

Optimizing Sustainable Tourism: A Multi-Objective Approach

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Abstract

This study develops a comprehensive multi-objective optimization (MOO) framework to address the complex challenge of sustainable tourism management in Juneau, Alaska. By employing advanced genetic algorithms, particularly the NSGA-II approach, the research simultaneously optimizes two competing objectives: maximizing tourism revenue while minimizing negative impacts on infrastructure, environment, and local communities. The model incorporates real-world constraints including waste generation limits, water demand thresholds, CO2 emission caps, and policy adjustment boundaries derived from Juneau's specific conditions. Through the generation of a Pareto-optimal frontier, the study reveals inherent trade-offs between economic development and sustainability goals, providing policymakers with actionable insights. Results demonstrate that optimal tourist numbers and tax adjustments can enhance sustainability without exceeding carrying capacities. The robustness of the proposed approach is validated through sensitivity analysis, establishing its effectiveness in complex, real-world tourism planning scenarios where multiple competing objectives must be reconciled.

Keywords

Sustainable Tourism, Multi-objective Optimization, Genetic Algorithm.

1. Introduction

Sustainable tourism requires balancing economic benefits with environmental and social impacts. This study develops a multi-objective optimization model for Juneau, Alaska, using genetic algorithms to optimize tourism revenue while minimizing infrastructure and environmental pressures. The research provides decision-support for sustainable tourism management through Pareto-optimal solutions.

Sustainable tourism development has gained increasing attention in recent academic research. The low-carbon tourism model in Hailuoguo Geopark was examined, emphasizing the balance between environmental protection and tourism development [1]. Tax policies have been proposed as an effective tool for regulating tourism growth, providing valuable insights for tourism economic management [2]. An improved ideal interval method using genetic algorithms was developed, offering a quantitative approach for tourism environmental quality assessment that informs carrying capacity studies [3]. The "resource curse" framework has been introduced to highlight the importance of diversified tourism supply for sustainability [4]. Fuzzy multi-criteria decision making (F-MCDM) has been applied to evaluate glacier tourism satisfaction, establishing a scientific basis for optimizing tourist experiences [5]. Recent advancements have demonstrated the effectiveness of machine learning in predicting tourism demand [6], while innovative approaches have been proposed to mitigate overtourism through smart destination management systems [7]. In resource optimization, the Banker's algorithm has been employed for effective visitor flow management [8]. Enhanced genetic algorithm applications have achieved significant improvements in tourism route optimization [9]. A novel

multi-agent system has been introduced for dynamic tourism resource allocation [10], and a comprehensive framework has been developed for evaluating the carbon footprint of tourism activities [11].

The main contributions of the article can be summarized as follows: 1) The study develops a comprehensive multi-objective optimization framework for sustainable tourism management, effectively balancing economic benefits with environmental and social impacts through advanced genetic algorithms. 2) The research introduces a novel dual-objective function that simultaneously maximizes tourism revenue while minimizing negative impacts on infrastructure, environment, and local communities, providing a quantitative approach to assess tourism carrying capacity. 3) The application of NSGA-II algorithm generates a Pareto-optimal frontier that clearly visualizes the trade-offs between competing objectives, offering policymakers actionable insights for sustainable tourism planning

The structure of this paper is organized as follows: The first section presents Related Theories and Experiments, detailing the multi-objective optimization framework for sustainable tourism, including the formulation of dual objective functions (maximizing tourism revenue while minimizing negative impacts), constraint conditions based on Juneau's infrastructure and environmental data, and implementation of the genetic algorithm approach. The second section provides Results and Analysis, showcasing the Pareto-optimal solutions generated by the NSGA-II algorithm, visualization of trade-off relationships between economic benefits and sustainability impacts, and validation of the model's robustness through sensitivity analysis of tourist numbers and tax policies. The third section contains Conclusions, summarizing key findings about optimal tourism management strategies, discussing the practical implications for policymakers in balancing development and sustainability, and suggesting directions for future research in applying multi-objective optimization to tourism planning.

