Sustainable Tourist Trip Design Problem under Dual Constraints of Carbon Emission and Ecological Footprint: A Novel Framework Based on an Improved Multi-Objective Evolutionary Algorithm

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Abstract—With the rapid growth of global tourism, carbon emissions and ecological pressures from tourism activities have emerged as major barriers to sustainable destination development. Traditional Tourist Trip Design Problems (TTDPs) typically focus on maximizing tourist satisfaction or minimizing travel time and costs, often overlooking deeper environmental impacts. Existing green tourism studies tend to rely on a single carbon emission indicator, neglecting broader environmental factors such as water use, land consumption, and biodiversity impacts. This has created a need for a systematic trip optimization framework that simultaneously considers both carbon emissions and ecological footprint. To address this gap, this study proposes a multi-objective sustainable tourist trip optimization model that integrates carbon emissions and ecological footprint as dual environmental constraints. The framework aims to balance tourist preferences, travel costs, and ecological impacts within a unified optimization model. At the algorithmic level, an Adaptive Penalty-based NSGA-II (AP-NSGA-II) is developed, combining an adaptive penalty mechanism with lightweight local improvement strategies for efficient solution of the multi-objective problem. A representative eco-tourism scenario featuring 40 Points of Interest (POIs) is used to validate the framework. The dataset combines publicly available geographic data, literature-based parameter settings, and standardized simulated tourist preference profiles to ensure reproducibility. Controlled simulations are conducted for tourist groups of different sizes. Using Pareto optimality theory and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), the model generates illustrative itineraries under various preference scenarios. Experimental results show that, compared with baseline algorithms such as traditional NSGA-II, MOPSO, and ACO, the proposed AP-NSGA-II achieves higher Hypervolume (HV) performance, more evenly distributed Pareto fronts, and itineraries that reduce carbon emissions and ecological footprint while maintaining comparable tourist satisfaction. Overall, this study provides a practical methodological reference for multi-objective tourist trip design, demonstrating that tourist experience and ecological protection can be integrated within a single optimization framework. The proposed model also serves as a reproducible decision-support tool for evaluating trade-offs among preference, cost, carbon emissions, and ecological footprint, offering guidance for future sustainable tourism planning.

I. INTRODUCTION

Tourism is a major engine of global economic growth, contributing to regional development, job creation, and cultural exchange. However, the rapid rise of mass tourism has intensified its social and environmental impacts. Globally, the tourism industry accounts for roughly 8% of greenhouse gas emissions, with emissions increasing at an average rate of about 3.8% per year [1]. Beyond carbon emissions, tourism activities contribute to water depletion, land degradation, biodiversity loss, and increased solid waste. These challenges highlight the urgent need for strategies that balance economic benefits with ecological protection, promoting a transition toward sustainable tourism.

One promising approach is integrating sustainability principles into the Tourist Trip Design Problem (TTDP). TTDP focuses on planning optimal travel routes that align with tourists' personalized preferences under constraints such as time, budget, and opening hours of points of interest (POIs). Traditional TTDP methods prioritize maximizing tourist satisfaction or minimizing travel time and cost, often overlooking the environmental impacts of tourism activities. Recent research has begun to explore green tourist route planning, primarily by minimizing carbon emissions. However, most studies still focus on a single environmental dimension and fail to capture the broader ecological impacts on water, land, and biodiversity.

The current research gaps can be summarized in two key points:

1) Single ecological indicators are insufficient: Using only carbon emissions fails to reflect the full environmental impact of tourism, including accommodation, catering, and recreational activities.

2) Algorithmic limitations in multi-objective optimization: High-dimensional problems involving tourist preference, cost, carbon emissions, and ecological footprint

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are prone to local optima using traditional heuristics, resulting in poorly distributed Pareto fronts.

To address these challenges, this study proposes a multi-objective sustainable tourist trip design framework. The framework uses an improved evolutionary algorithm, specifically an Adaptive Penalty-based NSGA-II (AP-NSGA-II), to balance tourists' preferences with ecological sustainability under dual constraints of carbon emissions and ecological footprint. The scope of the study focuses on direct environmental impacts from local transportation, scenic spot visits, and tourism services, while excluding long-distance travel to maintain model clarity and reproducibility.

The paper is structured as follows:

- Section 2 reviews TTDP and sustainable tourism optimization literature.

- Section 3 details the multi-objective mathematical model and constraints.

- Section 4 presents the design and implementation of the AP-NSGA-II algorithm.

- Section 5 conducts simulation experiments using real eco-tourism area data, including data processing and visualization.

- Section 6 discusses and compares experimental results.

- Section 7 concludes the study and suggests future research directions.

II. Related Work

The Tourist Trip Design Problem (TTDP) has long been a central topic at the intersection of operations research and tourism management. This section reviews existing studies across three dimensions: traditional TTDP methods, sustainability integration in trip planning, and the use of multi-objective optimization algorithms in tourism, highlighting the unique contribution of this study.

A. Traditional Tourist Trip Design and Tourist Preference Modeling

Early TTDP research framed the problem as a variant of the Orienteering Problem with Time Windows (OPTW), aiming to generate personalized travel routes for different tourist groups. Heuristic methods were developed to consider tourist preferences, POI characteristics, distance, and time constraints, providing efficient itinerary solutions and enhancing tourist experiences [2]. While these studies laid a solid foundation for TTDP, most models adopted an "anthropocentric" perspective, focusing solely on maximizing satisfaction or minimizing travel cost, without accounting for environmental constraints or the ecological carrying capacity of destinations.

B. Extension of Sustainability Dimensions to Tourist Trip Design

As environmental concerns intensified, researchers began integrating sustainability indicators into TTDP. Several studies combined carbon emission assessments with route planning. For instance, Almaskati et al. (2024) proposed a method to minimize tourism-related environmental impacts by optimizing travel routes under emerging transportation trends [3]. Similarly, Ruiz-Meza et al. (2022) incorporated CO_2 emission targets into TTDP and applied multi-objective

algorithms such as NSACDE and ACO to handle environmental constraints [4].

