Bus-Pooling: Demand-Driven Flexible Scheduling for Intercity Transit

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Abstract: The mismatch between static bus schedules and dynamic passenger travel demand results in increased passenger waiting time and inefficient operation for intercity transit. To address this issue, a cross-route bus-pooling scheduling method is proposed to merge passengers from low-efficiency routes into alternative routes within a shared operation segment at a key station with significant ridership fluctuations. An optimization model is established with the objective of maximizing operational efficiency and minimizing total passenger waiting time considering the restrictions of load factor and arrival time window. Operational efficiency is primarily enhanced by reducing the opportunity cost and the energy consumption cost. The real-time bus operation status and ridership distribution characteristics are analyzed using an adaptive genetic algorithm (AGA) to obtain the optimal solution. Using real data, the case study shows that the proposed bus-pooling schedule obtains an increase of 10 bus runs with a significant rise in ridership by 22.75% within fleet size constraints. The average waiting time of suburban passengers decreases by 15.88%. Sensitivity analysis on the load factor threshold is discussed. This approach facilitates a dynamic equilibrium between feasible operation resources and travel demand, enhancing the effectiveness and sustainability of public transportation systems. **DOI:** 10.1061/JTEPBS.TEENG-8957. *© 2025 American Society of Civil Engineers.*

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Introduction

With the rapid process of urbanization, there has been a significant increase in communication, economic activity, and travel frequency in developing countries and regions. Intercity buses have emerged as a vital mode of transportation for interregional travel between cities (Ozdagoglu et al. 2022). However, many routes exhibit a shared operation segment. Among the 38 intercity routes in the Beijing-Hebei region, 31 routes have overlapping sections, accounting for 81.58%. The interaction between vehicles and ridership on different bus lines within these overlapping areas increases the complexity of bus scheduling and decreases the reliability of bus services. Traditional scheduling such as adjusting departure frequencies and optimizing timetables are no longer sufficient to meet the dynamic travel demand of passengers, which results in long wait times for passengers and inefficient bus operations. The application of the pooling concept in bus operations that merge passengers from low-efficiency routes into alternative routes introduces a novel perspective to address this problem and avoids the waste of resources.

For the scattered residential areas and wide departure intervals, stations along intercity bus lines have uneven ridership distributions both temporally and spatially, as depicted in Fig. 1. Dividing the route into two lines with different frequencies may resolve spatial ridership fluctuations and improve utilization rates, but it does not address the uncertainty of travel demand over time. For intercity bus services, it is essential to establish dynamic scheduling strategies based on the load factor to efficiently match passenger demand with bus capacity. The bus-pooling strategies, akin to a dynamic feeder service, can effectively address the spatiotemporal fluctuations of uneven ridership, achieving flexible scheduling of public transit.

To reduce passengers' waiting time and the operating costs of bus enterprises, this study proposes a cross-route bus-pooling scheduling optimization model that caters to the diverse travel demand of passengers across regions while improving overall bus operational efficiency. The main contributions are as follows:

1. A novel cross-route bus-pooling strategy is proposed to reduce uneven passenger distribution and increase the efficiency. Passengers from low-efficiency routes are merged into alternative routes during the shared operation segment at a key station.
2. A cross-route bus-pooling scheduling optimization model is established to maximize the operational efficiency and minimize the total passenger waiting time.
3. An adaptive genetic algorithm (AGA) is employed to solve the optimal pooling pairs, using the real-time data of bus load and arrival time in the case study.
4. It benefits suburban passengers with less average waiting time in a case study. Sensitivity analysis revealed the impact of different load factor thresholds on the model performance.

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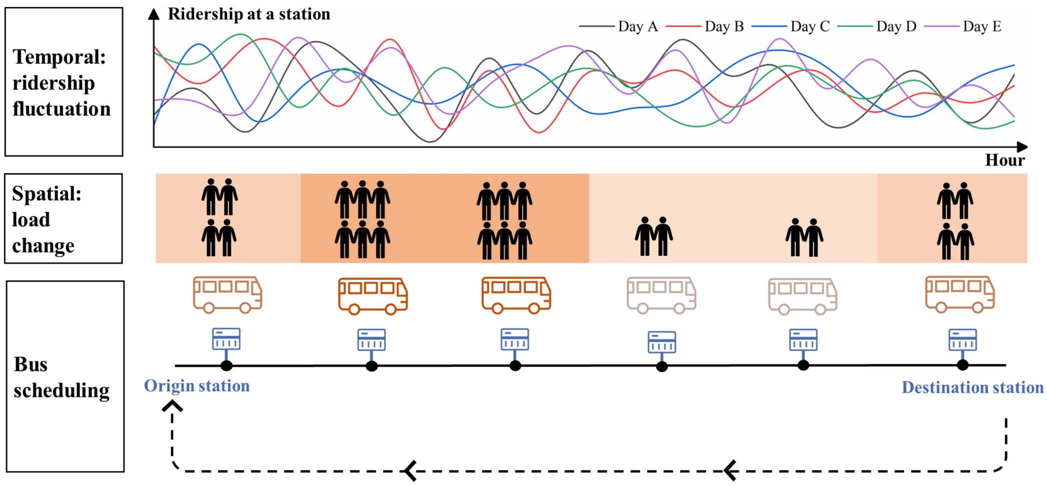

Fig. 1. Uneven distribution phenomenon of ridership.

The rest of the paper is organized as follows. Section "Literature Review" provides a literature review. Section "Bus-Pooling Scheduling Strategy" introduces the bus-pooling strategy. Section "Bus-Pooling Scheduling Optimization Model and Solution" establishes the bus-pooling scheduling optimization model and proposes an algorithm for solving it. Section "Case Study" presents the case study and results. Section "Discussion" provides the application and sensitivity analysis of the model. Finally, Section "Conclusions" is the conclusion and future research prospects.

Literature Review

Passenger Flow Characteristics Analysis

The analysis of passenger flow characteristics is crucial for bus scheduling optimization. This analysis utilizes multisource data, including integrated circuit (IC) card data, bus operational data, and global positioning system (GPS) data. Bus operational data are utilized to assess the running time, leading to improvements in unstable bus operation status (Kapatsila et al. 2024). The combination of IC card and GPS data enables the identification of passenger boarding and alighting information through single swipe, allowing for the calculation of bus operation information (Tang et al. 2020). The bus load factor is a crucial indicator for affecting passenger demand and operating efficiency. An automatic passenger counting (APC) system provides relatively accurate real-time bus load calculations (Jung and Casello 2020). The integration of historical passenger counts, real-time automated vehicle location, and APC significantly improves the accuracy of bus crowding information (Jenelius 2020). Providing real-time bus crowding information can help to reduce crowding discomfort by encouraging passengers to distribute themselves more evenly among buses (Drabicki et al. 2023). When the load factor is high, increasing the frequency of bus services is commonly used to address passenger discomfort caused by overcrowding (van Lierop et al. 2018).

Scheduling Optimization Strategy

Effective vehicle scheduling is crucial for meeting passenger service expectations and bus operators' interests within financial constraints. Optimization strategies primarily focus on station control and route adjustment to improve the frequency and reduce the passenger waiting time. Skip-stop strategies, a key component of station control optimization, have been extensively studied (Cao and Ceder 2019; Khan and Menéndez 2023; Vismara et al. 2021). It includes express services (skipping multiple stations), and short-turn operations (ending service mid-routes to start in the opposite direction), etc. Various combinations of skip-stop strategies, such as full-stop and skip-stop strategies (Li et al. 2023; Rodriguez et al. 2023), have been utilized to optimize bus scheduling. Bus route optimization strategies can be classified into single-route (de Souza and Sebastiani 2021; Zhou et al. 2019) and cross-route (Ahern et al. 2022; Filgueiras et al. 2023) approaches, including speed control, the adjustment of departure frequencies, and fleet sizes (Jiang 2022). Cross-route scheduling offers greater flexibility than single-route strategies, which can be implemented through long and short bus routes (Gkiotsalitis et al. 2019) or by generating alternative bus lines within the network (Avila-Ordóñez et al. 2022; Durán-Micco et al. 2022). It provides better adaptation to passenger demand fluctuations. Coordinated scheduling between buses and other public transportation modes is also a widely discussed topic (Calabrò et al. 2023; Sinha et al. 2022).

