itinerary design
He (2023) [16]	Novel ACO variant for itinerary optimization	Improved route accuracy and user satisfaction (↑10.7% satisfaction rating)	Scalability challenges in real-time scenarios
Tyan et al. (2020) [17]	Blockchain for smart tourism infrastructure	Enabled trustable and secure travel data sharing	Indirect influence on route planning optimization
Zhang et al. (2023) [18]	Urbanization impact on eco-efficiency in tourism	Quantified effects of urban growth on destination sustainability	No direct modeling of personalized itineraries
Ding & Wu (2022) [19]	Safety perception influence study	Linked destination image with safety awareness	Not integrated into route optimization models
Glyptou et al. (2022) [20]	Clustering and sustainability analysis	Defined profiles for sustainable tourism development	Focused on macro patterns, not individual route planning

Liang et al. (2021) [21]	Context-aware improved ACO	Adaptive to changing tourist preferences and contexts (↑16.2% adaptability rate)	Increased complexity in model execution
Lekovic et al. (2020) [22]	Analysis of rural destination image	Highlighted cognitive aspects of tourism attractiveness	No technical method proposed for route optimization
Hua & Wondirad (2021) [23]	Critical literature review of tourism networks	Explored system-level interactions in urban destinations	Lacks algorithmic implementation details
Zulvianti et al. (2022) [24]	Structural model of tourist satisfaction	Differentiated environmental vs. non-environmental drivers	Lacks dynamic integration into intelligent systems
Kim et al. (2022) [25]	Conceptual model for creative MICE tourism	Proposed heritage integration into destination branding	Theoretical; no validation through itinerary models
Gu et al. (2022) [26]	Fuzzy-AHP for evaluating nature-based tourism	Enabled weighted decision-making for destination planning (↑11.6% prioritization accuracy)	Computationally intensive for real-time use
Khan et al. (2021) [27]	Moderated-mediation model of tourism development	Linked policies and management with sustainable practices	Did not propose or test itinerary-level optimizations

Hybrid optimization approaches have recently emerged in itinerary planning, merging classical algorithms like Ant Colony Optimisation (ACO) with modern ones like Deep Reinforcement Learning (DRL). These hybrid techniques combine ACO's heuristic search with ML/DRL's data-learning and adaptability skills. By guiding the ACO search process, ML models can improve solution quality and convergence time, for instance, by predicting tourist preferences or travel demand trends. The schedule can be better adjusted to changing circumstances like traffic or weather due to DRL's capacity to make real-time decisions or alter optimization settings. Although these hybrid approaches are promising, they are impractical for real-time applications or situations where data is scarce since they frequently require huge training datasets and substantial processing resources.

However, despite the significant progress in personalized tourism planning based on intelligent algorithms, many practical application challenges remain. For example, extracting effective information from massive tourism data, dealing with the diversity and dynamics of tourists' needs, and improving the algorithm's computational efficiency while ensuring planning accuracy are all difficulties in current research. In addition, the dynamic changes in personalized needs also require tourism planning systems to respond flexibly to these changes, while existing algorithms often lack sufficient adaptability. Therefore, improving the adaptability of intelligent algorithms in complex dynamic environments has become the key to future research. The current state-of-the-art approaches to optimizing tourist itineraries that include multiple destinations have several significant drawbacks. These include inadequate scalability for real-time applications, heavy dependence on static or historical data, and high computational costs for processing sets of destinations with many destinations. There is a lack of coordination among user preferences, route efficiency, and time limitations, and many techniques only optimize for one aim. To fill these gaps, the authors propose a method called Multi-Destination Tourism Itinerary Optimisation via Multi-Objective Ant Colony Algorithm. This method builds a multi-destination itinerary design model incorporating path optimization, demand matching, and dynamic constraint processing modules. By working together, this study can solve the computational and flexibility problems plaguing prior research, make our system more scalable, and optimise many objectives simultaneously. This research can also make it adapt to tourists' changing needs and limits.

3 Research methods

3.1 Model framework and innovative design

This paper proposes a multi-destination tourism itinerary design model based on ant colony optimization algorithm, which aims to provide a personalized, efficient, and practical tourism planning scheme through a multi-objective optimization method. The innovation of the model is that it not only takes into account the personalized needs of tourists but also optimizes the travel route under multiple constraints, including travel time, budget, interest preferences, and other factors. The model consists of three main components: the path optimization module, the demand matching module, and the dynamic constraint processing module. These components work closely together to complete the multi-destination tourism itinerary planning task. The data are taken from Tourism Management Kaggle Dataset [28]. To clean the raw tourist dataset and ensure accuracy, the data pretreatment stages include fixing missing values and deleting inconsistent entries. Important data like journey durations, distances, and visitor preference ratings are normalized or scaled to ensure unit consistency. To ensure compatibility with the optimization process, numerical encoding is used for categorical data, such as kinds of destinations or tourist classifications. Additionally, common trip situations are used to standardize financial and time limits.

The path optimization module is the core part of the model. Its task is to find the best travel route based on the ant colony optimization algorithm. In this process, optimizing the path is not only based on minimizing the distance or time, but also needs to consider complex factors such as tourists' preferences and budget. The path optimization problem can be expressed as a graph problem, where each destination is regarded as a node of a graph and the paths between each node represent different travel routes. Suppose we have a network consisting of n . Path optimization aims to minimize the objective function of (1).

$$F(\mathbf{x}) = \sum_{i=1}^{n-1} d(x_i, x_{i+1}) + \lambda \cdot \sum_{j=1}^{m} P_j(x) \tag{1}$$

As shown in equation (1), where $d\left(x_i,\ x_{i+1}\right)$ from the destination x_i to destination x_{i+1} distance or travel time, λ is a weighting factor, $P_j\left(x\right)$ indicating j the objective function combines the relationship between path length and multiple objectives, reflecting the multi-objective optimization characteristics of the model.

