Multi-objective optimization for sightseeing bus problem: trade-off between tourists and operator

Zhou Jia[a], *Di Huang*[a,b]*, *Zhiyuan Liu*[a,b], *Zhitao Hu*[a], *Ronghui Liu*[c], *Wenwu Yu*[d]

[a] *School of Transportation, Southeast University, China.*

[b] *Key Laboratory of Transport Industry of Comprehensive Transportation Theory (Nanjing Modern Multimodal Transportation Laboratory), Ministry of Transport, China.*

[c] *Institute for Transport Studies, University of Leeds, Leeds, UK*

[d] *School of Mathematics, Southeast University, China.*

***Corresponding author.** Email: dihuang@seu.edu.cn

Abstract

The sightseeing bus plays a crucial role in catering to the needs of urban tourist groups. In crafting operational plans, operators aim to make trade-offs between maximizing tourist benefits and minimizing operational costs. This study introduces the multi-objective sightseeing bus problem, encompassing decisions related to bus fleet scheduling, route planning, and tourist assignment. A two-stage multi-objective Adaptive Large Neighborhood Search (MO-ALNS) algorithm is proposed to tackle this multi-objective integer programming model. Customized operators for assignment and routing are devised to augment the algorithm. Numerical experiments demonstrate the algorithm's effectiveness, offering valuable insights to aid operators in formulating cost-effective sightseeing bus operational plans. Sensitivity analysis underscores a notable correlation between the formulation of the operational plan and the distribution of tourist preferences, spatial distribution of Points of Interest, and vehicle capacity.

Keywords: Sightseeing bus planning, Tourist trip planning, Multi-objective optimization, Adaptive large neighborhood search (ALNS)

1. Introduction

Urban tourism and transportation are inherently interconnected. For individual tourists, navigating through a city can be a time-consuming and strenuous endeavor (Le-Klähn & Hall, 2015; Wu et al., 2022). Individuals tend to prefer utilizing public transportation modes over private vehicles (Buran & Erçek, 2022; Hasselwander et al., 2023; Sharma et al., 2023). Consequently, tourists prefer the convenience and efficiency of group travel within urban environments (Ruiz-Meza & Montoya-Torres, 2022; Stanitsa et al., 2023). Group tourism, characterized by diverse demands, reflects a dual aspect (Zheng & Liao, 2019). On one hand, preferences for each Point of Interest (POI) can vary among members of a tourist group, influencing their preferences for specific POI types. On the other hand, certain passengers within a group share similar preferences for specific types of POIs, such as a collective interest in historical and cultural sites. Sightseeing buses emerge as a viable solution to address the nuances of group tourism. sightseeing bus operators collect data on tourist preferences and travel needs, using this information to design tailored sightseeing bus routes and assignment of tourists to buses that provide personalized travel services for tourist groups.

The problem of designing sightseeing bus plans is referred to as the sightseeing bus problem (Hu et al., 2022). This problem involves a sophisticated decision-making process that includes assigning tourists to buses, determining the sequence of POIs to visit, and scheduling travel arrangements (Kolaee et al., 2024). From the perspective of operations research, this problem represents a synergistic combination of optimization challenges in both routing and assignment domains. The majority of problems within these two categories are NP-hard, rendering the solution of the sightseeing bus problem a particularly formidable challenge.

From the standpoint of sightseeing bus operating companies, the design of sightseeing bus plans must factor in both tourist benefits and operational costs. However, previous literature predominantly focuses on single-objective optimization models geared towards maximizing tourist benefits (Ruiz-Meza et al., 2022; Sarkar &

Majumder, 2022). While these models align effectively with tourist preferences, they frequently incur operational costs that are unsustainable in the long term. For instance, in the quest to maximize tourist benefits, a straightforward strategy would be to utilize all vehicles owned by the operating company in executing the sightseeing bus plan. However, this approach comes at the cost of a significant increase in operational expenses. This challenge may impede the operating company's capacity to deliver consistent, high-quality services over an extended period. Furthermore, single-objective optimization models inherently face challenges in addressing the intricate trade-off between tourist benefits and operational costs. They usually offer solutions that maximize tourist benefits or minimize operational costs. However, companies often seek multiple alternatives that strike a balance between these two objectives.

Furthermore, bus fleet scheduling has not yet been incorporated into the sightseeing bus problem. Typically, the number of vehicles used is considered a model input. However, factors such as labor costs and energy consumption associated with each vehicle make the fleet size a crucial factor in determining overall costs. Additionally, incorporating bus fleet scheduling can offer the operating company a broader range of operational strategies.

In addressing these challenges, this study introduces the multi-objective sightseeing bus problem, which integrates tourist benefits and operational costs as objectives within a multi-objective optimization model. This model simultaneously addresses bus fleet scheduling, tourist assignment, and vehicle routing decisions. A two-stage multi-objective Adaptive Large Neighborhood Search algorithm (MO-ALNS) is developed to effectively solve the model. Customized operators are designed to enhance the algorithm’s efficiency

1.1 Literature review

Currently, there is limited research on sightseeing bus operational plans. Deitch & Ladany (2000) emphasize the maximization of overall tourist route attractiveness through the design of a one-period bus touring problem. Hu et al. (2022) propose a joint optimization model for the allocation of tourists and bus routing, along with providing solution algorithms for this model. The current research on customized sightseeing buses is exclusively centered around maximizing tourist benefits, employing single-objective optimization models for modeling. Nevertheless, operating companies must simultaneously consider operational costs when formulating plans. From the perspective of operation research, the problem most closely resembling the SBP is the Tourist Trip Design Problem (TTDP) for groups. The TTDP refers to the problem of planning routes for tourists to visit multiple POIs considering a set of constraints (Gavalas et al., 2014).

Extensive research has yielded a plethora of variant models that address diverse characteristics inherent in TTDP for groups. The Orienteering Problem (OP) stands as the foundational model for conceptualizing the TTDP (Gunawan et al., 2016). In situations demanding the planning of multiple routes, the OP can be expanded into the Team Orienteering Problem (TOP) (Chao et al., 1996). TOP serves as the foundational model for TTDP for groups. In light of the numerous influencing factors in real-world scenarios, numerous studies have further developed upon this model. Multiple time windows are incorporated to depict the multi-window characteristics of POI opening hours in real-world scenarios (Tricoire et al., 2010). Considering the uncertainty in travel times within the city, Garcia et al. (2013) develop the TD-TOPTW model to address the challenges of using public transportation for tourism in urban areas. Considering the fluctuating benefits that a specific POI may provide to tourists at different times, Ekici & Retharekar (2013) integrate time-dependent rewards into the model. The Capacity Team Orienteering Problem (C-TOP) (Luo et al., 2013) introduces capacity constraints on each route, mitigating the risk of congestion along the routes. Ruiz-Meza et al. (2021) investigate the impact of transportation mode selection on travel paths and explore the multi-constraints multi-modal TOP with Time Windows.

Given the complexity of tourist demands, some research related to TTDP has employed multi-objective optimization to investigate the problem. Taking into account the heterogeneity of demands within tourist groups, maximizing equity in group benefits is often considered as one of the objectives (Ruiz-Meza et al., 2022; Ruiz-Meza & Montoya-Torres, 2021; Zheng & Liao, 2019). Moosavi Heris et al. (2022) consider the maximization of tour accessibility as one of the objectives and formulate a multi-objective optimization model. To address environmental sustainability (Dehdari et al., 2023), with a focus on environmental pollution and waste management, some studies (Kolaee et al., 2024; Ruiz-Meza et al., 2022; Ruiz-Meza & Montoya-Torres, 2021) incorporate minimizing emissions as an objective function into the model.

Table 1. Existing literature reviews on TTDP for groups.

Literature	Objective	Preference	Characteristics	Solution method
Vansteenwegen et al. (2009)	Max. of tourist benefits	Homogeneous	TOPTW	ILS
Montemanni et al. (2009)	Max. of tourist benefits	Homogeneous	TOPTW	Ant colony system
Labadie et al. (2012)	Max. of tourist benefits	Homogeneous	TOPTW	VNS
Lin & Yu (2012)	Max. of tourist benefits	Homogeneous	TOPTW	Simulated annealing
Garcia et al. (2013)	Max. of tourist benefits	Homogeneous	TD-TOPTW	ILS
Luo et al. (2013)	Max. of tourist benefits	Homogeneous	C-TOP	Adaptive ejection pool
Ekici & Retharekar (2013)	Max. of tourist benefits	Homogeneous	Time dependent rewards	Cluster-and-route
Souffriau et al. (2013)	Max. of tourist benefits	Homogeneous	Multiple Time Windows	Hybrid algorithm
Hu & Lim (2014)	Max. of tourist benefits	Homogeneous	TOPTW	Iterative three-component heuristic
Zheng & Liao (2019)	Max. of tourist benefits, max. equity	Heterogenous	Multi-objective	Nondominated sorting
Ruiz-Meza et al. (2021)	Max. of tourist benefits	Heterogenous	Transport mode selection	Greedy randomized adaptive search procedure
Ruiz-Meza & Montoya-Torres (2021)	Max. of tourist benefits, max. of equity, min. of emissions	Heterogenous	Multi-objective, transport mode selection	Weighed sum
Ruiz-Meza et al. (2022)	Max. of tourist benefits, max. of equity,	Heterogenous	Multi-objective	Hybrid algorithm

	min. of emissions			
Moosavi Heris et al. (2022)	Max. of tourist benefits, max. accessibility,	Homogeneous	Multi-objective	Multi objective genetic algorithm
Kolaee et al. (2024)	Max. of tourist benefits, min. of costs, min. of emissions	Homogeneous	Multi-objective	ALNS
This paper	Max. of tourist benefits, min. of operational costs	Heterogenous	Multi-objective	MO-ALNS

To the best of our knowledge, no exact approaches has been proposed for TTDP for groups and its variants. Several heuristics-based algorithms, including iterated local search (ILS) (Vansteenwegen et al., 2009) and variable neighborhood search (VNS) (Labadie et al., 2012), have been proposed to address this array of problems. Additionally, simulated annealing heuristics (Lin & Yu, 2012) and the ant colony system (Montemanni et al., 2009) have been adapted for solving this problem. Hu & Lim (2014) propose an iterative three-component heuristic algorithm to solve the TOPTW. Souffriau et al. (2013) propose an algorithm that combines iterated local search with a greedy random adaptive search to solve the Multi-Constraint Team Orienteering Problem with Multiple Time Windows (MC-TOPMTW).

1.2 Aims and contributions

Some limitations are present throughout the published literature on sightseeing bus and similar problems. While various models have been proposed, these models exclusively focus on tourist benefits, neglecting the operational costs for the operating company of sightseeing bus. From a pragmatic perspective, the design of sightseeing bus plan necessitates a balance between maximizing tourist benefits and minimizing operational costs. Incorporating bus fleet scheduling can offer the operating company a wider range of solutions. However, most studies have primarily focused on tourist assignment and vehicle routing. Moreover, given the NP-hard nature of the sightseeing bus problem, finding solutions remains exceptionally challenging. There is a lack of effective algorithms in the literature capable of addressing real-world scale instances of the multi-objective sightseeing bus problem. Finally, there exists a dearth of research on the impact of tourist preference distributions on sightseeing bus operations.

This study formulates a multi-objective optimization model for the sightseeing bus problem to addresses the intricate trade-off between tourist benefit and operational cost. The model encompasses three decision facets, including the bus fleet scheduling, vehicle routing, and the assignment of tourists to buses. Recognizing the inherently multi-objective nature of this problem, this study designs a customized two-stage multi-objective ALNS algorithm for its resolution. To address the decision characteristics involving bus routing and the assignment of tourists to buses, neighborhood search operators in two stages of searching are designed to expedite the solution process.

In an effort to fill these gaps, this study makes the following contributions. First, this study proposes a multi-objective optimization model to address sightseeing bus problem. The objectives of the model are associated with the benefit of tourists, and the operational cost of the sightseeing bus operating company. The model simultaneously addresses decisions related to bus fleet scheduling, vehicle routing, and tourist assignment. Second, a two-stage multi-objective ALNS algorithm is formulated. In light of the distinctive problem characteristics, customized operators are designed to enhance the algorithm’s efficiency. The outcomes of sightseeing bus plan are analyzed through real-world cases, providing operational recommendations for sightseeing bus operational companies.

The remainder of this study is structured as follows. Section 2 provides a formal problem statement of the multi-objective sightseeing bus problem and formulates this problem as a multi-objective mixed integer programming model. Section 3 introduces our customized two-stage multi-objective ALNS algorithm. Section 4 analyzes the results of the numerical experiments. Section 5 presents our conclusions.

2. Model formulation

2.1 Notations

For the ease of presentation, notations in this section are introduced in Table 2.

Table 2 List of notations.