Passenger Demand Response

Bus scheduling in response to passenger travel demand is a new research trend in the recent years. The customized bus line was designed to provide flexible and passenger-oriented services for ones with similar or specific travel demands (He et al. 2023; Lee et al. 2024; Ma et al. 2023). Some studies focused on timetable collaboration and fleet size setting to accommodate dynamic passenger demands (AlKheder et al. 2018; Guedes et al. 2019). Flexible scheduling strategies such as bus priority control, full route optimization, limited-stop services and short-turn operations were used to effectively address passenger demand uncertainties (Lee et al. 2022). Combining these strategies could perform better than single strategies (Heidarigharehsoo and Saidi 2023). The direct demand model was established to explore the effects of service frequency and headway variability on bus passenger travel (Deepa et al. 2023). Many studies addressed the dynamic travel demand issue by minimizing passenger waiting time with real-time information provided by bus operators (Ansarilari et al. 2024; Sadrani et al. 2022; Wang et al. 2024). However, most of the previous demand response scheduling schemes are designed based on the trip information ordered in advance, which is difficult to meet the real-time changes of demand.

Table 1. Overview of the literature on bus scheduling strategies

	Stop			Route			Timetable			Fleet size	
Author	Fixed	Skip	Express	Initial/single	Alternative	Cross	Fixed	Flexible	Demand driven	Fixed	Flexible
Cao and Ceder (2019)	—	X	—	X	—	—	X	—	—	—	X
Gkiotsalitis et al. (2019)	X	—	—	—	—	X	X	—	—	—	X
Vismara et al. (2021)	—	—	X	X	—	—	—	X	—	X	—
Durán-Micco et al. (2022)	X	—	—	—	X	—	X	—	—	—	X
Rodriguez et al. (2023)	—	X	—	X	—	—	—	X	—	X	—
Ansarilari et al. (2024)	X	—	—	X	—	—	—	—	X	X	—
Our paper	—	—	X	—	—	X	—	—	X	X	—

Note: "X" indicates that the corresponding bus scheduling strategy is addressed in the literature.

Summary

As summarized in Table 1, previous bus scheduling strategies often involve skip-stop approaches, route adjustments, modifications to timetables, or changes in fleet size. Mostly, the bus routes are taken as fixed and inflexible. However, these strategies may not be fully applicable to intercity bus routes in which the travel demand is changing randomly across regions and days. Aims to minimize the bus operating cost and total passenger waiting time through pooling, a cross-route bus-pooling scheduling optimization model with fixed fleet size was developed in this study to improve vehicle dispatching schemes and shrink the turnover time by generating pooling pairs.

Bus-Pooling Scheduling Strategy

Bus-Pooling Condition

The cross-route bus-pooling scheduling strategy should meet the following prerequisites:

1. the routes are long and have a high mileage that exceed the typical bus operating distance (e.g., 30 km), including overlapping operational sections and stations;
2. the selected key bus-pooling station should be located at overlapping stations on the routes with sufficient parking space to accommodate two buses;
3. the time window between the two adjacent buses arriving at the key station meets a certain threshold; and
4. the combined load factor of two adjacent buses that consecutively arrive at the key station should be less than or equal to a certain threshold.

Bus-Pooling Strategy

The cross-route bus-pooling scheduling strategy involves combining buses from two routes based on the pooling conditions at the key station. The bus-pooling illustration is displayed in Fig. 2. When two consecutive buses arriving at the selected key station satisfy the conditions of bus-pooling, passengers of the front bus need to wait for passengers of the following bus to transfer to the front bus. Afterward, the front bus continues its route, while the following bus returns to the origin station corresponding to its route.

Key Station Selection

The key station for implementing the bus-pooling strategy is selected based on the fluctuation of ridership at overlapping stations of two bus routes. The indicator of range R is calculated by the difference between the maximum and minimum ridership, providing a quick assessment of the fluctuation range of ridership (Zhang et al. 2024). The standard deviation indicator σ measures the variability of ridership by calculating the deviation between ridership and the mean of ridership across different time periods, reflecting real-time fluctuations (Sivalingam et al. 2023). Based on the ridership of all buses at overlapping stations, metrics of the range R and standard deviation σ are calculated to measure the fluctuation of ridership. The station with the highest values for these two metrics

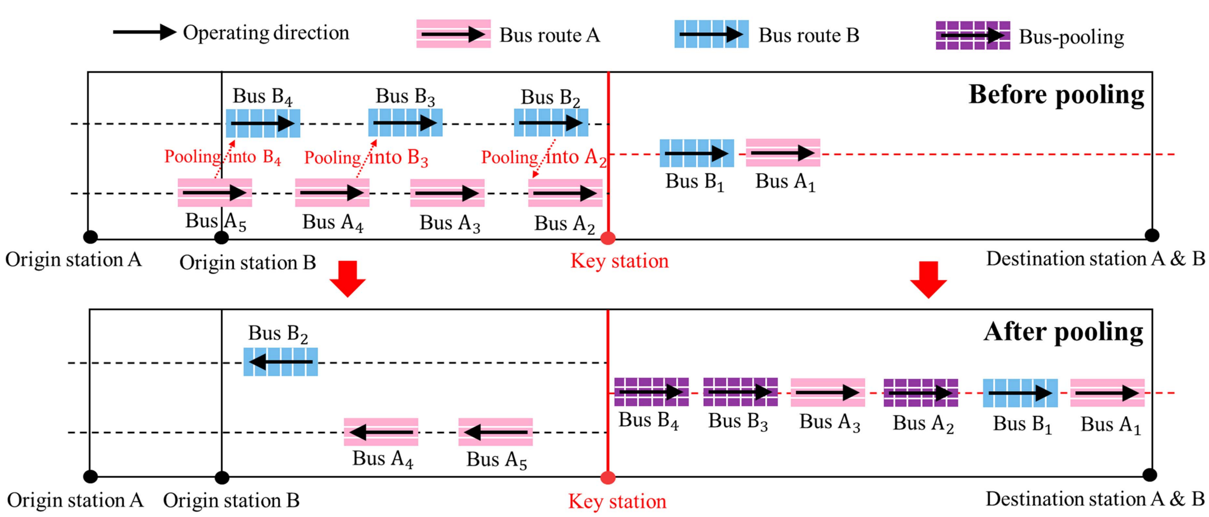

Fig. 2. Bus-pooling illustration.

exhibits the greatest fluctuation in ridership among all overlapping stations and is selected as the key station. Moreover, if the highest values of two metrics do not correspond to the same station, the station with the highest value of deviation σ is selected as the key station.

Bus-Pooling Scheduling Optimization Model and Solution

Model Assumptions

A scheduling strategy for two intercity bus routes with overlapping stations and operation time is proposed based on the following assumptions. The model notation and definitions are provided in the Notation list.

1. The operating time, travel distance, and number of stations are consistent for both directions on the same route, and the bus types for the two routes are consistent.
2. The sizes of the fleet and personnel are equivalent to those in the original scheduling plan.
3. Bus-pooling is implemented without changing the order of the buses; therefore, bus station skipping and overtaking are not considered.
4. The passenger waiting time on the front bus is within a certain threshold.
5. The selected key station has available parking space for two buses.
6. Passengers have advanced knowledge of bus-pooling messages provided by bus operators.
7. The travel time between stations, calculated based on bus card and scanning data, is known.
8. The income of drivers is influenced solely by working hours, which is independent of bus frequency, i.e., labor wages are not considered.
9. The advertising revenue of the bus enterprise and government subsidies are not crucial indexes for bus scheduling and can be disregarded.

Bus-Pooling Scheduling Optimization Model

Phrase Description

When the arrival time window and load factor of two buses at the key station satisfy the bus-pooling conditions, the pooling begins to merge passengers from the following bus into the front bus. Bus route A operates with a frequency of $A_u (u = 1, 2, 3, \ldots, a)$ and has a total number of buses n_A, which starts from the suburban origin station O_A to the urban destination station D_A numbered $(1, 2, \ldots, k, \ldots, x)$. Bus route B operates with a frequency of $B_v (v = 1, 2, 3, \ldots, b)$ and has a total number of buses n_B, which starts from the suburban origin station O_B to the urban destination station D_B numbered $(1, 2, \ldots, k, \ldots, y)$. The key station is denoted by station K with station number k, which divides the route into two parts: suburban and urban areas.

1. Pooling pair

   A pooling pair consisting of two buses from Routes A and B is denoted by $p_r = (p_r^E, p_r^F)$ and $r = 1, 2, \ldots, n_p$, $p_r^E, p_r^F \in \{A_u, B_v\}$, where p_r^E is the front bus, p_r^F is the following bus, and n_p is the number of pooling pairs. The set of all pooling pairs is $P = \{(p_r^E, p_r^F) | r = 1, 2, \ldots, n_p\}$, and the sets of the front buses and the following buses are denoted as $P_E = \{p_r^E | r = 1, 2, \ldots, n_p\}$ and $P_F = \{p_r^F | r = 1, 2, \ldots, n_p\}$, respectively.