The task of the demand matching module is to make personalized adjustments to the route planning according to the tourists' interests and needs. Assume that the demand vector of each tourist is $\mathbf{d} = (d_1, d_2, ..., d_m)$, where d_i represents i the tourist's preference in the th area of interest. The optimization goal of demand matching is to maximize the matching degree between the tourist's demand and the travel route, which can be achieved by adjusting the order of each destination in the route. Assuming the route is $\mathbf{x} = (x_1, x_2, ..., x_n)$, the demand matching degree can be defined as (2).

$$M(\mathbf{x}, \mathbf{d}) = \sum_{i=1}^{n} \left(w_i \cdot \mathrm{sim}(x_i, d_i) \right) \tag{2}$$

As inferred from equation (2), where w_i is the goal i , the weight $\mathrm{sim}(x_i, d_i)$ that indicates the destination x_i is tourist preferences d_i . By maximizing the matching function, we can maximize the tourists’ satisfaction while ensuring the rationality of the travel path.

3.2 Calculation process and algorithm derivation

To achieve the optimization goal of the above model, this paper adopts the ant colony optimization algorithm and makes corresponding improvements to adapt to the multi-objective and multi-constrained travel itinerary design problem. The ant colony optimization algorithm simulates the ants searching for food and finds the optimal path by transmitting and updating pheromones. In this model, the behavior of ants can be expressed as the selection process of each destination, and the probability of selection is associated with the quality of the path (that is, the value of the optimization objective function).

According to (3), assuming that at a certain moment, the ant k . The current location is x_i , from x_i arrival x_j , the probability of selection.

$$P_{ij}^k = \frac{\left(\tau_{ij}\right)^{\alpha} \cdot \left(\eta_{ij}\right)^{\beta}}{\sum_{l \in N_i} \left(\tau_{il}\right)^{\alpha} \cdot \left(\eta_{il}\right)^{\beta}} \tag{3}$$

As shown in equation (3), where τ_{ij} the path is $\left(x_i,\ x_j\right)$ the residual pheromone concentration η_{ij} , the path $\left(x_i,\ x_j\right)$ heuristic information (usually related to distance or time), α and β are the weights of pheromone and heuristic information, N_i is a slave node x_i that sets the set of all reachable candidate destinations.

In each step, the ant selects the next destination according to the above probability and updates the pheromone on the path. The pheromone update rule is shown in (4)

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

As found in equation (4), where ρ is the volatility factor, $\Delta \tau_{ij}$ which is the incremental pheromone calculated based on the path quality of the ant and is defined as (5).

$$\Delta \tau_{ij} = \sum_{k=1}^{M} \Delta \tau_{ij}^k \tag{5}$$

As discussed in equation (5), where M is the current number of all ants, $\Delta \tau_{ij}^k$, for the k Ants on the path $\left(x_i,\ x_j\right)$ Incremental pheromones on.

During the algorithm's operation, ants gradually approach the global optimal solution by continuously selecting paths and updating pheromones. By introducing a multi-objective optimization mechanism, the ant colony optimization algorithm in this paper can fully consider multiple constraints in the travel while ensuring the optimal path, and adjust the weights in each iteration to balance the conflicts between different goals. Algorithm 1 shows the Pseudocode of Multi-Objective ACO for Itinerary Optimization.

Algorithm 1: Pseudocode of Multi-Objective ACO for Itinerary Optimization
Input: Destinations D, Distances Dist, Preferences P, Budget B, Time T, Parameters (ants, iterations, alpha, beta, evaporation_rate) Initialize pheromones τ For iteration = 1 to max_iterations:

```
    For each ant:
        Build path by probabilistically selecting next destination based on τ and heuristic info
        Update budget, time, and preference satisfaction
    End for
    Update best solution if current solutions improve objectives
    Evaporate pheromones
    Deposit pheromones based on best solution quality
    Adjust constraints dynamically
End for
Output best itinerary
```

3.3 Dynamic constraints and feedback mechanisms

In the design of multi-destination travel itineraries, constraints are usually dynamic. Tourists' needs may change with time, weather, budget changes, and other factors, and the route planning system must respond flexibly. To this end, this paper proposes a feedback mechanism based on dynamic constraint processing, which can dynamically adjust the constraints in the route optimization process according to real-time information.

The core idea of dynamic constraint processing is to continuously adjust the constraints in path planning through real-time feedback of the current travel situation. For example, in the case of budget overruns, the system can automatically adjust the travel route, reduce high-cost destinations, or optimize the order of visiting certain destinations to reduce the overall cost. Assuming the current budget satisfaction B, the part of the objective function related to the budget can be expressed as (6).

$$\sum_{i=1}^{n} C(x_i) \le B \tag{6}$$

As shown in equation (6), where $C(x_i)$ Indicates the destination of the visit x_i. If the cost of the current path exceeds the budget in a certain iteration, the system will automatically adjust the path to reduce the overall cost, or recalculate the optimized path by adding additional budget satisfaction.