2. Related Theories

Multi-Objective Optimization (MOO) models address complex decision-making scenarios where multiple, often competing objectives must be optimized concurrently, such as maximizing performance while minimizing cost and resource utilization. Unlike conventional single-objective approaches that converge to a single optimum, MOO generates a Pareto frontier - a collection of non-dominated solutions where improvement in one objective necessitates compromise in others. The algorithmic approaches to MOO can be broadly categorized into a priori, a posteriori, and interactive methods. A priori techniques like the weighted sum method scalarize multiple objectives into a single function through user-defined weights, though this requires careful weight selection and may miss concave portions of the Pareto front. More sophisticated evolutionary algorithms such as NSGA-II (Non-dominated Sorting Genetic Algorithm II) employ non-dominated sorting to rank solutions and crowding distance metrics to maintain diversity, enabling effective exploration of the solution space. Other advanced methods include MOEA/D (Multi-Objective Evolutionary Algorithm Based on Decomposition) which decomposes the problem into multiple single-objective subproblems, and reference-point based approaches like R-NSGA-II that incorporate preference information. Mathematical programming techniques like the ϵ -constraint method systematically vary constraints on all but one objective to generate Pareto solutions. These algorithms typically involve iterative refinement, where solution quality improves through generations while maintaining diversity across the Pareto front, ultimately providing decision-makers with a comprehensive set of trade-off alternatives for informed selection based on application-specific requirements and preferences. Pareto optimality in MOO refers to solutions where improving one objective worsens another. These non-dominated solutions form the Pareto front,

representing optimal trade-offs between competing objectives. No solution exists that's better in all objectives simultaneously.

3. Experiments

The objective functions are classified into two categories: maximizing tourism revenue $P(x, y)$ and minimizing negative impacts $Z(x)$. In order to achieve sustainable tourism, integrated sustainability in multi-objective optimization emphasizes a balance between the four dimensions of economy, environment, society and infrastructure to ensure the long-term sustainability of tourism development.

The objective function $Z(x)$ provides a comprehensive measure of the impact of tourism activities on sustainable development by integrating infrastructure pressures, environmental impacts and local sentiment. Through minimizing negative impacts objective function $Z(x)$ can maximize tourism revenue objective function $P(x, y)$ without exceeding the carrying capacity of infrastructure and the environment, thus achieving the goal of promoting integrated sustainable development.

$$\begin{cases} \max P(x, y) = \alpha_1 x(1 + y) \\ \min Z(x) = 2I(x) + \frac{E(x)}{E_0(x)} + \frac{1 - S(x)}{1} \end{cases} \quad (1)$$

The significance of the objective function is that it can consider the infrastructure pressure, environmental impacts and local people's sentiment comprehensively after standardize them. Infrastructure pressure, environmental impacts, and local dissatisfaction can be reduced simultaneously by minimizing $Z(x)$; while the extent of tourism economic development can be reflected by maximizing $P(x, y)$, thus further balancing the economic benefits of tourism with the carrying capacity of infrastructure, the environment and society. Finding the optimal number of tourists x and the adjustment ratio of tourism-related taxes and fees y to optimize sustainable benefits and maximize economic benefits.

(1) Infrastructure stress index

$$\begin{aligned} I_1(x) &\leq I_1^0(x) \\ I_2(x) &\leq I_2^0(x) \end{aligned} \quad (2)$$

According to the City of Juneau's survey of waste generation and potable water demand, this study gets the maximum amount of waste generated in recent years $I_1^0(x) = 12$ thousand tons, the maximum demand for potable water $I_2^0(x) = 12.87$ MG. Formula 6 ensures that the number of tourists will not exceed the carrying capacity of the infrastructure and avoids the damage of the infrastructure due to overuse.

(2) Environmental impact index

$$E(x) \leq E_0(x) \quad (3)$$

Overall, the emissions show fluctuating changes during this period, but the overall trend is relatively smooth, with no obvious continuous increase or decrease. The emissions in 2012 were the lowest at 35,734.68671 tons, while the emissions in 2019 peaked at 92,404.1 tons, and it was investigated that the State of Alaska suffered from the Swan Lake Fire on September

17th, which may have been the be the main reason for the surge in CO2 emissions in that year, which declined significantly after 2019, possibly due to a decrease in industrial activity as a consequence of the COVID-19. As a result, the environmental capacity threshold $E_0(x) = 12.5$ thousand tons.