   The research time is selected according to the overlap operation time of two bus routes, during which the following bus of a pooling pair can start the next run after it returns to the origin station O_A or O_B. The total number of additional bus runs $\Delta n_p = \sum_{r \in P_F} \Delta n_r$, $\Delta n_r \geq 0$, $\Delta n_P \geq 0$ and the number of bus runs Δn_r added before the end of the research time T_{end} is calculated via Eq. (1)

$$\Delta n_r = \begin{cases} \left[\dfrac{T_{\text{end}} - T_r^K}{t_r^{KO}} \right], & T_r^K < T_{\text{end}}, r \in P_F \\ 0, & T_r^K \geq T_{\text{end}}, r \in P_F \end{cases} \tag{1}$$

   where T_r^K = time at which bus r arrives at station K; and t_r^{KO} = travel time of the following bus from key station K to station O.

2. Frequency

   The total number of buses n^0 for two bus routes is the sum of n_A and n_B. The number of pooling buses $2n_p$ is calculated by $2n_p = n_{A_p} + n_{B_p}$, which includes the number of pooling buses n_{A_p} and n_{B_p} for Bus routes A and B. The number of the non-pooling buses n_{np} is the sum of $n_{A_{np}}$ and $n_{B_{np}}$. The equations $n_{A_p} = n_{A_P}^E + n_{A_P}^F$ and $n_{B_p} = n_{B_P}^E + n_{B_P}^F$ represent the number of buses for Routes A and B that do not participate in bus-pooling, where $n_{A_P}^E$ and $n_{A_P}^F$ are the number of front and following buses from Route A in pooling pairs. Similarly, $n_{B_P}^E$ and $n_{B_P}^F$ are the number of front and following buses from Route B in pooling pairs. Moreover, $n_{A_P}^F$ and $n_{B_P}^F$ are the number of bus returned to the origin stations O_A and O_B. The number of suburban buses n' after pooling is calculated by Eq. (2)

$$n' = n^0 + \Delta n_p = n'_A + n'_B$$
$$\begin{cases} \Delta n_p = n_{A_P}^F + n_{B_P}^F \\ n'_A = n_A + n_{A_P}^F \\ n'_B = n_B + n_{B_P}^F \end{cases} \tag{2}$$

   where n'_A and n'_B = total number of buses for Routes A and B after pooling.

3. Passenger flow

   For Route A, the original ridership, the number of passengers from the suburban stations before (and including) the key station, and the number of passengers from urban stations after the key station are denoted as $Q_A^0 = \sum_{i=1}^{n_A} \sum_{j=1}^{x} q_i^j$, $Q_{A_{sub}}^0 = \sum_{i=1}^{n_A} \sum_{j=1}^{k} q_i^j$, and $Q_{A_{urb}}^0 = \sum_{i=1}^{n_A} \sum_{j=k+1}^{x} q_i^j$, respectively. Similarly, for Route B, the original ridership, the number of passengers at suburban stations and the number of passengers at urban stations are denoted as $Q_B^0 = \sum_{i=1}^{n_B} \sum_{j=1}^{y} q_i^j$, $Q_{B_{sub}}^0 = \sum_{i=1}^{n_B} \sum_{j=1}^{k} q_i^j$, $Q_{B_{urb}}^0 = \sum_{i=1}^{n_B} \sum_{j=k+1}^{y} q_i^j$, respectively. Moreover, the number of passengers boarding at station j on each run i is defined as q_i^j. The number of passengers in the urban area after pooling is calculated as $Q'_{urb} = Q'_{A_{urb}} + Q'_{B_{urb}} = [\lambda_A (x - k)(H_{res}/n_{A_{np}} + n_{A_p}^E)] + [\lambda_B (y - k)(H_{res}/n_{B_{np}} + n_{B_p}^E)]$, where $\lambda_A = Q_{A_{urb}}^0 / H_{res}$ and $\lambda_B = Q_{B_{urb}}^0 / H_{res}$ represent the passenger arrival rates at urban area stations during the research time H_{res}, which are measured in person/min.

   After the implementation of the pooling strategy, the headways for both bus routes in the suburban area are $h'_{A_{sub}} = H_{res}/n'_A$ and $h'_{B_{sub}} = H_{res}/n'_B$, respectively. The number of suburban bus runs for both routes has increased, resulting in a decreased headway compared to the historical operation data.

The number of passengers in the suburban area after pooling is calculated as the sum of the original number of suburban passengers and the additional number of passengers from bus-pooling, that is $Q'_{sub} = Q'_{A_{sub}} + Q'_{B_{sub}} = (Q^0_{A_{sub}} + n^F_{A_p}\Delta Q_{A_p}) + (Q^0_{B_{sub}} + n^F_{B_p}\Delta Q_{B_p})$, $n_{A_p}, n_{B_p} \in P_F$. The increase in the number of passengers from pooling is estimated based on the average number of passengers ΔQ_{A_p} or ΔQ_{B_p}. The average number of passengers per bus on the route is calculated by $\Delta Q_{A_p} = [Q^0_{A_{sub}}/n_A]$, $\Delta Q_{B_p} = [Q^0_{B_{sub}}/n_B]$. The total number of passengers after pooling is calculated as $Q' = Q'_{urb} + Q'_{sub}$.

4. Passenger waiting time

The passenger waiting time can be considered to be half of the headway on average, in accordance with the literature on high-frequency bus services. It is due to the unpredictable and unscheduled arrival of passengers at bus stations (Dai et al. 2020). Before pooling, the total waiting time for all passengers is $T^0_W = \frac{1}{2}(H_{res}/n_A Q^0_A + H_{res}/n_B Q^0_B)$. The average passenger waiting time t^0_W is $t^0_W = T^0_W/(Q^0_A + Q^0_B)$. After pooling, the additional waiting time cost should consider both the waiting time cost for passengers on the front bus and the transfer time cost for passengers on the following bus. The time cost for passengers transferring from the following bus to the front bus primarily consists of the time spent boarding and alighting. According to Khan and Menéndez (2025), the boarding and alighting time for each passenger are 3 s and 2 s, respectively. Compared to the average passenger waiting time, it accounts for only 2.22%. The impact of transfer time on the additional waiting time cost is minimal, equivalent to an average waiting time of 0.08 min, which does not require quantitative analysis. Therefore, the additional waiting time cost caused by pooling primarily focuses on the waiting time cost for passengers on the front bus. The additional waiting time of passengers on the front buses at the key station is $\Delta T'_W = 1/2 \cdot 1/\delta(h'_{A_{sub}} \sum_{P^F_r \in A_u} I^K_{P^E_r} + h'_{B_{sub}} \sum_{P^F_r \in B_v} I^K_{P^E_r})$, $\delta > 0$, where $I^K_{P^E_r}$ is the number of front bus passengers in a pooling pair at the key station, δ represents the pooling tolerance coefficient for passengers waiting at the key station, indicating their tolerance for additional waiting time cost, which relates to factors such as passenger travel purpose, income level, cultural background, weather conditions, etc. If passengers' tolerance of waiting time for pooling at the key station is consistent with those at regular stations, the tolerance factor is set as 1; otherwise, it is set as 1/2 (Hashikami et al. 2023).

After pooling, the total waiting time T'_W for all passengers includes the waiting time for suburban passengers, the waiting time for urban passengers, and the additional waiting time $\Delta T'_W$ for passengers in the front bus of a pooling pair at the key station, that is $T'_W = 1/2H_{res}[(Q'_{A_{sub}}/n'_A + Q'_{B_{sub}}/n'_B) + (Q'_{A_{urb}}/(n_{A_{np}} + n^E_{A_p}) + Q'_{B_{urb}}/(n_{B_{np}} + n^E_{B_p}))] + \Delta T'_W$. The average passenger waiting time after pooling is $t'_W = T'_W/Q'$.

Objective Function

The bus-pooling scheduling optimization model aims to minimize the costs of bus operation and passengers, which includes the opportunity cost, the energy consumption cost, and the passenger waiting time cost. It can effectively improve transport efficiency for bus enterprises and satisfy the diverse travel demand of passengers.

1. Bus operating cost

The operating cost C_{ope} of the bus enterprise can be calculated as the sum of the opportunity cost C_{opp} and the energy consumption cost C_{con} minus the total revenue C_{rev} generated from total number of passengers after pooling, as $C_{ope} = C_{opp} + C_{con} - C_{rev}$.

The additional bus runs result in a corresponding increase in ridership, leading to a rise in the revenue of bus enterprises after pooling. The bus revenue is calculated by $C_{rev} = \alpha_c \beta_c Q'$, $0 < \alpha_c < 1$, $\beta_c > 0$, where α_c represents the revenue weight coefficient of the bus enterprise and β_c is the average ticket price, measured in yuan/person.