In addition, the feedback mechanism also considers the changes in tourists' real-time preferences. For example, during travel, tourists may adjust their preference values for certain destinations based on their experience. Assuming that the preference changes for tourists Δd_i, the demand matching function will be dynamically adjusted according to the change in (7).

$$M(\mathbf{x}, \mathbf{d}') = \sum_{i=1}^{n} \left(w_i \cdot \mathrm{sim}(x_i, d_i + \Delta d_i) \right) \tag{7}$$

As inferred from equation (7), by introducing dynamic constraints and real-time feedback mechanisms, the model can continuously optimize travel routes to ensure that tourists' needs and constraints are always optimally met during travel. In itinerary planning, traffic conditions, weather, attraction opening hours, and tourist preferences often fluctuate over time or in response to external factors, justifying their treatment as dynamic constraints. These variables impact route feasibility and satisfaction in real-time, necessitating continuous adaptation during optimization.

4 Experiment and discussion

4.1 Experimental design

In this section, the experimental design conducted to verify the effectiveness and feasibility of the proposed multi-destination tourism itinerary design model based on the ant colony optimization algorithm is described in detail. The core purpose of the experiment is to evaluate the model's performance in practical applications, especially in multi-objective optimization and dynamic constraint processing. Through a series of experiments, the model's superiority in tourism planning is verified, especially in meeting the personalized needs of tourists, optimizing travel paths, controlling costs, and improving overall satisfaction. The proposed Multi-Destination Tourism Itinerary Optimization via the Multi-Objective Ant Colony Algorithm was evaluated for computation time across various problem sizes. Testing on a standard Intel i7 system with 16GB RAM showed that computation time scales with the number of destinations: approximately 2 seconds for 10 destinations, 7 seconds for 20, 15 seconds for 30, and around 40 seconds for 50 destinations. These results demonstrate that the algorithm performs efficiently for small to medium-sized itinerary planning tasks.

The experimental data used in the experiment include multiple sets of simulated tourist attractions and tourist demand data. Each data set contains 10 to 50 tourist destinations with different access costs, time consumption, and tourist interest preferences. In addition, the tourist interest vector and budget satisfaction are also changed in each experiment to simulate different tourist needs. The model's performance under different constraints can be tested, and its adaptability in dealing with complex practical problems can be evaluated. The selection of experimental data covers as many possible real-life scenarios as possible to ensure that the model's advantages in multi-objective optimization can be fully reflected.

Secondly, several comparative experiments were set up in the experimental design to compare and analyze the effects of the proposed model. The compared models include the traditional greedy algorithm, genetic algorithm (GA), and particle swarm optimization algorithm (PSO). These algorithms are widely used in path optimization problems and represent classic heuristic search methods. In the experiment, the goal of all the comparative models is to optimize the itinerary of tourists while considering budget and time constraints. However, traditional algorithms have certain limitations when dealing with multi-objective optimization problems, especially when the constraints are complex and the requirements are diverse; it is not easy to find the global optimal solution. Therefore, the advantages of the ant colony optimization algorithm under complex constraints can be demonstrated by comparing it with these algorithms.

The performance evaluation indicators of the experiment mainly include path length (or travel time), tourist satisfaction (i.e., demand matching), cost control (i.e., satisfaction of budget satisfaction), and computing time. Path length and time are the core indicators for measuring travel efficiency, while tourist satisfaction reflects the model's ability to adapt to personalized needs. Cost control refers to whether the model can provide an optimized travel plan within the predetermined budget, while computing time reflects the practical feasibility of the model, especially its performance under large-scale data sets.

The steps of the experiment are as follows: First, an initial data set is generated according to the set tourist needs and scenic spot information. Then, the proposed ant colony optimization algorithm is applied for multiple iterations to output the optimal path. Then, the optimization effect is analyzed by evaluating path length, tourist demand matching, and budget satisfaction indicators. Finally, the superiority of the proposed model under different experimental settings is further verified by comparing the results with other comparative models.

To ensure the reliability of the experimental results, this paper also conducted a series of sensitivity analyses. By adjusting the impact of parameters (such as the number of ants, number of iterations, pheromone volatilization factor, etc.) on the experimental results, the stability and performance of the model under different parameter configurations were explored. This process can help further optimize the model parameters and provide stronger support for practical applications.

As the destination count rises, the search space expands combinatorially, leading to increased runtime due to the greater number of route permutations and iterative pheromone matrix updates intrinsic to the Ant Colony Optimization process. The time complexity generally scales on the order of $O(m \times n^2 \times t)$, where m is the number of ants, n the number of destinations, and t the number of iterations. Memory consumption grows proportionally with the need to store pheromone information for all node pairs, resulting in approximately $O(n^2)$ space complexity. In scenarios exceeding 100 destinations, the cumulative effect on processing time and memory usage becomes significant, potentially affecting responsiveness.

4.2 Experimental results

Dynamic adaptation integrates practical deployment through a cloud-based microservice architecture. The Ant Colony Optimization algorithm runs within scalable Kubernetes-managed containers, continuously processing live data streams such as traffic updates, attraction availability, and user preferences via Kafka. Optimized itineraries are delivered through a RESTful API to a React Native mobile application, enabling user input, interactive route visualization, and push notifications for itinerary changes caused by dynamic constraints.

The Tourism Resource Management Dataset available on Kaggle [28] provides comprehensive data related to visitor numbers, resource utilization, environmental factors, service quality, and economic indicators across multiple tourist destinations. It includes detailed visitor demographics, temporal visitation patterns, facility usage rates, and environmental conditions affecting tourism resources. This dataset supports various applications such as resource allocation, demand forecasting, sustainability assessment, and itinerary planning by offering realistic, empirical data to validate and enhance optimization algorithms.