Although these studies improved awareness of transportation-related emissions, they remained limited to a single environmental dimension, ignoring other ecological impacts such as water and land use or biodiversity loss. To address this gap, researchers have introduced the Ecological Footprint (EF) model, which considers the full environmental consumption of tourism activities, including accommodation, catering, and infrastructure [5]. However, translating complex EF calculations into computable dynamic constraints for TTDP remains largely unexplored.

C. Application and Limitations of Multi-Objective Optimization in Tourism Planning

Sustainable Tourist Trip Design Problems (STTDP) often involve conflicting objectives, making meta-heuristic algorithms a popular solution approach. Methods such as Genetic Algorithm (GA), Simulated Annealing (SA), and Ant Colony Optimization (ACO) can handle multi-objective conflicts through intelligent search strategies [6]. For example, Pitakaso et al. (2024) applied multi-objective optimization to balance tourist preferences with sustainability goals [7].

However, when objectives expand to four or more dimensions—such as satisfaction, cost, carbon emissions, and ecological footprint—traditional NSGA-II algorithms struggle with reduced selection pressure, uneven Pareto front distribution, and entrapment in local optima [8]. Recent advances in the Green Vehicle Routing Problem (Green VRP) literature suggest that adaptive mechanisms and constraint penalty strategies can significantly enhance algorithm performance under high-dimensional environmental constraints [9].

D. Uniqueness and Innovative Positioning of This Study

The literature review highlights a clear "fault line" in STTDP research (Figure 1): ecological assessment models are often too complex to integrate dynamically, while existing multi-objective algorithms are insufficient for handling high-dimensional ecological constraints [10].

This study addresses these gaps through three key innovations:

- Expanded Theoretical Framework: Dual environmental constraints—carbon emission and ecological footprint—are simultaneously incorporated into the TTDP, enabling a more comprehensive assessment of tourism's environmental impact.

- Algorithmic Innovation: An Adaptive Penalty NSGA-II (AP-NSGA-II) algorithm is developed, balancing convergence and diversity in high-dimensional multi-objective optimization for tourism planning.

- Application to Sensitive Scenarios: The framework is applied to an ecologically fragile national nature reserve, providing quantitative decision support for sustainable eco-tourism management.

III. Methodology

This section outlines the comprehensive strategy, the mathematical model construction, and the enhanced multi-objective optimization algorithm (AP-NSGA-II) used in the study. Key points include:

1) Overall Strategy:
- A systematic framework is adopted to integrate tourist preferences, travel costs, and environmental constraints (carbon emissions and ecological footprint) into a unified Tourist Trip Design Problem (TTDP).

- The workflow emphasizes reproducibility and scientific rigor by defining clear data requirements, variable definitions, and algorithmic logic.

2) Mathematical Model Construction:
- The model formalizes the TTDP as a multi-objective optimization problem, incorporating dual environmental constraints.

- Decision variables represent itinerary choices, route sequences, and time allocations at each Point of Interest (POI).

- Objective functions include maximizing tourist satisfaction, minimizing travel costs, and minimizing ecological impacts.

- Constraints account for POI operating hours, travel time, and limits on carbon emissions and ecological footprint.

3) Improved Multi-Objective Optimization Algorithm (AP-NSGA-II):
- Combines adaptive penalty mechanisms with lightweight local improvement strategies to handle high-dimensional, multi-objective optimization efficiently.

- Maintains a balance between convergence toward the Pareto front and diversity among solutions.

- Ensures that solutions respect environmental constraints while generating feasible and practical itineraries.

4) Scientific and Reproducible Design:
- Input data types, variable definitions, and logical architecture of the algorithm are clearly specified.

- The methodology supports reproducible experiments, enabling other researchers to test the framework under similar eco-tourism scenarios.
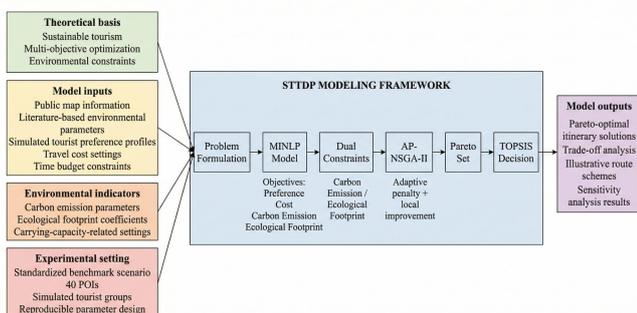

Fig. 1. Conceptual framework of the proposed STTDP model under dual environmental constraints

B. Research Strategy and Technical Route

This study follows a structured approach that blends theoretical modeling, algorithm design, and simulation verification. Here's a breakdown of the process:

1) Theoretical Modeling: The study begins by constructing a Mixed-Integer Non-Linear Programming (MINLP) model. This model is developed based on the principles of sustainable development theory and operations research methods. It incorporates four core objectives:
- Maximizing tourist preference

- Minimizing travel cost

- Minimizing carbon emissions

- Minimizing ecological footprint

2) Algorithm Design: To solve this high-dimensional, multi-objective optimization problem, the study designs an improved Non-dominated Sorting Genetic Algorithm (AP-NSGA-II). This algorithm features an adaptive penalty mechanism, which aims to effectively balance and optimize the four objectives.

3) Simulation Verification: The final step involves verifying the effectiveness of both the model and the algorithm through controlled simulation experiments. These experiments use a standardized benchmark scenario and compare the performance of the proposed AP-NSGA-II algorithm with that of baseline algorithms.

This method ensures that the theoretical model is not only robust but also practical, validated through simulations that assess its real-world applicability.