The opportunity cost is a widely used concept in economics and is defined as the potential benefit foregone when choosing one option over others. Mirzaei and Siano (2022) applied this concept to develop a charging/discharging scheduling plan for electric vehicle (EV) parking lots. By considering the opportunity cost losses of EV parking lot operators, the plan aimed to prevent a reduction in their profits when EV owners left before the preset time. In the context of public transport, the availability of unused space on buses can enhance the passenger experience but also leads to the bus enterprise forgoing potential profits that could be generated by utilizing that space for other purposes. Therefore, the value of the unused space is defined as the opportunity cost, reflecting the excess transportation capacity and quantifying the potential loss in transporting additional passengers. The opportunity cost C_{opp} at the key station after pooling is represented by Eq. (3)

$$C_{opp} = \alpha_c \beta_c \sum_{p \in P} \begin{cases} (Q_e - I^K_p), & I^K_p \le Q_e \\ 0, & I^K_p > Q_e \end{cases} \qquad 0 < \alpha_c < 1, \beta_c > 0 \tag{3}$$

$$I^K_p = I^K_{p^E_r} + I^K_{p^F_r}$$
$$\mathrm{p}^E_r \in P_E, \qquad \mathrm{p}^F_r \in P_F \tag{4}$$

where Q_e = rated capacity of the front bus; and the total number of passengers I^K_p is the sum of passengers in the front bus $I^K_{p^E_r}$ and the following bus $I^K_{p^F_r}$ of a pooling pair from two routes.

As intercity buses cover long distances, the impact of energy consumption needs to be considered. The operating distance after pooling is estimated based on the number of increased operating bus runs. The energy consumption cost is calculated via Eq. (5)

$$C_{con} = \alpha_c \chi_c L' \qquad 0 < \alpha_c < 1, \qquad 0 < \chi_c \tag{5}$$

$$L' = L'_A + L'_B, \qquad \begin{cases} L'_A = (n_A + n^F_{A_p})L_A \\ L'_B = (n_B + n^F_{B_p})L_B \end{cases} \tag{6}$$

where χ_c = energy price unit distance for buses, measured in yuan/km; L' = total distance after pooling, measured in km; and L_A and L_B = operation mileages of Route A and B, respectively, measured in km.

2. Passenger waiting time cost

The passenger waiting time cost after pooling is $C_t = \alpha_t \beta_{t-c} T'_W$, $0 < \alpha_t < 1$, $0 < \beta_{t-c} < 1$, where α_t is the passenger time weighting coefficient; and β_{t-c} is the coefficient for converting passenger waiting time into travel cost measured in yuan/min, whose value is related to the national economic level of the central city.

3. Objective function

Two primary factors, namely, the operation status of bus enterprises and passenger travel demand are considered in the optimization model. The objective is to minimize both the operating cost C_{ope} for bus enterprises and the total waiting time cost C_t for passengers, which aims to enhance the operational efficiency and provide an excellent passenger experience. The expression is shown in Eq. (7a)

$$\min Z = C_{opp} + C_{con} - C_{rev} + C_t \tag{7a}$$

subject to:

$$|T^K_{p_r^E} - T^K_{p_r^F}| \leq \Delta T \tag{7b}$$

$$T^K_W \leq \Delta t \tag{7c}$$

$$\omega^K_{P_r^E} + \omega^K_{P_r^F} \leq \Delta\omega, \qquad 0 \leq \omega^K_{P_r^E} \leq 1, \qquad 0 \leq \omega^K_{P_r^F} \leq 1 \tag{7d}$$

$$0 < \Delta n_p < n^0, \qquad 0 < \Delta n_r \tag{7e}$$

$$\alpha_c + \alpha_t = 1, \qquad 0 < \alpha_c < 1, \qquad 0 < \alpha_t < 1 \tag{7f}$$

$$0 < \beta_c, \qquad 0 < \chi_c, \qquad 0 < \beta_{t-c} < 1 \tag{7g}$$

The constraint conditions include bus-pooling constraints, bus comfort constraints, and cost weight constraints. Specifically, Eq. (7b) ensures that the arrival time window of two buses at the key station falls within a threshold range determined from historical data. Eq. (7c) sets a limit on the acceptable waiting time for passengers pooling at the key station within a threshold range. Eq. (7d) ensures that the load factor of two buses before and after the key station does not exceed 1, thereby satisfying the pooling conditions and maintaining passenger comfort. Eq. (7e) guarantees that the maximum number of additional bus runs does not exceed the total number of operational buses during the research time. Eq. (7f) describes the complementarity between the operating cost of bus enterprises and the cost of passenger waiting time, with their sum equaling 1. Eq. (7g) ensures that the average bus ticket price and energy price remain positive, with the coefficient for converting the passenger waiting time cost greater than 0 and less than 1.

Adaptive Genetic Algorithm

The established cross-route bus-pooling scheduling is a complex nonlinear programming (NLP) problem that cannot be directly solved using traditional linear mathematical programming methods. A genetic algorithm (GA) is a globally optimizing adaptive probabilistic search algorithm known for its simplicity, versatility, strong generality, and robust performance, making it suitable for tackling high-dimensional complex problems. However, the traditional genetic algorithm, which relies solely on specific crossover and mutation probabilities without considering the strengths and weaknesses of these operators, encounters significant limitations with regard to convergence. To address this issue, adaptive genetic algorithm (AGA), proposed by Srinivas and Patnaik (1994), aims to improve the convergence speed of the algorithm, which employed the adaptive solution formulas for crossover probability P_c and mutation probability P_m via Eq. (8)

$$P_c = \begin{cases} \dfrac{g_1(f_{\max} - f')}{f_{\max} - \bar{f}} & f' \geq \bar{f} \\ g_2 & f' < \bar{f} \end{cases}$$
$$P_m = \begin{cases} \dfrac{g_3(f_{\max} - f)}{f_{\max} - \bar{f}} & f \geq \bar{f} \\ g_4 & f < \bar{f} \end{cases} \tag{8}$$

where $f_{\max}$ and $\bar{f}$ = maximum and average fitness values in the population. The value of f' is the larger fitness value between two individuals crossed, and f is that to be mutated. The variables $g_1 - g_4$ are all constants in the (0,1] interval.

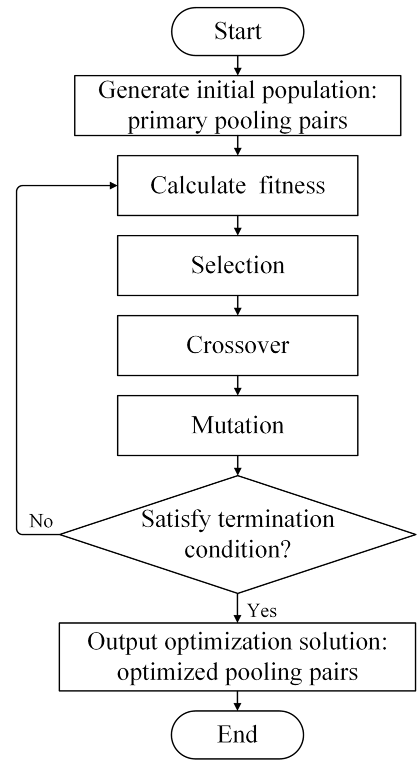

Fig. 3. Flow of the adaptive genetic algorithm.

AGA is utilized to solve the proposed model, as illustrated in Fig. 3. The primary objective is to obtain approximate optimal solutions and ultimately determine the best pooling pairs. Initially, valid pooling pairs are calculated and encoded using binary strings to generate the initial population. The fitness function is defined as $f = Z$, and the value of the fitness function is calculated for each pooling pair, considering the relevant constraints. The fitness function is used to optimize individuals and form a new population using roulette wheel selection, single-point crossover, and single-point mutation operations. The populations resulting from the crossover and mutation operations are screened using the adaptive crossover probability and adaptive mutation probability. These steps are repeated until a satisfactory termination condition is met, which in this case is when the number of generations reaches a predefined limit. The algorithm terminates when the fitness function values are optimized, indicating that the population has achieved the optimal solution.

Case Study

Data Preparation

Intercity bus routes No. 838 (Route A) and No. 917 Express (Route B) in Beijing, which have different origin stations in the rural area but the same destination station in the urban area, were selected for the case study, as shown in Fig. 4. Route A covers 67 km with 24 stations. It operates from 4:40 a.m. to 7:00 p.m., with an average travel time of 105 min. Route B covers 109 km with 62 stations. It operates from 4:30 a.m. to 5:30 p.m., with an average travel time of 148 min. The average daily ridership for Route A is 5,195, while Route B has 3,193. These two routes have overlapping stations at K_1, K_2, and K_3. The vehicles in these two routes have 63 seats and the maximum passenger capacity is 86. No significant weather changes or emergency situations occurred during the research time.

According to 5,346 pairs of origin-destination (OD) data for Route A and 2,910 pairs of OD data for Route B on May 14, 2021 (Friday), an analysis of passenger distribution throughout the day in Fig. 5 reveals an obvious morning peak period from 5:00 a.m. to 8:00 a.m., which was consequently selected as the research time. There were 38 buses of Route A and 24 buses of Route B, which are described by $A_u(u = 1, 2, 3, \ldots, 38)$ and $B_v(v = 1, 2, 3, \ldots, 24)$.

