Cooperative Optimization of Train Timetabling and Stop Planning Considering Passenger flow allocation for Intercity Railway

Ruicheng Wang, Changfeng Zhu, Yunqi Fu, Jie Wang, Linna Cheng, Rongjie Kuang

Abstract—**Coordinating timetabling and station stop plans is of significant importance. It enhances passenger travel and maximizes railway revenue. We analyze passenger flows and calculate the probability of a passenger selecting a particular train. This helps us distribute passenger flow effectively.Based on this, we propose a multi-objective optimization model for intercity railway timetables and station stop plans. The model aims to lower operational costs and reduce travel expenses. It includes constraints like departure times, stop durations, and stop frequencies. We use an Adaptive Large Neighborhood Search (ALNS) algorithm to solve it under bounded rationality.A case study on a specific intercity railway demonstrates the effectiveness of both the model and the algorithm. We also study key parameters to understand their effects on timetabling and station stops. The findings reveal that passenger allocation plays a significant role in coordinated optimization. When the minimum load factor threshold rises, there are fewer train stop plans. At the same time, passenger travel costs increase while enterprise costs decrease. This aligns with the operator's approach. Ultimately, this study offers valuable decision-making insights for railway operators and passengers alike.**

Index Terms—**Intercity railway; Train timetable; Train stop plan; Passenger flow allocation**

I. INTRODUCTION

Urbanization and the development of city clusters are accelerating. This has caused a significant surge in intercity passenger demand. This growth is driven by several key factors, including sustained economic expansion and population growth. Demand is also rising for efficient networks that seamlessly connect urban hubs.

Nevertheless, contemporary intercity rail services face significant challenges. These include long waiting times, poor punctuality, and insufficient capacity. Such issues hinder their ability to meet passenger needs effectively. Accordingly, the coordinated optimization of timetables and stop plans is essential. Developing robust and tailored train operation plans is crucial, as this approach enhances the competitiveness of intercity rail services and improves overall service quality.

In early research, timetable and stop plan optimization were treated independently. For timetable optimization, Liu et al. [1] introduced new constraints, incorporating train capacity and service oversaturation. They then developed a nonlinear integrated optimization model with the objective of minimizing passenger wait times and operational costs. This model helped design full-day train timetables, integrating both coupled and decoupled operations and managing bidirectional vehicle allocation. Gong et al. [2] further advanced this field of study. They incorporated variables like frequency, headway, and route selection, resulting in a comprehensive NLIP model for optimization. Other scholars have examined the integration of different rail transit systems. For instance, Liang et al. [3] studied cross-line operations, modeling services between urban railways and subways. Their model derived optimal subway cross-line schemes, subsequently integrating them into the urban railway timetable. This methodology successfully enhanced operator revenue while also reducing passenger waiting times.

Several studies have focused on energy consumption issues. Yu et al. [4] highlighted a key insight. Train traction constitutes a significant portion of energy use. Based on this, they proposed an energy-efficient optimization model. The model generates interval operation curve alternatives. These curves help design an energy-saving train timetable. Variations in passenger demand also play a critical role. This is true for demand across time and space. Zhong et al. [5] studied scheduling with flexible train formations. Their goal was improving energy efficiency. The model also accommodated demand fluctuations. They optimized carriage numbers and train speeds. Similarly, Shi [6] addressed peak flow oversaturation scenarios. The research incorporated dynamic passenger flows. Control strategies were introduced to optimize timetables. This approach reduced platform waiting times and mitigated congestion.

Some researchers combined timetable optimization with other constraints. This helped them achieve coordinated solutions. Song et al. [7] analyzed flexible train formations in urban rail. They also studied passenger flow distribution characteristics. This allowed joint optimization of timetables

Manuscript received April 29, 2025; revised July 10, 2025.

This work was supported in part by the National Natural Science Foundation of China (No.72161024) and "Double-First Class" Major Research Programs, Educational Department of Gansu Province (No.GSSYLXM-04).

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and vehicle use. The work provides valuable insights for operational planning. Li et al. [8] introduced new train operation modes. They built a spatiotemporal network for vehicle utilization. This coordinated vehicle departure paths with the timetable. The approach ensured the feasibility of operational schemes. Advances in algorithms and models have further enriched this field. Chai et al. [9] addressed periodic and non-periodic timetables. They designed an efficient Lagrange relaxation decomposition algorithm. Separately, Wang et al. [10] focused on delayed passenger demand. Their work used a two-step optimization model. This model was based on the Cell Transmission Model (CTM).

Regarding station stop plan optimization, Park et al. [11] reformulated the problem as a path optimization task. They developed a multi-objective linear programming model based on a multi-commodity flow structure, which was solved using the D-W decomposition algorithm. Extending this approach, Qi et al. [12] incorporated operational intervals and passenger allocation, transforming the problem into a mixed-integer linear program solved using GAMS. Somporn [13] developed three alternative skip-stop plans to align stop plans with passenger needs by optimizing total passenger and enterprise costs. In studies integrating energy consumption, Zheng et al. [14] devised a method for calculating urban rail energy use. They subsequently constructed an optimization model for station stop plans to promote sustainable transportation practices. Other researchers have prioritized passenger experience and demand. Luo et al. [15] considered passenger sensitivities to travel time and distance in train selection, proposing an integer programming model to minimize total travel time. Han et al. [16] introduced a coordinated optimization model for station stop plans and fare distribution. The model aimed to maximize passenger satisfaction and seat occupancy rates and was solved using uncertainty theory and a Lagrange relaxation algorithm. To further enhance passenger satisfaction, Tang et al. [17] developed a bilevel programming model. The upper level optimizes station stop plans, while the lower level incorporates a game-theory-based passenger flow equilibrium model. Zhao et al. [18] extended this coordination with a multi-objective model that simultaneously considers travel time, stop plans, and passenger satisfaction, providing a reference for integrated planning. Finally, Li et al. [19] addressed high-speed railway stop plans, focusing on the spatiotemporal balance of train departures and passenger flow adaptation.

However, treating timetable and station stop optimizations separately limits the potential for generating optimal solutions. Consequently, some scholars have pursued coordinated optimization approaches. For example, Valentina et al. [20] developed a model focused on adjusting for passenger flow fluctuations after a plan is operational, aiming to reduce unmet demand. Other studies have constructed spatiotemporal networks to tackle coordinated optimization issues. Chen et al. [21] built such a network to jointly optimize train timetables, station stop plans, and speed levels via a sequential iterative approach. Similarly, Tian et al. [22] applied a spatiotemporal network representation to convert scheduling and stop decisions into an integer linear programming model, which was solved using a branch-and-price method. Yang et al. [23] simplified the optimization problem. They represented operational costs via dwell time minimization. Passenger satisfaction was represented by minimizing departure time deviations. This method achieved a combined optimization of station stop plans and timetables. Recognizing that peak-period congestion can compromise safety, Shi et al. [24] analyzed passenger flow characteristics to match train assignments with station congestion levels. In parallel, Jiang et al. [25] employed skip-stop strategies to alleviate congestion on highly trafficked railway lines. Furthermore, Yue et al. [26] incorporated passenger service quality and railway transportation benefits into their model. Their findings suggest that excessive stop times and the number of stops lower passenger satisfaction and reduce ticket purchase willingness. Li et al. [27] proposed a demand-responsive optimization strategy that adjusts timetables and stop plans based on passengers' expected departure times to enhance operational efficiency. Wang [28] addressed interline passenger transfers by constructing a spatiotemporal network representing both train and passenger flows. The research subsequently proposed a coordinated model that integrates in-line and cross-line trains. Meng et al. [29] developed a coordinated optimization model based on candidate station stop plans, using time-varying passenger demand as input to maximize railway operational revenue. Building on this, Qi et al. [30] incorporated both passenger and freight demand into a model for flexible train formations in passenger-freight co-mobility, which was solved using VNS and CPLEX.

