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Multi-Objective Evolutionary Optimization for Qujing's Cultural-Tourism Routes

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Abstract

Tourism development in emerging destinations requires balancing economic benefits with ecological sustainability. In this study, we investigate the case of multi-attraction tourism planning in Qujing City, where the dual challenge lies in maximizing economic-experiential value while minimizing congestion-ecological stress. We formulate this problem as a bi-objective optimization model, integrating attraction revenues, visitor preferences, route costs, and site capacities into a unified framework. To solve the model, we employ NSGA-II enhanced with customized crossover and mutation operators specifically designed for route structures and visitor allocations. These operators enable efficient exploration of feasible solutions while maintaining capacity and time-window constraints. Extensive experiments across different scales of scenic scenarios demonstrate that our method consistently outperforms greedy and randomized baselines in terms of hypervolume and sustainability indicators. The results highlight the effectiveness of incorporating problem-specific operators into evolutionary algorithms and provide practical insights for sustainable tourism management in Qujing and other similar destinations.

Keywords

Multi-Objective Optimization, NSGA-II, Qujing City Case Study, Customized Genetic Operators

1. Introduction

Tourism has become a key driver of regional economic growth and cultural exchange in China, but its rapid expansion has also raised pressing concerns regarding sustainability and resource allocation. Qujing City, located in eastern Yunnan Province, is an emerging tourism destination that features a rich combination of natural and cultural attractions, such as the Pearl River Source, Jiulong Waterfalls, Luoping Rapeseed Flower Fields, and Huize Ancient City. While these resources provide substantial opportunities for tourism development, the city faces the dual challenge of maximizing its economic and experiential value while mitigating congestion and ecological pressures [1].

On the one hand, the prosperity of tourism industries depends on increasing visitor flows, enhancing travel experiences, and generating economic benefits. This requires well-designed itineraries, efficient transportation systems, and resource integration strategies that collectively improve both revenue and visitor satisfaction. On the other hand, the excessive concentration of tourists in popular sites often results in overcrowding, diminished service quality, and ecological degradation, which threaten the long-term sustainability of the destination. Striking a balance between these two conflicting objectives is therefore crucial for Qujing's tourism planning [2].

Although existing studies have investigated topics such as demand forecasting, transportation optimization, and carrying capacity control at the site level, relatively few have considered the integrated perspective of multi-site tourism systems, where economic performance and ecological sustainability must be jointly addressed. For Qujing, whose tourism development relies on both coordinated multi-attraction routes and diversified visitor segments, there is an urgent need for systematic models that can capture the trade-offs between maximizing economic-experiential value and minimizing congestion-ecological stress [3].

In this study, we formulate Qujing's tourism development as a multi-objective optimization problem. The first objective, economic-experiential value maximization, incorporates ticket revenues, transportation costs, and visitor preference alignment to improve overall returns and satisfaction. The second objective, congestion-ecological stress minimization, explicitly models capacity constraints and spatiotemporal visitor distribution to reduce crowding and environmental risks. By applying optimization algorithms to this dual-objective framework, we aim to provide decision support for Qujing's tourism industry, enabling policymakers to design strategies that simultaneously enhance economic benefits and ensure sustainable development [4].

The main contributions of this paper are summarized as follows:

1) We propose a novel multi-objective optimization model for Qujing's tourism development that simultaneously considers economic-experiential value maximization and congestion-ecological stress minimization. This dual-objective framework captures the inherent trade-offs between revenue generation, visitor satisfaction, and sustainable resource utilization.

2) To effectively solve the proposed model, we introduce the NSGA-II algorithm, which is well-suited for handling conflicting objectives and generating a set of Pareto-optimal solutions. This enables policymakers to flexibly choose strategies according to different priorities.

3) We conduct extensive experiments by comparing our approach with several baseline methods, including greedy heuristics and randomized strategies. The re-

sults demonstrate that our method achieves superior performance in balancing economic returns, visitor experience, and ecological sustainability.

The rest of this article is organized as follows. In the Section 2, we introduced the relevant research work, and in the Section 3, we presented the proposed problem model and algorithm implementation. In the Section 4, we conducted experiments and provided a detailed analysis of the experimental results. Finally, in the Section 5, we summarized this article.