C. Variable Definition and Data Collection Requirements

To support the mathematical model, the study defines a set of structured variables covering multiple dimensions. These variables are standardized to ensure they can be generated from accessible sources such as public map data, literature-based parameter intervals, and reproducible simulation settings. The key variables include:

1) Spatial and Temporal Variables:
- Geographical Coordinate Matrix: The coordinates of each Point of Interest (POI) to accurately define locations.

- Dynamic Travel Time Matrix: The travel time between POIs, accounting for various travel conditions and modes of transportation.

- Recommended Visiting Time: The optimal time suggested for each POI visit, aiding in itinerary planning.

- Opening Time Window: The time frame during which each POI is open for visitation.

2) Preference and Economic Variables:
- Tourist Preference Index: A score (ranging from 0 to 100) for each POI based on historical evaluation data, reflecting how much tourists prefer visiting each location.

- Direct Economic Cost: The cost for tourists associated with visiting each POI (e.g., ticket price) and traveling between POIs (e.g., inter-zone transportation fares).

3) Environmental Impact Variables (Core):
- Carbon Emission Factor: This includes:

a) The CO2 equivalent emission rate per unit distance for different transportation modes (e.g., car, bus, train).

b) The direct carbon emission intensity generated by tourist activities at each POI, considering factors like energy use or waste generation during visits.

- Ecological Footprint Factor: The conversion coefficient used to estimate the global hectares (gha) required for the biological carrying capacity consumed by tourists, specifically during activities like dining, accommodation, and recreation.

By standardizing and structuring these variables, the study ensures that the model is not only comprehensive but also based on reliable and replicable data sources, providing a solid foundation for analysis and decision-making.

D. Mathematical Model Construction

This model for the tourist itinerary problem seeks to optimize the travel experience while considering multiple objectives. Let's break down the decision variables, objectives, and constraints presented:

1) Decision Variables:

- X'_{ij}: A binary variable that represents whether a tourist travels directly from POI i to POI j. If $X_{ij} = 1$,, the tourist travels directly between these two points, otherwise $X_{ij} = 0$.

- Y_i: A binary variable representing whether POI i is visited. If $Y_i = 1$, then POI i is visited, otherwise $Y_i = 0$.

2) Objective Functions:

The model incorporates four conflicting objectives that balance different aspects of the tourist experience:

a) Objective 1: Maximize Tourist Preferences (TP)

$$Z_1 = \sum_{i=1}^{N} P_i \cdot Y_i \quad (1)$$

This objective maximizes the overall tourist satisfaction by prioritizing the preferences of the tourists for each POI. Here, P_i represents the preference score for POI i, and Y_i indicates whether POI i is visited.

b) Objective 2: Minimize Travel Costs (TC)

$$Z_2 = \sum_{i=1}^{N} \sum_{j=1}^{N} C_{ij} \cdot X_{ij} + \sum_{i=1}^{N} E_i \cdot Y_i \quad (2)$$

This objective seeks to minimize the total cost of travel, including transportation costs (C_{ij} is the cost from POI i to POI j) and the direct costs of visiting each POI (E_i is the cost of visiting POI i, including ticket and additional consumption).

c) Objective 3: Minimize Carbon Emissions (CE)

$$\min Z_3 = \sum_{i=1}^{N} \sum_{j=1}^{N} (D_{ij} \cdot \gamma_v) \cdot X_{ij} + \sum_{i=1}^{N} (t_i \cdot \gamma_a) \cdot Y_i \quad (3)$$

This objective minimizes carbon emissions generated from both transportation and tourism activities. The first term involves transportation emissions where D_{ij} is the distance between POIs i and j, and γ_v is the carbon emission coefficient per unit distance for transportation. The second term calculates emissions from activities at each POI, where

t_i is the visiting time at POI i, and γ_a is the carbon emission rate per unit time for activities.

d) Objective 4: Minimize Ecological Footprint (EF)

$$\min Z_4 = \sum_{i=1}^{N} (EF_{food,i} + EF_{built,i} + EF_{waste,i}) \cdot Y_i \quad (4)$$

This innovative objective assesses the ecological footprint of tourism by considering the consumption of resources (food, infrastructure, waste) at each POI. Each of these components ($EF_{food,i}, EF_{built,i}, EF_{waste,i}$) is converted into standardized ecological footprint areas (in global hectares, gha), reflecting the hidden ecological impacts of tourism.

3) Constraints:

Several constraints ensure the feasibility and sustainability of the proposed itinerary:

a) Route Continuity Constraint:

Each visited POI must have exactly one incoming edge and one outgoing edge to ensure a continuous route. This constraint guarantees that the tourist visits POIs in a logical, feasible sequence without any disconnected travel paths.

b) Time Window Constraint:

The arrival time at each POI *i* must fall within its designated opening hours, defined by $[[e_i, l_i].]$, where e_i is the opening time and l_i is the closing time of POI *i*.

c) Total Time Constraint:

The total time spent on the itinerary, including both travel time and visiting time at each POI, must not exceed the maximum available time T_{max} that tourists have for their trip. This ensures that the itinerary is realistic and feasible within the given time frame.

d) Environmental Carrying Capacity Constraints (Hard Constraints):

The total carbon emissions for a given itinerary must not exceed the carbon quota CE_{max}, ensuring that the trip adheres to sustainability standards in terms of carbon footprint.

The total ecological footprint must not exceed the regional threshold EF_{max}, ensuring that tourism does not exceed the local environmental carrying capacity.

4) Summary:

This model aims to optimize a tourist itinerary by balancing the four objectives of maximizing tourist satisfaction, minimizing travel costs, reducing carbon emissions, and minimizing the ecological footprint. The constraints ensure the feasibility of the proposed route within the available time and environmental limits, while the decision variables enable a flexible approach to modeling tourist behavior. The model is structured to evaluate the trade-offs between these objectives, helping to create sustainable and enjoyable travel experiences.

