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Optimization of Passenger Train Line Planning Adjustments Based on Minimizing Systematic Costs

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Abstract

Optimizing passenger train line planning is a complex task that involves balancing operational costs and passenger service quality. This study investigates the adjustment and optimization of train line plans to better align with passenger demand and operational constraints, while minimizing systematic costs. These costs include train operation expenses (e.g., line usage fees and station service fees), passenger travel costs, and hidden costs such as imbalances in station stops. Line usage fees refer to charges for using railway tracks, whereas station service fees cover services provided at train stations. The optimization process employs a Simulated Annealing Algorithm to adjust train compositions, capacity configurations, and stop patterns to better match passenger demand. The results indicate a 13.89% reduction in the objective function value, reflecting improved overall efficiency. Notably, most costs are reduced, including train operating costs and passenger travel costs. However, ticketing service fees—which are calculated as a percentage of passenger fare revenue—increased slightly due to additional backtracking in passenger travel paths, which raised the total fare collected. Overall, the optimization improves the operational performance of the train network, enhancing both efficiency and service quality.

Keywords: passenger train line planning; systematic costs; fleet utilization; simulated annealing algorithm; capacity utilization

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1. Introduction

High-speed railways are renowned for their speed, convenience, safety, and efficiency. To ensure the efficient operation of high-speed railway systems, operators engage in tasks such as route planning, timetable design, and rolling stock scheduling. However, during the formulation of transportation plans, comprehensive costs incurred by both passengers and operators are often overlooked. This oversight can result in passenger attrition and operational losses, ultimately hindering the sustainable development of high-speed rail systems.

The high-speed railway operation planning process is illustrated in Figure 1. At the strategic level, the physical network is designed, followed by line planning, timetable design, rolling stock scheduling, and crew planning. At the operational level, train dispatching is implemented [1]. Among the various strategic decisions, line planning and rolling stock scheduling are the most critical factors influencing train operating costs. However, in current practice, line planning is developed first, followed by timetable design and then rolling stock scheduling. Although this sequential decision-making process simplifies problem-solving, it limits the ability to achieve globally optimal system performance, as

rolling stock scheduling is constrained by fixed line plans and timetables. Numerous studies have addressed issues related to line planning and rolling stock scheduling. A summary of the existing research is presented below.

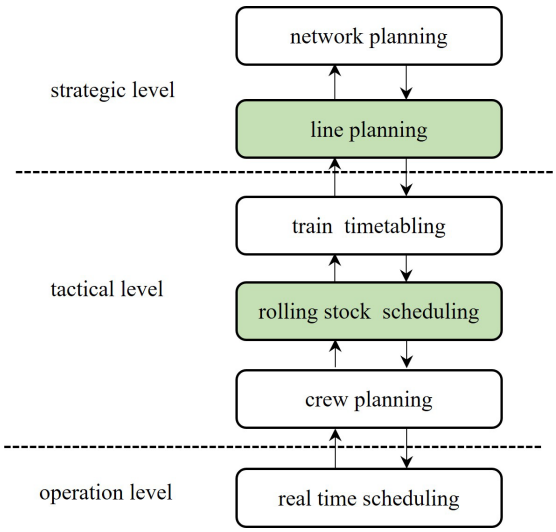


Figure 1. High-speed railway operation planning process.

In the context of route planning optimization, the primary objective is to maximize benefits or minimize costs for railway operators. Canca et al. [2] developed an optimization model for train operation planning aimed at minimizing operating costs and proposed an adaptive large neighborhood search algorithm to solve it. Cacchiani et al. [3] formulated a mixed-integer linear programming (MILP) model for train operation planning with the goal of minimizing total train travel time, determining key factors such as stop patterns and departure/arrival times at each station. Another line of research focuses on optimizing train operation plans from the perspective of passenger demand, with the aim of minimizing passenger travel costs. For example, Talebian et al. [4] proposed an optimization model for train line planning that minimizes total passenger travel delay and the number of unserved passengers, using a hypergraph-based approach. Polinder et al. [5] incorporated the deviation between passengers' expected and actual departure times into the objective function, introduced the concept of average perceived travel time, and constructed a corresponding train line planning model. Xu et al. [6] investigated high-speed railway stop planning and timetabling optimization by accounting for temporal fluctuations in passenger demand. They integrated passenger satisfaction regarding train arrival times into the objective function and designed a customized algorithm to solve the model.

In other studies on train line planning, some researchers have emphasized the importance of incorporating passenger choice behavior into the optimization process. A common approach involves formulating a bi-level programming model. Tang et al. [7] developed a bi-level model in which the upper level aims to optimize the average vehicle occupancy rate and passenger travel cost, while the lower level captures passenger route choice behavior through a flow allocation model. A genetic Simulated Annealing Algorithm (SAA) was designed to solve the upper-level problem, and a continuous averaging method was applied at the lower level. The model's effectiveness was demonstrated through a case study of Shanghai Metro Line 16. Hai et al. [8] proposed a bi-level programming model for train scheduling, in which the upper level minimizes passenger travel cost and travel time, while the lower level minimizes enterprise profit losses. Based on passenger preferences, Yang et al. [9] constructed a bi-level model with the objective of maximizing passenger departure time satisfaction in the upper level and minimizing operating costs in the lower

level. Liu et al. [10] examined changes in passenger flow in urban rail transit systems under different train schedules. They developed a bi-level programming model incorporating passenger attraction, transformed it into a mixed linear programming problem, and validated its effectiveness using data from the Beijing urban rail transit network.

Zhu et al. [11] applied a bi-level programming model to address the train timetabling problem in urban rail transit systems. The upper-level model aims to minimize total passenger costs by determining train departure times, while the lower-level model focuses on minimizing individual passenger travel costs. They formulated an optimization model and developed a two-stage genetic algorithm incorporating a continuous averaging method. Yu et al. [12] proposed a bi-level programming model for bus lane allocation in multimodal transportation networks. The upper-level model seeks to minimize passengers' average travel time, while the lower-level model addresses the traffic assignment problem. The model is solved using a combination of column generation, branch-and-bound techniques, continuous averaging, and other methods.

In the field of rolling stock scheduling, Kroon et al. [13] argued that when train schedules significantly influence passenger demand, high-speed train scheduling can help mitigate passenger flow fluctuations. They developed a scheduling model under dynamic passenger flow conditions and designed an iterative heuristic algorithm to solve it. Cacchiani et al. [14] adopted a staged optimization approach to address the high-speed train scheduling problem and applied a Benders decomposition algorithm to solve the model. Peeters and Kroon [15] formulated a high-speed train operation model that integrates timetabling and seat allocation. They used passenger travel cost, load factor, and train operating cost as key performance indicators for evaluating line planning strategies. Cadarso et al. [16] studied the application of high-speed trains on congested main lines with high departure frequencies. Their model considered storage capacity constraints at high-speed rail sections and the deployment of flexible train formations. The effectiveness of the proposed method was validated using the Madrid high-speed rail network in Spain.

Alfieri et al. [17] sought to improve the efficiency of rolling stock scheduling by determining the optimal number of configurations for different types of rolling stock units and constructing an optimization model based on a multi-commodity flow framework. The correctness of the model was validated using data from the Dutch railway network. Canca et al. [18] addressed the routing plan optimization problem while incorporating rolling stock maintenance constraints. They formulated a mixed-integer programming (MIP) model and proposed a weekly optimization framework for rolling stock scheduling, aiming to minimize empty train movements and balance the weekly mileage of each train unit.

Canca and Eva [19] addressed the collaborative optimization problem of rolling stock scheduling and yard location. They developed a general mixed-integer programming (MIP) framework and proposed a sequential solution algorithm. The algorithm first determines the minimum number of vehicles required to execute the complete weekly train line plan. Then, it identifies the set of daily routes that must be operated each day. Finally, a genetic algorithm is applied to determine the weekly cycles and yard locations. Abbink et al. [20] formulated a train allocation problem within the rolling stock routing context, constructed a mathematical optimization model, and solved it using CPLEX.