(3) Constraint on the range of the number of tourists

$$x_{\min} \leq x \leq x_{\max} \quad (4)$$

The city government of Juneau regulated the number of cruise ships, which led to a decrease in the number of tourists. Therefore, our study determined that the visitor number thresholds $x_{\min} = 1.41$ million people, $x_{\max} = 1.71$ million people.

(4) Policy adjustment scope constraints

$$0 \leq y \leq 1 \quad (5)$$

The global outbreak of COVID-19 from 2019 to 2022 caused a sharp rise in unemployment rates during this period, making it not universally representative. Based on the unemployment rates of other years in the city of Juneau, the overall unemployment rate is 5.8%. In order to avoid over-adjustment leading to market imbalances, there is a need to ensure that tax and fee adjustments are within the limits allowed by the policy.

Finally, integrate the above - mentioned constraint conditions to obtain a complete set of constraint conditions:

$$\left\{ \begin{array}{l} I_1(x) \leq I_1^0(x) \\ I_2(x) \leq I_2^0(x) \\ E(x) \leq E_0(x) \\ x_{\min} \leq x \leq x_{\max} \\ 0 \leq y \leq 1 \end{array} \right. \quad (6)$$

4. Results and Analysis

After constructing a sustainable tourism model for the city of Juneau, selecting an appropriate method to solve the model is a crucial step. Since the model involves multiple variables and complex constraints, it is a kind of nonlinear programming problems. Therefore, the genetic algorithm is chosen for solving it. The following is the detailed solution process, combined with the objective functions $P(x, y)$ and $Z(x)$ for illustration:

Genetic algorithms (GAs) represent a class of evolutionary computation techniques inspired by Darwinian principles of natural selection and Mendelian genetic mechanisms. As a population-based metaheuristic optimization method, GAs emulate biological evolution by maintaining a pool of candidate solutions that undergo iterative improvement through computationally simulated genetic operations. The algorithm operates by first initializing a diverse population of potential solutions encoded as chromosomes, typically represented as binary strings, real-valued vectors, or other data structures appropriate to the problem domain. Through successive generations, these solutions are evaluated using a fitness function that quantifies their performance against the optimization objectives. The following pseudocode of the algorithm[3] is illustrated, explained with the objective functions $P(x, y)$ and $Z(x)$:

Algorithm 1: Genetic Algorithm for Sustainable Tourism Optimization

Input: Population size N , chromosome length L , Encoding length n , maximum generations T , crossover probability P_c , mutation probability P_m , convergence threshold ϵ , decision variable ranges $[x_{min}, x_{max}]$, $[y_{min}, y_{max}]$.

Output: Pareto optimal solutions for $P(x, y)$ and $Z(x)$.

```
1:  i ← 1
2:  t ← 1
3:  for i in 1 to N
4:    individuali ← rand{binary_encode(xi_binary), binary_encode(yi_binary)}
5:  end for
6:  for t in 1 to T
7:    for i in 1 to N
8:      xi ← binary_to_value(xi_binary, x_min, x_max, n)
9:      yi ← binary_to_value(yi_binary, y_min, y_max, n)
10:     fitness(i) ← w1 * P(xi, yi) - w2 * Z(xi)
11:    end for
12:  end for
13:  F ← ∑i=1N fitness(i)
14:  for i in 1 to N
15:    p(i) ← fitness(i) / F
16:    with Pc
17:      Choose a random crossover point
18:      Swap the binary substrings after the crossover point
19:    with Pm
20:      Randomly select one bit in the binary encoding
21:    0 ← 1
22:    1 ← 0
23:  end for
24:  if t = T or the best fitness(i) ≤ ε
25:    break
26:  end if
27:  return 0
```

N : Population size, representing the number of individuals in the initial population.

L : Chromosome length, representing the length of the binary encoding for each individual.

T : Maximum number of generations, representing the maximum number of iterations for the genetic algorithm.

P_c : Crossover probability, representing the probability of performing crossover on two parent individuals.

P_m : Mutation probability, representing the probability of mutating a gene in an individual.

ϵ : Convergence threshold, used to determine if the algorithm has converged.

When the termination condition is satisfied, the optimal individuals in the current population are output, and the Pareto optimal surfaces of $P(x, y)$ and $Z(x)$ are shown in Figure 1.