In summary, extensive research exists on the coordinated optimization of train timetables and station stop plans, with numerous scholars proposing a variety of solutions. However, little attention has been dedicated to integrating passenger flow distribution within these coordinated models. Addressing this research gap, the present study introduces a large-scale passenger flow distribution method. This method specifically accounts for the unique characteristics of intercity railway passenger movements. The approach prioritizes large-scale passenger flows and constructs a corresponding distribution model based on the Logit framework. Furthermore, this paper integrates the new passenger flow model with the established coordinated optimization model. This integration forms a multi-objective optimization framework that explicitly considers passenger flow distribution. The resulting integrated model is then solved using an Adaptive Large Neighborhood Search (ALNS) algorithm.

II. PROBLEM STATEMENTS

A. Construction of Passenger Flow Allocation Model

The majority of passenger flow on intercity railways consists of commuter traffic. These passengers typically have fixed origins and destinations and demand a high degree of service punctuality. Therefore, prioritizing these commuter flows is imperative to enhance overall transportation efficiency. Consequently, this study adopts a large-scale prioritization strategy for passenger flow allocation.

Let S = {1, 2, …, n} denote the set of stations on an intercity railway line, and let I = {1, 2, …, m} represent the set of trains. Initially, passenger turnover is computed using the existing origin–destination (OD) matrix and is subsequently updated into a new turnover matrix P. In this matrix, the passenger turnover $P_i^{s,s'}$ from station *s* to station *s′* by train *i* is defined as follows

$$P_i^{s,s'} = \sum_{i\in I}\sum_{s\in S}\left(q_i^{s,s'} \times d_i^{s,s'}\right) \tag{1}$$

Where, $q_i^{s,s'}$ denotes the passenger flow carried by train *i* from station *s* to station *s′*, $d_i^{s,s'}$ denotes the inter-station distance from station *s* to station *s′*.

The passenger flow corresponding to the maximum turnover is designated as $q_i^{s,s'}$. A differential calculation is then performed to update the passenger flow OD matrix. The updated passenger flow $q_x^{s,s'}$ is as follows

$$q_x^{s,s'} = q_i^{s,s'} - U \tag{2}$$

$$U = find\left[H = \min H\right] \tag{3}$$

$$H = c_i - q_r \tag{4}$$

Where, H denotes the difference matrix between the rated passenger capacity and the actual loaded passenger flow; U denotes the smallest element in the difference matrix;

In conjunction with the Logit model, the probability that passengers select train *i* for travel is expressed as follows

$$p_i = \frac{\exp\left(\varpi\rho_i\right)}{\sum\exp\left(\varpi\rho_i\right)} \tag{5}$$

$$\rho_i = \sum_{s\in S}\sum_{i\in I}\left(x_i^s \times qt_i^s + r_i^s\right) \tag{6}$$

Where, ϖ denotes the familiarity of passengers with different trains; p_i denotes the probability of passengers choosing train *i* for travel; ρ_i denotes generalized travel cost. x_i^s denotes whether train *i* stops at station *s*. if it stops, the value is 1, otherwise, it is 0; qt_i^s denotes the stop time of train *i* at station *s*; r_i^s denotes the travel time of train *i* from station *s* to station *s+1*.

Combining Equations (2) and (5), the passenger flow allocated to the train by the passenger group $\Gamma_{s,s'}^i$ is as follows

$$\Gamma_{s,s'}^i = p_i \times q_x^{s,s'} \tag{7}$$

B. Assumptions

(1) This paper assumes that all trains begin at the initial station (station 1) and terminate at the terminal station (station n), and overtaking of the train is not allowed.

(2) Furthermore, the analysis disregards any time losses resulting from deceleration and acceleration at stations.

(3) In addition, trains of the same type are assumed to maintain a constant speed within each segment of the route.

C. Constraints

(1) Departure Time Constraints at the Origin Station

To ensure operational reliability, each train must depart from the origin station no earlier than its scheduled time and within the allowable fluctuation range. Accordingly, the departure time constraint at the origin station is defined as follows

$$t_i^{\mathrm{E}} \le t_{i1}^{\mathrm{d}} \le t_i^{\mathrm{E}} + \Delta t, \forall i \in \mathrm{I} = \{1,2,\cdots,\mathrm{m}\} \tag{8}$$

Where, t_i^{E} denotes the estimated departure time of the train; t_{i1}^{d} denotes the time when train *i* departs from station 1; Δt is fluctuation time.

(2) Train operation time constraint

$$r_i^s = t_{i,s+1}^{\mathrm{a}} - t_{i,s}^{\mathrm{d}} \tag{9}$$

Where, $t_{i,s+1}^{\mathrm{a}}$ denotes the arrival time of train *i* at station *s+1*; $t_{i,s}^{\mathrm{d}}$ denotes the time when train *i* departs from station *s*.

Equation (9) defines the travel time as the difference between the arrival time at the subsequent station and the departure time, thereby ensuring the continuity of the train's operation.

(3) Stay time constraint

$$x_i^s = 1, s \in \left\{1,\mathrm{n}\right\}, \forall i \in \mathrm{I} \tag{10}$$

$$qt_i^s = t_{i,s}^{\mathrm{d}} - t_{i,s}^{\mathrm{a}} \tag{11}$$

$$x_i^s \times t_\tau^{\mathrm{l}} \le qt_i^s \le x_i^s \times t_\tau^{\mathrm{h}}, \forall i \in I, s \in \{2,3,\cdots,\mathrm{n}\text{-}1\} \tag{12}$$

Where, $t_{i,s}^{\mathrm{a}}$ denotes the arrival time of train *i* at station *s*; t_τ^{l} and t_τ^{h} denote minimum and maximum stop times;

Equation (10) guarantees that the train stops at both the first and last stations, irrespective of the duration of its stay. Equation (12) ensures that the train's stopping time complies with the specified time constraints.

(4) Passenger capacity constraints

$$\sum_{i\in\mathrm{I}}\sum_{s\in\mathrm{S}}\Gamma_{s,s'}^i \le c_i, \forall s \in \mathrm{S}, \forall i \in \mathrm{I} \tag{13}$$

Where, c_i denotes the rated passenger capacity of train *i*.

(5) Stop constraint

In order to ensure that each station achieves a predetermined service frequency without inefficiently utilizing transportation capacity, the number of train stops at each station is standardized. This standardization enhances both the convenience and balance of train services.

$$\sum_{i=1}^{n} x_i^s \ge R_{\mathrm{l}}, \forall s \in \mathrm{S} \tag{14}$$

$$\sum_{i=1}^{n} x_i^s \le R_{\mathrm{h}}, \forall s \in \mathrm{S} \tag{15}$$

Where, R_{l} and R_{h} denote the minimum and maximum number of stops.

(6) Passenger load factor threshold constraint

$$\Theta \times c_i \le \sum_{s\in\mathrm{S}}\sum_{i\in\mathrm{I}}\Gamma_{s,s'}^i, \forall s \in \mathrm{S}, \forall i \in \mathrm{I} \tag{16}$$

Where, Θ denotes the passenger load factor threshold coefficient, which has a value range of [0,1].

D. Objective function

D.1. Passenger travel cost

Since ticket prices for intercity railway trains are relatively fixed, and the primary factors influencing passengers' travel costs are the waiting time and the train's stop duration during operation, the travel cost for passengers φ_1 is defined as follows

$$\min \varphi_1 = \Phi_1 \sum_{s\in \mathrm{S}}\sum_{i\in \mathrm{I}}\left(dt_i^{s,s'} + zt_i^{s,s'} + \Gamma^{i}_{s,s'} \times x_i^s \times q_i^s\right) \quad (17)$$

To derive the cumulative waiting time of passengers, we employ a principle analogous to a Riemann integral to approximate the duration passengers spend after arriving at the station. As illustrated in Fig. 1, if passengers board the train to their destination, their waiting time is represented by the red triangular area. Conversely, if passengers are unable to board the train due to insufficient capacity, they must wait for the next train, and their additional waiting time is depicted by the blue rectangular area.