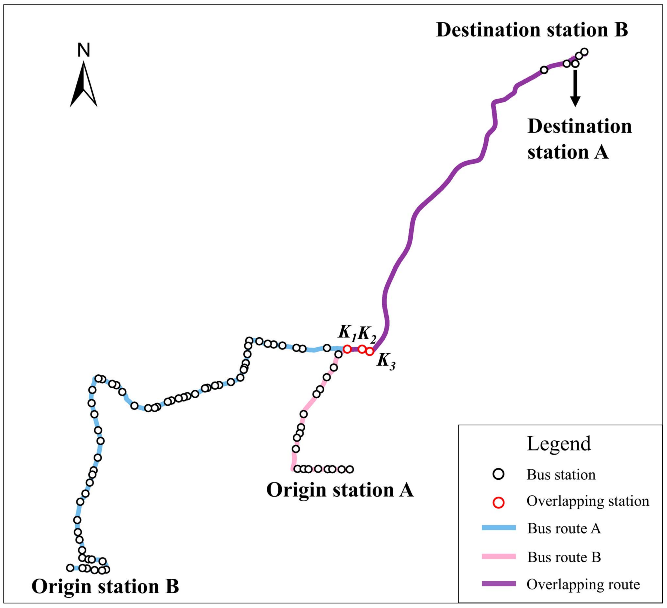

Fig. 4. Bus route 838 and 917 Express directions.

Key Station

The ridership distributions for the two routes at the three overlapping stations (number K_1, K_2, K_3) are illustrated in Fig. 6. An analysis of the changes in ridership across all buses at these stations was conducted. Both the range R and standard deviation σ were adopted as metrics to jointly assess the fluctuation of ridership at three stations, which are calculated in Table 2. Since station K_1 had the largest value (the bold values in Table 2) in both metrics, it was selected as the key station K for bus-pooling.

Model Solution

Model Parameters

Based on IC card data, the number of passengers during the selected morning peak hours were 1,741 for Route A and 1,094 for Route B. The time interval ΔT of buses was deduced to be 5 min

Table 2. Ridership fluctuation metrics at three overlapping stations

	Range (R)		Standard deviation (σ)	
Station	Route A	Route B	Route A	Route B
K_1	**60**	**50**	**13.16**	**12.97**
K_2	56	42	13.10	11.65
K_3	54	42	12.73	11.53

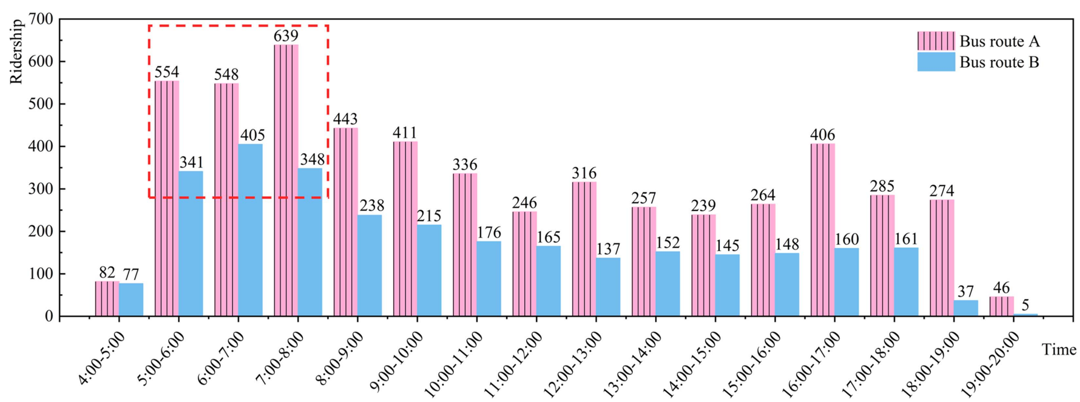

Fig. 5. Research time of Routes A and B.

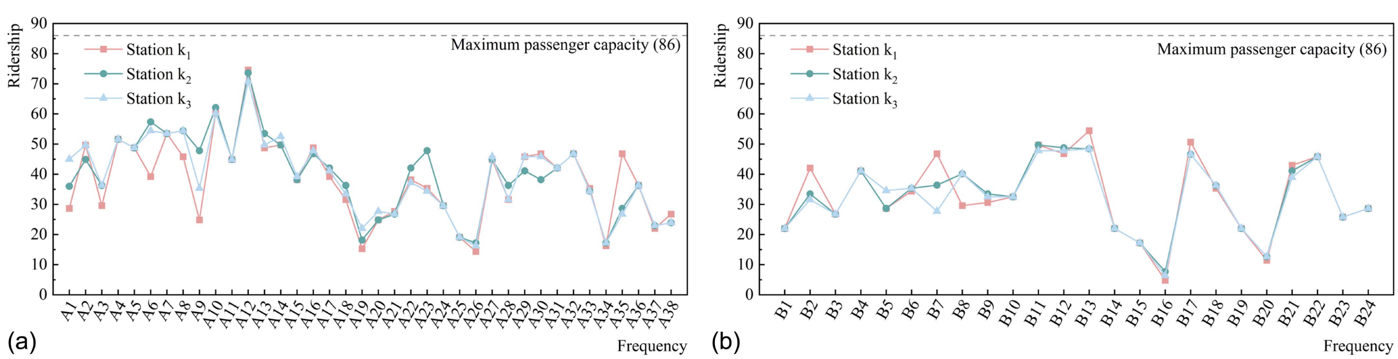

Fig. 6. The ridership of all buses for Routes A and B at overlapping stations.

according to average departure interval. The load factor threshold $\Delta\omega$ was defined as 1 considering the in-vehicle crowding discomfort of passengers. The fare system for these two routes charged a base fare of 2 yuan for distances up to 10 km, with an additional 1 yuan for every 5 km thereafter. The maximum fare for Route A was 14 yuan, while for Route B, it was 21 yuan. Beijing's bus IC cards primarily consisted of general, student, and senior cards, offering 50%, 75% discounts, and free travel, respectively. On Route A, 82.94% of passengers used a general card, 6.72% used a student card, and 8.67% used a senior card. On Route B, these percentages were 81.63%, 8.50%, and 8.14%, respectively. Therefore, the per capita fare β_c was set to 8 yuan/person based on the types of IC card used by passengers.

The time-conversion cost coefficient β_{t-c} was set at 0.8 yuan/min according to the level of gross domestic product (GDP) per capita in Beijing. The vehicles of two routes mainly used diesel, with a fuel consumption of 30 L per 100 km and an average diesel price of 8 yuan/L, so the energy consumption cost χ_c was set to 2.4 yuan/km. Suppose that the patience of passengers waiting for bus-pooling in the front bus is half that of passengers waiting at regular bus stations, resulting in a tolerance coefficient δ of 0.5. The bus operating cost and passenger waiting time cost were considered equally important, thus, α_c and α_t are set to 0.5. The detailed values are given in Table 3.

Solution Calculation

With the objective of minimizing Z, considering the relevant constraints, AGA was utilized to solve the cross-route bus-pooling optimization model based on the extracted bus load factor and arrival time data from operational buses of two routes. On a laptop computer [Intel (R) Core (TM) i5-8300H @ 2.30 GHz; 8G RAM; Microsoft Windows 10], the running time of the AGA for this case was 183 s (population size = 100; generations = 200). When 17 pooling pairs were generated, the objective function Z reached its optimal value of 6,443,415.82 yuan. The detailed optimized timetable by the model is provided in the Appendix. The corresponding routes are displayed in Fig. 7. Among these routes, 10 pooling pairs involve different bus routes, while seven pooling pairs are matched within the same route. Specifically, 10 pooling pairs were able to successfully return to the origin station before the end of peak hours (8:00:00 a.m.). These pairs were (A1, A2), (A3, A4), (A6, B1), (B2, B3), (A8, B4), (B5, A11), (B7, B8), (A14, B9), (A15, A16), and (A18, A19).

Table 3. Model parameter settings

Parameter	Value	Unit
α_c	0.50	—
α_t	0.50	—
β_c	8.00	yuan/person
β_{t-c}	0.80	yuan/min
χ_c	2.40	yuan/km
δ	0.50	—
ΔT	5.00	min
$\Delta\omega$	1.00	—

Optimization Result Analysis

Bus Operational Efficiency

During the morning peak hours, the passenger flow changed significantly before and after implementing the bus-pooling strategy on two routes. The combined total number of bus runs for the two routes increased from 62 to 72, representing a 16.13% increase compared to the original scheduling. There were 10 additional bus runs in total, including five bus runs from Route A and five bus runs from Route B. This increase effectively reduced the headway between vehicles, resulting in a more even distribution of load factor across different buses, regardless of when they arrived at stations. Additionally, the total ridership grew from 2,835 to 3,480 according to average number of passengers calculated by $\Delta Q_{A_p} = [Q^0_{A_{sub}}/n_A]$ and $\Delta Q_{B_p} = [Q^0_{B_{sub}}/n_B]$ from additional bus runs in Routes A and B, indicating a significant increase of 22.75%. Specifically, the ridership on Route A increased from 1,741 to 2,071, while that on Route B increased from 1,094 to 1,409. The additional operational bus runs and increased passenger flow on two routes signify a substantial enhancement in bus operational efficiency.