E. Improved Multi-Objective Optimization Algorithm (AP-NSGA-II)

The study addresses the challenge of applying the traditional NSGA-II algorithm to high-dimensional, multi-objective problems that include strict environmental hard constraints. One of the key issues with traditional NSGA-II is the loss of population diversity due to the generation of a large number of infeasible solutions. To overcome this, the

study introduces the AP-NSGA-II algorithm, which incorporates several key improvements to enhance performance and ensure the generation of feasible solutions while maintaining population diversity.

1) Key Improvements in the AP-NSGA-II Algorithm:

a) Adaptive Penalty Function:

Dynamic Penalty Application: Before calculating crowding distance and non-dominated sorting of individuals, the algorithm applies a dynamic penalty to individuals that violate critical constraints, such as time windows, carbon emission limits, or ecological footprint limits.

Penalty Coefficient: The penalty coefficient, $\lambda(g)$, increases non-linearly as the number of iterations g increases, which means that as the algorithm progresses, penalties for infeasibility become more severe. The penalty function is defined as:

$$F_{penalty}(x) = F_{obj}(x) + \lambda(g) \cdot \max(0, V_k(x))^\beta \quad (5)$$

where $V_k(x)$ is the violation amount for the k-th constraint. The goal of this approach is to allow for moderate violations in the early stages of the algorithm to explore a wider solution space, but to gradually enforce stricter feasibility requirements in the later stages to ensure convergence to feasible and optimal solutions.

2) Problem Feature-Based Crossover and Mutation Operators:

Heuristic Crossover: Rather than using random crossover as in traditional NSGA-II, the AP-NSGA-II algorithm uses a heuristic crossover approach. In this method, sub-path segments that exhibit desirable environmental attributes (e.g., low carbon emissions or low ecological footprint) are preferentially retained from the parent generation. This helps to ensure that better environmental performance is maintained across generations.

Local Search Mutation: To improve the quality of the generated solutions, the algorithm incorporates local search mutation using 2-opt and 3-opt neighborhood search mechanisms. These methods allow the algorithm to fine-tune mutated individuals, improving the routes by removing inefficient, overlapping segments. This directly helps to reduce travel costs (Z2) and carbon emissions (Z3), leading to better overall solutions.

3) TOPSIS Optimal Solution Decision:

Once the Pareto front is generated, the TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) method is employed to identify the most suitable solution from the set of non-dominated solutions.

Weight Vector: The decision-maker sets a weight vector that reflects the priority of different objectives (e.g., tourist preference priority, eco-priority, or a balanced approach). Based on these weights, the TOPSIS method selects the most recommendable compromise solution, ensuring that the final recommendation aligns with the desired priorities (e.g., environmental impact reduction, tourist satisfaction).

4) Summary of AP-NSGA-II Features:

Penalty Mechanism: Helps ensure that infeasible solutions are gradually penalized, allowing for exploration of feasible solutions as the algorithm progresses.

Heuristic Operators: Tailored crossover and mutation strategies retain environmentally beneficial features, improving the overall sustainability of the solution.

TOPSIS Selection: The decision-making process is streamlined by the TOPSIS method, which automatically selects the optimal solution based on the decision-maker's preferences.

By combining these innovative mechanisms, the AP-NSGA-II algorithm improves both the efficiency and effectiveness of solving high-dimensional, multi-objective problems with strict environmental constraints, offering a better balance between exploration, feasibility, and convergence (Figure 2).
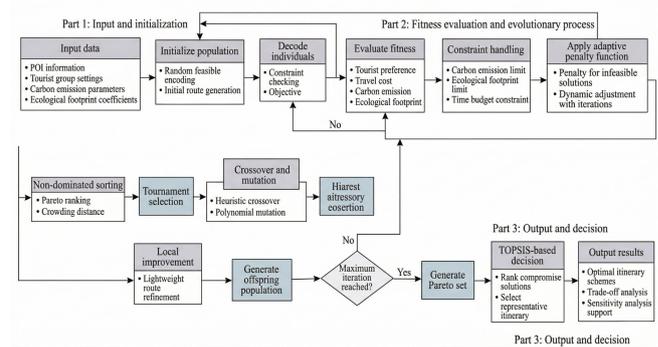

Fig. 2. Flowchart of the proposed AP-NSGA-II algorithm

IV. EXPERIMENTAL DESIGN AND DATA

A. Experimental Scenario and Data Sources

This study simulates an eco-tourism scenario inspired by typical protected tourist destinations in China. The aim is to create a reproducible experimental setup under ordinary research conditions, using standardized simulation instances rather than site-specific deployments. Here's a breakdown of the data sources and attributes used in the simulation:

1) Spatial Network of Points of Interest (POIs):

The study constructs a spatial network containing 40 representative Points of Interest (POIs). These POIs are selected to reflect eco-tourism destinations and are used for methodological validation.

POI Attributes:

- Coordinates: Generated from publicly available map information.

- Visiting Time: The recommended time to visit each POI is generated based on standardized simulation rules.

- Carrying-Capacity-Related Settings: These settings are derived from the attributes that influence environmental impacts, such as the ecological footprint and carbon emissions.

2) Tourist Preference Scores:

Tourist Preference (Pi): The preference scores for each POI are represented by standardized synthetic values on a 0-100 scale. These values are designed to reflect the heterogeneous nature of tourist interests without relying on proprietary platform data. This approach allows for a more generalized and replicable study.

3) Core Environmental Variables:

a) Carbon Emission Data:

- The carbon emission factor for inter-zone transportation is parameterized within a range of 0.12 ~ 0.25 kgCO2/km, depending on the assumed travel mode.