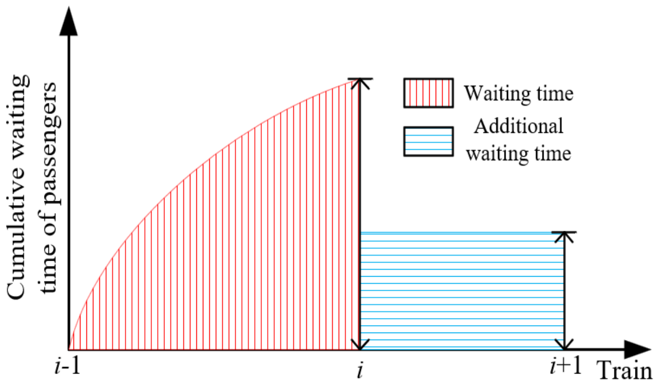

Fig. 1. Cumulative waiting time of passengers

Therefore, based on the interval between consecutive trains, the total waiting time $dt_i^{s,s'}$ for passengers arriving at station s and proceeding to station s' to board train i is the sum of the cumulative waiting time and the additional waiting time, as detailed below

$$\begin{aligned} dt_i^{s,s'} &= \frac{1}{2}\times\left(t^{\mathrm{d}}_{i,s} - t^{\mathrm{d}}_{i-1,s}\right)\times k_i^{s,s'} + \\ &\left(t^{\mathrm{d}}_{i+1,s} - t^{\mathrm{d}}_{i,s}\right)\times\left(k_i^{s,s'} - \Gamma^{i}_{s,s'}\right), \forall i\in \mathrm{I}, \forall s,s'\in \mathrm{S} \end{aligned} \quad (18)$$

Where, $k_i^{s,s'}$ denotes the number of passengers who plan to take train i from station s to station s'.

The in-vehicle time $zt_i^{s,s'}$ for passengers arriving at station s and heading to station s' on train i is as follows

$$zt_i^{s,s'} = \Gamma^{i}_{s,s'} \times \sum_{s\in \mathrm{S}} r_i^s, \forall i\in \mathrm{I}, \forall s,s'\in \mathrm{S} \quad (19)$$

D.2. Enterprise operating cost

The operational costs of the enterprise primarily consist of variable and fixed expenditures, including train operation and train stopping costs. Variable costs, in particular, are closely associated with the number of trains in operation and their respective stopping schedules. Consequently, the enterprise's operating costs are expressed as follows:

$$\min \varphi_2 = \Phi_2 \sum_{i\in \mathrm{I}}\left[n_i \times\left(\bar{\alpha} + d_i^{s,s'}\times\bar{\beta}\right) + \sum_{s\in \mathrm{S}} x_i^s \times \bar{\gamma}\right] \quad (20)$$

Where, n_i denotes the number of trains; $\bar{\alpha}$ denotes the fixed train operating costs; $\bar{\beta}$ denotes the average train running cost; $\bar{\gamma}$ denotes the average train stopping cost.

III. Algorithm Introduction

The collaborative optimization of intercity railway timetables and stop plans constitutes a nonlinear integer programming problem. This type of problem is characterized by considerable model complexity. Consequently, this study employs the Adaptive Large Neighborhood Search (ALNS) algorithm to address this challenge and derive integrated optimization outcomes.

The algorithm dynamically adjusts operator selection probabilities and strategies based on historical performance. This process allows the algorithm to achieve superior domain-specific solutions, enhance computational efficiency, and avoid entrapment in local optima.

A. Reconstruction of solutions and operator selection

This paper utilizes four types of operators to reconstruct the current optimal solution: the train removal operator, the train insertion operator, the stop station removal operator, and the stop station insertion operator. Through these operators, the corresponding decision variables for both the train schedule and the stop station scheme are systematically optimized and updated.

Each operator is selected based on distinct demand conditions and weighting criteria. These criteria determine whether to modify or preserve specific components of the schedule and station configurations. This flexibility allows for both large-scale structural changes and fine-tuned adjustments to the solution. The operator selection framework is illustrated in Fig. 2.

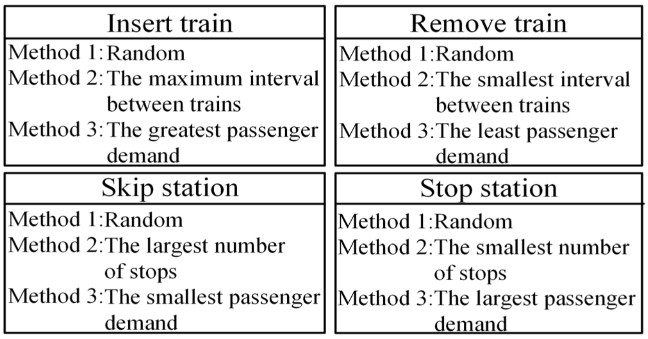

Fig. 2. Operator selection method of ALNS algorithm

B. Algorithm flow

Step1: Perform parameter initialization by setting the maximum number of iterations (*iter_max*) and initializing the iteration counter (*iter*=1). At this stage, critical data—such as passenger flow demand and station spacing—are input.

Step2: Employ a greedy algorithm to generate an initial solution, thereby establishing a preliminary plan for the current optimal solution and computing its corresponding objective value.

Step3: Reconstruct the solution by sequentially selecting removal and insertion operators based on varying conditions and operator selection probabilities. This reconstruction yields a new solution along with its updated timetable and stop plan.

Step4: Calculate the objective value associated with the new solution.

Step5: Execute the update optimization procedure on the current solution.

Step6: Adjust the operator selection method and update the iteration count.

Step7: If the termination conditions are satisfied, halt the procedure; otherwise, repeat Steps 3 through 6.

IV. Case Study

A. Case introduction

An intercity railway features terminal stations at points 1 and 11, spanning a distance of 58 km. The line includes nine intermediate stations situated between these two terminals. The line extends from station 1 to station 11 in the downward direction, as illustrated in Fig. 3. All inter-station distances are detailed in Table I.

TABLE I
DISTANCE BETWEEN STATIONS OF INTERCITY RAILWAYS

Station	Station Distance (km)	Station	Station Distance (km)
1	0	8	5
2	5	9	11
3	2	10	6
4	3	11	3
5	2	12	5
6	4	13	8
7	4		

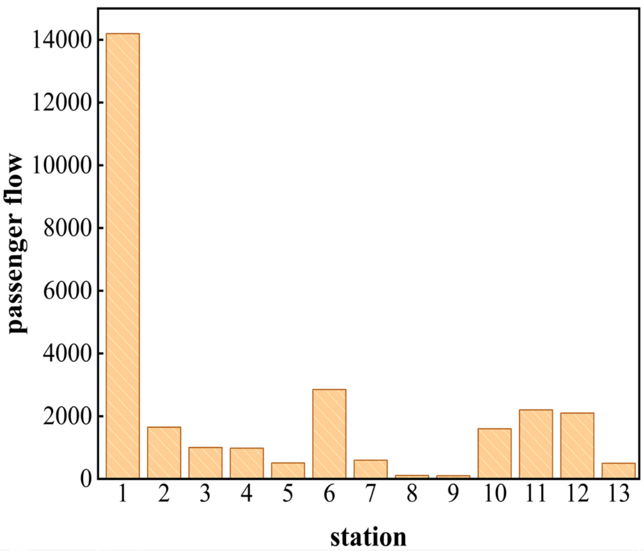

Fig. 4. Average daily passenger flow of the intercity railway

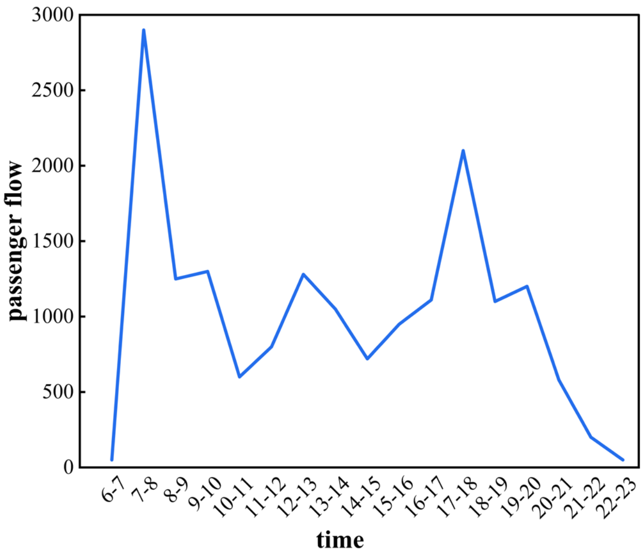

Fig. 5. Number of passengers in the down direction of the intercity railways

Due to the uneven distribution of urban economies and populations, intercity railway stations experience significant disparities in passenger flow. For example, some stations handle over 14,000 daily passengers, while others in less populated areas serve fewer than 2,000. Figure 4 illustrates the average daily passenger throughput at each station. Beyond these spatial imbalances, passenger demand also exhibits distinct temporal patterns.