Bus operational efficiency includes two key aspects: vehicle utilization and operational passenger efficiency. Vehicle utilization is measured by two metrics: ridership per vehicle and operational

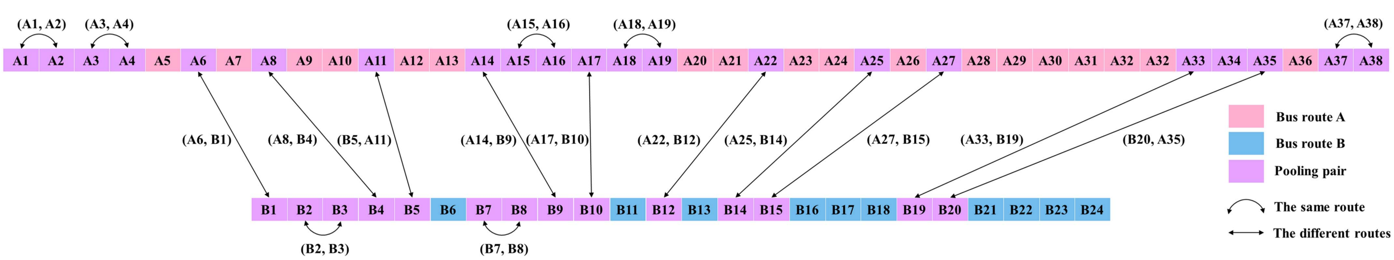

Fig. 7. Optimal solution of bus-pooling pairs.

Table 4. Changes in the evaluation indicators of bus operational efficiency

	Before pooling			After pooling			Improved ratio (%)		
Indicator	Route A	Route B	Total	Route A	Route B	Total	Route A	Route B	Total
The number of bus runs	38	24	62	43	29	72	13.16%	20.83%	16.13%
Ridership	1,741	1,094	2,835	2,071	1,409	3,480	18.95%	28.79%	22.75%
Ridership per vehicle	46	46	46	49	48	48	7.63%	5.46%	5.70%
Ridership per operational mileage	26	10	16	31	13	20	18.95%	28.79%	22.75%

Table 5. Changes in the passenger waiting time

Waiting time (min/person)	Before pooling			After pooling			Improved ratio (%)		
	Route A	Route B	Total	Route A	Route B	Total	Route A	Route B	Total
Mean	2.37	3.75	2.90	2.86	3.57	3.15	20.89%	−4.72%	8.58%
Suburban mean	2.37	3.75	2.96	2.09	3.10	2.49	**−11.63%**	**−17.24%**	**−15.88%**

mileage per vehicle. Operational passenger efficiency is evaluated through the ridership per operational mileage. The indicator of operational mileage per vehicle remains consistent, and the values of other relevant indicators for bus operational efficiency before and after bus-pooling are displayed in Table 4. The overall unused space for the two routes decreased from 3,089 to 1,627 person, representing a 47.33% reduction compared with that before pooling, which avoids a waste of 5,848 yuan in opportunity cost. Due to the distinct operational characteristics of routes, there were variations in the changes observed in the two routes after implementing the bus-pooling strategy.

There was a significant increase in passenger flow and operational bus runs attributable to the pooling strategy, resulting in a notable raise in bus turnover speed and a reduction in the waste of bus capacity resources. In terms of ridership per vehicle, Route A increased from 46 to 49 persons per bus, which was greater than that of Route B because Route A had more additional passenger flow than Route B does. Regarding the indicator of ridership per operational mileage, Route A increased from 26 to 31 persons per km, and Route B increased from 10 to 13 persons per km. The indicator values for both routes showed significant improvements, primarily due to the bus-pooling strategy increasing turnover speed and attracting additional ridership. It provides an effective solution to the issue of insufficient long-distance intercity bus capacity without altering fixed fleet sizes. These improvements offer significant advantages to bus enterprises by enhancing the overall efficiency of bus operation.

Passenger Waiting Time

The bus-pooling strategy can significantly reduce the average waiting time for suburban passengers, as detailed in Table 5. Although the total average waiting time of Route A experienced an increase of 29 s due to additional waiting time at the key station., Route B experienced a slight decrease of 4.72% compared to the initial scheduling because of having only three bus runs as the front bus in pooling pairs and a higher additional passenger ratio compared to Route A. This indicates that the implementation of a bus-pooling strategy can effectively reduce the time passengers spend waiting for their trips without significantly impacting their travel experience.

Since the numbers of suburban passengers were 1,625 and 969 for Routes A and B, respectively, which dominated ridership by 93.34% and 88.57%, respectively, the discussion on waiting time for suburban passengers has practical application significance. Notably, the average waiting time for suburban passengers from both routes decreased from 2.96 to 2.49 min per person, indicating a 15.88% decrease due to the pooling strategy due to the increased bus runs in the suburban segments of the routes.

Specifically, the average waiting time for suburban passengers on Route A and Route B decreased by 11.63% and 17.24% respectively, compared to the initial scheduling. The primary reason for this improvement was the increased bus runs on the suburban routes, which accelerated the turnover speed. For a suburban passenger who travels on Route B 30 times a month with an average waiting time of 10 min per trip, the bus-pooling strategy can benefit a total time savings of 51.72 min each month. It demonstrates the effectiveness of the bus-pooling strategy in reducing the waiting time for suburban passengers and better catering to their travel demands. Furthermore, the implementation of the bus-pooling strategy enhances social equity by improving the accessibility of public transportation services in suburban areas.

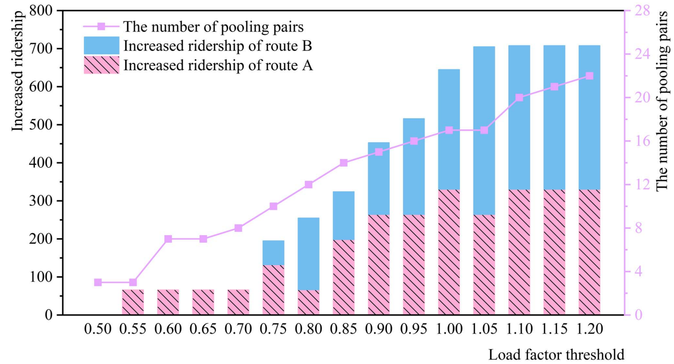

Fig. 8. Changes in ridership under different load factor threshold settings.

Discussion

Sensitivity Analysis on Load Factor Threshold

The performance of the proposed model is measured by the ridership change before and after pooling with the restriction of the load factor threshold, as displayed in Fig. 8. With an increase in the threshold, the number of pooling pairs and accompanying ridership constantly increase. When the load factor threshold is below 0.55, there are no additional bus runs, resulting in a zero increase in passenger flow. There is only an increase in additional bus runs observed for Route A at a threshold of [0.55, 0.70]. At a value of 1.05, both the number of pooling pairs and the increased ridership are optimal, making it suitable as the threshold in practical applications. If the overlapping segments of routes run through the highway where standing is not allowed for passengers (similar to the case study), 1.0 can be set as the optimal threshold, considering safety and passenger comfort. Moreover, when the threshold exceeds 1, despite the subtle increase in additional passenger flow, it may result in crowding within the bus compartments, potentially compromising passengers' overall travel comfort.

Bus-pooling is a passive behavior for passengers who may have a psychological resistance to this strategy. The perceived comfort of passengers can make the waiting time feel longer than it actually is, reducing their tolerance. Therefore, the tolerance coefficient δ is used to analyze the relationship between waiting time cost and bus comfort (load factor threshold), as shown in Fig. 9. The waiting time cost increases as the load factor threshold rises at the same level of tolerance. When the threshold exceeds 0.7, passenger tolerance sharply decreases, leading to a faster rise in waiting time cost.