Wagenaar et al. [21] developed a mixed-integer linear programming (MILP) model for rolling stock scheduling that incorporates passenger flow demand and empty train return operations. The effectiveness of the model was validated through a practical case study on the Dutch railway network. Haahr et al. [22] compared two solution approaches for rolling stock scheduling: the first employed CPLEX to solve the MILP model, while the second used column-and-row generation algorithms to address an extended version of the model. The results demonstrated that both approaches effectively tackled the rolling

stock scheduling problem. Giacco et al. [23] incorporated rolling stock maintenance into the routing optimization problem. They formulated an MILP model with maintenance constraints and solved it using a commercial solver. Hoogervorst et al. [24] constructed both arc-based and path-based optimization models for rolling stock scheduling, aiming to minimize passenger travel delays. These models were validated through a case study on the Dutch railway network. Lai et al. [25] developed an MILP model for rolling stock scheduling that considers maintenance requirements, yard capacity, and scheduling rules. They designed a hybrid heuristic algorithm to solve the model. Tréfond et al. [26] proposed a simulation–optimization framework for robust rolling stock planning. They formulated an integer linear programming (ILP) model and compared its results with those obtained using the French National Railways' PRESSTO software, which is a reference tool used by SNCF to minimize operating costs and incorporate maintenance slots. The comparison showed that the ILP model improved plan robustness while satisfying both operational and maintenance constraints.

Existing collaborative optimization studies at the planning level primarily focus on the coordination between train scheduling and rolling stock scheduling in high-speed railway systems [27–30]. However, at the route planning level, insufficient consideration of high-speed train deployment can lead to elevated execution costs, making it difficult to achieve system-level optimality for the overall transportation network. Currently, there is a lack of research on high-speed train routing-based optimization of train operation plans that simultaneously considers train operating costs, passenger travel costs, and station-related expenses, while systematically integrating these factors into the train line planning process. In practical applications, to better meet passenger travel demand and reduce operational costs for railway operators, it is essential to optimize train line planning based on high-speed train routing, with explicit consideration of systematic costs.

This study adopts high-speed train routing as the fundamental unit of analysis and integrates multiple decision-making elements of train line planning to investigate the optimization of high-speed railway passenger train line planning under an integrated routing framework, with explicit consideration of systematic costs. In this context, a train route is defined as the complete operational path of a rolling stock unit, starting from its originating station and ending at its terminal station. It may include multiple connected train services operated by the same unit. This definition emphasizes the physical circulation and operational scheduling of the trainset, rather than merely representing a passenger service route.

First, the concept of systematic cost—which includes train operating costs, passenger travel costs, and station balance costs—is defined, and the corresponding optimization problem for passenger train line planning is formulated. The criteria that trigger the need for optimization are also analyzed. Second, considering constraints related to transportation resources, operational organization, service levels, and train capacity, a train line planning optimization model is developed with the objective of minimizing systematic costs. Finally, a neighborhood search algorithm is designed, and the proposed model and algorithm are validated through a case study of the Beijing–Shanghai high-speed railway.

While previous studies have proposed various cost-oriented models for train line planning, they have typically focused on either operator-side costs—such as energy consumption and line usage fees—or passenger-side metrics, such as travel time and transfer delays, often within bi-level or independently structured frameworks [31–33]. However, few studies have explicitly unified these components into a comprehensive and fully quantifiable systematic cost function that integrates both hard operational costs and soft service-related penalties. In contrast, this study introduces a novel formulation of systematic cost that not only captures train operating and passenger-related expenses but

also incorporates balanced stop distribution as a structural factor influencing long-term capacity utilization and service equity. Moreover, unlike models that passively evaluate predefined plans, our framework actively triggers optimization based on temporal variations in passenger flow and mismatches in load factors, enabling dynamic adjustment of train routes, stop patterns, and departure times. From a practical perspective, this integrated approach supports real-world implementation in high-speed rail systems, where fluctuating demand and the complexity of service coordination necessitate holistic and cost-sensitive optimization strategies.

The main contributions of this study include the definition of systematic cost within the context of high-speed railway transportation organization, the integration of high-speed train routing into line planning, the development of a nonlinear mixed-integer programming (MINLP) model based on train routes, and the design of a Simulated Annealing Algorithm (SAA) to solve the model. The specific innovations of this study are as follows:

1. A systematic cost metric is proposed for train line planning optimization, enabling a comprehensive assessment of optimization performance. In addition, optimization trigger mechanisms are designed to determine when updates to the line plan are necessary, thereby supporting smoother and more adaptive transportation operations.
2. Line planning is optimized based on train routing, ensuring both the feasibility of train deployment and the operational stability of the resulting plan.
3. A neighborhood search strategy is developed to jointly optimize individual train routes and the overall line plan, achieving coordination between localized routing decisions and system-level operational efficiency.

2. Methods

2.1. Problem Description

The objective of line planning is not only to meet passenger travel demand but also to minimize operational costs. While supply and demand are inherently interrelated, the overall system cost is additionally influenced by the line planning strategy and passengers' travel behavior.

This study focuses on optimizing passenger train line planning within a high-speed railway network, with the objective of minimizing total systematic cost. Systematic cost is defined as the sum of railway operators' costs (e.g., track usage fees, energy consumption, and service charges), passengers' generalized travel costs (including departure time adjustments, in-vehicle travel time, and transfer-related risks), and implicit penalties resulting from unbalanced train stop distributions. Figure 2 illustrates the relationship between systematic cost and the railway system's supply and demand. As shown in the figure, each component of systematic cost is influenced by both the line planning strategy and the distribution of passenger flow. Moreover, there is an inherent interdependence between railway supply and demand, which collectively shape the overall transportation system. Therefore, systematic cost must be considered in the line planning process to effectively balance supply and demand while minimizing total cost.

Given a high-speed railway network $G = (V, E)$, with time-varying passenger demand among O–D pairs, the objective is to determine a set of passenger train lines (each consisting of multiple trains) such that

- Each train has an optimized routing path, stop pattern, formation type, and departure/arrival times;
- The passenger flow is reasonably assigned to the available travel plans;
- The resource constraints, such as track capacity and time windows, are satisfied.

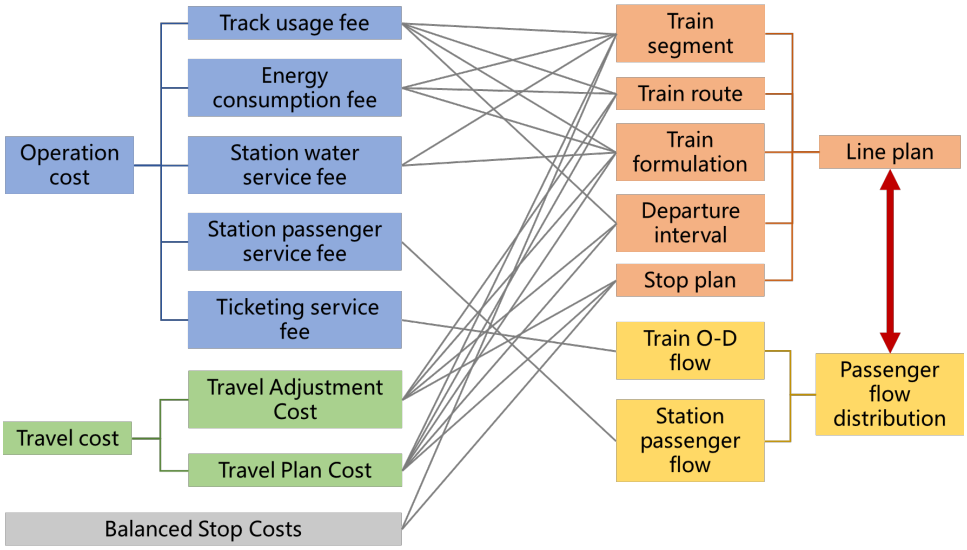


Figure 2. Illustration of the relationship between the systematic cost and railway supply and demand.