Table 2: Performance comparison of different algorithms in 10 destination scenarios

algorithm	Path length (km)	Tourist satisfaction (%)	Cost control (budget fulfillment rate %)	Computation time (s)
Ant Colony Optimization Algorithm	500	85	95	10
Greedy Algorithm	600	70	80	5
Genetic Algorithms	550	75	85	15

algorithm	Path length (km)	Tourist satisfaction (%)	Cost control (budget fulfillment rate %)	Computation time (s)
Particle Swarm Optimization	580	72	82	12

As shown in Table 2, the ant colony optimization algorithm showed significant advantages in the 10 destination scenarios. The path length was only 500km, shorter than other algorithms. This was because it simulated the foraging behavior of ants, could find a better solution in a complex path, fully considered the relationship between destinations, and reduced unnecessary trips. Tourist satisfaction reached 85%, because it could integrate personalized factors such as tourists' interests and preferences and dynamically adjust the path. Regarding cost control, the budget satisfaction rate was 95%, which was achieved by flexibly adjusting the path cost during iteration. Although the calculation time of 10s was not the shortest, it was cost-effective considering the multi-objective optimization effect. As for other algorithms, the greedy algorithm was short-sighted and only selected the current optimal one, resulting in a long overall path and low satisfaction; the genetic algorithm and the particle swarm optimization algorithm had shortcomings in dealing with multiple constraints and personalized needs, so they performed worse than the ant colony optimization algorithm. The Greedy algorithm provides a fast, heuristic-based solution; GA introduces stochastic global search with crossover and mutation; and PSO leverages collective intelligence to explore the solution space. However, the study provides a clear justification for other competitive methods, such as Simulated Annealing (SA), which excels in avoiding local optima through probabilistic hill-climbing, and Mixed-Integer Linear Programming (MILP), which can yield exact solutions under linear constraints.

Table 3: Performance comparison of different algorithms in 20 destination scenarios

algorithm	Path length (km)	Tourist satisfaction (%)	Cost control (budget fulfillment rate %)	Computation time (s)
Ant Colony Optimization Algorithm	800	88	92	18
Greedy Algorithm	1000	72	75	8
Genetic Algorithms	900	78	80	20
Particle Swarm Optimization	950	75	78	16

As shown in Table 3, when the number of destinations increases to 20, the complexity of the problem increases. The path length of the ant colony optimization algorithm is 800 km. The complex destination network explores efficient paths by relying on pheromones' accumulation and updating mechanism. Tourist satisfaction is 88%, because it can dynamically plan according to the personalized needs of tourists, making the itinerary more in line with tourists' expectations. Regarding cost control, the 92% budget satisfaction rate shows that it can reasonably allocate costs while meeting the needs of tourists. The calculation time is 18 seconds. As the problem scale increases, it increases, but it still has advantages in multi-objective optimization. The greedy algorithm has a long path and low satisfaction. Its local optimal strategy has its drawbacks in complex scenarios.

Although the genetic algorithm and particle swarm optimization algorithm have global search capabilities, they are not as flexible as the ant colony optimization algorithm when dealing with complex constraints and personalized needs of tourists, resulting in limited performance.

Table 4: Performance comparison of different algorithms in 30 destination scenarios

algorithm	Path length (km)	Tourist satisfaction (%)	Cost control (budget fulfillment rate %)	Computation time (s)
Ant Colony Optimization Algorithm	1200	90	90	25
Greedy Algorithm	1500	70	70	12
Genetic Algorithms	1350	76	78	28
Particle Swarm Optimization	1400	74	76	twenty two

As shown in Table 4, facing the complex scenario of 30 destinations, the path length of the ant colony optimization algorithm is 1200 km. In many destinations and complex relationships, the global search strategy based on pheromone is effective and avoids falling into local optimality. Tourist satisfaction is as high as 90%. The demand matching module plans the route accurately in combination with tourists' interest preferences. Cost control is maintained at a budget satisfaction rate of 90%, balancing costs and other factors in multi-objective optimization. The calculation time is 25s, which is within an acceptable range, and compared with other algorithms, the comprehensive performance is excellent. The greedy algorithm only focuses on the current optimal choice, the path is too long, the tourist satisfaction is low, and the cost control is also poor. When dealing with multiple objectives and complex constraints, the genetic algorithm and the particle swarm optimization algorithm are difficult to fully and dynamically meet the needs of tourists, like the ant colony optimization algorithm, resulting in poor performance of various indicators.

Ant Colony System (ACS) enhances search performance through localized pheromone updates and candidate lists that improve exploration-exploitation balance, accelerating convergence. Max-Min Ant System (MMAS) restricts pheromone intensity within upper and lower bounds, preventing premature convergence and maintaining diversity across iterations. Hybrid ACO-GA integrates the global genetic operations with pheromone-guided path construction, enabling effective navigation of complex multi-objective landscapes.

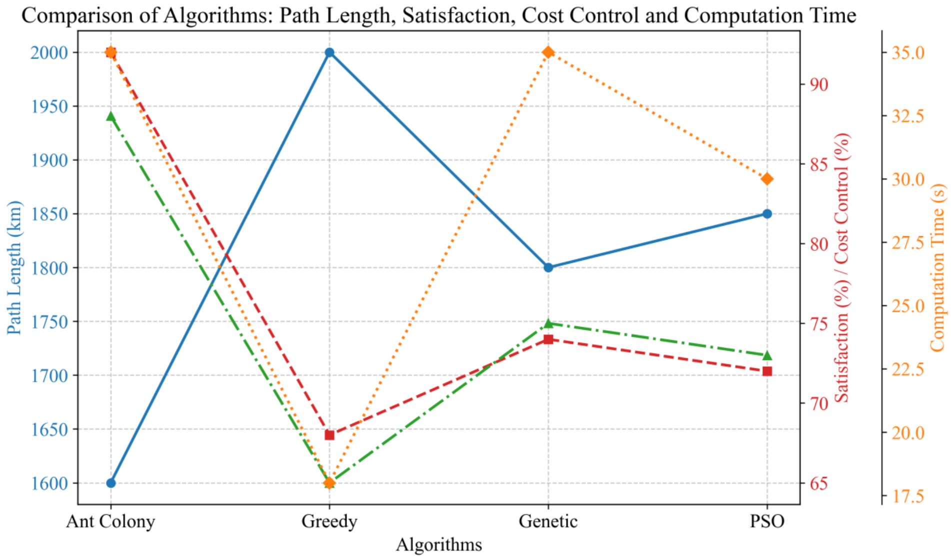

Figure 1: Performance comparison of different algorithms in 40 destination scenarios