Notation	Description
Sets	
N'	The set of POIs.
N	The set of POIs and start node 0 and end node $\lvert N' \rvert +1$, $N = N' \cup \{0, \lvert N' \rvert +1\}$.
K	The set of buses.
U	The set of tourists.
Parameters	
$P_{i,u}$	The profit in POI i for tourist u.
v_i	The visiting time in POI i.
$[a_i, b_i]$	The time window in POI i.
t_{ij}	The travel time between POI i and POI j.
$Q_k^{\max}$	The maximum number of tourists on bus k.
σ	The start time of the bus.
α	The cost incurred per unit of time during the operation of the bus.
β	The fundamental cost associated with dispatching the bus.
$Pt_{\min}$	The minimum score acceptable to tourists.
θ	The minimum number of POIs that tourists should visit.
Decision variables	
x_{ij}^k	A binary variable for the decision on the sequence of POIs, i.e., $x_{ij}^k = 1$ if bus k visits POI j immediately after POI i; $x_{ij}^k = 0$, otherwise.
$y_{i,u}^k$	A binary variable for the relationship among tourists, buses and POI, i.e., $y_{i,u}^k = 1$ if POI i is included in the route of bus k for tourist u; $y_{i,u}^k = 0$, otherwise.
z_u^k	A binary variable for the assignment of tourist to bus, i.e., $z_u^k = 1$ if tourist u travels in bus k; $z_u^k = 0$, otherwise.
s_i^k	Non-negative variable representing the start time in POI i in route k.
Auxiliary variables	
δ_{ik}	A binary variable for the decision on selection of POIs, i.e., $\delta_{ik} = 1$ if POI i is included in the route of bus k; $\delta_{ik} = 0$, otherwise.

2.2 Problem description

The sightseeing bus problem encompasses two primary stakeholders: tourists and bus operators. From the tourists' perspective, their goal is to maximize the satisfaction of their trips. Considering the fact that the interests of tourists are diverse, the tourist's satisfaction can be interpreted by whether the visiting scenic spots (denoted by POIs) is in line with their interests. However, it is essential to recognize that there exists considerable variance in the preferences of tourists within a tourist group. For instance, a history enthusiast would prioritize museums and historical landmarks during the journey. Consequently, the operator is tasked with devising multiple sightseeing bus routes that cater to the diverse needs of these tourists.

One intuitive strategy for addressing this challenge is to increase the number of available routes, thereby offering tourists a wider range of choices. However, this approach becomes impractical due to the associated escalation in operational costs. Thus, a more realistic approach is required, which could simultaneously balance the tourist benefits and the operational cost of sightseeing bus operating companies.

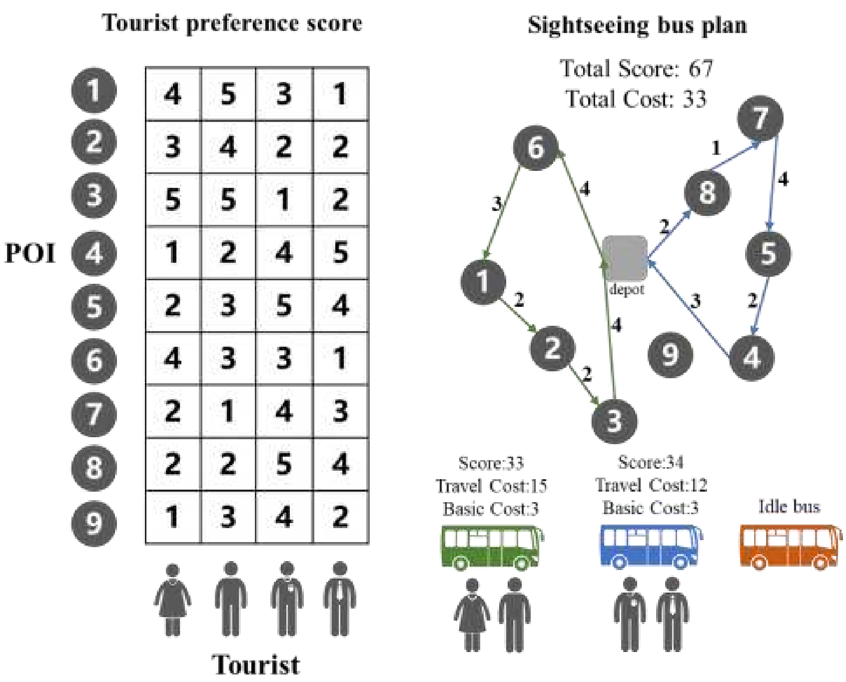


Fig. 1. A sightseeing bus problem example.

In sum, this study presents a multi-objective model for the sightseeing bus problem. This model is designed to make well-informed decisions regarding bus fleet scheduling, bus routing and assignment of tourists to buses. The objectives of this model are twofold: first, to maximize overall tourist benefits of the group; second, to minimize the operational costs incurred by the operator. Additionally, this study assumes that the bus returns to the starting point upon completing the route.

A number of assumptions have been made, underlining the developed mathematical models, which are listed herein for providing clarity to the reader:

(1) The vehicles are homogeneous, with the same starting and ending points, the same departure time, and identical capacities.

(2) When visiting a POI, vehicles must remain for a certain duration to allow tourists to explore and enjoy the location.

(3) The operating company has a fixed total number of vehicles available for service, from which it can choose the number of vehicles to deploy.

(4) Tourists' travel preferences are heterogeneous, with each tourist having different levels of preference for various POIs, as reflected in tourists' POI scores.

(5) There is a minimum service guarantee for tourists. In this study, it is required that each tourist visits at least a certain number of POIs.

(6) The available time for all vehicles is limited. The service must be completed within the specified time frame.

2.3 Multi-objective sightseeing bus problem

The MO-SBP can be defined on a directed network $G=(N,E)$, where N is the set of nodes that is partitioned into set of POIs N' and start node 0 and end node $|N'|+1$, and $E=\{(i,j)|i,j\in N'\}\cup\{(0,i)|i\in N'\}\cup\{(i,|N'|+1)|i\in N'\}\cup\{(0,|N'|+1)\}$ is an edge set. The start node and end node respectively represent the starting and ending point of a single-day itinerary for the tourist group. In the tourism context, these points typically correspond to the hotels where the tourists stay. The edge set consists of four parts: the first part comprises the edges between POIs, representing vehicle movement between POIs; the second part consists of edges from the start node to POIs, representing vehicles departing to POIs; the third part consists of edges from POIs to the end node, representing vehicles returning to the endpoint after completing service; and the fourth part is a dummy edge from the start node to the end node, representing vehicles that are not used. Each edge has a corresponding travel time t_{ij}, with the dummy edge having a travel time $t_{ij} = 0$.

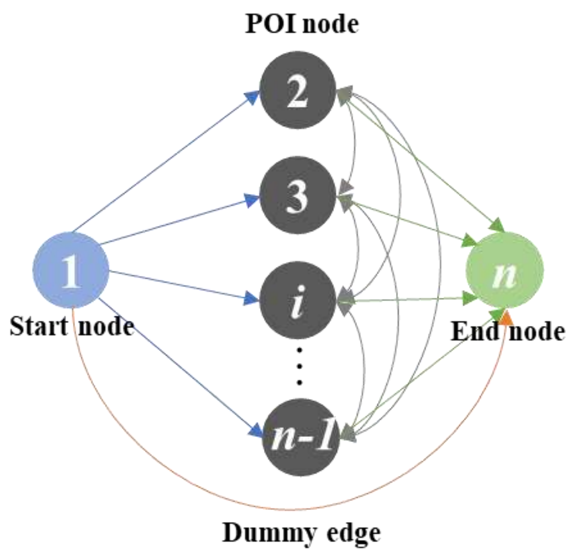


Fig. 2. Network of MO-SBP.

This study assumes a uniform departure and arrival pattern for tourists within a travel group, with all tourists starting and ending their journeys at the same location. Let K denote the set of buses with capacity $Q_k^{\max}$. Each node $i \in N$ can only be visited during the time window $[e_i, l_i]$. The time windows of the starting node and ending node are set to the earliest commencement time and the latest conclusion time for a single-day itinerary. Each vehicle visiting POI $i \in N'$ remains at that point for a duration v_i. The MO-SBP also considers a set of heterogenous tourists U. Each tourist $u \in U$ has a specific score $P_{i,u}$ for each POI $i \in N'$. $P_{i,u}$ describes the benefits by visiting POI i for tourist u.

The MO-SBP can be formulated as a multi-objective MIP model as follows.

$$\max \sum_{k\in K}\sum_{u\in U}\sum_{i\in N'} P_{i,u} y_{i,u}^k \tag{1}$$

$$\min \alpha \sum_{k\in K}\sum_{(i,j)\in E} t_{ij} x_{ij}^k + \beta \sum_{k\in K}\sum_{j\in N'} x_{1j}^k \tag{2}$$

s.t.

$$\sum_{j\in N'} x_{1j}^k = \sum_{j\in N'} x_{jn}^k = 1, \ \forall k \in K, \tag{3}$$

$$\sum_{j\in N'} x_{ij}^k = \sum_{j\in N'} x_{ji}^k = \delta_i^k, \ \forall i \in N', k \in K, \tag{4}$$

$$s_0^k = \sigma, \quad \forall k \in K \tag{5}$$

$$s_i^k + v_i + t_{ij} - (1 - x_{ij}^k)M \le s_j^k, \ \forall i, j \in N, k \in K, \tag{6}$$

$$e_i \le s_i^k \le l_i, \ \forall i \in N, k \in K, \tag{7}$$

$$\sum_{k\in K} z_u^k = 1, \ \forall u \in U, \tag{8}$$

$$\sum_{u\in U} z_u^k \le Q_k^{\max}, \ \forall k \in K, \tag{9}$$

$$y_{i,u}^k \le \delta_i^k, \ \forall i \in N', k \in K, u \in U, \tag{10}$$

$$y_{i,u}^k \le z_u^k, \ \forall i \in N', k \in K, u \in U, \tag{11}$$

$$y_{i,u}^k \ge \delta_i^k + z_u^k - 1, \ \forall i \in N', k \in K, u \in U, \tag{12}$$

$$\sum_{i\in N'} \sum_{k\in K} y_{i,u}^k \ge \theta \ \ \forall u \in U \tag{13}$$

$$x_{ij}^k \in \{0,1\}, \ \forall (i,j) \in E, k \in K, \tag{14}$$

$$y_{i,u}^k \in \{0,1\}, \ \forall i \in N', k \in K, u \in U \tag{15}$$

$$z_u^k \in \{0,1\}, \ \forall k \in K, u \in U \tag{16}$$

Eqs. (1) and (2) are the objectives of the model. Eq. (1) maximizes the total benefits of all the tourists of the group. Eq. (2) minimizes the operational costs of the operator, where $\alpha \sum_{k\in K} \sum_{(i,j)\in E} t_{ij} x_{ij}^k$ represents the cost incurred during the operation of the sightseeing bus, $\beta \sum_{k\in K} \sum_{j\in N'} x_{1j}^k$ denotes the fundamental cost associated with dispatching the bus.

Eqs. (3)–(14) are the constraints of the model. Eq. (3) imposes that each bus departs from the starting node and travels towards the end node, or stays in the start node. Eq. (4) is the flow balance constraint, ensuring that each bus must exit a POI after entering it. Eq. (5) specifies the departure time for each vehicle. Eq. (6) determines the connectivity and timeline of each route of bus. Eq. (7) regulates the time window.

Specifically, the constraint regarding the end point limits the total duration of a single day itinerary. Eq. (8) guarantees that each tourist is assigned to only one bus. Eq. (9) ensures that the number of tourists on a bus does not exceed the bus's capacity. Eqs. (10)–(12) indicate that tourist u can obtain a score for POI i only when and if tourist u is assigned to bus k, and bus k visits POI i. Eq. (13) represents the minimum service guarantee constraint, ensuring that each tourist visits at least θ POIs. Eqs. (14)–(16) define the domains of decision variables.

3. Two-stage multi-objective ALNS algorithm

The proposed MO-SBP can be viewed as a combination of the generalized assignment problem and the team orienteering problem, both of which have proved to be NP-hard (Cattrysse & Van Wassenhove, 1992; Chao et al., 1996). Considering the impracticality of solving real-world scale MO-SBP instances using exact algorithms, this study has opted for a meta-heuristic approach, namely the two-stage multi-objective ALNS algorithm. This choice is motivated by the algorithm's notable scalability, enabling convenient customization to accommodate the characteristics of MO-SBP.