2.2. Notations

To improve readability and facilitate understanding of the mathematical model, the key symbols and their definitions used throughout the paper are summarized in Table 1.

Table 1. Notation list.

Symbol	Meaning
$G = (V, E)$	Different components of train operational costs (e.g., track usage, energy)
RS	Set of origin–destination (O–D) pairs
$(r, s) \in RS$	An O–D pair
$y_{rs}(x)$	Passenger departure time distribution for O–D pair (r, s)
$\hat{x}_{rsk}$	Ideal departure time for travel plan p_{rsk}
x^1_{rskn}, x^2_{rskn}	Start and end of the attracting time window for plan p_{rsk} in iteration n
p_{rsk}	A specific travel plan between O–D pair (r, s)
n_{rsk}	Number of train segments in travel plan p_{rsk}
l^u_{rsk}	u-th train segment in travel plan p_{rsk}
i^u_{rsk}, j^u_{rsk}	Indices of origin and destination stations for segment u
$r_p(l)$	Fare rate of train segment l
w	Value of passenger unit travel time
$\rho(v)$	Transfer risk coefficient at station v
$a^{l^u_{rsk}}_{j^u_{rsk}}, d^{l^u_{rsk}}_{i^u_{rsk}}$	Arrival and departure times at the endpoints of segment l^u_{rsk}
C_1 to C_5	Components of operational costs: track usage, energy, ticketing, station service, and water
C_6	Passenger travel adjustment cost
C_7	Passenger travel plan cost
Z_1	Total operational cost of the railway operator
Z_2	Total cost of passenger travel
Z_3	Balanced stop cost
Z	Overall systematic cost of the train line plan
T	Number of time periods in a day
$r_v(t)$	Proportion of services at station v during time period t
$r^{l^g_i}_{seg}(j)$	Stop ratio in segment j of train l^g_i
l^g_i	The i-th train in line g
$V\left(l^g_i\right)$	Stations covered by train l^g_i
$X\left(l^g_i\right)$	Stop pattern of train l^g_i
$B\left(l^g_i\right), M\left(l^g_i\right), D\left(l^g_i\right)$	Train formation, type, and departure time of l^g_i

2.3. Systematic Costs

Since railway transportation primarily serves passengers, optimizing passenger train line planning is inherently a complex and systematic task. The optimization process must balance the interests of both railway operators and passengers, thoroughly analyze the potential cost components across all stages of train operations and passenger travel, and quantitatively evaluate these components to calculate the total systematic cost.

2.3.1. Components of Train Operations

From the perspective of railway operations, the entire train operation process comprises several key components, including train movement, energy consumption, passenger services, vehicle depreciation, and maintenance. These elements constitute the core operational activities necessary for delivering high-quality passenger rail services.

- Train Operation

The costs associated with train operations primarily include track usage fees, denoted as C_1, which refer to the charges incurred for accessing various track segments. These fees are typically categorized into basic track usage fees, nighttime usage fees, and additional charges for operating on congested or external tracks. The total cost is influenced by multiple factors, including the train's route mileage, track classification, traffic density, time of day (e.g., nighttime operations), and the unit pricing for both basic and supplementary services.

- Energy Consumption

The energy utilization costs associated with train operations primarily consist of contact network usage fees and electricity costs C_2, which represent the energy consumption required for the total ton-kilometers of traction trains. These costs include both self-provided and external service fees, such as contact network and electricity fees for self-provided services, basic and night contact network fees for self-provided services, as well as corresponding fees for external services. The classification of these costs is based on the respective railway bureaus (for EMUs) or traction bureaus (for electric locomotives).

The contact network and electricity fees are primarily influenced by factors such as the segment mileage, total weight traversing the segment, and the unit price of the contact network usage fee for each segment. Additionally, passenger air conditioning fuel costs are driven by factors including train kilometers, train types, air conditioning allocation, and fuel prices.

- Passenger Services

The costs related to passenger services during train operations include ticketing service fees C_3, station passenger service fees C_4, and station water service fees C_5. Ticketing service fees refer to the charges paid to ticketing platforms or service providers for the processing, issuance, and management of passenger tickets. These fees are typically calculated as a percentage of the total ticket revenue. Station passenger service fees represent the costs incurred by railway stations in delivering services such as check-in, boarding management, waiting lounges, guidance systems, and customer assistance. These fees vary based on station classification and passenger volume. Station water service fees are the charges associated with providing water replenishment services to trains during scheduled stops, and are usually determined by the type of train and its stop duration. For example, ticketing service fees depend on the number of passengers, ticket revenue, and service fee rates. Station passenger service fees are influenced by passenger volume, station grade, and service costs, while water service fees are determined by the type of train, service time, and unit water price.

Summing up these operational costs yields the total cost for railway providers:

$$Z_1 = \sum_{i=1}^{5} C_i \tag{1}$$

2.3.2. Cost Components of Passenger Travel

The entire passenger travel process includes several stages: departure adjustments, enroute travel, station waiting, and intermediate transfers. Each stage incurs specific costs, including time-related expenses and costs arising from uncertainties or overcrowding.

- Travel Adjustment Costs

Considering time-varying demand, passengers have their preferred departure times. However, due to the planned nature of railway operations, passengers must adjust their travel times when selecting travel options, resulting in a deviation from their preferred departure times. Let the unit travel adjustment cost be κ, and let the travel intensity distribution for the origin–destination (O–D) pair $(r, s) \in RS$ be $y_{rs}(x)$,where $x \in [t_1, t_2]$ represents the time interval, and there are N_{rs} travel options between O-D pair (r, s). According to the passenger flow allocation method proposed by Zhao et al. [28], due to train seating capacity constraints, passenger travel choices are made through multiple iterations, with the optimal travel option and its associated time window changing in each iteration. Assuming that passenger flow allocation undergoes N iterations, in the $n-th$ iteration, for the $k-th$ travel option p_{rsk}, the departure time is $\hat{x}_{rsk}$, the attracting time window is $\left[x^1_{rskn}, x^2_{rskn}\right]$, and the loading ratio for this iteration is θ_n.

In this context, x represents the passenger's preferred departure time, while $\hat{x}_{rsk}$ denotes the scheduled departure time of the travel plan. The interval $[x^1_{rskn}, x^2_{rskn}]$ defines the range during which passengers are willing to adjust their travel time to board the corresponding train service. The travel intensity distribution $y_{rs}(x)$ indicates the probability density of passengers choosing time x. The unit cost κ captures the economic or psychological penalty associated with this deviation.

Moreover, Equation (2) integrates x only over the range $[x^1_{rskn}, x^2_{rskn}]$, which ensures that x does not fall outside the defined interval. Therefore, the concern of x being outside the range is inherently avoided by the integration limits. The total travel adjustment cost for all passengers in this iteration is given by

$$C_6 = \sum_{n=1}^{N} \sum_{(r,s)\in RS} \sum_{k=1}^{N_{rs}} \int_{x^1_{rskn}}^{x^2_{rskn}} \theta_n \kappa |x - \hat{x}_{rsk}| y_{rs}(x) dx \tag{2}$$

- Travel Plan Costs

During the travel process, passengers experience multiple stages, including in-transit travel, station waiting, and intermediate transfers, each of which incurs specific costs such as ticket expenses, time costs, and transfer risks. Ticket expenses are determined based on the prescribed fare rate and the distance traveled along the corresponding train segment. Time costs represent the value of total travel time, which includes in-transit running time, station waiting time, and transfer time; the unit value of time is typically estimated using the average wage per unit time. Transfer risks arise from uncertainties in making connections at intermediate stations, imposing psychological stress on passengers. These risks are modeled as an additional perceived time penalty added to the actual transfer time. Notably, transfer risks are generally lower at higher-grade transfer stations, which offer more frequent and reliable services, thereby enhancing the overall travel experience.