In daily operations, the intercity railway primarily serves commuters and students. This service pattern results in a bimodal passenger flow, with peak volumes occurring during the morning rush hour (7:00–8:00 a.m.) and the evening rush hour (5:00–6:00 p.m.). Figure 5 shows the number of passengers traveling in the down direction.

To optimize transportation capacity utilization, a maximum of six trains is permitted during peak hours. This decision is based on objective data and empirical evidence. The corresponding model parameters are presented in Table II.

TABLE II
VALUES OF MODEL-RELATED PARAMETERS

Parameters	Value
t_τ^{h}、t_τ^{l} (min)	8、4
R_h、R_l (min)	6、1
c_i	600
Δt (min)	3
$\overline{\alpha}$ (yuan · one train^{-1})	4000
$\overline{\beta}$ (km · yuan^{-1})	70
$\overline{\gamma}$ (one time · yuan^{-1})	100
Φ_1	1
Φ_2	0.63

B. Analysis of model results

The proposed algorithm was implemented in Python to solve the model. Due to the model's high complexity, an insufficient number of iterations may fail to yield a feasible or satisfactory solution. Therefore, the number of iterations was set to 100. The resulting Pareto optimal frontier and hypervolume iteration curves are presented in Figures 6 and 7.

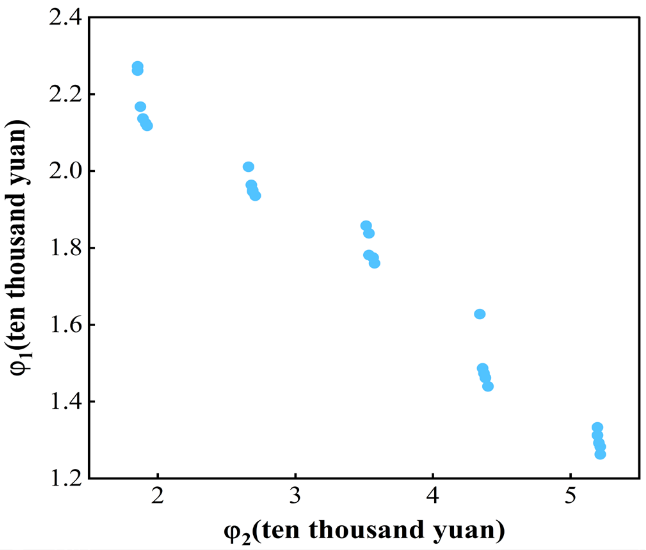

Fig. 6. Pareto frontier solution set

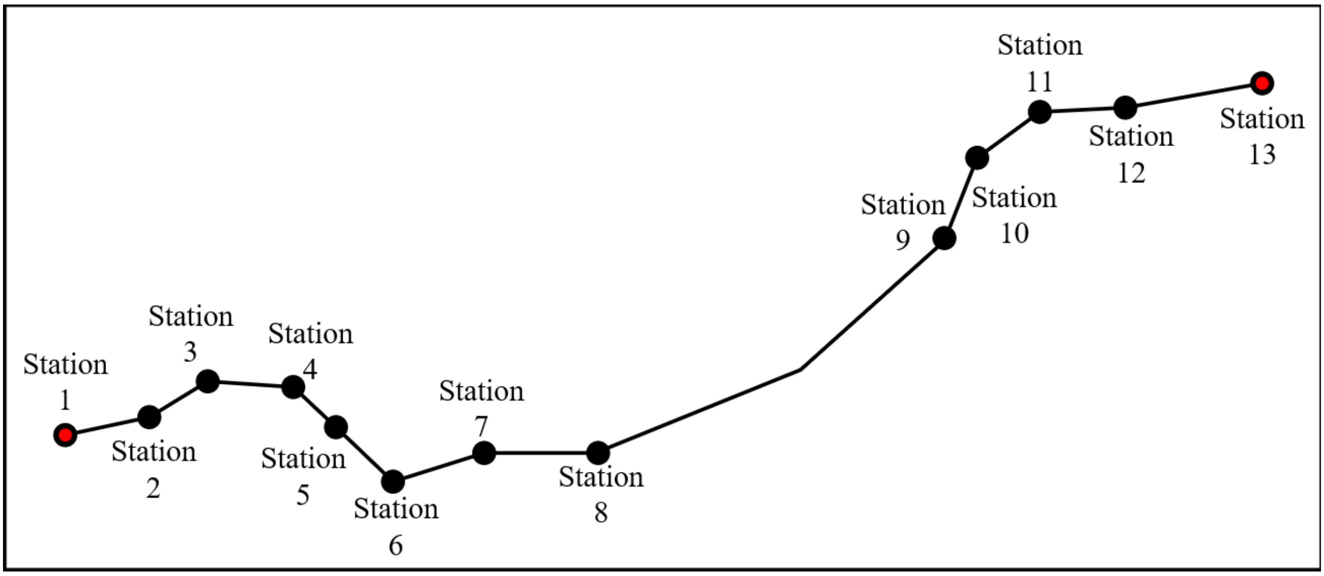

Fig. 3. Overview of the Intercity Railway lines

Fig. 7. illustrates that some Pareto solution sets are relatively clustered, suggesting that reducing one objective function has only a minimal impact on the other. In these cases, adjustments to the train schedule and stop plan exert a limited influence on passenger travel, resulting in only slight changes in travel cost. Conversely, some Pareto solution sets are more dispersed, indicating a significant interaction between the two objective functions. Under these circumstances, the implementation of a wide range of train schedules and distinct stop plans inevitably introduces significant variations in the overall travel experience for passengers. For instance, when trains are designed to follow diverse timetables, some offering express services with fewer stops while others make more frequent stops, the resulting differences in travel durations and associated costs become strikingly apparent. Specifically, reducing enterprise operating costs substantially increases passenger travel expenses. Fig. 9. and 10. provide detailed visual representations of the train operation diagrams that correspond to several of the identified Pareto solutions.

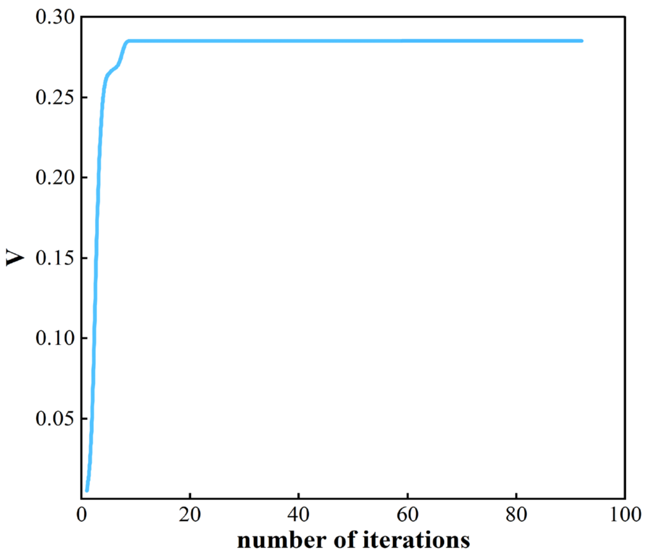

Fig. 7. HV iteration curve

Fig. 8. illustrates several frequently occurring train stop plans in the optimization results. Implementing the first type of stop plan, where trains stop at every station, ensures that passenger demand across all stations is met without leaving any station unserved. This approach represents a relatively conventional train stopping strategy. The second stop plan involves selective bypassing of stations 8 and 9. This decision is based on the relatively low passenger flow demand at these stations, making it unnecessary to allocate excessive resources for stops there. By skipping these stations, transportation enterprises can reduce operational costs while also decreasing travel time for passengers. The fifth and sixth stop plans are strongly correlated with the passenger flow allocation model. Prioritizing high-demand stations leads to the emergence of express trains with fewer stops, thereby minimizing travel costs and time for passengers traveling between high-demand locations.