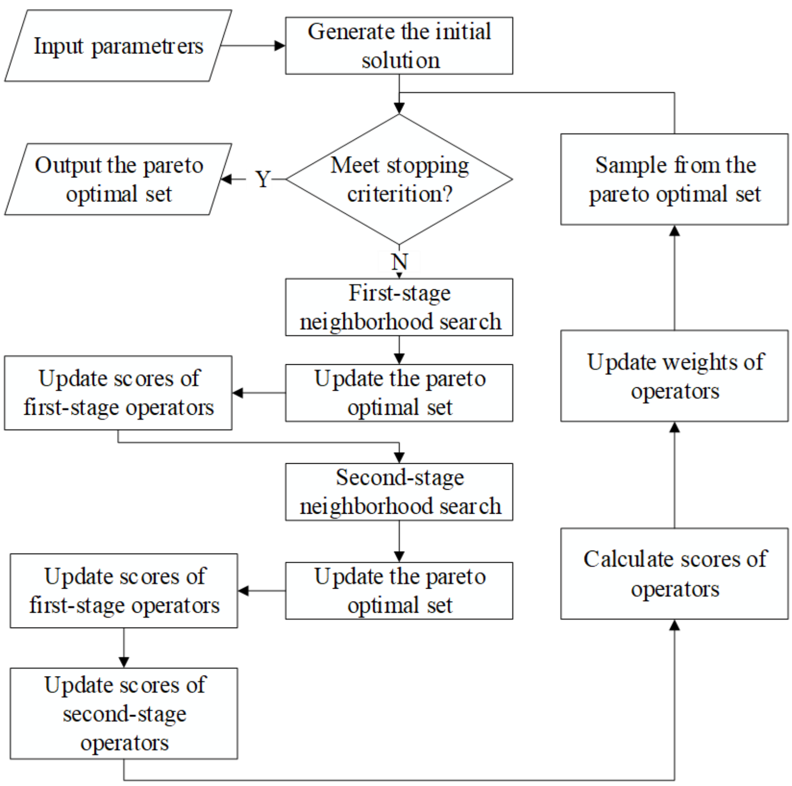


Fig. 3. The procedure for the two-stage multi-objective ALNS.

Building upon the ALNS algorithm (Ropke & Pisinger, 2006), a customized two-stage multi-objective ALNS algorithm is proposed to address the MO-SBP problem by incorporating decision features related to routing and the assignment of tourists to buses, along with the multi-objective nature of the problem. Neighborhood search-based multi-objective algorithms have been employed to tackle numerous real-world problems (Kordi et al., 2023; Rifai et al., 2016). The two-stage multi-objective ALNS algorithm operates by initiating a solution and iteratively refining it using various destroy and repair operators. Since the MO-SBP problem can be decomposed into two parts: assignment of tourists to buses and bus routing, the algorithm addresses these aspects through a two-stage process (see Fig. 3).

3.1 Initialization

The initialization phase is responsible for generating feasible solutions to the problem. This study employs a two-stage method with random elements to produce initial solutions. In the first stage, tourists are assigned to buses, and in the second stage, bus routing is conducted. During the first stage, tourists are allocated to buses by categorizing them into $|K|$ groups, ensuring an equivalent number of tourists in each group, and subsequently assigning $|K|$ groups of tourists to the buses.

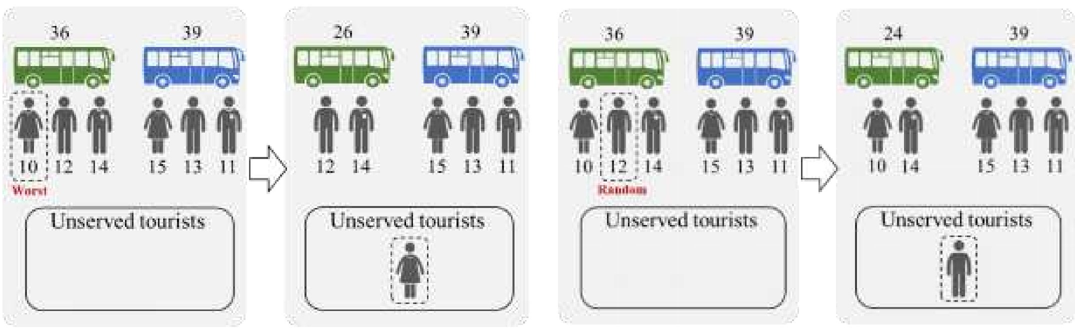
Moving on to the second stage, routing is conducted for the buses. This study defines (bus, POI) as a binary tuple strategy, where implementing this strategy involves inserting a POI at a location that minimizes the total travel time for the bus. Each binary tuple corresponds to a score, representing the points that the bus can accumulate by visiting the poi. All feasible tuples are enumerated to form a list, denoted by TL. The tuples in TL are then sorted in descending order based on their scores, and the strategy associated with the tuple with the highest score is implemented. The tuple (bus, POI) will be removed after implementation. This process is repeated until there are no feasible binary tuple strategies remaining.

3.2 First-stage neighborhood search

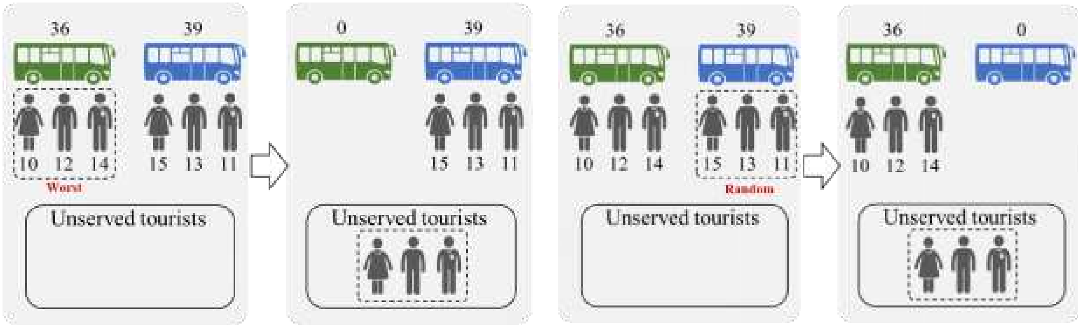
The first-stage neighborhood search explores the feasible space by altering the assignment of tourists to buses (see Fig. 4 and Fig. 5). In this stage, a destroy-and-repair method is employed for neighborhood search. Operators at two hierarchical levels, one for tourists and the other for buses, have been designed to solve the problem, with the aim of introducing varying degrees of change to the current solution. In Fig. 4, the numbers below the tourists indicate their scores, while the numbers above the buses indicate the buses' scores. In Fig. 5, the numbers to the right of the buses represent the buses' scores. The adopted search operators are as follows.

Destroy Operators:

- **Greedy Tourist Removal (GTR)**: Remove the tourist with the lowest score. This operator assists the algorithm in exploring downward directions by emphasizing the matching of tourists and buses.
- **Random Tourist Removal (RTR)**: Randomly remove one tourist. This is a commonly used operator in neighborhood search algorithms.
- **Greedy Bus Removal (GBR)**: Remove all tourists on the bus with the lowest score. This operator assists the algorithm in discarding buses that are currently performing poorly, offering an opportunity for the tourists on that bus to be transferred to other buses.
- **Random Bus Removal (RBR):** Randomly remove all tourists on one bus. This operator brings significant changes to the current solution.



(a) Greedy tourist removal (b) Random tourist removal

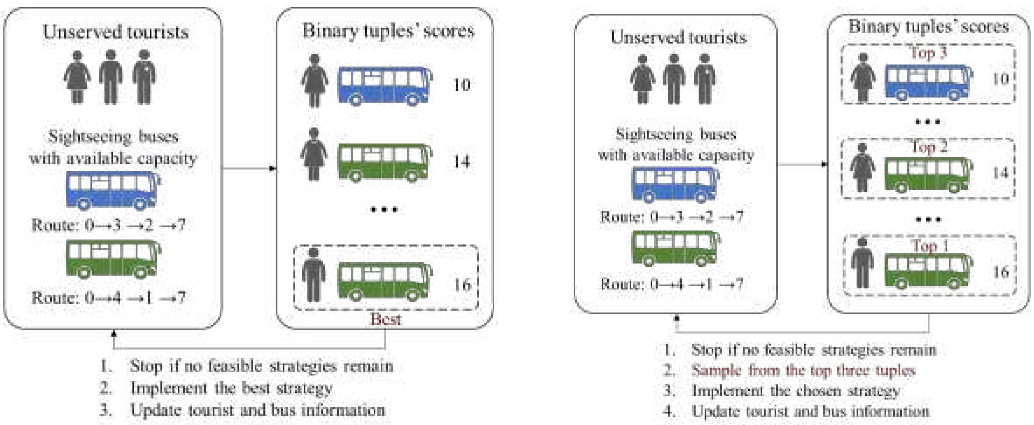


(c) Greedy bus removal (d) Random bus removal

Fig. 4. First-stage destroy operators.

Repair Operators:

- **Greedy Tourist Insertion (GTI)**: Binary tuple (tourist, bus) represents an allocation strategy of adding the tourist to the bus. Each tuple corresponds to a score, indicating the points obtained after adding the tourist to the bus. Enumerate all possible tuples to form a list, sort all tuples in descending order based on their scores. Implement the strategy with the highest score from list TL'. After the implementation of the specified strategy, remove all tuples in TL' with the same tourist as the specified strategy. Repeat these steps until no feasible binary tuple strategies remain.
- **Biased Tourist Insertion (BTI)**: Building upon greedy insertion, this operator introduces randomness. Instead of implementing the strategy with the highest score each time, sample from the top three tuples in terms of scores during each iteration.



(a) Greedy tourist insertion (b) Biased tourist insertion

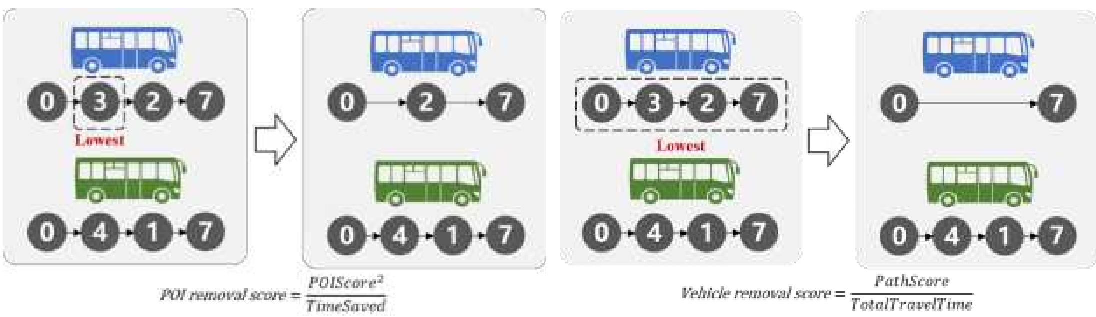
Fig. 5. First-stage repair operators.

3.3 Second-stage neighborhood search

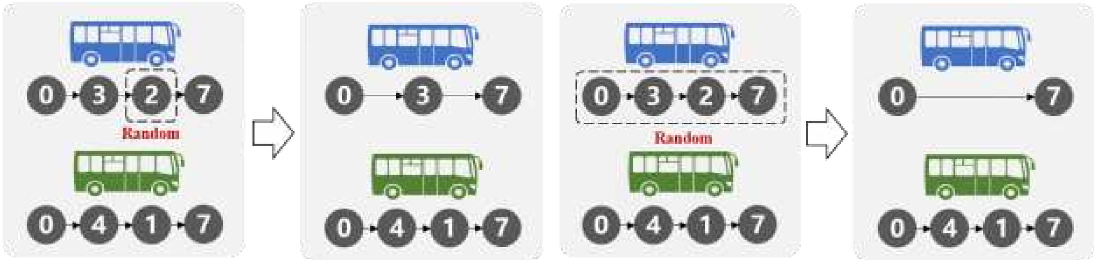
The second-stage neighborhood search explores the feasible space by altering the paths of buses (see Fig. 6 and Fig. 7). Similar to the first stage, a destroy-and-repair method is employed in this stage. Operators at two levels, one for POIs and the other for routes, are utilized in the neighborhood search during the routing phase. In Fig. 5, the numbers to the right of the buses represent the buses' scores. The adopted search operators are as follows.

Destroy Operators:

- **Greedy POI Removal (GPR)**: Define the removal score of an existing POI in the current path as the square of the POI score divided by the time saved by removing the POI. Remove the POI with the lowest score in the existing path.
- **Random POI Removal (RPR)**: Randomly remove one POI. This is a commonly used operator in neighborhood search algorithms.
- **Greedy Route Removal (GRR)**: Define the removal score of a vehicle in the existing path as the sum of scores for all POIs visited by the vehicle divided by the total travel time (Vansteenwegen et al., 2009). Remove all POIs visited by the vehicle with the lowest score in the existing path.
- **Random Route Removal (RRR)**: Randomly remove all POIs visited by one bus. This operator brings significant changes to the current solution.