Assuming that the O–D pair $(r,s) \in RS$ has N_{rs} travel paths, each path p_{rsk}, $k = 1, 2, \cdots, N_{rs}$ consists of n_{rsk} train segments, represented as

$$l^1_{rsk}\left(i^1_{rsk}, j^1_{rsk}\right), l^2_{rsk}\left(i^2_{rsk}, j^2_{rsk}\right), \cdots, l^{n_{rsk}}_{rsk}\left(i^{n_{rsk}}_{rsk}, j^{n_{rsk}}_{rsk}\right)$$

Here, $l^u_{rsk}\left(i^u_{rsk}, j^u_{rsk}\right)$ denotes the $u-th$ segment of train l^u_{rsk} from station $v^{l^u_{rsk}}_{i^u_{rsk}}$ to station $v^{l^u_{rsk}}_{j^u_{rsk}}$, with mileage $\left|l^u_{rsk}\right|$.

The fare rate of train l^u_{rsk} is $r_p\left(l^u_{rsk}\right)$, the unit time value is w, and the transfer risk at station v is $\rho(v)$. Thus, the total cost of the travel plan p_{rsk} can be expressed as

$$|p_{rsk}| = \sum_{u=1}^{n_{rsk}}\left[r_p\left(l^u_{rsk}\right)\cdot\left|l^u_{rsk}\right| + w\left(a^{l^u_{rsk}}_{j^u_{rsk}} - d^{l^u_{rsk}}_{i^u_{rsk}}\right)\right] + \sum_{u=1}^{n_{rsk}-1}\rho\left(v^{l^u_{rsk}}_{j^u_{rsk}}\right) \tag{3}$$

Here, $a^{l^u_{rsk}}_{j^u_{rsk}}$ and $d^{l^u_{rsk}}_{i^u_{rsk}}$ represent the arrival and departure times of train l^u_{rsk} at the $j^u_{rsk} - th$ and $i^u_{rsk} - th$ stations, respectively.

The total cost of all passengers' travel plans is

$$C_7 = \sum_{n=1}^{N}\sum_{(r,s)\in RS}\sum_{k=1}^{N_{rs}}\int_{x^1_{rskn}}^{x^2_{rskn}}\theta_n|p_{rsk}|y_{rs}(x)dx \tag{4}$$

Thus, the total cost of the entire passenger travel process is

$$Z_2 = C_6 + C_7 = \sum_{n=1}^{N}\sum_{(r,s)\in RS}\sum_{k=1}^{N_{rs}}\int_{x^1_{rskn}}^{x^2_{rskn}}\theta_n(\kappa|x-\hat{x}_{rsk}| + |p_{rsk}|)y_{rs}(x)dx \tag{5}$$

- Balanced Stop Costs

In addition to direct costs, the design of train operation plans may impose adverse impacts on operational organization, resource utilization, and capacity efficiency, thereby generating hidden costs. Among these, the cost associated with unbalanced stop distribution—referred to as balanced stop cost—is particularly significant.

The design of train stop plans is a critical component of line planning optimization, as it directly influences both the passenger travel experience and the feasibility of subsequent scheduling. While the objective is to match service supply with passenger demand, achieving a balanced distribution of stops across stations is often challenging. Such imbalances can diminish overall line capacity and hinder effective timetable construction. Ensuring stop balance is therefore essential for maintaining operational order and maximizing capacity utilization. As a result, the potential hidden costs associated with stop imbalances must be explicitly accounted for in the planning process.

A train stop plan can be represented as a two-dimensional 0–1 matrix in time and space. Balanced stops refer to both temporal and spatial equilibrium in train stops, including balanced scheduling of services at stations across different time periods and balanced stop distribution across line segments. Assuming the day is divided into T time periods, for a station $v \in V$, the service frequency in each time period as a proportion of the total daily service frequency is denoted as $r_v(t)$, $t = 1, 2, \cdots, T$. Additionally, if trains with terminal station capabilities are divided into $seg\left(l^g_i\right)$ segments by station nodes, the stop ratio for the $i-th$ segment is represented as $r^{l^g_i}_{seg}(j), j = 1, 2, \cdots, seg\left(l^g_i\right)$.

From a temporal perspective, balanced stop scheduling ensures that service frequencies at each station are evenly distributed across different time periods, thereby maintaining consistent service levels even during off-peak hours. From a spatial perspective, balanced

train stops refer to uniform stop ratios across various segments of the railway line, which help provide evenly distributed service coverage along the entire route.

To evaluate the temporal and spatial balance of train stops, a min–max index is employed—a commonly used metric that assesses distributional balance independent of the system's scale or the number of participants. Based on this approach, quantitative indicators are designed to compute the balanced stop cost from both temporal and spatial perspectives. The balanced stop cost can be expressed as

$$Z_3 = \sum_{v \in V} max\{r_v(t) | t = 1, 2, \cdots, T\} + \sum_{g \in G} \sum_{i=1}^{m_g} max\left\{ r_{seg}^{l_i^g}(j) \middle| j = 1, 2, \cdots, seg\left(l_i^g\right) \right\} \quad (6)$$

- Systematic Costs

By integrating the entire process of train operations and passenger travel, the systematic cost of passenger train line planning is defined as the sum of railway operational costs, passenger travel costs, and hidden costs. To enable a more comprehensive and flexible evaluation, weights can be assigned to each cost component, allowing for the construction of a weighted aggregate measure of total systematic cost.

The optimization problem for passenger train line planning, aimed at minimizing systematic costs, can be described as follows:

Given a high-speed railway network $G = (V, E)$, where V and E represent the sets of stations and segments, respectively, and considering passenger demand distribution over time and space as well as railway operational parameters, the objective is to minimize systematic costs. This optimization is subject to constraints related to network resource allocation and passenger service levels, resulting in a set of line plans G that meet passenger travel demands.

Each line $Cir(g) = \left(l_1^g, l_2^g, \cdots, l_{m_g}^g\right)$ consists of m_g trains, where each train l_i^g, $i = 1, 2, \cdots m_g$, can be represented as

$$l_i^g = \left\{ V\left(l_i^g\right), X\left(l_i^g\right), B\left(l_i^g\right), M\left(l_i^g\right), D\left(l_i^g\right) \right\}$$

Here,

$V\left(l_i^g\right)$ denotes the set of $h\left(l_i^g\right)$ stations along the route of train l_i^g;

$X\left(l_i^g\right)$ represents the stopping pattern of train l_i^g at each station;

$B\left(l_i^g\right)$, $M\left(l_i^g\right)$, $D\left(l_i^g\right)$ correspond to the train's formation, type, and estimated departure time, respectively.

2.4. Passenger Train Line Planning Optimization Model

2.4.1. Trigger Criteria Design for Passenger Train Line Planning Optimization

Frequent adjustments to train line planning not only increase the complexity of transportation management but also disrupt passengers' established travel patterns. To ensure operational stability, railway authorities generally refrain from making real-time adjustments in response to short-term passenger flow fluctuations. Instead, modifications to the line plan are implemented only when changes in passenger demand or operational efficiency exceed a predefined threshold, thereby triggering specific conditions under which plan adjustments are warranted.

- Passenger Flow Demand Fluctuation

When passenger flow demand fluctuates beyond a certain range, the existing train line planning may no longer align with actual travel needs, necessitating adjustment and re-optimization. By analyzing variations in passenger demand across different

origin–destination (O–D) pairs, a passenger flow fluctuation coefficient is computed. If this coefficient exceeds a predefined threshold, the line planning is triggered for adjustment.