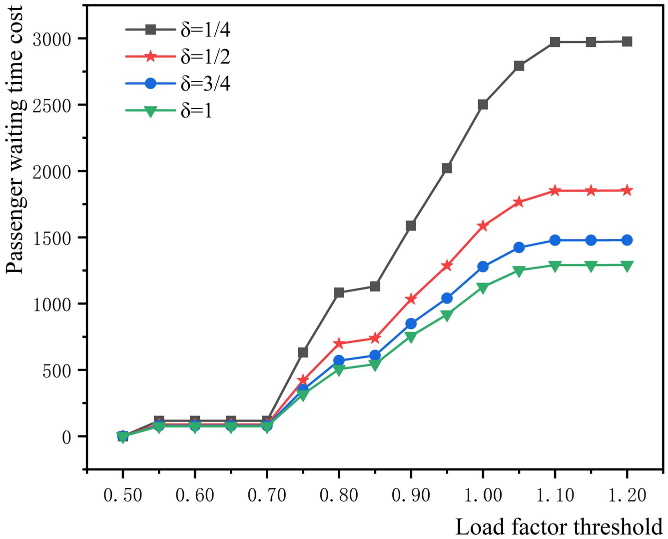

Fig. 9. The changes of waiting time cost with the load factor threshold setting.

Table 6. Pooling scheduling optimization results over five consecutive days

Date	Increased runs in Route A	Increased runs in Route B	Increased ridership in Route A	Increased ridership in Route B
05.10	4	4	312	287
05.11	4	5	301	362
05.12	5	4	323	308
05.13	6	4	367	265
05.14	5	5	330	315
Total	24	22	1,632	1,536

The total valid data of 41,940 OD pairs from two routes on five consecutive working days (May 10–14, 2021) were used for validating the general effectiveness and demonstrate the significant guiding value of the proposed model. The research period was determined in the morning peak from 5:00 a.m. to 8:00 a.m., with station K_1 selected as the key station (K_3 on May 10) based on two metrics: the range R and standard deviation σ of ridership. Based on the arrival time and load factor data of all buses on two routes at the key station, the AGA was used to solve the proposed model and generated the results of the pooling pairs, as displayed in Table 6. After real-time pooling scheduling optimization, the total increases in the number of runs and ridership for Route A accounted for 12.24% and 18.67%, respectively. For Route B, the growths were 16.79% and 26.32%, respectively. Moreover, the pooling pairs were generated based on the real-time fluctuations in passenger flow, with the number and combinations of pool pairs varying each day. This approach demonstrates significant optimization effect in solving the dynamic distribution of ridership.

Advantages Compared to Conventional Scheduling

Conventional bus scheduling typically involves adjusting departure buses, optimizing timetables, and refining route layouts, such as using shuttle buses and customized services. As a flexible scheduling solution, the bus-pooling can adjust vehicle departure intervals in the response to the actual passengers demands under the restriction of the bus fleet. Conventional fixed-frequency scheduling typically involves either increasing or decreasing the service frequency of bus routes to enhance the number of onboard passengers and improve the load factor of buses. However, they have certain limitations. Increasing frequency results in higher fixed vehicle costs, which raises operational cost of bus enterprises. On the other hand, reducing service frequency of two routes leads to the raised bus headway. Due to the characteristics of long travel distance and scattered residents in intercity buses, it will significantly increase

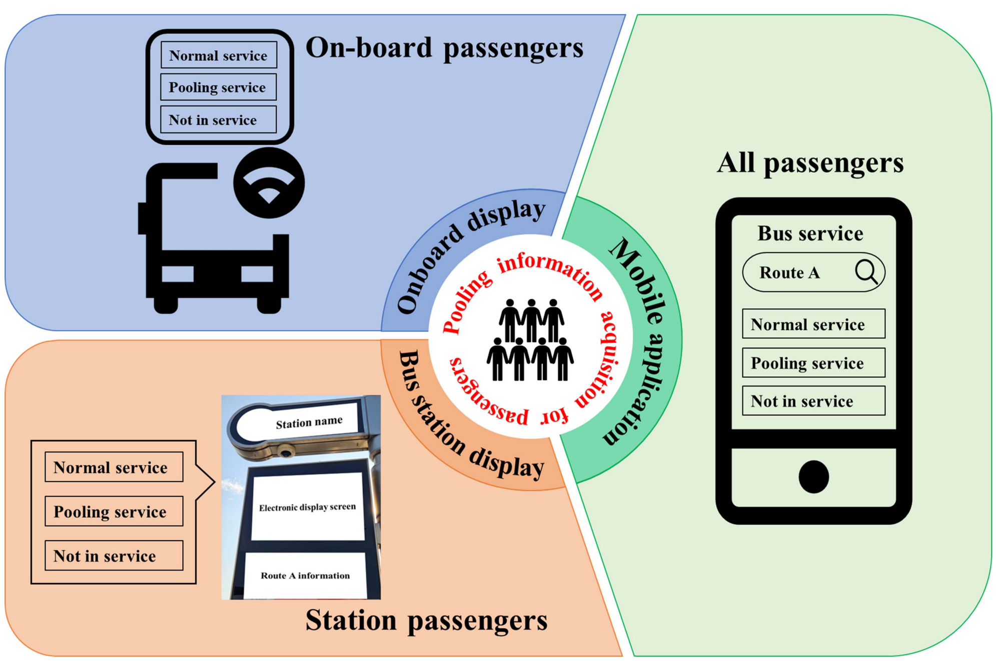

Fig. 10. The ways passengers obtain pooling information.

the passenger wait time and diminish their travel satisfaction of service convenience.

In comparison to conventional fixed-frequency scheduling, the proposed pooling strategy has advantages in the following aspects: (1) it can significantly reduce the fixed vehicle cost and improve vehicle utilization without additional vehicles and terminal yard area required for two redesigned routes; (2) it has a more flexible vehicle frequency design than the shuttle bus service; (3) bus-pooling is a dynamic decision response according to the bus load and arrive time in real time so that it is flexible for the dynamic travel demand of passengers, resulting in a more even distribution of passengers among all buses and improving passenger comfort; and (4) compared with a customized bus, it can better adapt to the real-time changes in ridership fluctuations and achieve more flexible feeder services.

Application

In practice, a bus-pooling strategy can benefit from the development of intelligent transportation systems (ITS), the Internet of Things (IoT), and information exchange technology. The bus arrival time at the station and the real-time load factor after the passengers' boarding is easy to acquire in the system. Real-time data can be collected through onboard sensors and communication devices on buses. From the interaction with the central server, precise monitoring of the bus load and arrival time can be achieved. The central server has efficient data processing and analysis capabilities, allowing for real-time processing of large volumes of data and decision-making based on preset pooling conditions. In practice, the smart scheduling system has currently enabled 21,285 buses in Beijing to achieve regional dispatching, which can also perform well for bus-pooling strategies. When two buses from two routes arrive consecutively at the key station under the thresholds of the time difference less than 5 min and the load factor less than 1, bus-pooling instructions are issued. Once the pooling decision is made, the dispatcher of bus enterprises sends instructions to the drivers of relevant buses via onboard devices. Moreover, to enhance passengers' awareness and acceptance of the pooling strategy, effective pooling information and additional waiting time will be offered to the passengers in advance through variable message signs (VMS) on the bus, at the bus station, websites, as well as the application for the smart phone, as shown in Fig. 10. Passengers can acquire effective pooling information in advance through various devices to make subsequent travel decisions. Some traditional scheduling methods, such as shuttle bus operations, will result in buses being "not in service." Compared to "normal bus" and "not in service," the pooling service has more advantages.

Bus-pooling scheduling, similar to taxi ride-sharing, is more flexible and efficient compared to traditional scheduling. It offers significant practical value, particularly in the following aspects: (1) Resource optimization and efficiency gains: both systems enable shared vehicle use to improve vehicle utilization and increase operational frequency, which reduces the operating cost of the enterprise through better resource allocation. (2) Flexible scheduling and demand-driven operations: bus-pooling adjusts scheduling plans dynamically based on real-time passenger demand, similar to the demand-responsive routing in taxi ride-sharing. It eliminates the need for passenger reservations, which formulates the best scheduling plan in real time adapting to fluctuating ridership. (3) Enhanced travel experience: real-time scheduling in bus-pooling offers passengers a more convenient and efficient travel experience by reducing their average waiting time, overcoming the constraints of fixed routes and providing more flexible, demand-oriented services.

Conclusions

This study has developed a cross-route bus-pooling scheduling optimization model with the aim of generating pool pairs at a key station that allocate passengers from one bus to another, thereby increasing operational bus runs and reducing operational and passenger-related costs while adhering to a set of constraints. It effectively enhances the transport efficiency of buses and prevents the waste of unused resources, which promotes the sustainable development of public transportation. The model utilizes AGA to obtain an approximate optimal solution based on real-time data, considering pooling conditions. The main findings are as follows:

1. The proposed model is a universal framework that considers the bus operating cost, including the opportunity cost, energy consumption cost, and the passenger waiting time cost. The model caters to diverse passenger demands while enhancing bus operational efficiency.
2. AGA is employed to solve the model, with a computation time of 183 s, enabling real-time calculations of pooling demand. It is suitable for intercity routes with significant interstation distances.
3. In the case study, 10 additional operational bus runs were generated, leading to an increase in ridership from 2,835 to 3,480 and a 15.88% decrease in the average waiting time of suburban passengers. The total waiting time saving in a month reach to 34.89 or 51.72 min, respectively, for a passenger of Routes A or B.
4. Bus-pooling provides real-time response decision to enhances vehicle utilization under the restriction of fleet size. The number of pooling pairs and additional ridership constantly increase with the load factor threshold, which can be set by 1.0 as the optimal value in practice.