2. Related Work

With the rapid expansion of tourism worldwide, balancing economic growth and sustainable development has become an increasingly critical challenge. For emerging destinations such as Qujing City, the trade-off between maximizing economic-experiential value and minimizing congestion-ecological stress is relatively underexplored. Nevertheless, several strands of research in sustainable tourism, multi-objective optimization, and heuristic baselines provide valuable insights for this study.

2.1. Sustainable Tourism and Multi-Objective Optimization

In tourism management, incorporating both economic benefits and environmental protection into optimization frameworks has become a growing trend. Pitakaso *et al.* (2024) proposed a multi-objective model for sustainable tourist trip design, integrating visitor preferences, site capacities, and environmental constraints to generate Pareto-optimal solutions [5]. Similarly, Aliahmadi *et al.* (2025) introduced a multi-objective optimization approach for personalized trip planning that balances visitor experience with resource efficiency [6]. These studies highlight the effectiveness of multi-objective modeling in reconciling tourism development with ecological sustainability.

2.2. Applications of NSGA-II in Tourism and Resource Allocation

NSGA-II [7] is one of the most widely adopted evolutionary algorithms for solving multi-objective optimization problems, and it has been successfully applied to transportation, scheduling, and resource allocation [8]. In the tourism domain, Zhu *et al.* (2025) applied NSGA-II to sustainable tourism management, showing how the algorithm can balance economic revenue with ecological constraints [9]. Yang and Bian (2023) developed a multi-objective optimization model to evaluate sustainable tourism capacity, further validating the suitability of NSGA-II for tourism-related optimization problems [10]. These studies provide methodological support for employing NSGA-II in this paper.

2.3. Baseline Methods and Heuristic Comparisons

In comparative experiments, greedy heuristics, randomized strategies, and local search methods are commonly employed as baselines in tourism optimization and scheduling problems. For instance, greedy insertion and nearest-neighbor heuristics are often used to construct initial solutions for tourist routes, while randomized allocation and simple local search operators (e.g., 2-opt, 3-opt) provide quick but less optimal benchmarks [11]. Although these methods are limited in quality, they serve as practical references to demonstrate the advantages of advanced evolutionary algorithms in solution quality and objective balance.

In summary, existing studies on sustainable tourism and multi-objective optimization have made progress in integrating economic and ecological dimensions, but most focus on either single attractions or high-level management issues. Research on multi-attraction coordination that explicitly addresses both economic-experiential maximization and congestion-ecological minimization remains scarce. By formulating this problem as a dual-objective optimization model, employing NSGA-II for solution generation, and benchmarking against greedy and randomized methods, this study contributes to bridging this research gap and offers a systematic approach to sustainable tourism planning.

3. Methodology

This section introduces the mathematical formulas and specific algorithms modeled in this article.

3.1. Problem Formulation

In this section, we formulate the Qujing multi-attraction tourism optimization as a multi-objective optimization problem (MOP). The model simultaneously considers (i) maximizing the economic-experiential value of tourist routes, and (ii) minimizing congestion and ecological stress caused by excessive visitor concentration. For the convenience of reading, we have summarized the symbols that appear in the text in **Table 1**.

Table 1. Symbols.

Symbol	Description
$V = \{0,1,\cdots,n\}$	Set of sites, where 0 denotes the origin/destination (e.g., downtown Qujing).
$T = \{1,\cdots,H\}$	Set of time periods (e.g., hours or half-days).
K	Set of tourist groups with heterogeneous preferences.
$E \subseteq V \times V$	Directed network of feasible travel arcs.
t_{ij}	Travel time from site *i* to site *j*.
c_{ij}^{travel}	Travel cost on arc (i,j).
r_i	Economic revenue (e.g., ticket price) of site *i*.
u_i	Satisfaction score of site *i*.
w_{ik}	Preference weight of group *k* for site *i*.
cap_i	Maximum ecological/operational capacity of site *i*.
f_r	Fixed cost of opening route *r*.
Q_{scale}	Scaling factor for per-capita travel costs.
$x_{ij}^r \in \{0,1\}$	Equals 1 if route *r* includes arc (i,j).
$y_i^r \in \{0,1\}$	Equals 1 if route *r* visits site *i*.