(a) Greedy POI removal (b) Greedy route removal

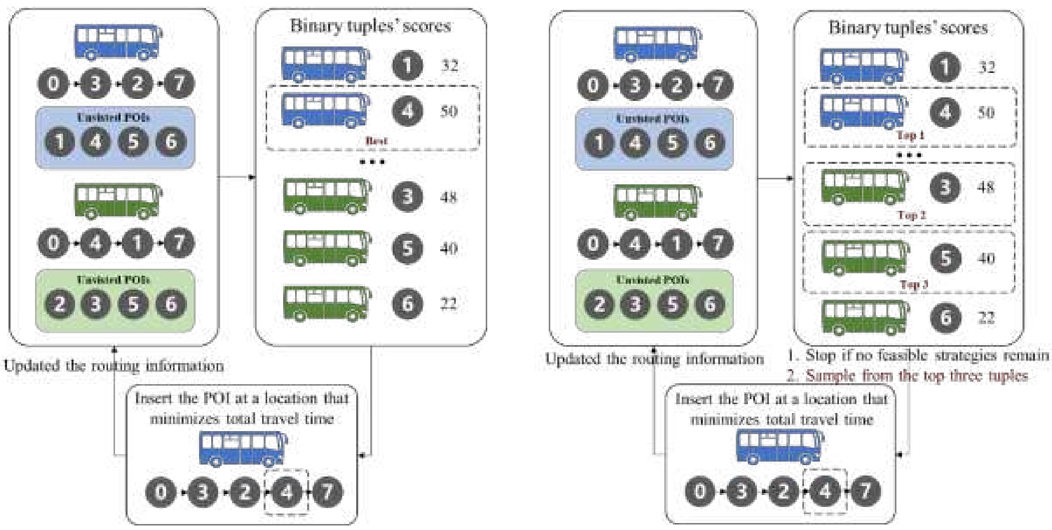


(c) Random POI removal (d) Random route removal

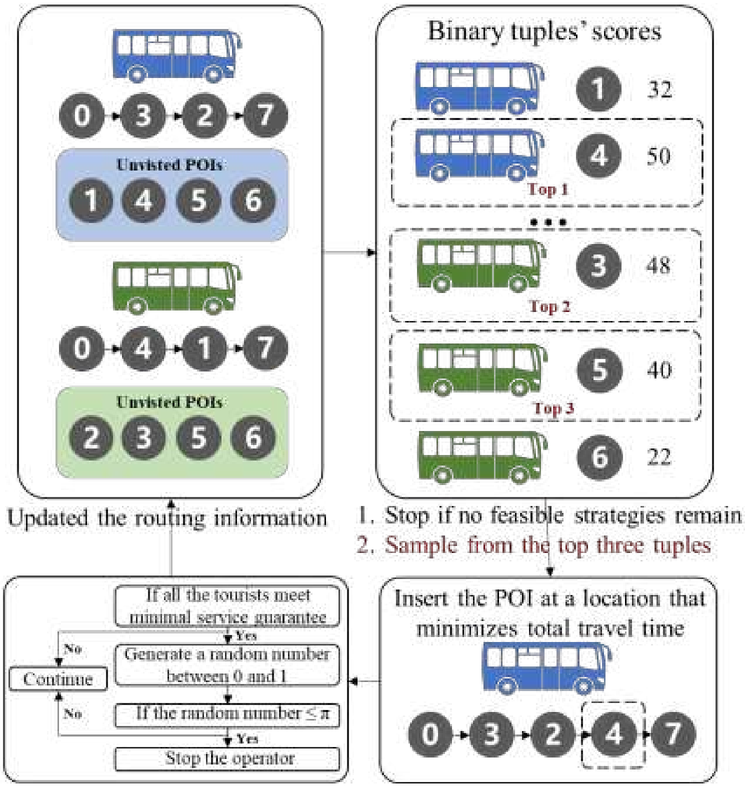
Fig. 6. Second-stage destroy operators.

Repair Operators:

- **Greedy POI Insertion (GPI)**: Utilize the same strategy as the routing part in the initialization stage, greedily adding the POI with the highest score until no feasible binary tuple strategies remain.
- **Biased POI Insertion (BPI)**: Building upon GPI operator, this operator introduces randomness. This operator samples from the top three binary tuples with the highest scores during each iteration, repeats these steps until no feasible binary tuple strategies remain.
- **Random POI Insertion (RPI)**: This operator is introduced to obtain lower-cost solutions. It samples from the top three binary tuples with the highest scores during each iteration. When the minimum requirements of all tourists have been met, a random number between 0 and 1 is generated. If this random number is less than π, the process of the operator stops.



(a) Greedy POI insertion (b) Biased POI insertion



(c) Random POI insertion

Fig. 7. Second-stage repair operators.

3.4 Weight adjustment

In the proposed two-stage multi-objective ALNS algorithm, the selection of operators is implemented through a roulette wheel mechanism. Each operator is assigned a weight, and the algorithm samples operators based on these weights. The two-stage multi-objective ALNS algorithm in this study involves two stages. Therefore, it is necessary to maintain a weight pool for both the destroy and repair operators for each stage. In other words, four weight pools need to be maintained.

In the initialization phase, each operator is assigned equal weight. After a number of iterations, the weights of the operators are adjusted based on their performance within the algorithm. Let $\omega_{j,k}$ represent the weight of the operator j in segment k, $\pi_{j,k}$ represent the score of the operator j in segment k, $t_{j,k}$ represent the number of invocations for the operator j in segment k, $\eta \in [0,1]$ represent a parameter that controls the effectiveness of the weight adjustment process. The weight $\omega_{j,k+1}$ for the next segment is calculated using the following formula:

$$\omega_{j,k+1} = \begin{cases} \omega_{j,k} & \text{if } t_{j,k} = 0 \\ (1-\eta)\,\omega_{j,k} + \eta\pi_{j,k} / t_{j,k} & \text{if } t_{j,k} \neq 0 \end{cases} \tag{17}$$

The update strategy for operator scores is as follows: After the completion of the first-stage neighborhood search, it is examined whether new pareto-optimal solutions have been generated. If new pareto-optimal solutions are obtained, the invoked first-stage destroy and repair operators receive an increment in their scores. Similarly, following the conclusion of the second-stage neighborhood search, the algorithm checks for the emergence of new pareto-optimal solutions. If new pareto-optimal solutions are identified, scores are incremented for the invoked first-stage destroy and repair operators, as well as the second-stage destroy and repair operators.

3.5 Stopping Criteria

The algorithm can be configured with various convergence criteria based on requirements:

1. The convergence criterion for the algorithm is defined as the termination point when the cumulative number of iterations without the emergence of new Pareto-optimal solutions reaches a specified threshold, denoted as $Iter$.

2. The algorithm stops when it reaches a predefined time threshold.

3. The algorithm stops after reaching a maximum number of iterations.

4. Numerical experiments

The proposed multi-objective sightseeing bus problem and the two-stage multi-objective ALNS algorithm are numerically verified in this section. The algorithm was coded in Python and Gurobi 10.0.3 with standard tuning implemented on a personal computer with an Intel Core i9-13900H running at 2.60 GHz with 32 GB RAM.

4.1 Data Settings

A real-world example is constructed in Nanjing, China. 33 POIs are selected in Nanjing City as experimental data. These POIs can be classified into four categories: “Historical and Cultural”, “Modern Recreational”, “Natural Ecological”, and “Origin”, based on their respective types. The travel time information between POIs was obtained by invoking the Amap driving route planning interface (available at: https://lbs.amap.com/).

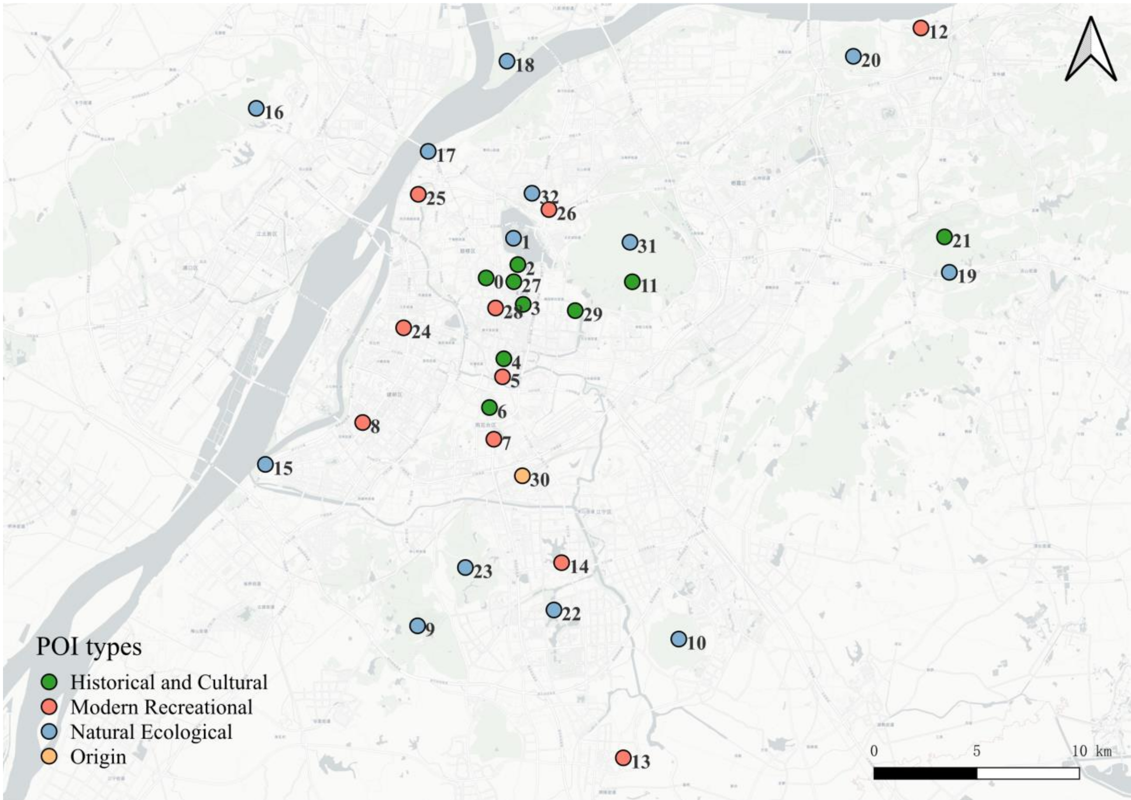


Fig. 8. Popular POIs selected in Nanjing City.

The starting and ending point for the sightseeing buses are both designated at Nanjing South Station. The departure times for all sightseeing buses are uniformly scheduled at 8:00, with the latest designated time for return to the end point set at 20:00. At each POI, the sightseeing buses will pause for a duration of either 1, 2, or 3 hours, providing tourists with ample time for leisure activities. The cost incurred per unit of time during the operation of the bus α is set at 0.4 CNY per minute. The fundamental cost associated with dispatching the bus β is set at 40 CNY.

4.2 Performance of solution algorithm

This section evaluates the performance of our two-stage multi-objective ALNS algorithm in solving the mathematical formulation introduced in Section 2 across our set of 9 test-scale instances.

Table 3 Data settings for test-scale-instances.

Case	$\lvert U \rvert$	$\lvert N \rvert$	$\lvert K \rvert$	Q^{max}
TS-1	20	10	2	15
TS-2	20	10	2	20
TS-3	30	10	2	20
TS-4	30	20	3	20
TS-5	50	20	3	20
TS-6	100	20	4	30
TS-7	100	30	4	30
TS-8	200	30	8	30
TS-9	300	30	12	30

The details of test instances are presented in Table 3. Instances are designed by controlling the number of tourists $\lvert U \rvert$, the number of POIs $\lvert N \rvert$, the number of buses $\lvert K \rvert$, and the capacity of each bus Q^{max}. Similar to Section 4.1, all POI data is sourced from Nanjing City, while tourist preference information is generated through a random program.

In all experiments, the parameter that controls the effectiveness of the weight adjustment process η is set to 0.01, and parameter π used within the random POI insertion operator to control the termination is set to 0.5. The parameter tuning process is detailed in Appendix B.

First, the effectiveness of the algorithm is validated by comparing it with the epsilon constraint method using one small-scale cases TS-1 and TS-2 in Section 4.2.2. In Section 4.2.3, the superiority of the proposed algorithm is demonstrated by comparing it with four multi-objective optimization algorithms across various problem scales.

4.2.1 Quality indicators of the multi-objective optimization

In this study, four quality indicators (QI) are used to evaluate the quality of multi-objective optimization solutions: Hypervolume, Maximum Spread, Mean Ideal Distance, Spacing.

Hypervolume

The Hypervolume (HV) metric is employed to assess the quality of the pareto front (Li & Yao, 2020). HV stands out as one of the most commonly utilized quantitative evaluation indicators in multi-objective optimization, owing to its advantageous practical applicability and sound theoretical properties. Obtaining the actual Pareto front in real-world cases is often a challenging task. The computation of HV, however, does not rely on the availability of the true pareto front. It merely necessitates the provision of a reference point.

Given a solution set P and a reference point r, HV can be calculated as

$$HV(P) = \lambda\left(\bigcup_{p \in P} \{x \mid p \prec x \prec r\}\right) \tag{18}$$

where λ denotes the Lebesgue measure. As illustrated in Fig. 4, when there are three points in the solution set with a reference point denoted as r, the shaded region represents the Hypervolume value corresponding to this particular solution set. A larger HV value signifies a higher quality of the associated solution set.

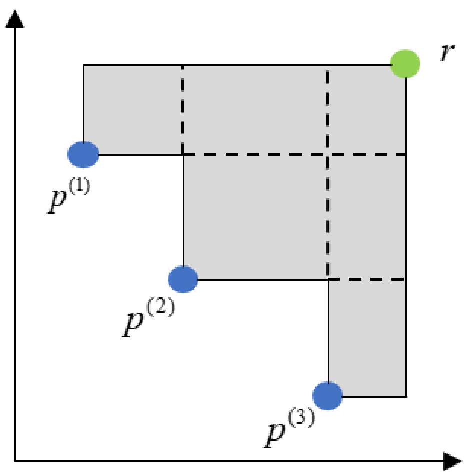


Fig. 9. The illustration of Hypervolume.