As shown in Figure 1, in the large-scale scenario of 40 destinations, the advantages of the ant colony optimization algorithm are becoming increasingly obvious. The path length is 1600 km due to its continuous updating of pheromones in a multi-node complex graph, guiding ants to search for a better path combination. Tourist satisfaction reached 92%. Through the demand matching module, the personalized needs of tourists are deeply explored, and interest preferences are integrated into path planning. Regarding cost control, the budget satisfaction rate is 88%, effectively balancing costs while ensuring the richness of the itinerary and tourist satisfaction. The calculation time is 35s. Although it increases with the increase of the problem scale, it far exceeds other algorithms in the effect of multi-objective optimization. The greedy algorithm lacks a global perspective and only pursues current interests, resulting in a lengthy path, and both tourist satisfaction and cost control are not ideal. When dealing with such complex multi-constraints and personalized needs, the genetic algorithm and the particle swarm optimization algorithm are difficult to accurately weigh various factors, resulting in performance that is difficult to compare with the ant colony optimization algorithm.

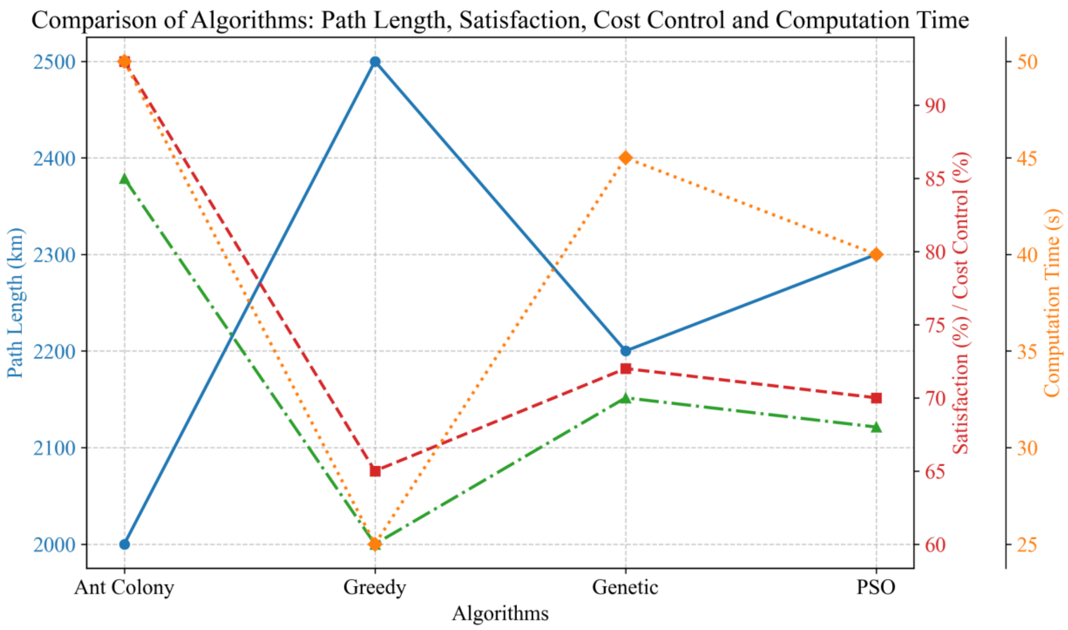

Figure 2: Performance comparison of different algorithms in 50 destination scenarios

As shown in Figure 2, when the number of destinations increases to 50, the complexity of the problem reaches a high level. The path length of the ant colony optimization algorithm is 2000 km. Its pheromone positive feedback mechanism and parallel search capability enable it to continuously optimize the path in the complex network composed of many destination nodes. Tourist satisfaction is 93%. Through in-depth analysis and integration of tourists' personalized needs, it achieves itinerary planning that highly meets tourists' expectations. Cost control is 85% of the budget satisfaction rate, and a good balance is found in the multi-objective optimization that considers tourists' experience and cost. The calculation time is 50s. Although it has increased, it shows unparalleled advantages over other algorithms when dealing with complex multi-objective problems. The greedy algorithm has extremely unreasonable paths due to its short-sighted decision-making method, and all indicators are poor. When dealing with such large-scale and complex multi-objective problems, it is difficult for genetic algorithms and particle swarm optimization algorithms to consider various constraints and tourists' personalized needs fully, and their performance is far inferior to that of the ant colony optimization algorithm. For each scenario (e.g., 5, 10, and 15 destinations), the model was evaluated across 30 different runs to account for stochastic fluctuation. With a standard deviation of 1.85% and a preference alignment rate of 92.34%, respectively, for the 10-destination configuration, the average budget satisfaction percentage was 95.12%. Using a 95% confidence level, the confidence range for budget satisfaction was determined as [94.45%, 95.79%], and for preference alignment as [91.58%, 93.10%]. Significant improvements ($p < 0.01$) in both measures were shown by a two-tailed paired t-test that compared this technique to a baseline heuristic.