- Direct carbon emissions generated by visiting each POI are represented as scenario-based values within predefined intervals. These emission values are treated as experimental parameters rather than precise field measurements, ensuring reproducibility.

b) Ecological Footprint Data:

- The ecological footprint for each POI is calculated based on the tourism ecological footprint framework developed by Gössling et al. (2012). The footprint includes contributions from catering, facility occupation, and waste consumption.

- The ecological footprint coefficient for a single visit to a POI is set within the range of 0.008 ~ 0.12 global hectares (gha).

- These values are treated as standardized parameters, and key POI attributes, including the distance matrix, are normalized during preprocessing for replicability.

B. Tourist Group Characteristics

To test the robustness of the algorithm, the study simulates 9 different tourist groups with varying characteristics. These groups are designed to reflect real-world scenarios with different preferences and sizes:

- Group Sizes: Ranging from 5 to 35 people.

- Daily Available Time: Each group is given a daily time limit ranging from 450 to 560 minutes.

- Starting Nodes: Different starting nodes are assigned to the groups to simulate various itinerary conditions, adding variability to the experimental setup.

These varying group characteristics ensure that the algorithm's performance can be tested under a variety of conditions, enhancing the robustness of the results.

C. Algorithm Parameter Configuration

The experiments were implemented using Python 3.11 in a standard personal-computer environment. To ensure a fair comparison between baseline methods and the proposed AP-NSGA-II algorithm, the key algorithm parameters were kept consistent across both methods:

- Population Size: Set to 100 for all methods.

- Maximum Number of Iterations: Set to 1000 iterations.

For the AP-NSGA-II algorithm specifically, the following parameters were used:

- Crossover Probability: Set to 0.85, which determines the likelihood of crossover occurring during the genetic algorithm process.

- Mutation Probability: Set to 0.15, indicating the probability that a mutation will occur in an individual solution.

- Initial Adaptive Penalty Coefficient λ\lambda$\lambda$: Set to 10. This coefficient increases with the number of iterations according to a predefined penalty schedule, enforcing stricter feasibility requirements as the algorithm progresses.

These configurations ensure that the experiment is carried out under consistent conditions, allowing for reliable comparisons of the proposed AP-NSGA-II algorithm against baseline methods.

D. Summary

- Experimental Setup: A standardized eco-tourism scenario based on 40 POIs with publicly accessible map data, synthetic tourist preference scores, and core environmental data (carbon emissions and ecological footprint).

- Tourist Group Characteristics: 9 simulated groups with varying sizes, time limits, and starting nodes to ensure robustness in testing.

- Algorithm Configuration: Consistent settings for baseline methods and AP-NSGA-II, with specific parameters for crossover, mutation, and adaptive penalties to optimize the solution process.

This setup provides a controlled and reproducible environment for testing the proposed algorithm, ensuring that the results are reliable and can be generalized to other eco-tourism scenarios.

V. RESULTS

This section objectively presents the experimental results of the multi-objective optimization model, focusing on comparing the performance of AP-NSGA-II with other mainstream algorithms in terms of convergence, diversity, and various optimization indicators.

A. Algorithm Performance and Efficiency Analysis

In this section, the study evaluates the performance of the proposed AP-NSGA-II algorithm by comparing it to other mainstream algorithms. Two core evaluation indicators are used: Hypervolume (HV) and Average Ratio of Pareto Optimal Solution (ARP).

- Hypervolume (HV): A larger HV value indicates better convergence and a wider distribution of the Pareto front in the objective space, which reflects the algorithm's ability to explore and approximate the optimal trade-offs between conflicting objectives.

- Average Ratio of Pareto Optimal Solution (ARP): This measures how well the algorithm approximates the Pareto front compared to the optimal solutions.

Convergence Analysis: As shown in Figure 3, which plots HV vs. the number of iterations, AP-NSGA-II exhibits faster convergence compared to the comparison algorithms. Over iterations, the HV value of AP-NSGA-II increases more rapidly and stabilizes at a higher level. This suggests that the adaptive penalty mechanism and local improvement strategy are effective in helping the population avoid poor

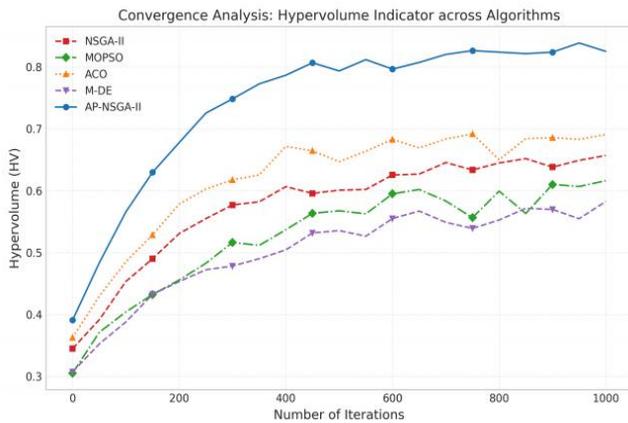infeasible regions, leading to quicker convergence toward high-quality Pareto solutions.

Fig. 3. Convergence analysis (HV indicator vs. number of iterations)

B. Multi-Dimensional Objective Trade-off Analysis (3D Pareto Fronts)

Given that the study involves four conflicting objectives—Tourist Preference (TP), Travel Cost (TC), Carbon Emission (CE), and Ecological Footprint (EF)—visualizing the trade-offs becomes challenging in a two-dimensional space. Instead, 3D Pareto front projections are used to show the solution sets for different pairs of objectives. Figure 4 presents these 3D Pareto front distributions using four different projection perspectives:

- (a) TP-TC-CE

- (b) TP-CE-EF

- (c) TC-CE-EF

- (d) TP-TC-EF

Trade-offs: From Figures 4(a) and 4(b), it is evident that there is a significant trade-off between Tourist Preference (TP) and the Ecological Footprint (EF) and Carbon Emission (CE). Higher tourist preferences generally lead to longer travel distances and higher resource consumption, which increases both CE and EF.