Maximum spread

The Maximum spread (MS) metric is a widely used spread indicator (Li & Yao, 2020). The quality of a solution set is related to the area which it covers. Given a solution set P, MS can be calculated as

$$MS(P)=\sqrt{\sum_{j=1}^{m}\left(Z_j^{\max}-Z_j^{\min}\right)^2} \tag{19}$$

Where m denotes the number of objectives, $Z_j^{\max}$ is the maximum value of objective function j in the solution set P, $Z_j^{\min}$ is the minimum value of objective function j in the solution set P. A larger value of MS indicates a better extensity.

Mean ideal distance

The Mean ideal distance (MID) metric measures the average distance between the solution set and the ideal point (Kordi et al., 2023). In multi-objective optimization, the ideal point refers to the point that represents the best possible value for each objective function. Given a solution set P, MS can be calculated as

$$MID(P)=\frac{\sum_{i=1}^{|P|}\sum_{j=1}^{m}\sqrt{\left(\frac{Z_j^i-Z_j^{best}}{Z_j^{\max}-Z_j^{\min}}\right)^2}}{|P|} \tag{20}$$

Where m denotes the number of objectives, $|P|$ denotes the number of elements in solution set P, $Z_j^{\max}$ is the maximum value of objective function j in the solution set P, $Z_j^{\min}$ is the minimum value of objective function j in the solution set P, Z_j^{best} is the best possible value of objective function j in the solution set P, Z_j^i is the value of objective function j of the solution i from solution set P. A lower MID value signifies a higher quality of the associated solution set.

Spacing

The Spacing (SP) metric is a popular uniformity indicator (Li & Yao, 2020). Given a solution set P, SP can be calculated as

$$SP(P)=\sqrt{\frac{1}{|P|-1}\sum_{i=1}^{|P|}\left(\bar{d}-d_1\left(p_i,P/p_i\right)\right)^2} \tag{21}$$

$$d_1\left(p_i,P/p_i\right)=\min_{p_k\in P/p_i}\sum_{j=1}^{m}\left|Z_j^i-Z_j^k\right| \tag{22}$$

Where m denotes the number of objectives, $|P|$ denotes the number of elements in solution set P, Z_j^i is the value of objective function j of the solution i from solution set P, $\bar{d}$ is the mean of all p_i for $p_i \in P$. A lower value of SP indicates a better uniformity.

4.2.2 Validation of the propose algorithm

The epsilon constraint method (ECM) is an exact algorithm for multi-objective optimization capable of obtaining optimal Pareto solutions. However, due to its extensive computation time on large-scale problems, the epsilon constraint method is limited to handling only small-scale multi-objective optimization problems. To validate the effectiveness of the proposed algorithm, the approximate Pareto solutions generated by the two-stage multi-objective ALNS algorithm are compared with the optimal Pareto solutions produced by the epsilon constraint method in case TS-1, TS-2.

The core idea of the epsilon constraint method is to transform a multi-objective optimization problem into multiple single-objective optimization subproblems. For each single-objective optimization problem, one of the original objective functions is retained, while the other objective functions are converted into constraints. For the problem in this study, Eq. (2) is chosen to be retained as the objective function, while Eq. (3) is used as a constraint to construct the subproblem (Ait Bouziaren & Aghezzaf, 2019). The epsilon-constraint subproblem is solved by Gurobi with standard tuning.

The epsilon-constraint subproblem can be formulated as a MIP model as follows.

$$\min \ \alpha \sum_{k \in K} \sum_{(i,j) \in E} t_{ij} x_{ij}^k + \beta \sum_{k \in K} \sum_{j \in N'} x_{1j}^k \tag{23}$$

subject to constraints (3)-(16),

and

$$\sum_{k \in K} \sum_{u \in U} \sum_{i \in N'} P_{i,u} y_{i,u}^k \ge \varepsilon \, . \tag{24}$$

In, this section, the termination condition for the MO-ALNS algorithm is set to when the cumulative number of iterations without the emergence of new Pareto-optimal solutions reaches a specified threshold $Iter = 2000$.

The experimental results demonstrate the rationality and effectiveness of the proposed model and algorithm. As shown in Fig. 10 and Fig. 11, the ECM algorithm generates numerous solutions for the operator to choose from. In case TS-1, with 20 tourists, a vehicle capacity of 15, and 2 available vehicles, all vehicles must be used to serve the tourists, resulting in no solutions with a different number of vehicles. In case TS-2, two clusters of solutions emerge. These clusters represent the set of solutions using one vehicle and the set of solutions using two vehicles, respectively.

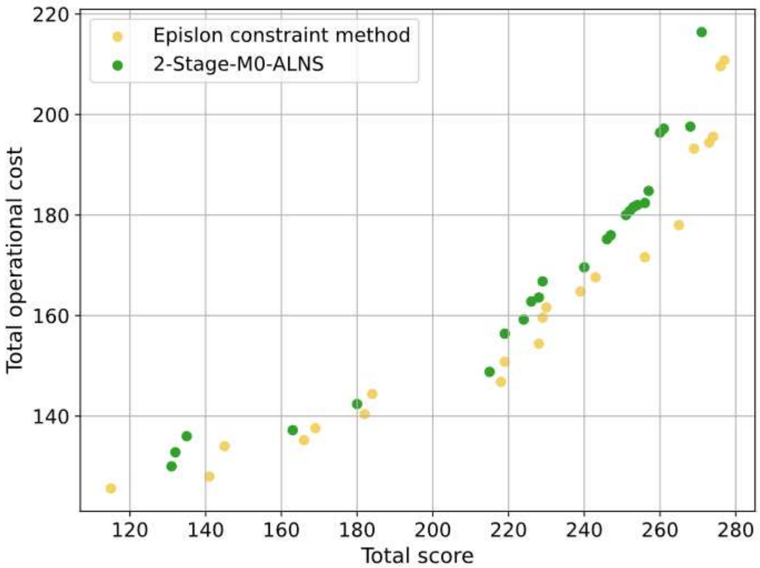


Fig. 10 Pareto solutions from ECM and MO-ALNS in TS-1.

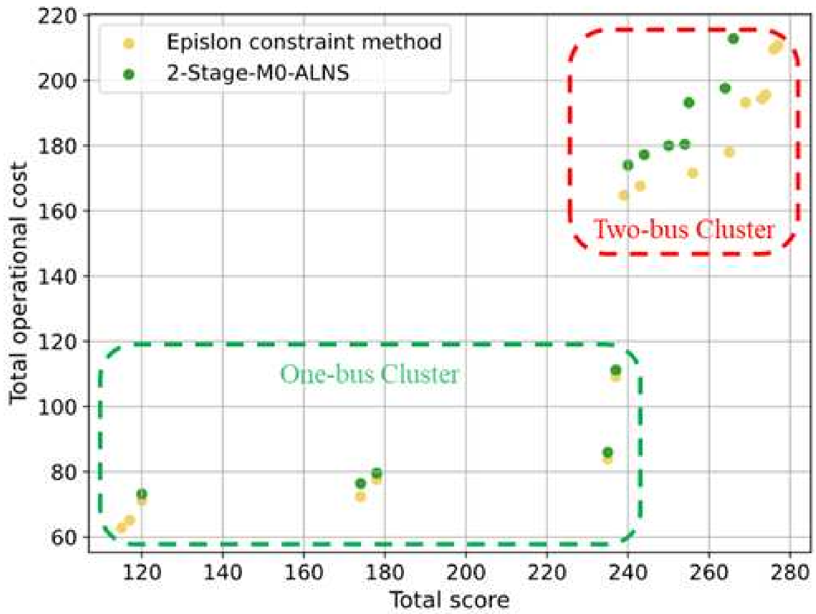


Fig. 11 Pareto solutions from ECM and MO-ALNS in TS-2.

Moreover, the Pareto solutions generated by the MO-ALNS algorithm are very similar to those produced by the ECM algorithm, with comparable quality indicators (see Table 4). However, the MO-ALNS algorithm has a significant efficiency advantage. While the ECM algorithm requires more than 15 hours to compute both cases, the MO-ALNS algorithm completes the computation in less than one minute.

Table 4 Computational results for TS-1 and TS-2.

TS-1					
Algorithm	HV	MS	MID	SP	Time(s)
ECM	10352.40	183.04	0.79	6.16	1111617
MO-ALNS	9762.80	164.51	0.78	5.16	23.8825
TS-2					
Algorithm	HV	MS	MID	SP	Time(s)
ECM	18018.40	219.43	0.86	8.14	58276
MO-ALNS	17372.80	202.00	0.79	15.20	8.218

4.2.3 Comparative analysis

For each instance, comparative analysis is conducted with the Non-Dominated Sorting Genetic Algorithm (NSGA-II) (Deb et al., 2002), Enhanced NSGA-II (Tan et al., 2021), Multi-Objective Large Neighborhood Search Algorithm (MO-LNS) (Kovacs et al., 2015) and Adaptive Large Neighborhood Search Algorithm (ALNS) (Kolaee et al., 2024). NSGA-II is a conventional optimization method for multi-objective problems. Moreover, it is acknowledged that neighborhood search algorithms are suitable for deployment in a discrete search space, as is the case with MO-SBP instances. To ensure fair comparisons, the termination condition for all algorithms is set to stop after the same computation time for each instance. Further details about the algorithm parameters can be found in Appendix A. For each case and algorithm, ten experiments were conducted, and the best result was recorded.

The comparative results from the experiments are presented in Table 5. A higher HV value indicates a superior quality of the obtained Pareto front. It is important to note that the reference point for HV calculation varies for each case, making HV comparisons between different cases meaningless. From Table 5, it is evident that NSGA-II performs poorly in solving MO-SBP, especially for larger instances. This may be due to the fact that the original NSGA-II was not designed with the specific characteristics of MO-SBP in mind. ENSGA-II performs well across various instance sizes, but its SP value is relatively high in some instances (TS-4, TS-8, TS-9). The three neighborhood search algorithms (ALNS, MO-LNS, MO-ALNS) show similar performance in solving MO-SBP. Compared to MO-LNS, ALNS performs better on larger instances (TS-7, TS-8). MO-ALNS demonstrates the most stable performance across all instance sizes.

Table 5 Computational results for test-scale instances.

		TS-1			
Algorithm	HV	MS	MID	SP	Time(s)
NSGA-II	6663.60	167.98	0.91	10.53	20.00
ENSGA-II	9928.00	154.61	0.84	10.19	20.00
ALNS	8505.20	145.02	0.80	5.04	20.00
MO-LNS	9306.00	168.00	**0.73**	10.76	20.00
MO-ALNS	**9992.00**	**174.64**	0.81	**4.82**	20.00
		TS-2			
Algorithm	HV	MS	MID	SP	Time(s)
NSGA-II	16317.60	**215.67**	0.87	**9.19**	20.00
ENSGA-II	17482.40	207.66	0.80	14.59	20.00
ALNS	17498.00	207.12	0.80	15.41	20.00
MO-LNS	17785.20	197.70	0.86	14.57	20.00
MO-ALNS	**17855.20**	211.76	**0.79**	14.84	20.00
		TS-3			
Algorithm	HV	MS	MID	SP	Time(s)
NSGA-II	13612.00	178.53	1.06	6.62	30.00
ENSGA-II	**18361.00**	**240.58**	0.88	7.18	30.00
ALNS	16096.40	183.39	**0.77**	8.27	30.00
MO-LNS	18113.20	183.58	0.88	4.14	30.00
MO-ALNS	18136.00	228.61	0.81	**3.02**	30.00
		TS-4			
Algorithm	HV	MS	MID	SP	Time(s)
NSGA-II	36516.40	215.84	0.93	13.38	60.00
ENSGA-II	55227.60	379.59	0.75	23.86	60.00
ALNS	57214.40	359.81	0.87	11.13	60.00
MO-LNS	59180.40	**406.44**	0.77	7.79	60.00
MO-ALNS	**60879.20**	374.26	**0.68**	**4.25**	60.00
		TS-5			
Algorithm	HV	MS	MID	SP	Time(s)

NSGA-II	29636.80	288.11	**0.80**	10.76	180.00
ENSGA-II	55324.00	582.18	0.88	8.64	180.00
ALNS	54427.60	474.84	0.89	10.96	180.00
MO-LNS	56146.00	**594.67**	0.92	**7.67**	180.00
MO-ALNS	**61016.80**	547.20	0.93	12.70	180.00
TS-6					
Algorithm	HV	MS	MID	SP	Time(s)
NSGA-II	146737.60	831.67	**0.83**	36.94	300.00
ENSGA-II	223877.60	1009.93	0.93	10.39	300.00
ALNS	209807.60	898.90	0.89	12.23	300.00
MO-LNS	227888.80	867.50	0.87	8.64	300.00
MO-ALNS	**240872.40**	**1028.08**	0.85	**8.37**	300.00
TS-7					
Algorithm	HV	MS	MID	SP	Time(s)
NSGA-II	198339.60	873.90	0.88	15.56	480.00
ENSGA-II	273872.00	1183.65	**0.85**	11.15	480.00
ALNS	254366.40	1130.41	0.86	7.87	480.00
MO-LNS	190169.20	986.97	**0.85**	17.66	480.00
MO-ALNS	**281387.20**	**1194.54**	**0.85**	**8.59**	480.00
TS-8					
Algorithm	HV	MS	MID	SP	Time(s)
NSGA2	269819.60	943.85	0.76	15.16	600.00
ENSGA2	526202.80	**1768.90**	0.69	21.86	600.00
ALNS	517192.00	1514.59	0.83	18.47	600.00
MO-LNS	471988.80	1380.98	0.72	13.92	600.00
MO-ALNS	**543218.00**	1671.77	**0.65**	**12.69**	600.00
TS-9					
Algorithm	HV	MS	MID	SP	Time(s)
NSGA2	290930.80	799.77	0.74	23.48	900.00
ENSGA2	702908.80	1523.73	0.78	29.15	900.00
ALNS	**723976.00**	2148.43	**0.73**	28.02	900.00
MO-LNS	679058.80	1727.75	0.79	26.82	900.00
MO-ALNS	711981.20	**2471.11**	0.76	**14.54**	900.00

4.3 Optimization Results

A simple example is initially employed to validate the efficacy of the algorithm. In this illustrative case, the total number of tourists in the tourist group is set at 30. Among them, 10 tourists exhibit a preference for "Historical and Cultural" POI, another 10 prefer "Modern Recreational" POI, and the remaining 10 favor "Natural Ecological"

POI. The scores for a tourist's preferred POI types are randomly generated as integers within the range of $[4, 5]$, while scores for non-preferred POI types are randomly generated as integers within the range of $[1, 3]$.There are three available sightseeing buses, each capable of accommodating 15 tourists. All 33 POIs in Section 4.1 are considered as candidate POIs. The termination condition for the MO-ALNS algorithm is set to when the cumulative number of iterations without the emergence of new Pareto-optimal solutions reaches a specified threshold $Iter = 2000$.