The limitation of this study is that the passengers detour cost associated with inconsistent terminals after pooling is not considered. Future research will address the effect of environment, infrastructure, and passenger travel behavior to the efficiency of bus-pooling systems. Furthermore, the proposed methodology can be extended to other fields, such as car sharing, courier services, and logistics to enhance transportation system efficiency and promote the sustainable development of the sharing economy in the future.

Appendix. Timetable after Pooling

The arrival time at stations for additional buses from two routes are calculated, where "RE" represents return buses and the "N" indicates next operational buses.

	Arrival time		Departure time	Arrival time	
Bus ID	Station O_A or O_B	Station K	Station K	Station D	Direction
A1	5:00:30	5:41:00	5:45:22	7:15:30	$O_A \rightarrow D$
A2	5:05:24	5:45:22	—	—	$O_A \rightarrow K$
A2RE	6:13:22	5:45:22	—	—	$K \rightarrow O_A$
A2N	6:13:22	6:53:20	—	—	$O_A \rightarrow K$
A3	5:10:24	5:49:52	5:54:13	7:22:05	$O_A \rightarrow D$
A4	5:15:02	5:54:13	—	—	$O_A \rightarrow K$
A4RE	6:22:13	5:54:13	—	—	$K \rightarrow O_A$
A4N	6:22:13	7:01:24	—	—	$O_A \rightarrow K$
A6	5:25:24	6:04:29	6:07:51	7:34:51	$O_A \rightarrow D$
B1	5:01:55	6:07:51	—	—	$O_B \rightarrow K$
B1RE	7:12:51	6:07:51	—	—	$K \rightarrow O_B$
B1N	7:12:51	8:19:57	—	—	$O_B \rightarrow K$
B2	5:02:04	6:13:41	6:14:07	7:10:24	$O_B \rightarrow D$

Appendix. (*Continued.*)

Bus ID	Arrival time: Station O_A or O_B	Arrival time: Station K	Departure time: Station K	Arrival time: Station D	Direction
B3	5:02:36	6:14:07	—	—	$O_B \rightarrow K$
B3RE	7:20:07	6:14:07	—	—	$K \rightarrow O_B$
B3N	7:20:07	8:32:55	—	—	$O_B \rightarrow K$
A8	5:35:14	6:16:24	6:18:28	7:50:05	$O_A \rightarrow D$
B4	5:10:04	6:18:28	—	—	$O_B \rightarrow K$
B4RE	7:24:28	6:18:28	—	—	$K \rightarrow O_B$
B4N	7:24:28	8:34:05	—	—	$O_B \rightarrow K$
B5	5:12:03	6:30:53	6:33:37	7:35:34	$O_B \rightarrow D$
A11	5:47:09	6:33:37	—	—	$O_A \rightarrow K$
A11RE	7:06:37	6:33:37	—	—	$K \rightarrow O_A$
A11N	7:06:37	7:53:05	—	—	$O_A \rightarrow K$
B7	5:20:34	6:38:07	6:42:09	7:43:05	$O_B \rightarrow D$
B8	5:26:34	6:42:09	—	—	$O_B \rightarrow K$
B8RE	7:49:09	6:42:09	—	—	$K \rightarrow O_B$
B8N	7:49:09	9:06:05	—	—	$O_B \rightarrow K$
A14	6:00:16	6:51:44	6:52:08	8:46:42	$O_A \rightarrow D$
B9	5:30:04	6:52:08	—	—	$O_B \rightarrow K$
B9RE	7:59:08	6:52:08	—	—	$K \rightarrow O_B$
B9N	7:59:08	9:22:40	—	—	$O_B \rightarrow K$
A15	6:05:15	6:56:08	6:59:57	8:53:12	$O_A \rightarrow D$
A16	6:09:54	6:59:57	—	—	$O_A \rightarrow K$
A16RE	7:34:57	6:59:57	—	—	$K \rightarrow O_A$
A16N	7:34:57	8:25:00	—	—	$O_A \rightarrow K$
A18	6:20:25	7:08:31	7:09:56	8:57:01	$O_A \rightarrow D$
A19	6:20:58	7:09:56	—	—	$O_A \rightarrow K$
A19RE	7:45:56	7:09:56	—	—	$K \rightarrow O_A$
A19N	7:45:56	8:34:54	—	—	$O_A \rightarrow K$

Note: Bold values represent 10 additional bus runs before the end of peak hours (8:00:00 a.m.).

Data Availability Statement

Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

Acknowledgments

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Notation

The following symbols are used in this paper:

A_u = operational frequency of Route A, and $u = (1,2,3,\ldots,a)$ is each run;
B_v = operational frequency of Route B, and $v = (1,2,3,\ldots,b)$ is each run;
C_{con} = energy consumption cost;
C_{ope} = bus operating cost;
C_{opp} = opportunity cost at the key station;
C_{rev} = bus operating revenue;
C_t = passenger waiting time cost;
D_A, D_B = destination station of Route A/B;
H_{res} = selected research time;
$h'_{A_{sub}}, h'_{B_{sub}}$ = headway of Bus route A/B in the suburban area;
I_p^K = total number of passengers on the bus at the key station;
$I^K_{p_r^E}, I^K_{p_r^F}$ = number of passengers on the front/following bus at the key station;
K = key station, station number is k;
L_A, L_B = total distance of Route A/B;
L' = total distance of two routes after pooling;
L'_A, L'_B = total distance of Route A/B after pooling;
n^0, n' = total number of bus runs for two routes before/after pooling;
n_A, n_B = total number of buses for Route A/B;
n_{A_p}, n_{B_p} = number of pooling buses for Route A/B;
$n^E_{A_P}, n^F_{A_P}$ = number of front/following buses from Route A;
$n_{A_{np}}, n_{B_{np}}$ = number of nonpooling buses for Route A/B;
$n^E_{B_P}, n^F_{B_P}$ = number of front/following buses from Route B;
n_{np} = number of nonpooling buses for two routes;
n_p = number of pooling pairs;
n'_A, n'_B = number of suburban bus runs for Route A/B after pooling;
O_A, O_B = origin station of Route A/B;
P = a set of all pooling pairs;
P_E, P_F = a set of the front/following buses;
p_r^E, p_r^F = the front/following bus;
Q^0, Q' = ridership of two routes before/after pooling;
Q_A^0, Q_B^0 = original ridership of Route A/B;
$Q^0_{A_{sub}}, Q^0_{A_{urb}}$ = passenger number of suburban/urban stations for Route A;
$Q^0_{B_{sub}}, Q^0_{B_{urb}}$ = passenger number of suburban/urban stations for Route B;
Q_e = rated capacity of the bus;
$Q'_{A_{sub}}, Q'_{A_{urb}}$ = number of suburban/urban passengers for Route A after pooling;
$Q'_{B_{sub}}, Q'_{B_{urb}}$ = number of suburban/urban passengers for Route B after pooling;
Q'_{sub}, Q'_{urb} = number of passengers in suburb/urb area after pooling;
q_i^j = ridership boarding at station j on each run i;
T_{end} = end of research time;
T_r^K = time of bus r to arrive at the key station;
$T^K_{P_r^E}, T^K_{P_r^F}$ = time of the front/following bus to arrive at the key station;
T_W^0, T'_W = total passengers' waiting time before/after pooling;
T_W^K = passenger' acceptable waiting time for pooling;
t_r^{KO} = time of the following bus from the key station to the origin station;
t_W^0, t'_W = average passenger waiting time before/after pooling;
x = destination station number of Route A;
y = destination station number of Route B;
Z = objective function;
α_c = cost weight coefficient of the bus enterprise;
α_t = passenger time weight coefficient;
β_c = average ticket price for the bus route, yuan/ person;
β_{t-c} = coefficient for converting passenger waiting time into travel cost, yuan/min;
Δn_P = total number of additional bus runs added;

Δn_r = the number of bus runs added before T_{end};
ΔQ_{A_p}, ΔQ_{B_p} = average number of passengers for Route A/B;
ΔT = threshold of arrival time window;
$\Delta T'_W$ = additional waiting time of passengers on front buses;
Δt = threshold of passenger acceptable waiting time;
$\Delta \omega$ = the load factor threshold;
δ = pooling tolerance coefficient for passengers;
λ_A, λ_B = passenger arrival rate of Bus route A/B at urban stations;
χ_c = energy price unit distance for the bus; and
$\omega^K_{P^E_r}$, $\omega^K_{P^F_r}$ = load factor of front/following buses at the key station.

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