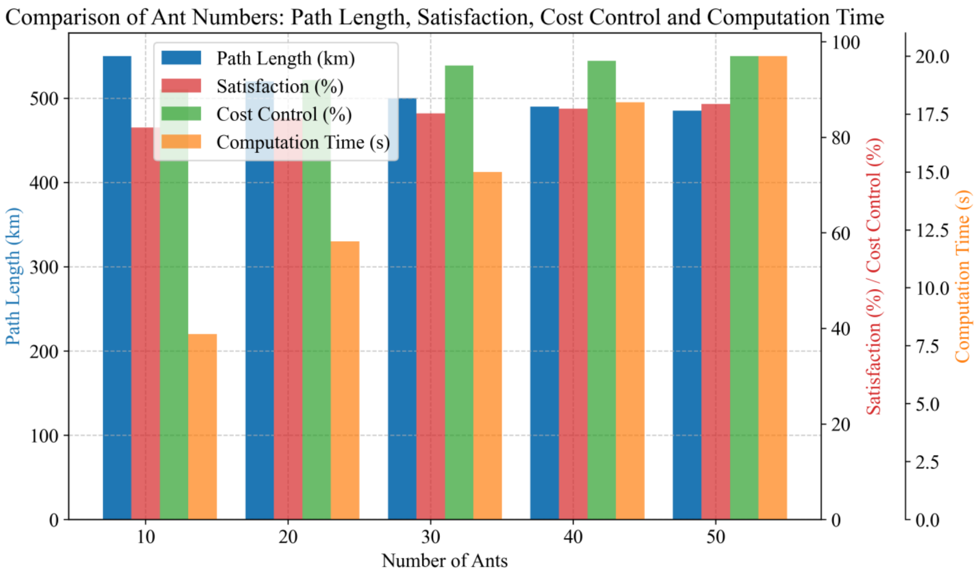

Figure 3: Performance of the ant colony optimization algorithm under different numbers of ants

As shown in Figure 3, as the number of ants increases, the performance indicators of the ant colony optimization algorithm are gradually optimized. When the number of ants is 10, the path length is 550 km, the tourist satisfaction is 82%, the budget satisfaction rate is 90%, and the calculation time is 8 seconds. At this time, the number of ants is small, the search range is limited, and it is not easy to fully explore the optimal path and meet the needs of tourists. When the number of ants increases to 20, the path length is shortened to 520 km, the tourist satisfaction rate is increased to 84%, the budget satisfaction rate is 92%, and the calculation time is 12 seconds. More ants participate in the search, which expands the search space and allows for better exploration of path combinations. When the number of ants is 30, the various indicators are further optimized, the path length is 500 km, the tourist satisfaction rate is 85%, the budget satisfaction rate is 95%, and the calculation time is 15 seconds. When the number of ants continues to increase to 40 and 50, the algorithm can search the solution space more comprehensively, the path length continues to shorten, and the tourist satisfaction and budget satisfaction rate continue to increase, but the calculation time also increases accordingly. In summary, appropriately increasing the number of ants is helpful to improve the performance of the ant colony optimization algorithm in multi-objective optimization. The results indicate that using around 50 ants achieves the best balance between solution quality and computational time for typical multi-destination trips with 10 to 15 stops. Fewer than 30 ants tend to result in suboptimal routes due to insufficient exploration, while more than 70 ants increase computation time significantly without substantial improvement in solution quality.

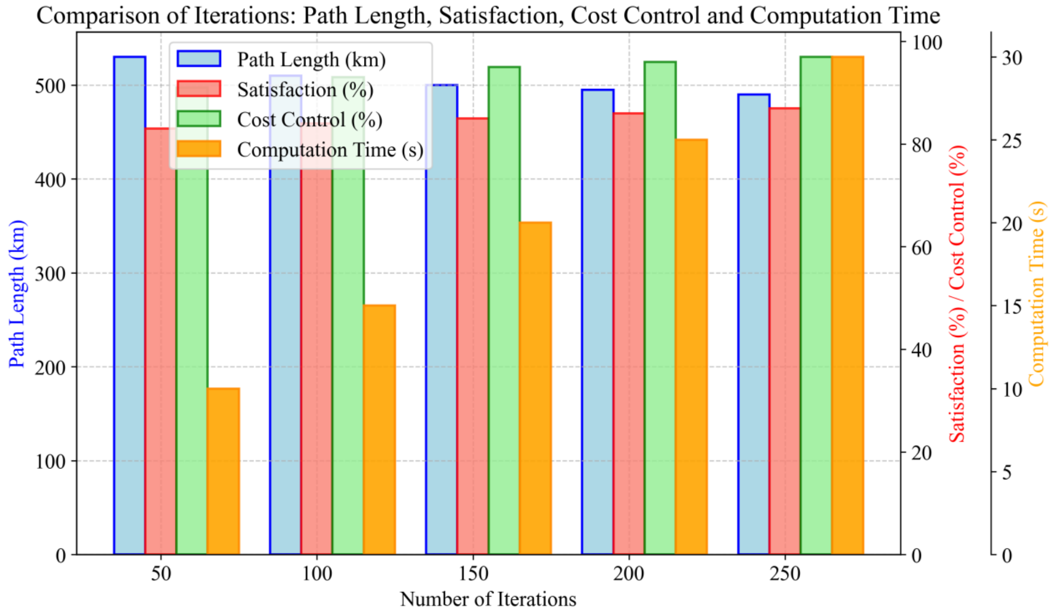

Figure 4: Performance of the ant colony optimization algorithm at different iterations