Continued

$q_t^{r,k} \geq 0$	Number of group k tourists assigned to route r in period t.
$z_r \in \{0,1\}$	Equals 1 if route r is activated.

The specific problem modeling is as follows.

The total number of tourists visiting site i during period t is:

$$N_{i,t} = \sum_{r=1}^{R} \sum_{k \in K} q_t^{r,k} y_i^r \tag{1}$$

Objective 1: Economic-Experiential Value Maximization (EEV)

We define the unit value of assigning one tourist from group k to route r as:

$$V_{r,k} = \sum_{i \in V} y_i^r \left(r_i + \alpha u_i w_{ik} \right) - \frac{1}{Q_{scale}} \sum_{(i,j) \in E} x_{ij}^r c_{ij}^{travel} \tag{2}$$

The first objective is then formulated as:

$$\max F_1 = \sum_{r=1}^{R} \sum_{k \in K} \sum_{t \in T} q_t^{r,k} V_{r,k} - \sum_{r=1}^{R} f_i z_r \tag{3}$$

This objective captures both direct economic revenue and enhanced visitor experience, while accounting for route operation and travel costs.

Objective 2: Congestion-Ecological Stress Minimization (CES) We define the load ratio of site i at time t as:

$$z_{i,t} = \frac{N_{i,t}}{cap_i} \tag{4}$$

To penalize congestion, we adopt a convex penalty function:

$$\Phi(z) = \begin{cases} 0, & z \leq \theta \\ \beta_1 (z - \theta)^2, & \theta < z \leq 1 \\ \beta_1 (z - \theta)^2, & z > 1 \end{cases} \tag{5}$$

The second objective is then:

$$\min F_2 = \sum_{i \in V} \sum_{t \in T} \Phi(z_{i,t}) + \lambda_{time} \sum_{i \in V} \sum_{t=2}^{H} \left(z_{i,t} - z_{i,t-1} \right)^2 + \lambda_{space} \sum_{t \in T} Var_i \left(z_{i,t} \right) \tag{6}$$

where the second and third terms encourage temporal smoothing and spatial balancing, reducing sharp peaks and uneven distribution of visitors.

The Qujing tourism optimization problem can thus be summarized as the following multi-objective optimization problem:

$$\max F_1, \min F_2 \tag{7}$$

subject to route feasibility, time windows, demand allocation, and capacity constraints.

3.2. Operators

To adapt NSGA-II to the specific characteristics of the Qujing tourism optimization problem, we designed tailored genetic operators that directly manipulate route structures and visitor allocations. Unlike conventional operators that act on continuous variables, our operators are problem-aware, ensuring feasibility and improving search efficiency. The proposed algorithm flowchart is shown in Figure 1.

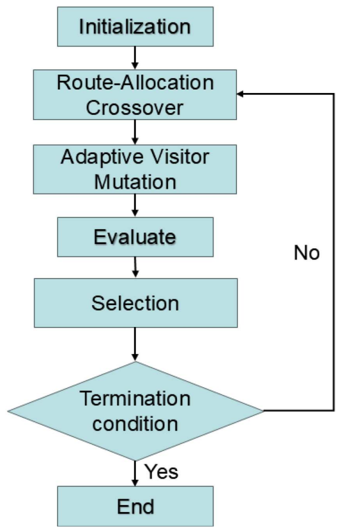

Figure 1. The flowchart of the proposed algorithm.

3.2.1. Route-Allocation Crossover

Given two parent solutions, each represented by a set of routes and corresponding visitor allocations, the crossover operator is designed to exchange both structural and allocation information:

1) Route-level exchange: A subset of routes from Parent A is combined with the complementary subset from Parent B. Overlapping routes are merged, and feasibility (capacity and time windows) is checked.

2) Visitor reallocation: For routes that appear in both parents, the offspring inherits a weighted average of their visitor allocations. The weights are biased towards the parent with higher fitness, promoting exploitation of good solutions.

3) Feasibility repair: If the offspring violates site capacity or budget constraints, a greedy repair step redistributes excess visitors to underutilized routes or adjusts timing to avoid congestion.