For an O–D pair $(r, s) \in RS$, assuming the current operation plan serves a passenger flow demand of q_{rs}^0, the passenger flow fluctuation coefficient is

$$\varepsilon_1 = \sum_{(r,s)\in RS} \left| q_{rs} - q_{rs}^0 \right| / \sum_{(r,s)\in RS} q_{rs}^0 \tag{7}$$

By setting an allowable threshold for fluctuations in passenger flow demand, a trigger mechanism is established to detect significant changes. If the threshold is exceeded, adjustments to the train operation plan are initiated.

- Change in Load Factor

Fluctuations in passenger flow demand can cause changes in operational indicators, even if passenger flow remains within allowable limits. Significant deviations in these indicators, driven by changes in passenger flow structure, may signal that the current line planning no longer meets actual transportation needs, thus requiring adjustments. Among various operational indicators, the load factor is often considered a key metric for evaluating plan effectiveness. Therefore, the average load factor is selected as the trigger criterion for adjustments to the train line planning. Assuming the average load factor of the current line planning is $\overline{ALF}^0$, and the average load factor for serving the actual passenger flow demand is $\overline{ALF}$, the load factor fluctuation coefficient is defined as

$$\varepsilon_2 = \left| \overline{ALF} - \overline{ALF}^0 \right| / \overline{ALF}^0 \tag{8}$$

When the load factor fluctuation coefficient exceeds the allowable threshold, adjustments to the line planning are necessary.

If any of the above trigger determination criteria are met, train line planning adjustments and optimizations should be carried out. Otherwise, the current operation plan can be considered sufficient to meet passenger travel demand, and no optimization is required.

2.4.2. Constraints

- Transportation Resource Constraints

Segment Throughput Capacity Constraints. The number of trains passing through a specific segment $e \in E$ must satisfy the throughput capacity constraints to ensure operational safety. Assuming the throughput capacity of segment e is C_e, the segment throughput capacity constraint can be expressed as

$$\sum_{g\in G} \sum_{i=1}^{m_g} \epsilon\left(l_i^g, e\right) \le C_e, \quad e \in E \tag{9}$$

Here, $\epsilon\left(l_i^g, e\right)$ represents the relationship between train l_i^g and segment e. If train l_i^g passes through segment e, then $\epsilon\left(l_i^g, e\right) = 1$; otherwise, $\epsilon\left(l_i^g, e\right) = 0$.

Constraints on Train Origin and Termination Capacity at Stations. Due to the operational characteristics, classification, and track-station layout of each station, the number of trains originating and terminating at a station must not exceed the station's origin and termination capacity. Assuming the origin and termination capacity of station $v \in V$ is C_v, the following constraint must be satisfied:

$$\sum_{g\in G} \sum_{i=1}^{m_g} \zeta^1\left(l_i^g, v\right) \le C_v, v \in V \tag{10}$$

$$\sum_{g\in G} \sum_{i=1}^{m_g} \zeta^2\left(l_i^g, v\right) \le C_v, v \in V \tag{11}$$

Here, $\zeta^1\left(l_i^g, v\right)$ represents the relationship between train l_i^g and station v regarding train origins: if station v is the origin station of train l_i^g, then $\zeta^1\left(l_i^g, v\right) = 1$; otherwise, $\zeta^1\left(l_i^g, v\right) = 0$. Similarly, $\zeta^2\left(l_i^g, v\right)$ represents the relationship between train l_i^g and station v regarding train terminations: if station v is the termination station of train l_i^g, then $\zeta^2\left(l_i^g, v\right) = 1$; otherwise, $\zeta^2\left(l_i^g, v\right) = 0$.

High-Speed Trainset Constraints. The train line planning relies on high-speed trainsets to fulfill train schedules. These trainsets are classified into various models, each with a specific seating capacity. Based on passenger flow demand, trainsets can be flexibly allocated to different schedules. The number of high-speed trainsets required must not exceed the available quantity of each model, ensuring the plan's feasibility.

For a given schedule $g \in G$, the number of trainsets used corresponds to the number of formations assigned to that schedule. The allocation of each trainset model is determined by its compatibility with the specific schedule.

$$\sum_{g \in G} \varrho\left(l_1^g, m\right) \cdot B\left(l_1^g\right) \leq RS_m, \quad m \in \overline{M} \tag{12}$$

Here, $\overline{M}$ represents the set of available high-speed trainset models, and $\varrho\left(l_1^g, m\right)$ denotes the compatibility relationship between schedule g and trainset model $m \in \overline{M}$: if the trainset model used for schedule g is m, then $\varrho\left(l_1^g, m\right) = 1$; otherwise, $\varrho\left(l_1^g, m\right) = 0$. RS_m represents the available number of trainsets for model m.

- Transportation Organization Constraints

Basic Timetable Constraints. For adjustments and optimizations of the train line planning within a specific timetable period, all trains in the adjusted plan must be selected from the basic operational timetable. This constraint can be expressed as

$$l_i^g \in \overline{L}, \quad i = 1, 2, \cdots, m_g, g \in G \tag{13}$$

Trainset and Formation Constraints. In the train line planning, the trainsets used for each schedule must be selected from the available high-speed trainsets, and their formations must comply with either single-unit or coupled-unit configurations. This can be expressed as

$$M\left(l_i^g\right) \in \overline{M}, \quad i = 1, 2, \cdots, m_g, g \in G \tag{14}$$

$$B\left(l_i^g\right) \in \{1, 2\}, \quad i = 1, 2, \cdots, m_g, g \in G \tag{15}$$

Schedule Connection Constraints. For each scheduled service, the connection time between consecutive trains must be no less than the minimum preparation time required for high-speed trainsets. This ensures that sufficient time is available for essential tasks such as trainset turnaround, inspection, and preparation. The constraint can be mathematically formulated as

$$d_1^{l_{i+1}^g} - a_{h\left(l_i^g\right)}^{l_i^g} \geq \tau_{connection}, \quad i = 1, 2, \cdots, m_g - 1, \ g \in G \tag{16}$$

Here, $\tau_{connection}$ represents the minimum preparation time required for high-speed trainsets during the train connection process.

Schedule Formation Constraints. Since each schedule is executed by a specific set of high-speed trainsets, the trainset model and formation within the same schedule must remain consistent. This can be expressed as

$$M\left(l_1^g\right) = M\left(l_2^g\right) = \cdots = M\left(l_{m_g}^g\right) \tag{17}$$

$$B\left(l_1^g\right) = B\left(l_2^g\right) = \cdots = B\left(l_{m_g}^g\right) \tag{18}$$

Train Arrival and Departure Time Constraints. The arrival and departure times of each train at adjacent intermediate stations must satisfy the corresponding running time for the segment, start–stop additional time, and station stop time constraints. For train $l_i^g, i = 1, 2, \cdots, m_g,\ g \in G$, the following constraints must be satisfied:

$$d_1^{l_i^g} = D\left(l_i^g\right) \tag{19}$$

$$a_{j+1}^{l_i^g} = d_j^{l_i^g} + x_j^{l_i^g} \cdot \tau_{ad} + t_{l_i^g, j}^{run} + x_{j+1}^{l_i^g} \cdot \tau_{ad}, \quad j = 2, 3, \cdots, h\left(l_i^g\right) \tag{20}$$

$$d_j^{l_i^g} = a_j^{l_i^g} + x_j^{l_i^g} \cdot \tau_{v_j^{l_i^g}}^{stop}, \quad j = 2, 3, \cdots, h\left(l_i^g\right) - 1 \tag{21}$$

Here, $x_j^{l_i^g}$ represents the stop indicator for train l_i^g at its $j-th$ intermediate station. If the train stops at the station, then $x_j^{l_i^g} = 1$; otherwise, $x_j^{l_i^g} = 0$.

τ_{ad} denotes the additional time for train starting and stopping.