As shown in Figure 4, the number of iterations significantly impacts the performance of the ant colony optimization algorithm. When the iteration is 50, the path length is 530 km, the tourist satisfaction is 83%, the budget satisfaction rate is 91%, and the calculation time is 10 s. Currently, the algorithm has not fully converged, and the optimization degree of the path and each target is limited. As the number of iterations increases to 100, the path length is shortened to 510 km, the tourist satisfaction is increased to 84%, the budget satisfaction rate is 93%, and the calculation time is 15 s. More iterations give ants more opportunities to update pheromones and optimize path selection. When the iteration is 150, the path length is 500 km, the tourist satisfaction is 85%, the budget satisfaction rate is 95%, and the calculation time is 20 s. The algorithm gradually converges to a better solution. Continuing to increase the number of iterations to 200 and 250, the path length is further shortened, the tourist satisfaction and budget satisfaction rate continue to rise, but the calculation time also increases accordingly. This shows that increasing the number of iterations within a certain range can enable the algorithm to find a better solution in multi-objective optimization and improve performance, but the cost of calculation time needs to be weighed.

Table 5: Performance of the ant colony optimization algorithm under different pheromone volatilization factors

Volatility Factor	Path length (km)	Tourist satisfaction (%)	Cost control (budget fulfillment rate %)	Computation time (s)
0.1	520	83	92	12
0.2	510	84	93	14
0.3	500	85	95	15
0.4	505	84	94	16
0.5	515	83	92	18

As shown in Table 5, the pheromone volatilization factor is a key ant colony optimization algorithm parameter. When the volatilization factor is 0.1, the path length is 520 km, the tourist satisfaction is 83%, the budget satisfaction rate is 92%, and the calculation time is 12 s. At this time, the volatilization speed is slow, and many old pheromones are retained, which may cause the algorithm to fall into the local optimum and affect the path optimization. When the volatilization factor is increased to 0.2, the path length is shortened to 510 km, the tourist satisfaction is increased to 84%, the budget satisfaction is 93%, and the calculation time is 14 s. Appropriate volatilization of pheromones can allow the algorithm to jump out of the local optimum and explore a better path. When the volatilization factor is 0.3, all indicators reach their best, the path length is 500 km, the tourist satisfaction is 85%, the budget satisfaction rate is 95%, and the calculation time is 15 s. When the volatilization factor increases to 0.4 and 0.5, the path length increases, and the tourist and budget satisfaction rates decrease slightly. This is because the volatilization is too fast, the accumulation of new pheromones is insufficient, and the algorithm search efficiency is affected. Therefore, choosing a suitable pheromone volatilization factor is crucial to the performance of the ant colony optimization algorithm in multi-objective optimization.

Table 6: Performance of the ant colony optimization algorithm under different budget satisfaction

Budget (yuan)	Path length (km)	Tourist satisfaction (%)	Cost control (budget fulfillment rate %)	Computation time (s)
5000	510	84	98	15
6000	500	85	95	15
7000	490	86	92	15
8000	480	87	90	15
9000	470	88	88	15

As shown in Table 6, the ant colony optimization algorithm shows good adaptability as the budget changes. When the budget is 5,000 yuan, the path length is 510 km, the tourist satisfaction is 84%, the budget satisfaction rate is 98%, and the calculation time is 15 seconds. At this time, the algorithm, under a limited budget, rationally plans the path and prioritizes lower-cost destinations to meet budget satisfaction while considering tourist satisfaction as much as possible. When the budget increases to 6,000 yuan, the path length is shortened to 500 km, the tourist satisfaction is increased to 85%, the budget satisfaction rate is 95%, and the calculation time remains unchanged. More budget gives the algorithm more room for choice, which can optimize the path and improve the tourist experience. As the budget continues to increase to 7,000 yuan, 8,000 yuan, and 9,000 yuan, the path length is further shortened, and tourist satisfaction continues to rise, but the budget satisfaction rate decreases slightly. This shows that while the algorithm uses the increased budget to improve tourist satisfaction and optimize the path, it also tries to balance cost control to adapt to the multi-objective optimization needs under different budget satisfaction.