Comparison of Solution Sets: AP-NSGA-II (represented by blue scatter points) consistently produces a solution set that is closer to the ideal origin of the coordinate axes (i.e., achieving lower TC, CE, and EF while maintaining high TP).
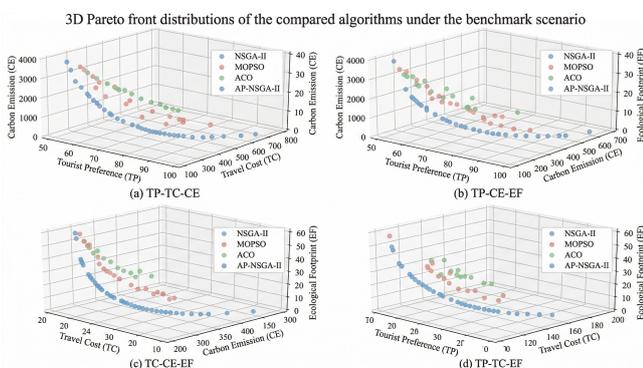

Fig. 4. 3D Pareto front distributions. (a) TP-TC-CE; (b) TP-CE-EF; © TC-CE-EF; (d) TP- TC-EF

C. Comparison between Single-Objective and Multi-Objective Models

To highlight the value of incorporating multi-objective ecological constraints, a comparison is made between the single-objective model (which focuses solely on maximizing Tourist Preference (TP)) and the multi-objective model used in this study.

Core Indicator Comparison:

Figure 5 compares the core indicators between the single-objective (Maximize TP) and the multi-objective comprehensive optimization models. The results reveal that:

- The multi-objective model achieves lower travel costs, carbon emissions, and ecological footprint compared to the single-objective model.

- The trade-off for these improvements is a slight reduction in overall tourist preference. This shows that while maximizing tourist preference alone does not consider ecological impacts, the multi-objective approach strikes a better balance between experience, cost, and environmental performance.

This confirms that incorporating dual ecological constraints improves the overall sustainability of the trip design.
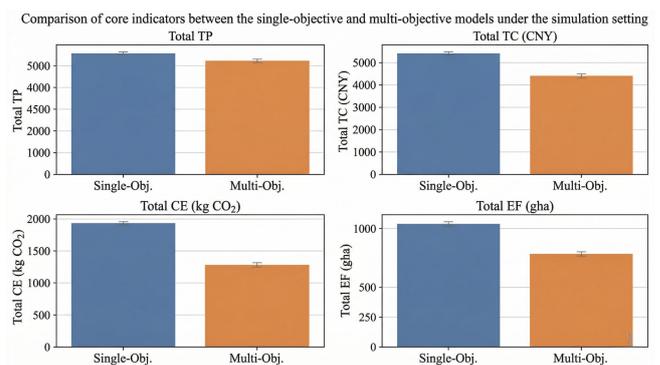

Fig. 5. Comparison of core indicators between single-objective (Maximize TP) and multi-objective comprehensive optimization models

D. Personalized ıtinerary Recommendation Examples

To further illustrate the utility of the model, Figure 6 presents two representative routes optimized for tourist groups with different preference settings:

- Route (a): An "eco-priority" route, which emphasizes low-carbon and low-footprint POIs. This route is optimized to minimize the ecological impact of the trip while still providing a satisfying tourist experience.

- Route (b): A "balanced" route, which aims to achieve a compromise between all objectives—Tourist Preference, Travel Cost, Carbon Emission, and Ecological Footprint. This route optimizes the visiting order of POIs to strike a balance across the conflicting objectives.

These routes are illustrative optimization outputs, designed to showcase how the model can tailor trip itineraries based on different priority settings. The routes are not intended for direct field deployment but rather to demonstrate how the algorithm can provide personalized recommendations under various sustainability constraints.
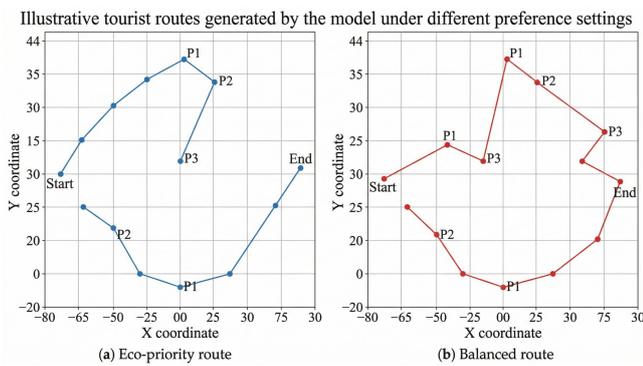
Illustrative tourist routes generated by the model under different preference settings

Fig. 6. Representative tourist routes generated by the system. (a) Eco-priority route; (b) Balanced route

E. Summary of Results

- AP-NSGA-II outperforms other algorithms in terms of convergence and diversity of solutions, achieving better HV values and a more uniform distribution of solutions.

- The 3D Pareto front analysis highlights the significant trade-offs between tourist satisfaction and environmental impacts, with AP-NSGA-II providing a solution set closer to the ideal origin.

- The multi-objective model with ecological constraints proves to be more balanced and sustainable than the single-objective (maximize TP) approach.

- Personalized itinerary recommendations demonstrate the flexibility of the model in generating eco-prioritized or balanced itineraries based on different decision-maker preferences.

These findings validate the effectiveness of the AP-NSGA-II algorithm in solving complex, multi-objective eco-tourism optimization problems while considering both tourist experience and environmental sustainability.

VI. DISCUSSION

A. Horizontal Comparison of Results and Difference Attribution

This section compares the findings of this study with existing literature and attributes the observed differences to methodological and conceptual advancements.