The corresponding pareto front, consisting of a total of 44 solutions, is presented in Fig. 13. As evident from the graph, there is a clear direct proportionality between the total score of tourists and total operational cost. This correlation implies a common trade-off scenario faced by both tourists and sightseeing bus operating company, where the maximization of travel benefits for tourists and the minimization of operational costs often present conflicting objectives. Consequently, operating company necessitates a comprehensive consideration of tourist service quality acceptance and operational costs when formulating plans for the operation of sightseeing buses. Solutions on the pareto front can be categorized into two clusters: the two-bus cluster and the three-bus cluster, denoting the differences in the number of buses utilized in each plan. Fig. 13 illustrates a noticeable cost disparity between these two clusters, exemplifying the additional expenses incurred by the operating company when incorporating an extra bus.

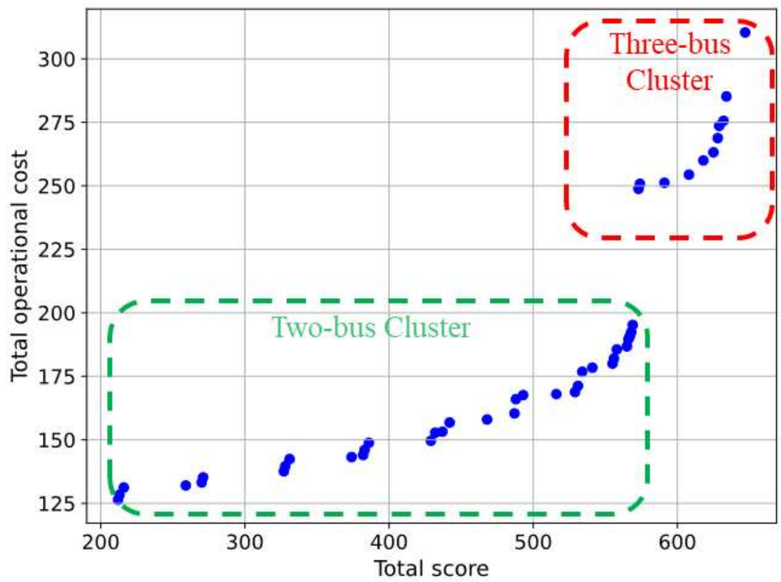


Fig. 12. Illustration of pareto front.

Fig. 14 illustrates the route details of a solution on the Pareto front. This particular solution is characterized by having the highest total score along the pareto front. It encompasses three distinct sightseeing bus routes. Each route is dedicated to visiting a specific type of POI: the route associated with Bus 1 focuses on exploring the POIs of "Historical and Cultural", Bus 2 the POIS of "Natural Ecological", and Bus 3 the POIs of "Modern Recreational".

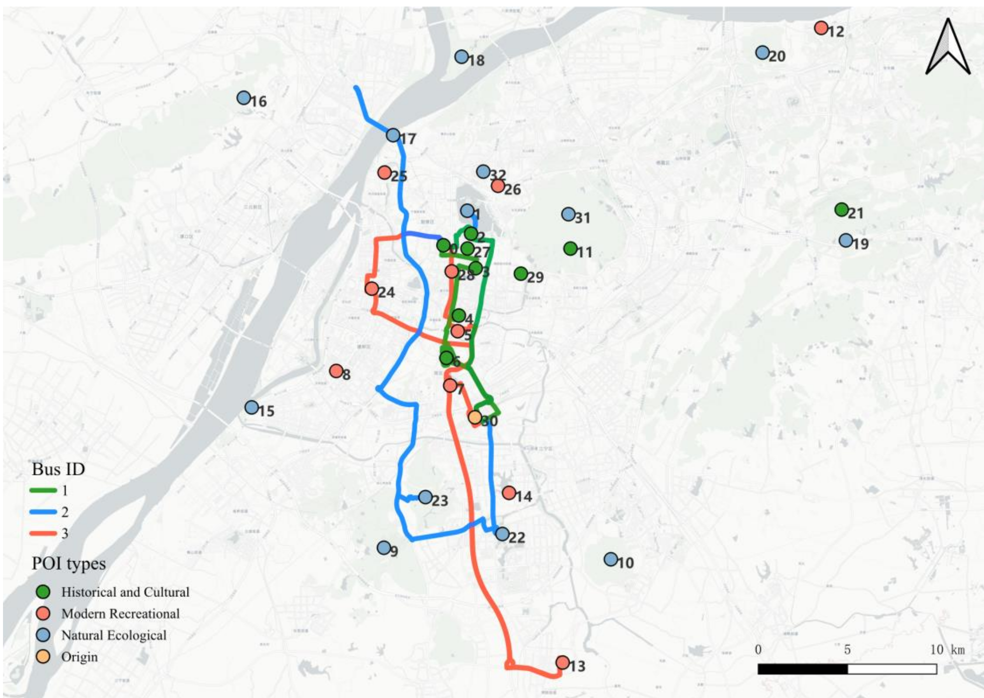


Fig. 13. One solution on the pareto front (max score).

Table 6 provides a more comprehensive overview of this solution, detailing the specific routes for each sightseeing bus, tourist scores on board, and relevant statistical information. As evident from the table, the standard deviation of tourist scores on each sightseeing bus is relatively low, suggesting a consistency in tourist preferences across buses. Consequently, the operating company may lean towards grouping tourists with similar preferences on the same bus to optimize overall tourist satisfaction.

Table 6 Sightseeing bus plan information (largest score).

Bus ID	Path	Total score	Tourist number	AVG of tourist scores	SD of tourist scores
1	30,2,0,3,4,6,30	233	10	23.30	1.49
2	30,1,0,17,23,22,30	184	9	20.44	0.88
3	30,5,0,24,13,7,30	230	11	20.91	1.13

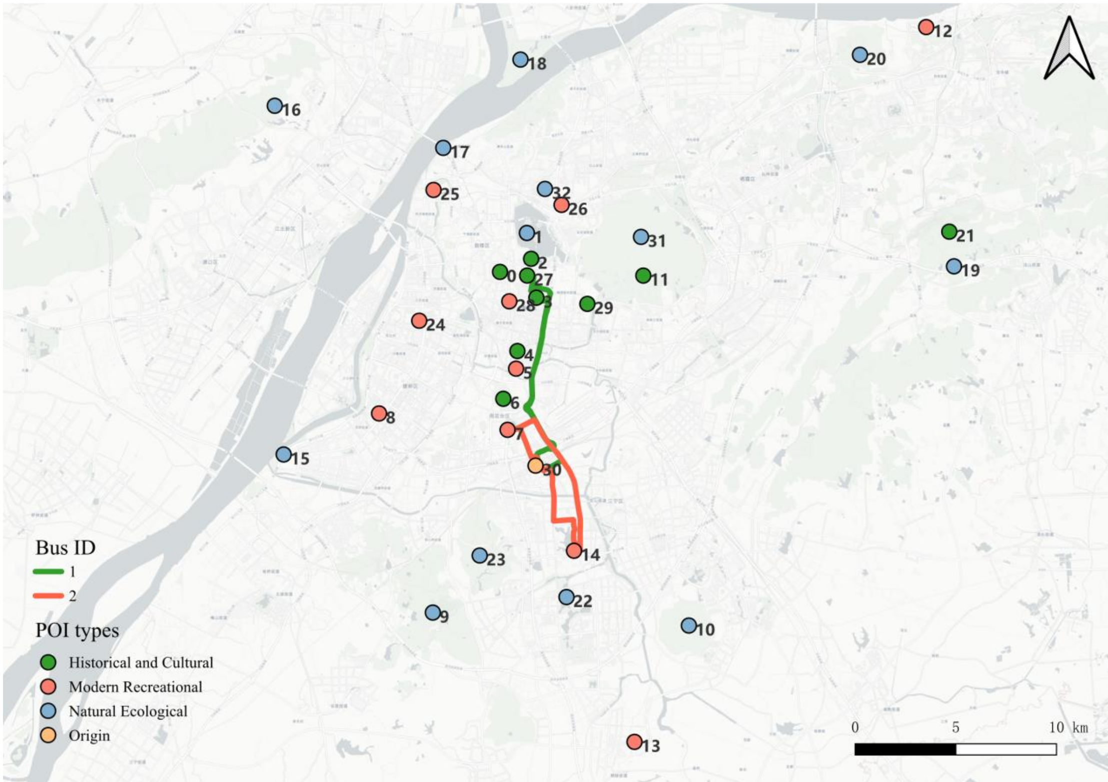


Fig. 14. One solution on the pareto front (min cost).

The routes of solution with the minimum cost on the pareto front are depicted in Fig. 15. This plan optimally employs two buses during operations, resulting in cost minimization. Regarding the design of bus routes, each bus predominantly visits a specific category of POI. Bus 1 concentrates on the POIs of “Historical and Cultural”, whereas Bus 2 predominantly visits POIs of “Modern Recreational”.

To showcase the diversity of solutions generated by the model, the plan with the minimum operational cost on the pareto front is further discussed. As shown in Table 7, in contrast to solutions aimed at maximizing scores, each bus in this plan exhibits a lower average tourist score, coupled with a larger standard deviation in tourist scores per bus. This observation suggests that, compared to score-maximizing solutions, the performance of this plan in meeting tourist demands is suboptimal. It can be attributed to the deployment of only two buses, leading to relatively constrained flexibility in tourist allocation.

Table 7 Sightseeing bus plan information (min cost).

Bus ID	Path	Total score	Tourist number	AVG of tourist scores	SD of tourist scores
1	30, 27, 3, 30	116	15	7.73	2.08
2	30, 7, 14, 30	96	15	6.40	3.02

4.4 Sensitivity Analysis

In this section, the impact of tourist group preference distribution and vehicle capacity on the model results is investigated. Similar to the setup in Section 4.3, the number of tourists is set to 30, and the total number of available vehicles is 3. All 33 POIs in Section 4.1 are considered as candidate POIs. The termination condition for the MO-ALNS algorithm is defined as reaching a specified threshold for the cumulative number of iterations $Iter = 2000$ without the emergence of new Pareto-optimal solutions.

4.4.1 Tourist group preference distribution

To further explore the impact of tourist preferences on the operational plan, this section conducts comparative tests. The capacity of vehicle is set to 15. Five sets of experiments are conducted by adjusting the distribution of preferences among tourist within the tourist group. The “Normal” group represents a scenario where preferences are uniformly distributed within the tourist group, aligning with Section 4.3. The

"Historical and Cultural" group indicates a preference for "Historical and Cultural" POIs among tourist group members. Similarly, the "Modern Recreational" and "Natural Ecological" groups reflect preferences for POIs in their respective categories. The "Random" group represents a scenario where preferences within the tourist group are generated through a random process, resulting in a more dispersed distribution.