$t_{l_i^g, j}^{run}$ represents the running time of train l_i^g for its $j-th$ segment.

$\tau_{v_j^{l_i^g}}^{stop}$ denotes the stop time of train l_i^g at its $j-th$ intermediate station.

High-Speed Trainset Maintenance Constraints. The running time and mileage of high-speed train schedules must comply with the standards for routine maintenance, which can be expressed as

$$|Cir(g)|_{total} \leq RT, \quad g \in G \tag{22}$$

$$|Cir(g)|_{mileage} \leq RM, \quad g \in G \tag{23}$$

Here, $|Cir(g)|_{mileage}$ mileage represents the mileage of schedule g, while RT and RM denote the maximum running time and mileage for routine maintenance of the schedule, respectively.

- Service Level Constraints

Demand Conservation Constraint. The train line planning must satisfy the travel demands of all passengers, ensuring that each passenger's travel needs are met with appropriate travel arrangements. Specifically, the total passenger flow across all travel paths must match the original travel demand. For the travel path $p_{rsk}, k = 1, 2, \cdots, N_{rs}, (r, s) \in RS$, the passenger flow is given by

$$f_{rsk} = \sum_{n=1}^{N} \int_{x_{rskn}^1}^{x_{rskn}^2} \theta_n y_{rs}(x) dx, \quad k = 1, 2, \cdots, N_{rs}, (r, s) \in RS \tag{24}$$

Thus, the number of stranded passenger kilometers for each O–D pair should be zero:

$$\left(q_{rs} - \sum_{k=1}^{N_{rs}} f_{rsk}\right) \cdot |sp_{rs}| = 0, \quad (r, s) \in RS \tag{25}$$

Here, $|sp_{rs}|$ represents the shortest path length of O–D pair (r, s) in the network.

Station Service Frequency Constraints. Stations have different classifications and handle varying scales of passenger demand. Therefore, the stopping frequency at each station must meet a minimum service frequency threshold to accommodate passenger

travel needs. A variable $\sigma_v^{l_i^g}$, $i = 1, 2, \cdots, m_g$, $g \in G, v \in V$, is defined to represent the relationship between trains and stations: if train l_i^g stops at station v, then $\sigma_v^{l_i^g} = 1$; otherwise, $\sigma_v^{l_i^g} = 0$.

The station service frequency constraint can be expressed as

$$\sum_{g \in G} \sum_{i=1}^{m_g} \sigma_v^{l_i^g} \geq fre_v^0, \quad v \in V \tag{26}$$

Here, fre_v^0 is the minimum service frequency threshold required for station v.

- Train Capacity Constraints

Since high-speed trains do not allow overcapacity ticket sales, passenger allocation must satisfy the train capacity constraints. Specifically, the passenger flow on each train segment must not exceed the train's seating capacity. For train l_i^g, $i = 1, 2, \cdots, m_g$, $g \in G$, the passenger flow on its $j-th$ train segment $seg_j^{l_i^g}$, $j = 1, 2, \cdots, seg\left(l_i^g\right)$, can be expressed as

$$f\left(seg_j^{l_i^g}\right) = \sum_{(r,s) \in RS} \sum_{k=1}^{N_{rs}} f_{rsk} \cdot \delta\left(p_{rsk}, seg_j^{l_i^g}\right), \quad j = 1, 2, \cdots, seg\left(l_i^g\right), i = 1, 2, \cdots, m_g, g \in G \tag{27}$$

The capacity constraint can then be expressed as

$$f\left(seg_j^{l_i^g}\right) \leq Cap_{M(l_i^g)} \cdot B\left(l_i^g\right), \quad j = 1, 2, \cdots, seg\left(l_i^g\right), i = 1, 2, \cdots, m_g, g \in G \tag{28}$$

Here, $Cap_{M(l_i^g)}$ represents the single-unit capacity of the train model l_i^g

2.4.3. Objective Function

To integrate train operation costs, passenger travel costs, and stop balancing costs into a unified systematic cost framework, weight coefficients are introduced. This transformation converts the original multi-objective optimization problem into a single-objective formulation, thereby enabling the construction of a passenger train line planning optimization model that minimizes total systematic cost. To account for potential errors in the passenger flow distribution algorithm, constraint (28) is reformulated as a penalty function, allowing deviations to be incorporated directly into the objective function.

$$Z_4 = \left(q_{rs} - \sum_{k=1}^{N_{rs}} f_{rsk}\right) \cdot |sp_{rs}| \tag{29}$$

$$minZ = \sum_{i=1}^{4} \alpha_i Z_i \tag{30}$$

s.t. denotes the set of constraints, which are represented by Equations (12)–(27) and (29)–(31).

To clarify the outcomes of this study, the proposed optimization model generates several key outputs that directly support high-speed rail line planning. Specifically, the model determines the optimal routing paths of EMU trainsets, indicating the sequence of service segments assigned to each rolling stock unit. It also outputs the stop patterns of all trains, specifying the stations where each train should stop. In addition, the model defines the departure and arrival times at each station for every train, thereby forming a complete and feasible timetable that satisfies all operational constraints. Furthermore, the train formation types and departure periods are jointly optimized to ensure alignment with both rolling stock circulation and passenger demand. Another important output is the passenger flow allocation, which reflects how passengers are distributed across available travel plans under capacity and service constraints. Finally, the model calculates

the total systematic cost, encompassing operator costs, passenger costs, and stop balancing penalties. Collectively, these outputs provide a comprehensive decision-making framework for passenger train line planning that balances operational efficiency and service quality.

2.5. Algorithm

The train line planning optimization problem has been proven to be a large-scale, non-convex, and NP-hard problem. Consequently, an efficient solution algorithm is required to obtain satisfactory results within a reasonable computational time. Given the generality and robustness of the Simulated Annealing Algorithm (SAA), an optimization algorithm based on the SAA framework is developed to solve the proposed model.

2.5.1. Optimization Strategy

The overall optimization strategy of the algorithm begins with determining whether the triggering conditions for train line planning adjustment are met. Once the conditions are satisfied, the Simulated Annealing Algorithm (SAA) framework is applied, guided by the objectives and constraints of the optimization model. A neighborhood search strategy is employed to generate neighboring solutions and iteratively update the current solution until the termination condition is reached. The main steps of the optimization algorithm are as follows:

- Adjustment Optimization Trigger Determination

Based on actual travel demand and the current train operation plan, the passenger flow fluctuation coefficient and seat occupancy fluctuation coefficient are calculated. The decision to trigger the adjustment and optimization of the train line planning is made by comparing these coefficients against predefined fluctuation thresholds. If any of the trigger conditions are met, the train line planning adjustment and subsequent optimization process are initiated.

- Initial Solution Construction and Evaluation

Based on the current solution and the structure of the optimization model, a neighborhood search is performed according to the predefined search strategy to generate a neighboring solution. The objective function value of the neighboring solution is then calculated, and its quality is evaluated to determine whether it should replace the current solution.

- Solution Update

The difference in objective function values between the neighboring solution and the current solution is calculated. Based on this difference, an acceptance criterion—typically derived from the simulated annealing framework—is applied to determine whether the neighboring solution should be accepted as the new current solution.

- Termination Condition Check

2.5.2. Neighborhood Search Strategy

The neighborhood search process is guided by the evaluation results of the current solution and the structure of the optimization model. It generates neighboring solutions based on the current distribution of passenger flow and various performance evaluation metrics. Initially, operational elements of the trains on each route are adjusted, either globally or individually. After these adjustments, the overall service level and transportation capacity are recalibrated. Finally, route integration is carried out to form a new neighboring solution.

- Route Train Adjustment Strategy

Since each route consists of multiple trains that share a common pool of train units, any adjustment to train composition must be applied simultaneously to all trains operating

on that route. Therefore, when selecting a composition adjustment strategy, it is necessary to consider the overall configuration of the route's capacity as well as the corresponding passenger load factors (i.e., seat occupancy rates).