Comparison with Ruiz-Meza et al. (2022): In contrast to Ruiz-Meza et al. (2022), which used carbon emissions as the only environmental constraint, this study introduces an additional ecological footprint (EF) indicator. The empirical results reveal a noteworthy finding: even when two routes exhibit similar carbon emissions, their ecological footprints can differ by as much as 15%.

Reason for Difference: This discrepancy arises from the heterogeneous resource-use profiles associated with different Points of Interest (POIs) in the study, which include factors such as water-related consumption, waste production, and built-environment occupation. These factors contribute to the ecological footprint, beyond just carbon emissions. For example:

Large artificial theme parks may have low carbon emissions due to electric shuttle buses, but their high operational costs and solid waste generation result in a high ecological footprint.

This finding supports Gössling's (2002) assertion that relying solely on carbon emission indicators cannot adequately reflect the true ecological cost of tourism. The study shows that a multi-dimensional approach, incorporating both carbon emissions and ecological footprint, provides a more comprehensive and accurate measure of tourism's environmental impact.

Algorithmic Comparison: At the algorithmic level, AP-NSGA-II outperforms traditional meta-heuristic algorithms like the standard NSGA-II, as shown in previous studies. This improvement is due to:

Crowding Distance Issue: In high-dimensional spaces (where the number of objectives ≥ 4), traditional algorithms like NSGA-II struggle with the crowding distance calculation, leading to the loss of search ability for boundary solutions. This limits their ability to explore the solution space effectively.

Adaptive Penalty Mechanism: The AP-NSGA-II algorithm overcomes this issue by introducing an adaptive penalty mechanism. This mechanism transforms complex ecological hard constraints (such as carbon emissions and ecological footprint) into soft penalties, allowing the algorithm to explore infeasible regions in the early stages of evolution. This leads to a broader, high-quality solution space, improving convergence and diversity.

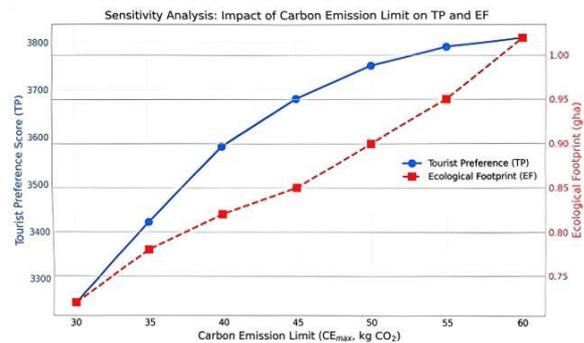### B. Sensitivity Analysis: Critical Effect of Carbon Emission Limits

Fig. 7. Sensitivity analysis of carbon emission limits on tourist preference and ecological footprint

A sensitivity analysis was conducted to explore how carbon emission limits (CEmax) influence the quality of the generated itineraries. Figure 7 illustrates the results, revealing the following key insights:

- Strict Carbon Emission Limits: As the carbon emission limit becomes more stringent, tourist preference decreases significantly, while the ecological footprint of selected nodes becomes more concentrated.

- Impact on Itinerary Flexibility: When the carbon threshold is set too low, the overall itinerary flexibility is reduced. This indicates that overly restrictive carbon limits can restrict the variety of viable itineraries, potentially diminishing tourist satisfaction.

Key Insight: The analysis emphasizes the importance of balancing environmental constraints. It suggests that a moderate approach to setting the carbon emission limit is crucial for maintaining flexibility while ensuring

environmental sustainability. Therefore, planners must carefully calibrate these limits to avoid overly restrictive constraints that may reduce the diversity and attractiveness of travel options.

C. Theoretical Contributions and Managerial implications

Theoretical Contributions: This study offers several important contributions to the field of sustainable tourism research:

1) Multi-Objective Optimization: By incorporating both carbon emissions and ecological footprint constraints, the study moves beyond traditional tourism trip design paradigms, which often prioritize tourist experience over environmental sustainability. It provides a novel mathematical formulation and algorithmic solution to address these dual constraints in a high-dimensional multi-objective optimization context.

2) Expanding the Quantitative Research System: This work contributes to the quantitative research system of sustainable tourism by addressing not just carbon emissions, but also the ecological footprint, which includes a broader spectrum of environmental impacts, such as waste production and resource consumption.

3) New Algorithmic Paradigm: The study presents a new algorithmic paradigm (AP-NSGA-II) for solving complex, high-dimensional tourism routing problems with ecological constraints. This approach enhances existing methods by improving convergence and solution diversity.

Managerial Implications: This research has practical implications for tourism destination managers and researchers:

1) Decision Support Tool: The model can serve as a decision-support prototype for evaluating the impact of various environmental thresholds (such as carbon and ecological footprint limits) on itinerary outcomes. By adjusting parameters like carbon emissions and ecological footprint limits, tourism planners can assess the trade-offs between tourist preferences, travel cost, carbon emissions, and environmental sustainability.

2) Methodological Reference for Future Tools: The framework developed in this study can serve as a methodological reference for developing lightweight itinerary recommendation tools for sustainable tourism. Such tools could be implemented on tourism platforms to assist in planning eco-friendly travel options for tourists, helping them make decisions that align with their preferences while promoting sustainability.

D. Summary of Key Insights

- Ecological Footprint vs. Carbon Emissions: This study introduces a more comprehensive measure of sustainability by incorporating both carbon emissions and ecological footprint. It highlights the significant differences in ecological impacts between routes with similar carbon emissions, challenging the notion that carbon alone is a sufficient measure of environmental sustainability.

- Algorithmic Advancements: The AP-NSGA-II algorithm improves upon traditional meta-heuristics like NSGA-II by effectively navigating high-dimensional solution spaces and solving multi-objective optimization problems with complex ecological constraints.

- Environmental Constraints and Itinerary Flexibility: Overly strict environmental constraints (like carbon emission limits) can reduce itinerary flexibility and tourist preference. A balanced approach to setting these limits is crucial to achieving sustainable tourism without sacrificing tourist satisfaction.