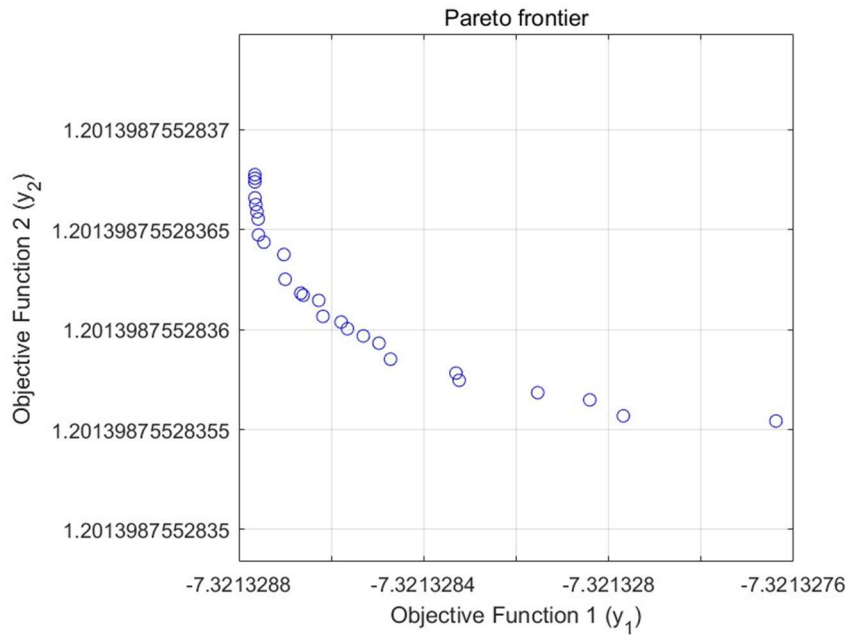


Figure 1. Pareto Frontier 1

Finally, our study obtains the corresponding analytical expression for the state variable function:

$$\begin{aligned}
 P(x, y) &= 2.344x(1 + y) \\
 I(x) &= 0.303x \\
 E(x) &= -5.24x^2 + 15.37x - 10.05 \\
 S(x) &= 5.583 - 7.139x + 2.389x^2
 \end{aligned}
 \tag{7}$$

The improved model is solved and the Pareto optimal front is obtained which shown in Figure 22. The analysis results indicate a trade-off relationship with negative correlation between the two objective functions. Specifically, when the value of objective function $P(x, y)$ decreases, the value of objective function $Z(x)$ increases accordingly. This means that during the optimization process, improving the performance of one objective often comes at the cost of sacrificing the performance of the other.

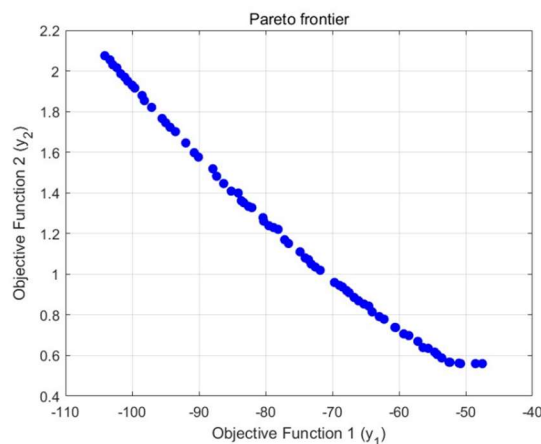


Figure 2. Parato Frontier 2

5. Conclusion

This study demonstrates that multi-objective optimization effectively balances tourism revenue maximization and negative impact minimization in Juneau's sustainable tourism development. The genetic algorithm successfully generated a Pareto frontier, revealing the inherent trade-off between economic benefits and environmental/social costs. The results confirm that optimal tourist numbers and tax adjustments can enhance sustainability without exceeding infrastructure and environmental carrying capacities. The model's robustness is validated through its ability to handle nonlinear constraints and produce stable Pareto-optimal solutions, providing policymakers with actionable insights for achieving long-term tourism sustainability while maintaining economic viability. These findings underscore the value of MOO approaches in complex, real-world decision-making scenarios where competing objectives must be reconciled.

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