For a route $Cir(g) = \left(l_1^g, l_2^g, \cdots, l_{m_g}^g\right), g \in G$, let the running mileage of train l_i^g be $\left|l_i^g\right|$, and the passenger load factor (LF) of the train be lf_i^g. The overall average load factor for the route is given by

$$ave_{lf(g)} = \sum_{i=1}^{m_g} Cap_{M(l_i^g)} \cdot B\left(l_i^g\right) \cdot \left|l_i^g\right| \cdot lf_i^g / \sum_{i=1}^{m_g} Cap_{M(l_i^g)} \cdot B\left(l_i^g\right) \cdot \left|l_i^g\right| \quad (31)$$

The overall average capacity for the route is

$$ave_{cap(g)} = \sum_{i=1}^{m_g} Cap_{M(l_i^g)} \cdot B\left(l_i^g\right) \cdot / \sum_{i=1}^{m_g} \left|l_i^g\right| \quad (32)$$

Based on the average capacity and average load factor of a given route, corresponding adjustment strategies for train composition can be formulated. These strategies may include adding or removing carriages, or changing the train type to better match passenger demand and improve resource utilization.

If the average capacity of route $g \in G$ falls within the range of long trains or double-unit trains, for routes with lower load factors, an adjustment strategy to reduce the train composition or capacity is applied. Specifically:

If the average load factor of route g is within a certain low range (e.g., 40% to 60%), with a certain probability (e.g., 0.7), the composition is adjusted to a long train with a smaller capacity or to a single-unit train that meets the load factor requirement and undergoes double-unit operation.

If the average load factor of route g is below a specific threshold (e.g., 40%), with a certain probability (e.g., 0.9), it is adjusted to a single-unit train that meets the load factor requirement.

During the adjustment, the available train units' capacity constraints must be met.

If the average capacity of route $g \in G$ falls within the range of short trains, for routes with higher load factors, an adjustment strategy to increase the train composition or capacity is applied. Specifically:

For short trains in the current solution, if the load factor is higher than a certain threshold (e.g., 85%), with a certain probability (e.g., 0.1), the composition is adjusted to a double-unit train or a long train that meets the load factor requirement.

During the adjustment, the available train units' capacity constraints must be met.

For any route $g \in G$, based on the current solution's distribution of the train load factors, the adjustment direction of the train composition for each train in the route is determined. If the adjustment directions of the trains within the route are inconsistent or differ significantly, the route is split, and trains with the same adjustment direction undergo the same train type composition adjustment.

During the adjustment, the available train units' capacity constraints must be met.

Suspend Routes with Low Load Factors. If the average capacity of route $g \in G$ falls within the range of short trains and its load factor is below a certain threshold (e.g., 25%), the operation of the route is suspended.

Increase Train Operations. For long trains or double-unit trains with a load factor exceeding a specified threshold (e.g., 85%), or for short trains that cannot be further expanded in composition, it is necessary to examine whether other trains operating at adjacent time slots in the basic schedule serve the same high-demand section. If such trains are identified, additional train operations can be introduced accordingly. During this adjustment process, the availability constraints of rolling stock for each train type must be strictly observed.

- Overall Adjustment Strategy for the Plan

Adjust Stopovers. For each station, the current service frequency is calculated. If the service frequency falls below the predefined lower limit, additional stops are assigned to trains that currently do not stop at the station. These stop additions are prioritized in ascending order based on the service ratio within each time period and the proportion of trains passing through the station. This process continues until the minimum service frequency requirement is satisfied or all passing trains are scheduled to stop at the station.

Route Integration. Train routes that utilize the same train composition model are integrated to improve rolling stock utilization and operational efficiency. During this integration process, connection and maintenance schedule constraints must be strictly satisfied. For scattered routes involving different train composition models, integration is still possible if these constraints are met; in such cases, an appropriate train composition model is selected based on the availability of trainsets to facilitate route integration.

2.5.3. Algorithm Process

The proposed model is solved under the framework of SAA. The involved algorithm parameters are shown in Table 2.

Table 2. Algorithm parameters in SAA.

Parameter	Definition
T_0	The initial temperature at the beginning of SAA
T_f	The final target temperature for termination
T	The current temperature in the calculation process
θ	The temperature decay ratio in each outer loop
N_k	The maximum iteration number in each inner loop

The SAA process designed in this article is shown in Figure 3. The input, output, and specific steps of the algorithm are as follows:

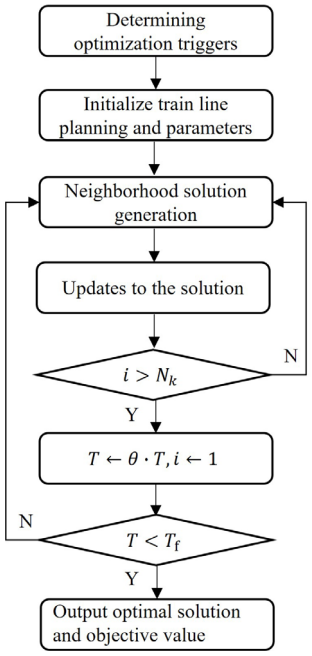


Figure 3. Simulated Annealing Algorithm process.

Input: High-speed railway network $G = (V, E)$, full-day operation period $[t_1, t_2]$, total demand for each O–D pair $(r, s) \in RS$ denoted as q_{rs}, travel intensity distribution

$y_{rs}(x), x \in [t_1, t_2]$, initial train line planning route set G_0, basic operation diagram $\overline{L}$, station $v \in V$ departure and arrival capacity C_v, required stopping time τ_v^{stop}, and service frequency lower limit n_v^0, segment $e \in E$ passing capacity C_e, ticket price rate $r_p\left(l_i^g\right)$ for train $l_i^g, i = 1, 2, \cdots, m_g$, $g \in G$ and its $j-th$ segment running time $t_{l_i^g,j}^{\text{run}}, j = 1, 2, \cdots, h\left(l_i^g\right) - 1$, available trainset models M$^-$\bar{M}M$^-$, trainset holdings for each model $RS_m, m \in \overline{M}$, connection maintenance time $\tau_{connection}$, stop/start additional time τ_{ad}, maximum route running time RT, and running mileage RM, fluctuation threshold for trigger condition, unit travel adjustment time cost κ, unit time value w, initial and final temperature T_0, T_f for the algorithm, maximum iteration number of inner loop N_k, and temperature decay ratio θ.

Output: The train line planning route set G^* and the objective function value $Z(G^*)$.

Step 1: Trigger Judgment for Adjustment and Optimization.

Follow the method described in Section 2 for trigger judgment. If any trigger condition is met, proceed to Step 2 for train line planning adjustment and optimization. If none of the conditions are met, terminate the algorithm.

Step 2: Evaluation and Initialization of Initial Train Line Planning.

Calculate the objective function value $Z(G_0)$ for the initial train line planning route set G_0. Set the current solution and its objective value as $G \leftarrow G_0, Z(G) \leftarrow Z(G_0)$, and the optimal solution and its objective value as $G^* \leftarrow G_0, Z(G^*) \leftarrow Z(G_0)$. Set the inner loop iteration count $i \leftarrow 1$, and the current temperature $T \leftarrow T_0$. Proceed to Step 3.

Step 3: Constructing and Evaluating Neighborhood Train Line Planning.

Based on the current solution G, construct the neighborhood solution G_i using the evaluation results and the neighborhood search strategy described in Section 2.5.2. Calculate the objective function value $Z(G_i)$. Proceed to Step 4.

Step 4: Solution Update.

Calculate $\Delta Z \leftarrow Z(G_i) - Z(G)$.

If $\Delta Z \leq 0$, update the current solution and its objective value: $G \leftarrow G_i, Z(G) \leftarrow Z(G_i)$, and the optimal solution and its objective value: $G^* \leftarrow G_i, Z(G^*) \leftarrow Z(G_i)$.