- Practical Application: The study's findings provide tourism planners with a tool to balance environmental sustainability and tourist satisfaction in trip design, and the model could be adapted for use in real-world itinerary planning systems aimed at sustainable tourism.

This work provides both theoretical advancements in multi-objective optimization for tourism and practical guidance for sustainable tourism planning and decision-making.

VII. CONCLUSION

This study addresses the ongoing tension between tourism development and ecological protection by proposing a framework for the Sustainable Tourist Trip Design Problem (STTDP), which incorporates dual constraints on carbon emissions and ecological footprint. The framework aims to balance personalized travel demand with ecological sustainability, providing valuable insights for both tourism planning and policy making. The study constructs a multi-objective mixed-integer programming model with four key objectives: tourist preference, travel cost, carbon emission, and ecological footprint. An improved NSGA-II algorithm (AP-NSGA-II) is developed to solve this problem, using an adaptive penalty mechanism to handle the dual constraints effectively.

A. Key Findings from Simulation Experiments:

1) Necessity of Dual Ecological Constraints:
- Incorporating the ecological footprint in addition to carbon emissions is crucial for capturing the broader resource-use burdens of tourism that are often overlooked when only carbon emissions are considered.

- The multi-objective optimization model demonstrates that it is possible to reduce both carbon emissions and ecological footprint while maintaining tourist preference at an acceptable level. This highlights the importance of considering both environmental constraints in sustainable tourism planning.

2) Superiority of the AP-NSGA-II Algorithm:
- Under the environmental constraints and multi-objective settings tested in the study, the AP-NSGA-II algorithm outperforms traditional baseline algorithms in terms of both convergence behavior and Pareto-solution diversity.

- This indicates that the adaptive penalty mechanism in AP-NSGA-II effectively addresses the challenges of high-dimensional, multi-objective tourism planning problems by improving the algorithm's ability to explore feasible solutions while maintaining diversity.

3) Scientific Basis for Policy Making:

The sensitivity analysis performed in this study reveals a non-linear relationship between environmental constraints (e.g., carbon emissions and ecological footprint) and itinerary quality (e.g., tourist preference, travel cost). This underscores the importance of setting reasonable threshold values for environmental constraints to strike the right balance between ecological protection and tourist experience.

B. Research Limitations and Future Prospects

While this study provides valuable insights into sustainable tourism planning, several limitations should be acknowledged:

1) Ecological Footprint Estimation:

The ecological footprint coefficients used in the model are simplified scenario parameters and do not fully capture the seasonal or context-dependent variations in ecological impacts. Future studies could refine these coefficients based on more detailed, region-specific datasets to provide a more accurate representation of ecological impacts.

2) Simplified Transportation Modeling:

The transportation modes between Points of Interest (POIs) are modeled in a simplified manner for the sake of transparency and experimental clarity. However, this simplification does not fully account for the complexity of multimodal travel behavior (e.g., combining different modes of transportation such as buses, trains, and walking). Future research could explore more detailed transportation models that better reflect real-world travel behaviors.

C. Future Research Directions:

1) Refinement of Ecological Footprint Parameter Setting:

Future research should focus on refining the ecological footprint parameters by incorporating more publicly available data and considering comparative scenarios (e.g., different seasons or types of tourism activities). This will allow for more accurate ecological footprint calculations and improve the model's realism.

2) Extension of the STTDP Framework:

The current STTDP framework can be extended to include additional transportation options and more complex models of travel behavior. This would help capture the diverse transportation options that tourists may use and allow for a more comprehensive and realistic simulation of the travel process.

3) Standardized Experimental Protocols:

To further enhance comparability and reproducibility across studies, it would be beneficial to provide open benchmark instances and standardized experimental protocols. This would facilitate further development and validation of sustainable tourism planning models, enabling better cross-study comparisons and improvements in algorithmic performance.

D. Contributions and Implications

This study makes several significant contributions:

- Theoretical Contribution: It introduces a novel approach to the Sustainable Tourist Trip Design Problem (STTDP) by incorporating both carbon emissions and ecological footprint as dual constraints in tourism optimization. This breaks away from traditional approaches that focus primarily on tourist experience or carbon emissions, offering a more holistic view of sustainable tourism.

- Algorithmic Contribution: The development of the AP-NSGA-II algorithm, with its adaptive penalty mechanism, provides a powerful tool for solving complex multi-objective optimization problems in tourism. This improvement can be applied to a wide range of similar optimization problems in operations research and sustainable development.

- Managerial Implications: The study offers policy-makers and tourism managers valuable insights into how to balance ecological protection with tourist preferences. By adjusting the thresholds for carbon emissions and ecological footprint, they can make informed decisions that promote sustainable tourism without sacrificing the quality of the tourist experience.

E. Conclusion

This study provides a comprehensive framework for sustainable tourism planning that effectively balances tourist preferences with environmental sustainability under dual constraints of carbon emissions and ecological footprint. The AP-NSGA-II algorithm offers a powerful solution for navigating the complex trade-offs inherent in multi-objective tourism optimization. By incorporating more detailed ecological data, extending the model to handle diverse transportation modes, and establishing standardized experimental protocols, future research can further improve the accuracy and applicability of the STTDP framework, providing practical tools for sustainable tourism development.

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AVAILABILITY OF DATA

The data used in this study consist of standardized simulation inputs, literature-based parameter settings, and processed benchmark-instance information described in the methodology section. No proprietary personal data were used.

AUTHOR CONTRIBUTIONS

Boming Gan was responsible for the conceptualization, methodology, and original draft preparation of the manuscript. ZhiGe Zu contributed to data curation, formal analysis, and validation. Jie Gao was responsible for supervision, manuscript review and editing, and project administration. All authors have read and agreed to the published version of the manuscript.

COMPETING INTERESTS

The authors declare no competing interests.