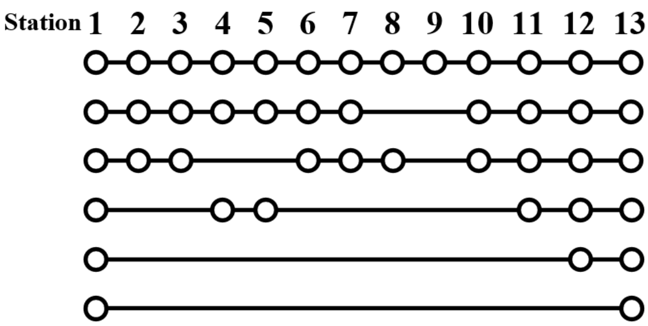

Fig. 8. Frequent train stop plans

To further investigate the differences among various Pareto solutions, a comparative analysis was conducted, with the specific data presented in Table III. The table shows that the number of trains operated ranges from two to six. When two trains are operated, the enterprise's operating cost is the lowest, though the travel time cost for passengers remains relatively high. In contrast, operating six trains leads to the highest operating cost for the enterprise, which is observed to escalate by 181.64% compared to the scenario where only two trains are in service. However, this significant cost escalation is offset by a substantial 44.43% reduction in passenger travel time costs. This change enhances the travel experience by reducing delays and improving scheduling efficiency.

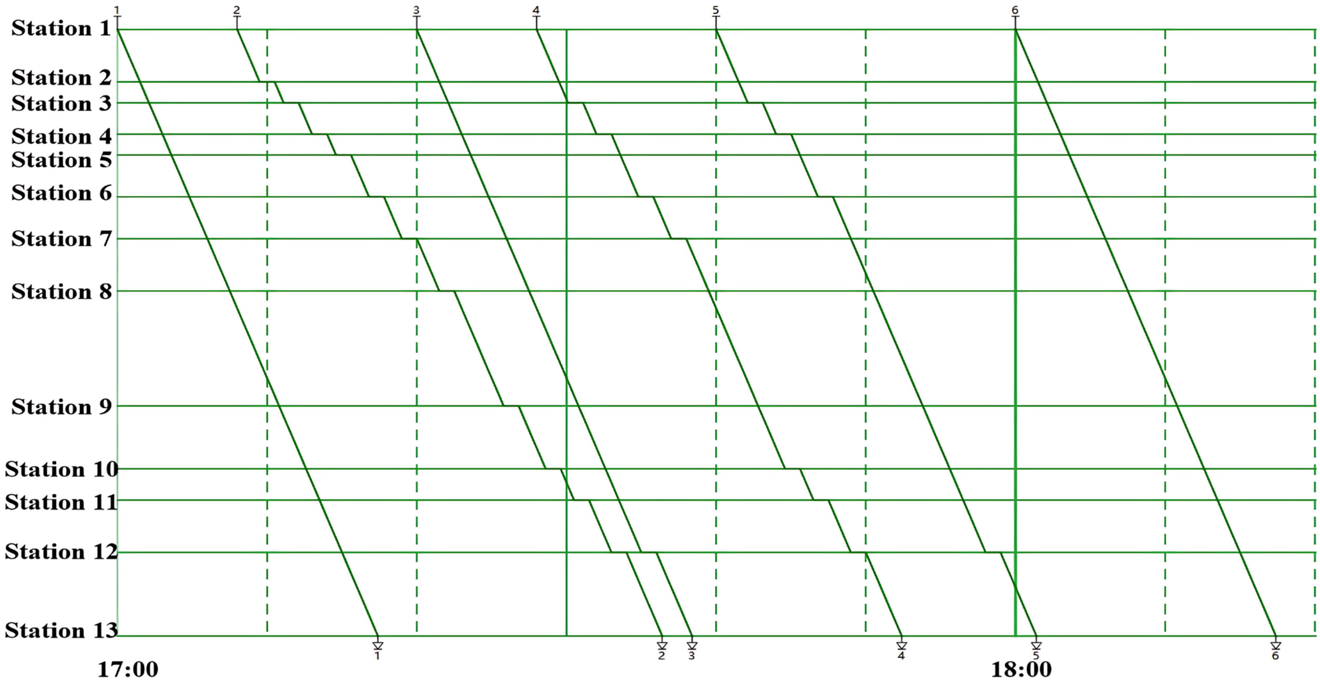

Fig. 9. Operation diagram with 6 trains

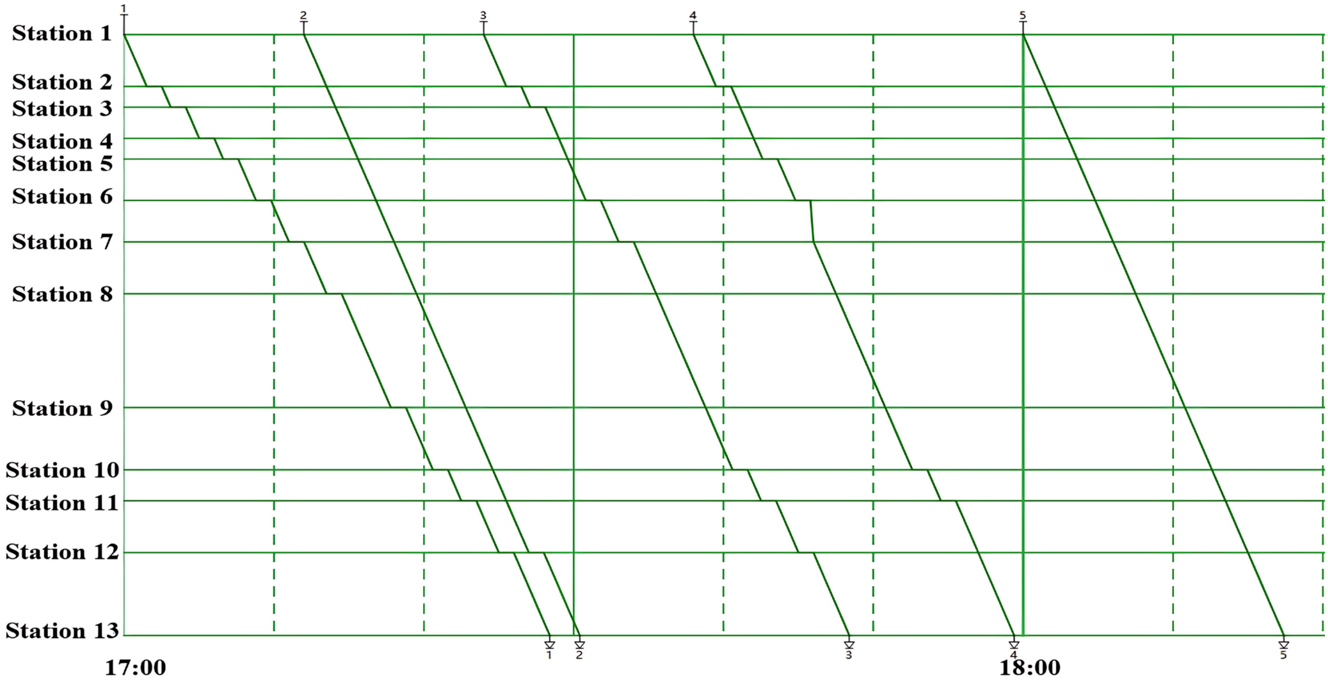

Fig. 10. Operation diagram with 5 trains

These results demonstrate that increasing the number of train operations raises enterprise costs but decreases passenger travel time costs, thereby potentially attracting more passengers to intercity railway travel.