This operator allows the offspring to inherit diverse route structures while maintaining feasible visitor flows.

3.2.2. Adaptive Visitor Mutation

To avoid premature convergence and to explore underutilized parts of the solution space, we employ a mutation operator that adaptively perturbs visitor allocations:

1) Local redistribution: A fraction of visitors assigned to congested sites is shifted to alternative sites within the same route or to parallel routes serving similar attractions.

2) Temporal adjustment: Visitors are shifted across adjacent time periods to

reduce peak congestion while preserving demand satisfaction.

3) Adaptive intensity: The mutation probability is increased for individuals with higher congestion penalties F_2, encouraging stronger exploration when ecological stress is high, and reduced otherwise.

3.2.3. Advantages of the Customized Operators

1) Feasibility preservation: Operators are designed to directly handle capacity and time constraints, reducing the need for excessive repair.

2) Problem awareness: By incorporating route structure and visitor flows, the search process explicitly targets the trade-off between economic-experiential value and congestion-ecological stress.

3) Diversity and exploitation balance: Route-level crossover provides structural diversity, while adaptive mutation fine-tunes allocations, together enabling efficient convergence towards a well-distributed Pareto front.

4. Experiment

4.1. Study Area and Data

The experiments are conducted in the context of multi-attraction tourism planning in Qujing City, Yunnan Province. We select 5 - 11 representative attractions (e.g., Pearl River Source, Jiulong Waterfalls, Luoping Rapeseed Flower Fields, Huize Ancient City, Shengjingguan, etc.) together with one central depot (downtown or high-speed railway station) as the starting and ending point.

1) Time discretization: A day is divided into $H = 6$ time periods (e.g., morning/afternoon/evening across weekdays and weekends).

2) Tourist groups: We consider $K = 3$ groups (family tourists, hiking/photography, leisure sightseeing). Each group is associated with demand volume D_k and preference weights w_{ik} for different attractions.

3) Capacities: Each attraction i has a maximum ecological/operational capacity cap_i, with seasonal adjustments for peak seasons.

4) Economic and experiential values: Revenue r_i is derived from ticket prices, while satisfaction scores u_i are estimated based on historical survey and rating data.

5) Transportation network: Travel time t_{ij} and travel cost c_{ij}^{travel} between sites are estimated using real-world road distances.

The experimental data are constructed by integrating publicly available information (attraction lists and ticket prices from official tourism sources, travel distances from online maps, satisfaction scores from survey/rating platforms) with modeled assumptions on tourist group preferences and ecological capacities, following common practices in tourism optimization studies.

4.2. Experimental Setup and Results

In our implementation, the population size is set to 100, and the algorithm runs for 300 generations. The crossover probability is fixed at 0.9, while the mutation probability is set as the reciprocal of the number of decision variables $1/d$. For the congestion penalty function, the threshold is set to $\theta = 0.8$, with penalty coefficients $\beta_1 = 1$, $\beta_2 = 20$, and $\gamma = 10$. The weights for the temporal smoothing term and the spatial balancing term are both assigned the value of 0.5.

To ensure the stability of the experiments, each algorithm was independently executed 30 times, and the quality of the obtained Pareto fronts was evaluated using the hypervolume (HV) indicator. All objective values were normalized prior to evaluation, and the reference point for HV calculation was set to (1.1, 1.1). The detailed results are reported in Table 2. A larger HV indicates a better Pareto front—*i.e.*, broader coverage of the objective space and closer convergence toward the ideal point.

Table 2. Comparison results of HV with different classical quantities and methods.

	Ours	Random-based	Greedy-based
$N = 5$	**96.34 (3.21)**	78.41 (4.67)	87.78 (4.08)
$N = 7$	**91.17 (4.12)**	76.34 (6.73)	83.14 (5.91)
$N = 9$	**84.97 (3.92)**	70.87 (8.43)	76.28 (6.31)
$N = 11$	**81.13 (3.11)**	61.59 (10.21)	69.91 (8.15)

We designed experiments with different scales of sightseeing scenarios by varying the number of attractions, specifically N = 5, 7, 9, and 11. As shown in Table 2, our proposed method consistently outperforms all baseline approaches. This improvement can be attributed to the problem-specific crossover and mutation operators carefully designed for this study. To provide a more intuitive comparison, the detailed numerical analysis is presented in Figure 2.