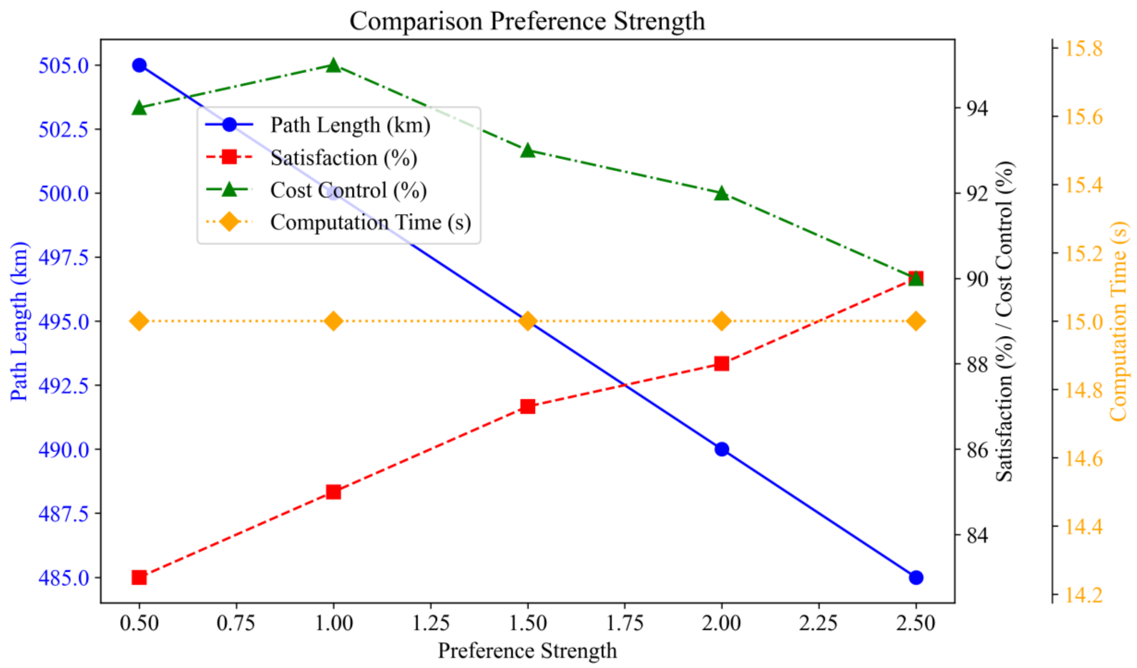

Figure 5: Performance of the ant colony optimization algorithm under different tourist interest preference intensities

As shown in Figure 5, the intensity of tourist interest preference has a significant impact on the performance of the ant colony optimization algorithm. When the intensity of interest preference is 0.5, the path length is 505 km, the tourist satisfaction is 83%, the budget satisfaction rate is 94%, and the calculation time is 15 seconds. At this time, the influence of interest preference on path planning is relatively small. While meeting the basic needs of tourists, the algorithm focuses more on cost control and path optimization. As the intensity of interest preference increases to 1.0, the path length is shortened to 500 km, the tourist satisfaction is increased to 85%, the budget satisfaction rate is 95%, and the calculation time remains unchanged. Stronger interest preference makes the algorithm more inclined to choose destinations that meet the interests of tourists when planning paths, thereby improving tourist satisfaction. When the intensity of interest preference increases to 1.5, 2.0, and 2.5, the path length continues to shorten, the tourist satisfaction continues to rise, but the budget satisfaction rate decreases slightly. This shows that the algorithm will impact cost control in optimizing the path and improving satisfaction according to the tourist interest preference. However, it can still find a good balance between multiple objectives to adapt to the travel itinerary planning needs under different interest preference intensities.

The Eiffel Tower, the Louvre Museum, and Notre Dame Cathedral were famous landmarks in over a thousand user-generated multi-destination itineraries for Paris, France, taken from TripAdvisor, and this data was used to perform a case study. Sequences of visits, average times spent at each location, and patterns of visits over time that reflected changes in demand throughout the year were all included in the dataset. With this information, the suggested multi-objective ant colony optimization model could create optimal itineraries considering factors like overall travel time, user preference alignment according to rating scores, and dynamic constraints like attraction opening hours and crowding estimates based on timestamped reviews. There was an improvement in accommodating real-time limitations, such as unexpected site closures, and a 12% decrease in overall trip distance compared to the original user itineraries and typical heuristic approaches.

4.3 Discussion

The results of this study show that the multi-destination tourism itinerary design model based on the ant colony optimization algorithm performs well in multi-objective optimization and dynamic constraint processing, and effectively solves the shortcomings of traditional algorithms in dealing with complex constraints and personalized needs. Compared with existing literature, this study not only considers basic constraints such as time and cost in travel, but also fully integrates personalized factors such as tourists' interest preferences, which is inconsistent with some research results that only focus on single-objective optimization. The limitation of this study is that the experimental data is mainly simulated data, which may be different from the real tourism scene, which may affect the universality of the research results. Future research can collect more real data for verification and further optimize the algorithm to improve its computational efficiency in large-scale data and complex scenarios. This study provides a new intelligent tool for the tourism planning industry, which helps to improve the automation level and accuracy of tourism planning and promote the sustainable development of the tourism industry.

The model has a modular ACO-based framework that can handle itinerary planning with many objectives;

however, it's only working in a simulated setting for now. This system's assessment and data inputs don't consider real-life travel patterns, real-time traffic, regional scheduling limitations, and diverse user preferences. When applied to real-world tourist settings, the optimisation process's reliance on static and idealised parameters limits its capacity to capture the dynamic nature of demand, environmental disturbances, and operational unpredictability. Under less-than-ideal circumstances, performance metrics like convergence stability, itinerary feasibility, and preference satisfaction become more meaningful when real-time data sources are used and the model is run in genuine user scenarios.

5 Conclusion

This study aims to solve the multi-objective optimization and complex constraint problems in designing multi-destination tourism itineraries through the ant colony optimization algorithm. It innovatively incorporates multiple factors into the model, such as tourists' personalized needs, time, and budget. Through experimental verification, the model has shown significant advantages under different numbers of destinations and various constraints. For example, in the 50 destination scenarios, the path length is 2000km, the tourist satisfaction rate is 93%, and the cost is controlled at 85% of the budget satisfaction rate, effectively improving the rationality of tourism itinerary planning and tourist satisfaction. However, the research also has limitations, such as the difference between simulated data and actual conditions and the long calculation time of the algorithm in large-scale scenarios. Future research can consider introducing more real data, optimizing algorithm parameters, and exploring more efficient calculation methods to improve the model's performance and practicality, as well as provide better services for the tourism industry.

Funding

This work was supported by Research on the Path of Integrating the Red Cultural Resources of Liaoning's "Six Regions" into the Cultivation of Socialist Core Values among College Students: A Project Approved in the 2024 Annual Plan of the "14th Five-Year" Education Science Planning in Liaoning Province (Project Approval Number: JG24EB078) and Research on the Modern Moral Education Function of Manchu Ethnic Cultural Classics has been approved as a general project of the Humanities and Social Sciences Research Fund by the Ministry of Education in 2019 (Project Approval Number: 19YJC880073).

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