TABLE III
PART OF THE PARETO SOLUTION SET

φ_1 (yuan)	φ_2 (yuan)	number of trains	number of stops
12630	52160	6	38
13330	51960	6	36
14740	43700	5	34
18380	35340	4	31
19500	26880	3	27
21680	18720	2	26
22730	18520	2	24

C. Parameter Analysis

Passenger load factor is an essential metric for evaluating a company's profitability, with higher load factors generally corresponding to increased profits. Setting a higher load factor threshold tends to benefit operational efficiency; however, it may necessitate the removal of trains that do not meet the criteria, potentially increasing passengers' travel costs. In contrast, a lower threshold relaxes operational requirements, which may lead to a greater diversity and number of train services. This, in turn, allows passengers to select options that better suit their travel needs, ultimately reducing travel time costs, albeit at the expense of higher operating costs. With other parameters held constant, the load factor threshold was varied in increments of 0.3 over the interval [0.2, 0.8] to derive the Pareto optimal frontier solution set and HV iteration curve under different thresholds, as illustrated in Fig. 11. and 12.

Analysis of Fig. 11. and 12. reveals that as the passenger load factor threshold increases, the number of non-dominated solutions gradually decreases. This trend arises because the passenger flow on certain trains may fall below the threshold, ultimately resulting in the suspension of service and a corresponding reduction in the variety of train schedules and stop plans. Furthermore, the HV iteration curve demonstrates that a higher threshold diminishes the model's solution space and reduces the algorithm's convergence performance. To further elucidate the differences among the various Pareto solutions, a comparative analysis was conducted, with the detailed data presented in Table IV.

TABLE IV
PART OF THE PARETO SOLUTION SET UNDER DIFFERENT THRESHOLDS

φ_1 (yuan)	φ_2 (yuan)	number of trains	number of stops	Θ
14060	52060	6	37	0.2
16130	43600	5	33	0.2
20430	35540	4	33	0.5
21720	26680	3	26	0.5
22060	26580	3	25	0.8
23350	18520	2	24	0.8

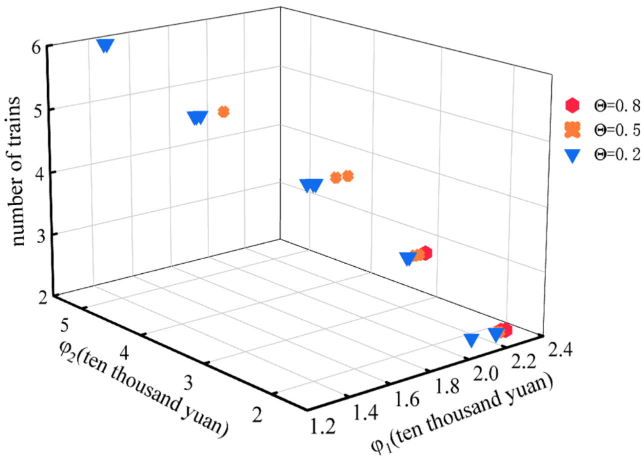

Fig. 11. Set of Pareto front solutions under different thresholds

To intuitively understand the relationship between the objective function, the number of stops, and train services, we analyzed four key metrics. As shown in Fig. 13. and 14., when the threshold is set to 0.5, the total number of train stops decreases as the number of operating trains is reduced. Consequently, passenger travel costs rise by 33.62%, while enterprise operating costs fall significantly by 57.32%. At this threshold, the data clearly shows that the reduction in enterprise costs far outweighs the increase in passenger costs, indicating that train plan adjustments have a more pronounced financial impact on the railway operator. This trend, where enterprise costs are generally more sensitive than passenger costs, also holds true for a threshold of 0.2.

Fig. 15. illustrates the train stop plans that occur more frequently under different thresholds. In the first approach, which is akin to the scenario without any threshold, trains stop at every station to ensure that services are accessible at each stop. This strategy is particularly designed to maximize convenience for daily commuters, guaranteeing that no station is overlooked regardless of its passenger demand. Moreover, because train operations are permitted only when the passenger flow reaches a predetermined threshold, the option for a Non-stop train service is eliminated. Consequently, there is an increase in the number of trains stopping at most stations and a corresponding rise in overall stop frequency, meaning that trains bypass only a limited number of stations.

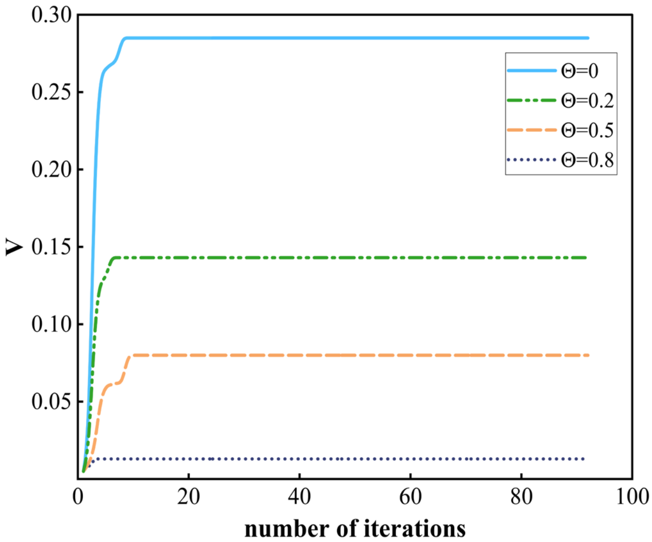

Fig. 12. HV iteration curves under different thresholds

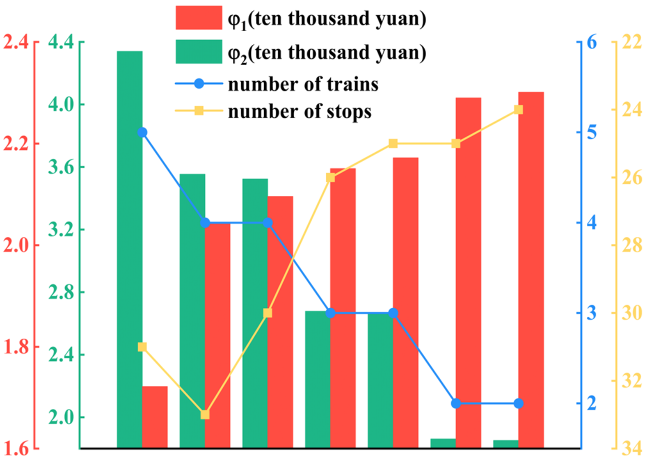

Fig. 13. Comparison of the objective function with respect to the number of stops and trains for threshold = 0.5

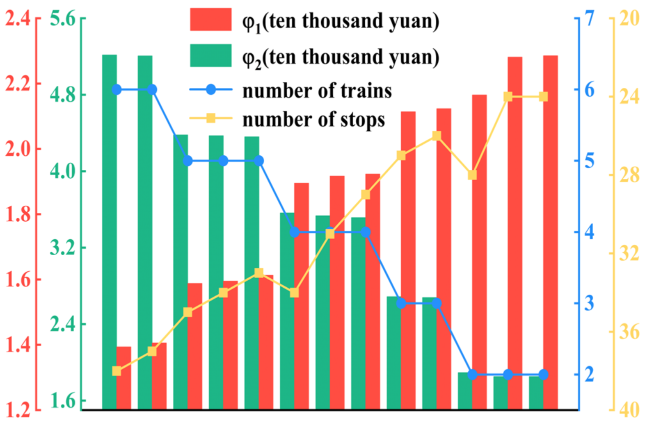

Fig. 14. Comparison of the objective function with respect to the number of stops and trains for threshold = 0.2