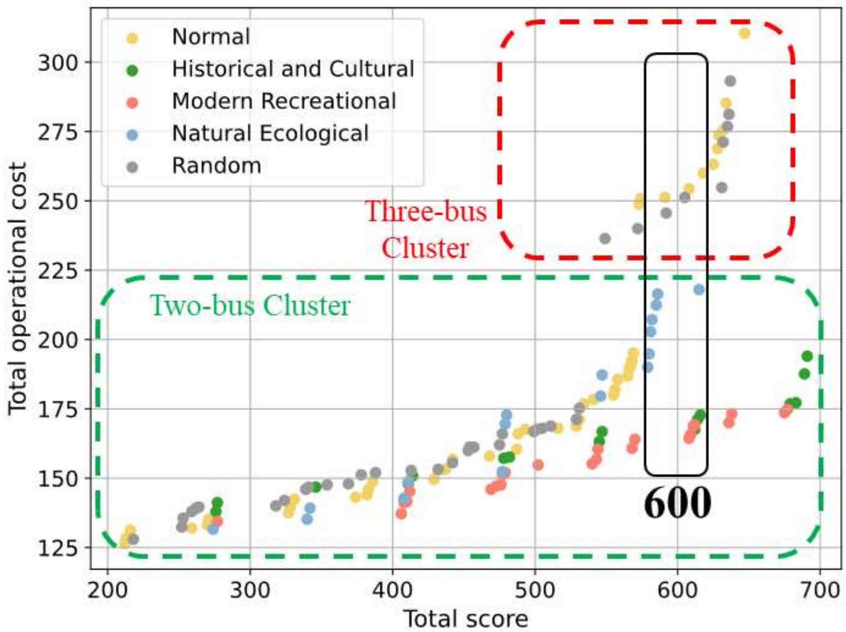


Fig. 15. The pareto front under different distributions of tourist preferences.

Fig. 16 depicts the pareto front corresponding to various tourist preference distributions. First, solutions around a total score of around 600 are discussed. Under equivalent total scores , the "Random" group and "Normal" group incur higher costs around 250, highlighting that a more dispersed distribution of tourist preferences within the tourist group necessitates increased operational expenses to maximize overall benefits; Notably, the "Historical and Cultural" group and "Modern Recreational" group exhibits the lowest costs around 175 while achieving the same total score, aligning with the concentrated geographical distribution of "Historical and Cultural" and "Modern Recreational" POIs in Nanjing city, particularly around the city center. Solutions involving "Natural Ecological" incur higher costs, which is attributed to the fact that "Natural Ecological" POIs are primarily located in the suburban regions of Nanjing, and the distances between them are comparatively substantial. Second, in the three-bus cluster, solutions involving the “Historical and Cultural” group, “Modern Recreational” group and “Natural Ecological” are absent. This is because adding an extra bus does not yield additional benefits for tourist groups whose members share the same preferences. However, for “Normal” and "Random" groups, where tourists have diverse preferences, adding more vehicles can help increase the overall score.

These findings suggest that, in the planning of sightseeing bus plans, it is advisable for operating companies to steer clear of scenarios with highly dispersed tourist preference distributions within the tourist group, as this could lead to elevated operational costs. Simultaneously, when crafting plans, a holistic consideration of both tourist preference distributions within the tourist group and the geographical distribution of POIs within the city is crucial.

4.4.2 Vehicle capacity

In this section, this study explores the influence of vehicle capacity on the operational plan. The tourist group preference distribution is the same as described in Section 4.3. To ensure the fleet can accommodate all tourists without wasting resources, experimental capacities are varied, including 10, 15, 20, 25, and 30.

Experiment A assumes uniform costs for all vehicle types. The results are presented in Fig. 17. Deploying three vehicles with a capacity of 10 is necessary to accommodate all tourists, resulting in the highest overall cost for the corresponding plan group. Simultaneously, the plan group with capacity 10 offers less flexibility in tourist assignment, leading to a smaller total score for the corresponding plans. Plans with capacities of 10, 15, 20, and 25 exhibit minimal differences since they can only provide two types of plan configurations: two buses or three vehicles. Capacity 30, capable of accommodating all tourists with a single vehicle, yields the smallest total score among the corresponding plans.

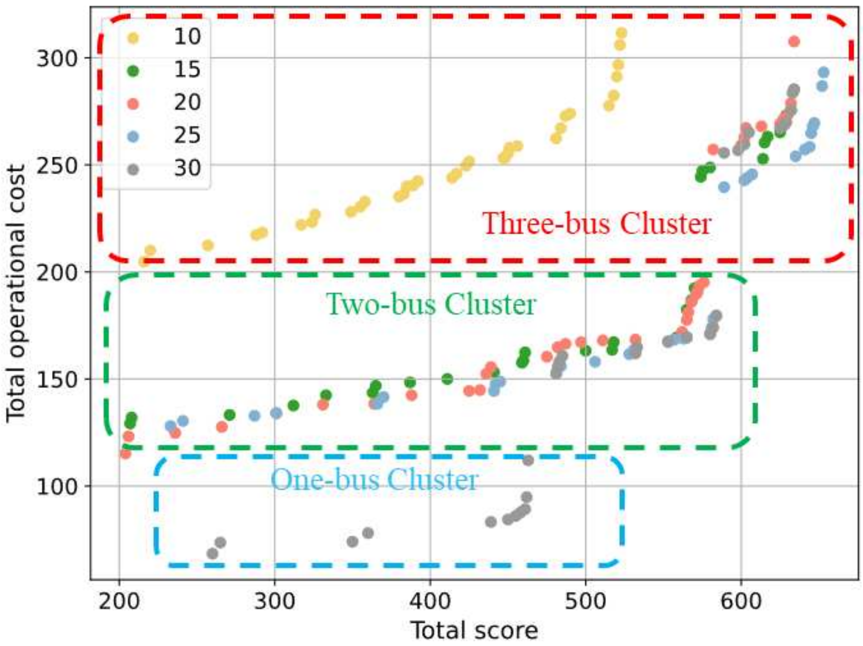


Fig. 16. The pareto front under different vehicle capacity (Experiment A).

Table 8 Vehicle type information.

Vehicle type	Capacity	β
1	10	0.10
2	15	0.15
3	20	0.20
4	25	0.25
5	30	0.30

Experiment B assumes varied costs for each vehicle type, as illustrated in Table 8. The results are depicted in Fig. 18. The plan group with a capacity of 30 presents plans that utilize only one vehicle, minimizing costs. Remarkably, the plan group with a capacity of 15 outperforms all others, incurring the lowest cost for the same total score. Despite increasing the capacity per vehicle, the plan groups with capacities of 20, 25 and 30 fail to provide plans that significantly improve tourist satisfaction relative to the increased costs. The plan group with a capacity of 10 necessitates three vehicles to accommodate all tourists, achieving the highest bus occupancy, yet its performance does not surpass that of the plan group with a capacity of 15, utilizing only two vehicles.

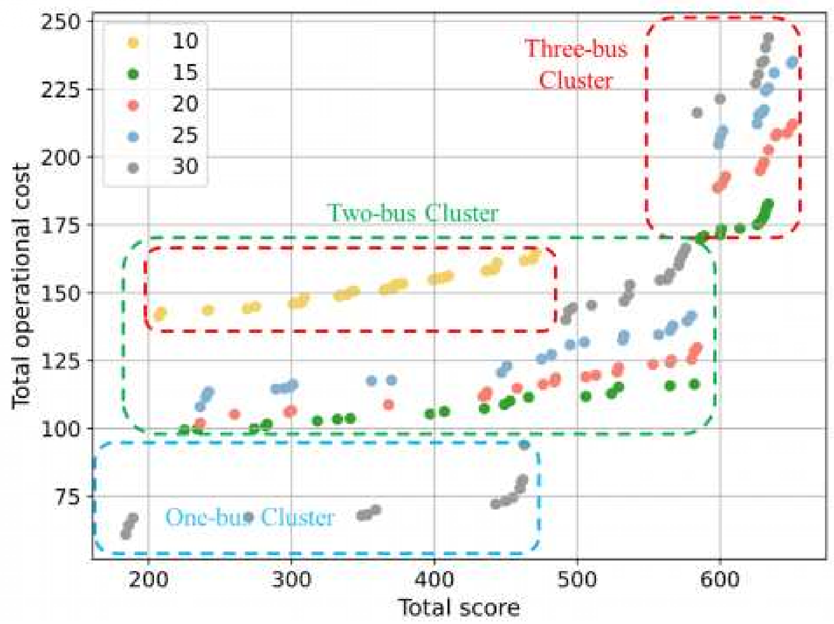


Fig. 17. The pareto front under different vehicle capacity (Experiment B).

Experiments A and B underscore the significance of vehicle type as a pivotal factor influencing the outcomes of the MO-SBP. The vehicle capacity plays an important role in determining both the number of buses utilized in a plan and the flexibility of the tourist assignment. It is noteworthy that increasing capacity does not ensure the acquisition of consistently superior plan groups.

5. Conclusion

In this study, the multi-objective sightseeing bus problem considering the trade-off between tourist benefits and operational cost was proposed. The problem was formulated as a multi-objective model with the objectives of maximizing the tourist benefits and minimizing the operational costs. The model encompasses decisions related to bus fleet scheduling, the routing for each bus, and the assignment of tourists to each bus. The two-stage multi-objective ALNS algorithm is applied to solve the proposed problem. Based on the problem characteristics, neighborhood search operators for the first stage (assignment) and the second stage (routing) were designed to address the problem.

The numerical results suggest that the proposed two-stage multi-objective ALNS algorithm effectively addresses the MO-SBP model. When compared to NSGA-II, ENSGA-II, MO-LNS, and ALNS, MO-ALNS demonstrates the most stable performance across various test-scale instances. The MO-SBP model provides sightseeing bus operators with diverse operational plans with different cost and tourist benefits, categorized by the number of buses used in the plan groups. The model results and sensitivity analysis offer two key insights for sightseeing bus operations: (1) Operational plan formulation closely correlates with the distribution of tourist preferences and various types of POIs. A more concentrated tourist preference and spatial distribution of similar POIs lead to a reduction in operational costs. (2) The choice of sightseeing bus type influences operational plan costs, but increasing capacity does not necessarily lead to increased tourist benefits. Opting for a moderate vehicle capacity is more advantageous for formulating operational plans that balance benefits and costs effectively.

The model and algorithm introduced in this study can be efficiently employed in devising operational plans for sightseeing buses within urban settings. Customized sightseeing buses are better equipped to meet the varied preferences of heterogeneous tourist groups, thereby elevating overall tourist satisfaction. Furthermore, the provided range of plan groups offers operational flexibility for sightseeing bus operators. This flexibility allows for a balanced consideration of benefits and costs, ensuring the sustained and stable provision of services over the long term.

The proposed MO-SBP model can be attributed to the tourist trip design problem, demonstrating extensibility regarding optimization objectives, transportation modes, and trip duration. It can be expanded to cases such as trip design considering reducing carbon emissions, trip design incorporating various transportation modes, and multi-day trip planning. The customized solution algorithm also exhibits flexibility in solving tourist trip design problems. The operators and the two-stage framework introduced offer robust adaptability.

In future studies, several potential enhancements could be considered. First, while this study focuses on employing a homogeneous bus fleet in operational plan design, exploring the concurrent use of different types of buses during operations could be valuable. Such an approach might lead to plans with reduced operational costs or increased tourist benefits. Second, this study assumes that the time spent at each POI is a fixed value. Future research could consider incorporating the time spent at POIs as part of the decision-making process.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This work is supported by the Fundamental Research Funds for the Central Universities (No. RF1028623241), the National Natural Science Foundation of China (No. 52311530090), the Jiangsu Provincial Scientific Research Center of Applied Mathematics (No. BK20233002), and the Open Project Program of the Key Laboratory of Transport Industry of Comprehensive Transportation Theory (Nanjing Modern Multimodal Transportation Laboratory) (No. MTF2023001).

References

Ait Bouziaren, S., & Aghezzaf, B. (2019). An Improved Augmented ε -Constraint and Branch-and-Cut Method to Solve the TSP With Profits. *IEEE Transactions on Intelligent Transportation Systems*, *20*(1), 195–204.

Buran, B., & Erçek, M. (2022). Public transportation business model evaluation with Spherical and Intuitionistic Fuzzy AHP and sensitivity analysis. *Expert Systems with Applications*, *204*, 117519.

Cattrysse, D. G., & Van Wassenhove, L. N. (1992). A survey of algorithms for the generalized assignment problem. *European Journal of Operational Research*, *60*(3), 260–272.

Chao, I.-M., Golden, B. L., & Wasil, E. A. (1996). The team orienteering problem. *European Journal of Operational Research*, *88*(3), 464–474.

Deb, K., Pratap, A., Agarwal, S., & Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, *6*(2), 182–197.

Dehdari, P., Wlcek, H., & Furmans, K. (2023). An updated literature review of CO2e calculation in road freight transportation. *Multimodal Transportation*, *2*(2), 100068.

Deitch, R., & Ladany, S. P. (2000). The one-period bus touring problem: Solved by an effective heuristic for the orienteering tour problem and improvement algorithm. *European Journal of Operational Research, 127*(1)*,* 69–77.

Ekici, A., & Retharekar, A. (2013). Multiple agents maximum collection problem with time dependent rewards. *Computers & Industrial Engineering*, *64*(4), 1009–1018.

Garcia, A., Vansteenwegen, P., Arbelaitz, O., Souffriau, W., & Linaza, M. T. (2013). Integrating public transportation in personalised electronic tourist guides. *Computers & Operations Research*, *40*(3), 758–774.