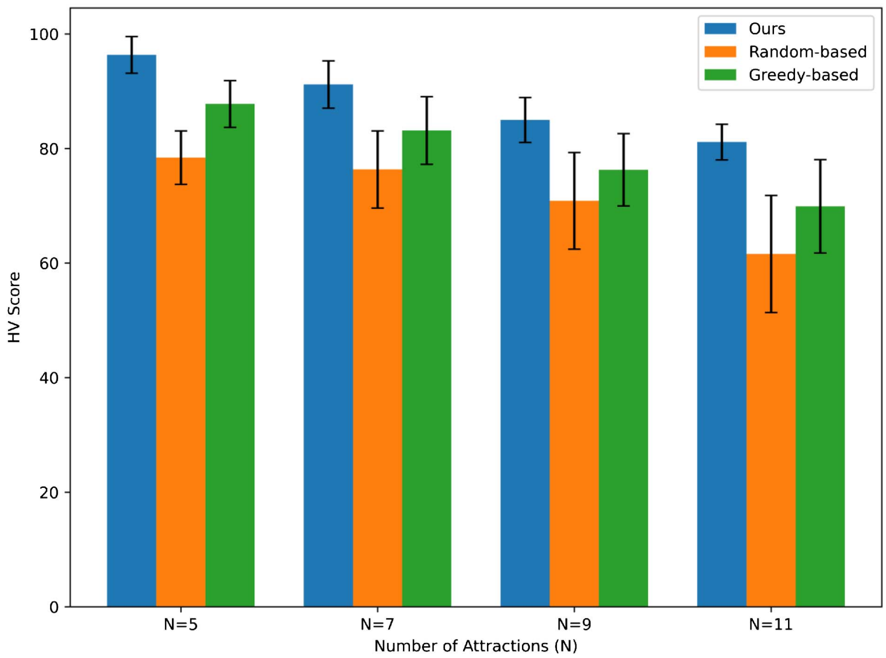

Figure 2. Bar chart comparing HV values of different algorithms.

4.3. Limitations Analysis

Despite the encouraging results, several limitations of this study should be acknowledged. First, the current framework relies on static demand assumptions and fixed parameter settings, which may not fully capture the temporal variability of tourist flows and ecological sensitivities in real-world contexts. Second, while the customized evolutionary operators enhance solution quality, their effectiveness may be sensitive to specific tuning choices and problem instances. These factors suggest that further validation under dynamic, large-scale, and heterogeneous conditions will be necessary to consolidate the generalizability of our findings.

5. Conclusions

In this paper, we addressed the problem of multi-attraction tourism optimization in Qujing City by formulating it as a dual-objective optimization model that simultaneously considers economic–experiential value maximization and congestion-ecological stress minimization. To solve this challenging problem, we developed a tailored approach based on NSGA-II with customized crossover and mutation operators, which explicitly integrate route structures and visitor allocation patterns into the evolutionary process.

Extensive experiments under different scenic scales demonstrated that our method consistently outperforms greedy and randomized baselines in terms of hypervolume and sustainability indicators. The results confirm that incorporating problem-specific knowledge into evolutionary operators can significantly enhance both solution quality and feasibility.

To enhance the practical significance of our results, we have clarified how the Pareto front can be directly applied by tourism managers. Specifically, the set of trade-off solutions enables decision-makers to design seasonal route packages that flexibly prioritize either economic profitability or ecological sustainability. For example, during peak holiday seasons managers may select routes from the profit-oriented region of the Pareto front, while in off-peak or environmentally sensitive periods they may adopt solutions emphasizing congestion reduction and ecological balance.

Overall, this study provides not only a methodological contribution by extending NSGA-II with domain-aware operators, but also practical insights for sustainable tourism management in Qujing and similar destinations. In future work, we plan to incorporate dynamic demand forecasting, real-time data integration, and more advanced multi-objective algorithms to further improve the robustness and applicability of our framework.

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Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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