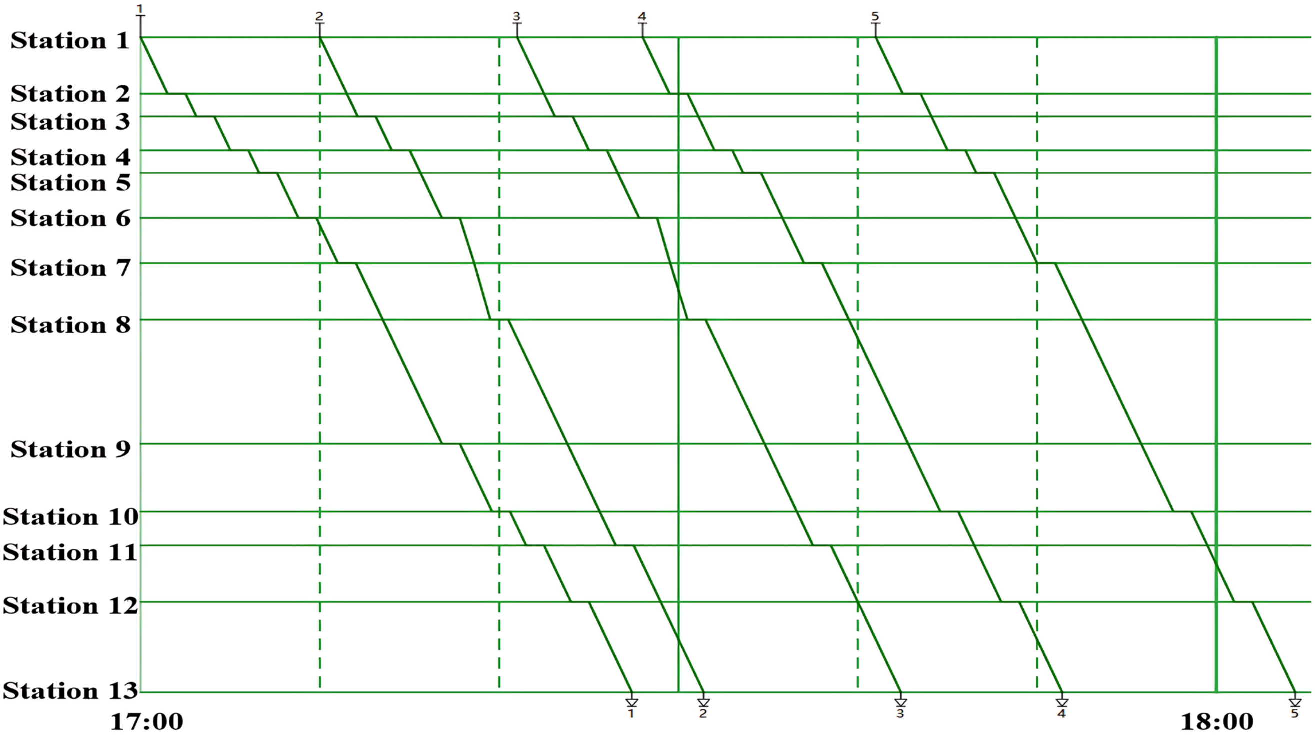

Fig. 16. Train operation diagram for threshold = 0.2

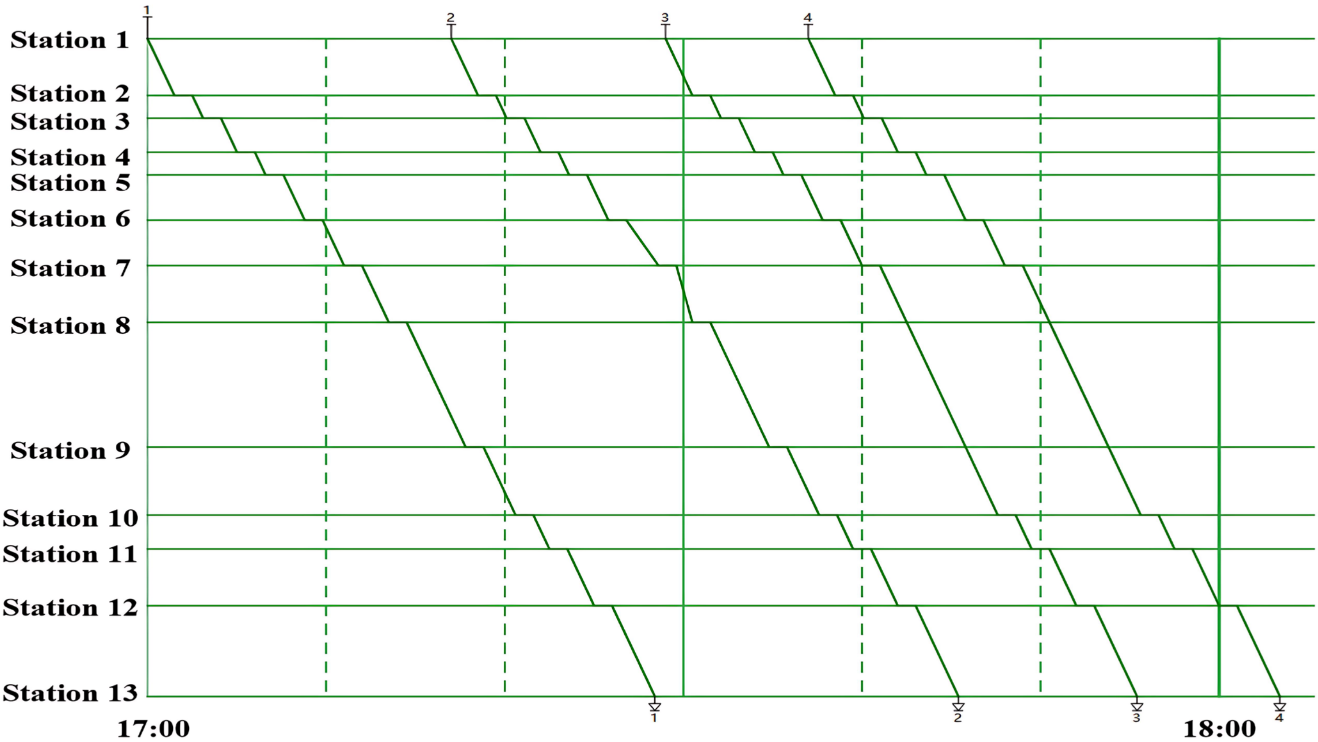

Fig. 17. Train operation diagram for threshold = 0.5

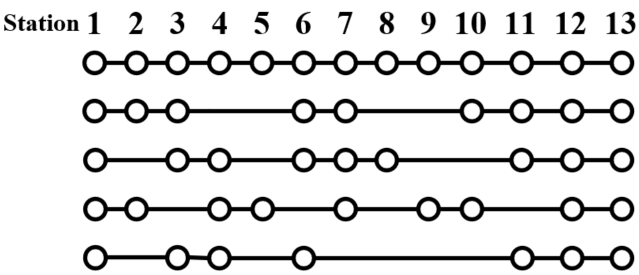

Fig. 15. Frequent train stop plans under different thresholds

As shown in Table IV, as the passenger load factor threshold increases, passenger travel costs rise while operating costs for enterprises decline. This phenomenon occurs because a higher threshold reduces the diversity of train schedules and stop patterns, thereby rendering stop-selective train operations unfeasible for handling a small number of passengers. Consequently, passengers face a reduced selection of available trains, often forced to choose services with longer transit times or additional stops, which significantly elevates travel time costs. Furthermore, as depicted in Fig. 12., increasing the passenger load factor threshold gradually simplifies the stop patterns of the operated trains, with a growing proportion of trains stopping at every station and a decreasing proportion stopping selectively. The train operation schemes corresponding to certain Pareto solutions are illustrated in Fig. 16. and 17.

V. CONCLUSIONS

(1) This paper presents an integrated optimization framework for train schedules and stopping plans that incorporates a novel passenger flow distribution method. By considering the unique characteristics of intercity railway passenger movements, our approach prioritizes routes with high passenger turnover. This method enhances both transportation efficiency and passenger satisfaction, yielding optimized schemes that are more responsive to passenger demand than those from existing models.

(2) The study reveals a fundamental trade-off between passenger travel costs and enterprise operating costs. From the dual perspectives of passengers and the enterprise, efforts to reduce passenger travel time by altering train schedules invariably lead to an increase in operational expenses. This analysis highlights the critical need for transit authorities to balance passenger convenience against its financial implications when developing efficient, passenger-centric transportation systems.

(3) The passenger load factor threshold is a critical parameter directly influencing service design and quality. Our findings show that an increasing threshold leads to wider train intervals and less diverse stopping schemes. This reduction in service variety consequently compels passengers to accept options with compromised timeliness. Ultimately, this trade-off significantly increases overall travel costs for the public, highlighting the complex social impact of operational efficiency targets.