Gavalas, D., Konstantopoulos, C., Mastakas, K., & Pantziou, G. (2014). A survey on algorithmic approaches for solving tourist trip design problems. *Journal of Heuristics*, *20*(3), 291–328.

Gunawan, A., Lau, H. C., & Vansteenwegen, P. (2016). Orienteering Problem: A survey of recent variants, solution approaches and applications. *European Journal of Operational Research*, *255*(2), 315–332.

Hasselwander, M., Nieland, S., Dematera-Contreras, K., & Goletz, M. (2023). MaaS for the masses: Potential transit accessibility gains and required policies under Mobility-as-a-Service. *Multimodal Transportation*, *2*(3), 100086.

Hu, Q., & Lim, A. (2014). An iterative three-component heuristic for the team orienteering problem with time windows. *European Journal of Operational Research*, *232*(2), 276–286.

Hu, Q., Zhang, Z., Baldacci, R., Tarantilis, C. D., & Zachariadis, E. (2022). The bus sightseeing problem. *International Transactions in Operational Research*, itor.13160.

Kolaee, M. H., Jabbarzadeh, A., & Al-e-hashem, S. M. J. M. (2024). Sustainable group tourist trip planning: An adaptive large neighborhood search algorithm. *Expert Systems with Applications*, *237*, 121375.

Kordi, Gh., Divsalar, A., & Emami, S. (2023). Multi-objective home health care routing: A variable neighborhood search method. *Optimization Letters, 17*(9)*,* 2257–2298.

Kovacs, A. A., Parragh, S. N., & Hartl, R. F. (2015). The multi-objective generalized consistent vehicle routing problem. *European Journal of Operational Research*, *247*(2), 441–458.

Labadie, N., Mansini, R., Melechovský, J., & Wolfler Calvo, R. (2012). The Team Orienteering Problem with Time Windows: An LP-based Granular Variable Neighborhood Search. *European Journal of Operational Research*, *220*(1), 15–27.

Le-Klähn, D.-T., & Hall, C. M. (2015). Tourist use of public transport at destinations – a review. *Current Issues in Tourism*, *18*(8), 785–803.

Li, M., & Yao, X. (2020). Quality Evaluation of Solution Sets in Multiobjective Optimisation: A Survey. *ACM Computing Surveys*, *52*(2), 1–38.

Lin, S.-W., & Yu, V. F. (2012). A simulated annealing heuristic for the team orienteering problem with time windows. *European Journal of Operational Research*, *217*(1), 94–107.

Luo, Z., Cheang, B., Lim, A., & Zhu, W. (2013). An adaptive ejection pool with toggle-rule diversification approach for the capacitated team orienteering problem. *European Journal of Operational Research*, *229*(3), 673–682.

Montemanni, R., Gambardella, L., 2009. Ant colony system for team orienteering problems with time windows. Foundations of computing and Decision Sciences 34 (4), 287–306.

Moosavi Heris, F. S., Ghannadpour, S. F., Bagheri, M., & Zandieh, F. (2022). A new accessibility based team orienteering approach for urban tourism routes optimization (A Real Life Case). *Computers & Operations Research*, *138*, 105620.

Rifai, A. P., Nguyen, H.-T., & Dawal, S. Z. M. (2016). Multi-objective adaptive large neighborhood search for distributed reentrant permutation flow shop scheduling. *Applied Soft Computing*, *40*, 42–57.

Ropke, S., & Pisinger, D. (2006). An Adaptive Large Neighborhood Search Heuristic for the Pickup and Delivery Problem with Time Windows. *Transportation Science*, *40*(4), 455–472.

Ruiz-Meza, J., Brito, J., & Montoya-Torres, J. R. (2021). A GRASP to solve the multi-constraints multi-modal team orienteering problem with time windows for groups with heterogeneous preferences. *Computers & Industrial Engineering*, *162*, 107776.

Ruiz-Meza, J., Brito, J., & Montoya-Torres, J. R. (2022). A GRASP-VND algorithm to solve the multi-objective fuzzy and sustainable Tourist Trip Design Problem for groups. *Applied Soft Computing*, *131*, 109716.

Ruiz-Meza, J., & Montoya-Torres, J. R. (2021). Tourist trip design with heterogeneous preferences, transport mode selection and environmental considerations. *Annals of Operations Research*, *305*(1–2), 227–249.

Ruiz-Meza, J., & Montoya-Torres, J. R. (2022). A systematic literature review for the tourist trip design problem: Extensions, solution techniques and future research lines. *Operations Research Perspectives*, *9*, 100228.

Sarkar, J. L., & Majumder, A. (2022). gTour: Multiple itinerary recommendation engine for group of tourists. *Expert Systems with Applications*, *191*, 116190.

Sharma, P., Heidemann, K. M., Heuer, H., Mühle, S., & Herminghaus, S. (2023). Sustainable and convenient: Bi-modal public transit systems outperforming the private car. *Multimodal Transportation*, *2*(3), 100083.

Souffriau, W., Vansteenwegen, P., Vanden Berghe, G., & Van Oudheusden, D. (2013). The Multiconstraint Team Orienteering Problem with Multiple Time Windows. *Transportation Science*, *47*(1), 53–63.

Stanitsa, A., Hallett, S. H., & Jude, S. (2023). Investigating pedestrian behaviour in urban environments: A Wi-Fi tracking and machine learning approach. *Multimodal Transportation*, *2*(1), 100049.

Tan, W., Yuan, X., Wang, J., & Zhang, X. (2021). A fatigue-conscious dual resource constrained flexible job shop scheduling problem by enhanced NSGA-II: An application from casting workshop. *Computers & Industrial Engineering*, *160*,

107557.
Tricoire, F., Romauch, M., Doerner, K. F., & Hartl, R. F. (2010). Heuristics for the multi-period orienteering problem with multiple time windows. *Computers & Operations Research*, *37*(2), 351–367.
Vansteenwegen, P., Souffriau, W., Vanden Berghe, G., & Van Oudheusden, D. (2009). Iterated local search for the team orienteering problem with time windows. *Computers & Operations Research*, *36*(12), 3281–3290.
Wu, F., Lyu, C., & Liu, Y. (2022). A personalized recommendation system for multi-modal transportation systems. *Multimodal Transportation*, *1*(2), 100016.
Zheng, W., & Liao, Z. (2019). Using a heuristic approach to design personalized tour routes for heterogeneous tourist groups. *Tourism Management*, *72*, 313–325.

Appendix A

Specific algorithm parameter settings:

- NSGA-II. The crossover fraction is 0.7, the mutation fraction is 0.3, The size of population is 200.
- ENSGA-II. The size of population is 50.
- MO-LNS. The parameter that controls the effectiveness of the weight adjustment process is set to 0.01.
- ALNS. The parameter controlling the effectiveness of the weight adjustment process is set to 0.01.
- MO-ALNS. The parameter that controls the effectiveness of the weight adjustment process is set to 0.01.

Appendix B

The proposed MO-ALNS algorithm mainly includes two parameters: η and π, where $\eta \in [0,1]$ represents a parameter that controls the effectiveness of the weight adjustment process, $\pi \in [0,1]$ is a parameter used within the random POI insertion operator to control the termination.

For a set of parameters, tuning is conducted using five test cases, TS-1 to TS-5. Each experiment is repeated ten times, and the average hypervolume, hypervolume standard deviation, average computation time, and computation time standard deviation are calculated. The termination condition for the MO-ALNS algorithm is set to when the cumulative number of iterations without the emergence of new Pareto-optimal solutions reaches a specified threshold $Iter = 2000$.

First, η is fixed at 0.01, and π values of 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, and 0.9 are experimented with. The experimental results are shown in Table 10. For the MO-ALNS algorithm, π is not a sensitive parameter. Therefore, $\pi = 0.5$ is chosen for subsequent parameter tuning.

Table 9 Results of the First Stage Parameter Tuning.

Case	π	HV Mean	HV STD	Time Mean	Time STD
TS-1	0.1	9067.160	310.795	11.146	5.277
	0.2	9433.360	203.294	14.043	5.379
	0.3	9451.160	214.397	14.953	4.536
	0.4	9499.880	208.091	14.506	7.018
	0.5	9453.440	275.249	13.435	5.394
	0.6	9493.520	228.200	12.476	3.577
	0.7	9399.520	208.074	14.267	4.340
	0.8	9545.280	217.590	13.637	5.251
	0.9	9595.400	195.752	16.534	5.480
	1	9306.720	150.428	11.308	3.878
TS-2	0.1	17058.680	584.768	6.154	3.486
	0.2	17259.280	258.140	7.369	3.318
	0.3	17200.000	185.945	6.468	3.135
	0.4	17114.080	324.265	6.074	3.284
	0.5	17401.520	208.387	8.837	2.840
	0.6	17448.200	168.818	8.288	3.286
	0.7	17329.560	166.611	6.343	2.091
	0.8	17375.560	226.537	7.700	3.519
	0.9	17393.120	269.288	7.298	4.262
	1	17216.840	217.077	5.546	3.078
TS-3	0.1	17050.380	794.815	17.927	8.530
	0.2	17610.960	675.873	18.520	9.787
	0.3	17555.680	540.504	13.950	3.874
	0.4	17359.040	558.449	18.677	6.078
	0.5	17627.460	846.738	19.441	7.234
	0.6	17623.780	616.338	21.732	7.447
	0.7	17404.040	376.508	18.292	4.665
	0.8	17661.620	518.764	22.230	7.118

	0.9	17600.080	487.285	19.473	3.823
	1	17527.440	1025.788	19.678	8.853
TS-4	0.1	55412.920	1573.063	55.369	14.574
	0.2	56568.400	2577.102	52.783	10.376
	0.3	57496.600	2637.223	55.767	7.823
	0.4	58533.480	2776.167	58.394	14.624
	0.5	56510.320	2017.181	50.617	12.994
	0.6	58454.400	2453.576	53.191	16.835
	0.7	57344.960	2351.398	58.396	9.222
	0.8	57600.640	2357.812	64.664	13.860
	0.9	58028.840	2519.803	56.783	16.449
	1	57813.440	2459.425	68.699	19.371
TS-5	0.1	54211.840	3744.060	136.777	49.450
	0.2	56955.240	2019.782	156.567	27.511
	0.3	56928.560	2513.118	147.614	34.970
	0.4	55869.800	1945.921	145.510	36.461
	0.5	57167.840	1526.275	169.381	33.302
	0.6	57027.880	2379.486	152.807	44.066
	0.7	56804.120	1717.235	160.663	46.361
	0.8	57269.000	1742.092	158.421	41.606
	0.9	56315.320	1344.736	159.888	55.633
	1	57489.440	2731.678	142.048	33.559

Next, π is fixed at 0.5 and η is adjusted. The values for η include 0.01, 0.1, 0.2, 0.4, 0.6, 0.8, and 0.9. The results are shown in Table 2. In most cases, the algorithm performs better when $\eta = 0.01$. Therefore, the final algorithm parameters are set to $\pi = 0.5$ and $\eta = 0.01$.

Table 10 Results of the Second Stage Parameter Tuning.

Case	η	HV Mean	HV STD	Time Mean	Time STD
TS-1	0.01	**9496.480**	**184.559**	13.541	4.826
	0.1	9135.200	986.847	10.534	3.383
	0.2	8790.280	1013.420	12.057	8.333
	0.4	9280.040	379.964	9.950	2.374
	0.6	9227.760	580.852	11.295	3.972
	0.8	7100.440	2136.118	6.185	4.719
	0.9	7790.600	2395.332	8.166	4.819
TS-2	0.01	**17324.920**	**150.866**	5.615	0.896
	0.1	17006.600	353.542	5.828	3.773

	0.2	16168.640	2672.722	5.935	2.988
	0.4	16025.960	2571.998	6.295	6.133
	0.6	15772.920	3746.567	4.357	2.029
	0.8	13371.640	6123.772	6.331	3.395
	0.9	16809.320	434.139	5.034	1.546
TS-3	0.01	**17659.060**	**440.428**	17.125	5.069
	0.1	17215.720	684.709	14.683	3.796
	0.2	17369.700	847.377	13.496	5.660
	0.4	15073.300	3640.232	14.605	7.226
	0.6	15841.800	3542.704	16.238	8.144
	0.8	15281.600	2282.703	15.772	16.883
	0.9	12895.140	3433.174	4.741	2.389
TS-4	0.01	56682.880	2627.503	48.578	14.857
	0.1	**57887.480**	**2318.678**	60.372	14.113
	0.2	52080.080	4815.307	46.993	19.200
	0.4	43169.360	11575.882	32.726	20.209
	0.6	33792.640	16880.960	30.121	25.124
	0.8	49857.920	15289.111	51.463	28.475
	0.9	39064.120	16983.573	30.230	23.028
TS-5	0.01	**56554.800**	1657.238	148.923	21.504
	0.1	55722.920	**1115.095**	139.655	39.555
	0.2	54980.800	6118.197	137.829	36.977
	0.4	45204.520	13523.541	85.421	42.696
	0.6	35645.600	15266.248	77.457	83.958
	0.8	41182.000	14341.270	82.699	75.057
	0.9	33420.240	19456.904	49.481	37.566