(4) The findings provide strategic insights for railway operators. Transportation enterprises should not focus solely on minimizing operating costs but must also consider the impact on service quality and customer satisfaction. While expanding train services elevates expenditures, this strategy can yield considerable advantages by reducing passenger wait times, enhancing market competitiveness, and ultimately boosting long-term revenue.

(5) This study assumes passengers behave with complete rationality, a simplification that may not fully capture actual travel behavior. Future research should integrate the concept of bounded rationality to more accurately model passenger decision-making. Additionally, incorporating flexible marshalling could support more adaptable and diverse train service plans.

REFERENCES

[1] J. Liu, D. Canca, H. Lv, and S. Ni, "Demand-adapted train timetabling with coupling-decoupling operations on a bidirectional intercity railway line," *Computers & Industrial Engineering*, vol. 189, pp. 109999-, 2024.

[2] C. Gong, X. Luan, L. Yang, J. Qi, and F. Corman, "Integrated optimization of train timetabling and rolling stock circulation problem with flexible short-turning and energy-saving strategies," *Transportation Research Part C*, vol. 166, pp. 104756-104756, 2024.

[3] H. Liang, Y. Jing, G. Sun, and Q. Song, " Suburban Railway Timetable Optimization Based onThrough Operation Mode," *Journal of Transportation Systems Engineering and Information Technology*, vol. 24, no. 06, pp. 126-134+158, 2024.

[4] L. Yu, Y. Bai, and Y. Chen, " Energy-Saving Timetable Optimization for Urban RailTransit Considering Regenerative Braking Energy," *China Transportation Review*, vol. 46, no. 12, pp. 98-105, 2024.

[5] L. Zhong, G. Xu, and W. Liu, "Energy-efficient and demand-driven train timetable optimization with a flexible train composition mode," *Energy*, vol. 305, pp. 132183-132183, 2024.

[6] J. Shi, L. Yang, J. Yang, and Z. Gao, "Service-oriented train timetabling with collaborative passenger flow control on an oversaturated metro line: An integer linear optimization approach," *Transportation Research Part B*, vol. 110, pp. 26-59, 2018.

[7] Z. Song, X. Tian, H. Niu, S. Wang, and H. Cao, " Integrated optimization of train timetable and rolling stock circulation with flexiblecomposition strategies for an urban rail transit line," *Journal of Railway Science and Engineering*, pp. 1-13, 2024.

[8] C. Li, J. Tang, Z. Bai, J. Zhao, Q. Dong, and X. Xing, "Research on Integrated Optimization of Rolling Stock Time-space Routing and Timetabling for Urban Rail Transit Line," *Journal of the China Railwany Society*, vol. 47, no. 02, pp. 24-34, 2025.

[9] N. Chai, Z. Chen, and W. Zhou, "Periodic and aperiodic train timetabling and rolling stock circulation planning using an efficient Lagrangian relaxation decomposition," *Computers & Operations Research*, vol. 180, p. 107062, 2025.

[10] H. Wang, F. Li, J. Liu, H. Ji, B. Jia, and Z. Gao, "Two-step optimization of train timetables rescheduling and response vehicles on a disrupted metro line," *Transportation Research Part C: Emerging Technologies*, vol. 174, p. 105078, 2025.

[11] B. H. Park, C.-S. Kim, and H.-L. Rho, "On the Railway Line Planning Models Considering the Various Halting Patterns," *Lecture Notes in Engineering and Computer Science*, vol. 2182, no. 1, p. 2146, 2010.

[12] Q. Jianguo, C. Valentina, Y. Lixing, Z. Chuntian, and D. Zhen, "An Integer Linear Programming model for integrated train stop planning and timetabling with time-dependent passenger demand," *Computers & Operations Research*, no. prepublish, pp. 105484-, 2021.

[13] S. Sahachaiseree, M. Sadrani, and C. Antoniou, "Stop plan optimisation for three-pattern skip-stop schemes for urban rail transit systems," *EURO Journal on Transportation and Logistics*, vol. 14, pp. 100149-100149, 2025.

[14] Y. Zheng, S. He, and S. Chi, " Train Stopping Scheme of Urban Rail Transit ConsideringEnergy Consumption," *China Transportation Review*, vol. 46, no. 08, pp. 64-71, 2024.

[15] L. Qin, H. Yufei, L. Wei, and Z. Xiongfei, "Stop Plan of Express and Local Train for Regional Rail Transit Line," *Journal of Advanced Transportation*, vol. 2018, pp. 1-11, 2018.

[16] B. Han and S. Ren, "Optimizing stop plan and tickets allocation for high-speed railway based on uncertainty theory," *Soft Computing*, vol. 24, no. prepublish, pp. 1-16, 2019.

[17] Z. Tang, " Optimization of Bi-level Passenger Train Operation Plan Based on GameEquilibrium of Passenger Flow," *Railway Transport and Economy*, vol. 46, no. 02, pp. 20-29+39, 2024.

[18] H. Zhao, X. Yang, and D. Wang, " Research on collaborative optimization of high-speed railway train stop planning and timetable considering passenger satisfaction," *Journal of Railway Science and Engineering*, pp. 1-13, 2024.

[19] Z. Li, J. Wu, S. Zhao, and X. Zhao, " Optimization Method for High-Speed Railway Train Stop Plan Oriented Temporal-Spatial Equilibrium and Passenger Flow Adaptability," *Railway Standard Design*, pp. 1-11, 2024.

[20] V. Cacchiani, J. Qi, and L. Yang, "Robust optimization models for integrated train stop planning and timetabling with passenger demand uncertainty," *Transportation Research Part B*, vol. 136, pp. 1-29, 2020.

[21] C. Angyang, Z. Xingchen, C. Junhua, and W. Zhimei, "Joint

optimization of high-speed train timetables, speed levels and stop plans for increasing capacity based on a compressed multilayer space-time network," *PloS one*, vol. 17, no. 3, pp. e0264835-e0264835, 2022.

[22] X. Tian, H. Niu, Y. Jiang, and H. Chai, "A variable-splitting Lagrangian decomposition for train timetabling and skip-stopping with train-type decision," *Transportation Research Part C*, vol. 163, pp. 104645-, 2024.

[23] L. Yang, J. Qi, S. Li, and Y. Gao, "Collaborative optimization for train scheduling and train stop planning on high-speed railways," *Omega*, vol. 64, pp. 57-76, 2016.

[24] J. Shi *et al.*, "Safety-oriented train timetabling and stop planning with time-varying and elastic demand on overcrowded commuter metro lines," *Transportation Research Part E: Logistics and Transportation Review*, vol. 175, p. 103136, 2023.

[25] F. Jiang, V. Cacchiani, and P. Toth, "Train timetabling by skip-stop planning in highly congested lines," *Transportation Research Part B: Methodological*, vol. 104, pp. 149-174, 2017.

[26] Y. Yue, S. Wang, L. Zhou, L. Tong, and M. R. Saat, "Optimizing train stopping patterns and schedules for high-speed passenger rail corridors," *Transportation Research Part C*, vol. 63, pp. 126-146, 2016.

[27] L. Yawei, H. Baoming, Y. Ruixia, and Z. Peng, "Integrated Optimization of Stop Planning and Timetabling for Demand-Responsive Transport in High-Speed Railways," *Applied Sciences*, vol. 13, no. 1, pp. 551-551, 2022.

[28] Y. Wang, "Train timetable and stopping plan generation based on cross-line passenger flow in high-speed railway network," *Measurement and Control*, vol. 58, no. 4, pp. 451-473, 2025.

[29] L. Meng and X. Zhou, "An integrated train service plan optimization model with variable demand: A team-based scheduling approach with dual cost information in a layered network," *Transportation Research Part B*, vol. 125, pp. 1-28, 2019.

[30] J. Qi, Y. Zhou, F. Meng, L. Yang, Q. Luo, and C. Zhang, "Joint optimization of train stop planning and timetabling with time-dependent passenger and freight demands in high-speed railway," *Transportation Research Part C*, vol. 172, pp. 105025-105025, 2025.

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