Otherwise, if $\exp\left[-\frac{\Delta Z}{T}\right] > Random(0,1)$, update the current solution and its objective value: $G \leftarrow G_i, Z(G) \leftarrow Z(G_i)$.

Update the inner loop iteration count $i \leftarrow i + 1$. Proceed to Step 5.

Step 5: Inner Loop Termination Condition Check.

If $i > N_k$, update the current temperature $T \leftarrow \theta \cdot T$ and set the inner loop iteration count $i \leftarrow 1$. Proceed to Step 6.

Otherwise, return to Step 3.

Step 6: Outer Loop Termination Condition Check.

If $T < T_f$, output the optimal solution and objective value, and terminate the algorithm.

Otherwise, return to Step 3.

3. Results and Discussion

3.1. Parameter Settings

3.1.1. High-Speed Rail Network and Train Data

This case study focuses on the Beijing–Shanghai high-speed railway (HSR) and its associated local segments, as illustrated in Figure 4. The Beijing–Shanghai HSR spans 1318 km and connects 26 stations via 56 one-way segments. The stations are classified into four levels based on administrative rank, departure and arrival capacity, and their roles within the network. Higher-level stations have a standard stop time of 3 min, while lower-level stations are assigned a stop time of 2 min; both can be adjusted according to the

operational timetable. As station level increases, transfer time tends to increase due to larger station layouts, while transfer risk generally decreases due to improved service reliability and frequency. Departure and arrival capacities are derived from the base timetable data. Each segment has a maximum capacity of 180 trains, and running times for each segment are calculated using actual train operation records.

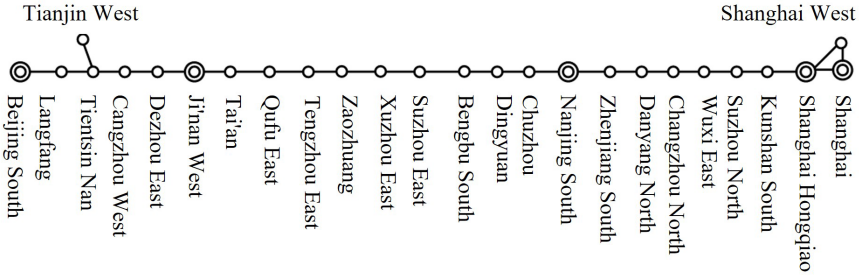


Figure 4. Partial road network diagram of Beijing–Shanghai high-speed railway.

The basic operational timetable is based on data from the third quarter of 2023. The reference train line planning for the local network of the Beijing–Shanghai HSR—including both mainline and cross-line services—is taken from 3 September 2023. The optimized line planning scheme for the same network is generated for 10 September 2023.

3.1.2. Passenger Flow Demand Data

The passenger flow demand data is based on actual travel ticketing data from the Beijing–Shanghai high-speed railway. The original passenger flow demand for the reference line planning of 3 September 2023, and the optimized passenger flow demand for the plan on 10 September 2023, are derived from this data. The average daily passenger flow for each O–D pair, calculated for each hour during the third quarter of 2023, is used to generate the demand intensity distribution function $y_{rs}(x), (r,s) \in RS, x \in [t_1, t_2]$. Since cross-line trains involve passenger flow data from multiple lines, this case study retains the original passenger flow distribution for cross-line trains on the main line segment without any adjustments or optimization.

3.1.3. Cost Parameter Settings

- Track Usage Fee Parameters

The section from Beijing South to Tianjin South is classified as a first-class, extremely busy line, with a track usage fee of CNY 101.7 per train-kilometer for short formations and CNY 152.7 per train-kilometer for long formations. The section from Xuzhou East to Bengbu South is also classified as a first-class, extremely busy line (second tier), with corresponding fees of CNY 105.5 and CNY 158.4 per train-kilometer for short and long formations, respectively. All remaining sections are classified as first-class busy lines, with a track usage fee of CNY 94.2 per train-kilometer for short formations and CNY 141.4 per train-kilometer for long formations. For night-time operations, a discounted rate of 40% of the standard fee is applied.

- Contact Network Usage Fee Parameters

The unit price for contact network usage is CNY 700 per 10,000 total gross ton-kilometers (tax included), with night trains charged at 40% of the standard rate.

- Station Passenger Service Fee Parameters

Beijing South and Nanjing South stations are first-tier busy stations, with a service fee of CNY 8 per person (tax included). Shanghai Hongqiao is a second-tier busy station, with

a service fee of CNY 9 per person (tax included). Other stations charge a service fee of CNY 5 per person for high-speed trains.

- Ticketing Service Fee Parameters

  The ticketing service fee is 1% of the total passenger fare income.

- Station Water Supply Service Fee Parameters

  The water supply service fee for short formation trains is CNY 24 per train trip, and for long formation trains, it is CNY 48 per train trip.

- Passenger Travel Cost Parameters

  The unit travel adjustment time cost for passengers is CNY 0.4 per minute, the unit travel time cost is CNY 0.5 per minute, and the high-speed train fare rate is CNY 0.55 per kilometer.

3.1.4. Other Parameters

The full operating hours are from 6:00 to 24:00. The train connection preparation time is set to 20 min, with the maximum operating time for a route being 48 h and the maximum operating distance limited to 4000 km. The stock of each train model is derived from actual data in the basic timetable. The trigger fluctuation threshold is set to 0.1. The weights for the objective function are $\alpha_1 = 1, \alpha_2 = 1, \alpha_3 = 100,000, \alpha_4 = 10$. The initial temperature is 10^7, the termination temperature is set at 5, the inner loop iteration count is 50, and the temperature reduction ratio is 0.5.

Table 3 shows the main parameters in this case study.

Table 3. Parameters in case study.

	Parameter	Setting
Operation parameters	C_e	180 trains
	τ_v^{stop}	3 min for high-level stations, 2 min for low-level stations
	$\tau_{connection}$	20 min
	RT	48 h
	RM	4000 km
	Operation period	6:00–24:00
Systematic cost parameters	Track usage fee (short/long)	CNY 101.7/152.7 (Beijing South to Tianjin South) CNY 105.5/158.4 (Xuzhou East to Bengbu South) CNY 94.2/141.4 (Other sections)
	Contact network usage fee	CNY 700 per 10,000 total gross ton-kilometers (40% cut at night)
	Station passenger service fee	CNY 8 (Beijing South/Nanjing South)/9 (Shanghaihongqiao)/5(other stations)
	Station water supply service fee (short/long)	CNY 24/48 per train
	Unit travel adjustment time cost	0.4 CNY/min
	Unit travel time cost	0.5 CNY/min
	High-speed train fare rate	0.55 CNY/km
Algorithm parameters	T_0	10^7
	T_f	5
	N_k	50
	θ	0.5

3.2. Result Analysis

3.2.1. Adjustment and Optimization Trigger Judgment

As outlined in Section 2, the trigger judgment is based on two factors: fluctuations in passenger demand and changes in seat occupancy.

- Passenger Demand Fluctuation

Based on the travel demand on the reference day and the optimization day, the passenger demand fluctuation coefficient, $\varepsilon_1 = 0.1932$, is calculated using Equation (10). This exceeds the trigger fluctuation threshold of 0.1, indicating that the passenger demand on the optimization day is significantly higher than that on the reference day. Therefore, it can be concluded that the reference line planning is inadequate to meet the travel demand on the optimization day, necessitating an adjustment and optimization of the line planning.

- Seat Occupancy Changes

The overall seat occupancy rate for the reference day's train line planning is 78.51%. Applying the passenger flow distribution for the optimization day to the reference line planning results in an overall seat occupancy rate of 81.4%. The seat occupancy fluctuation coefficient, $\varepsilon_2 = 0.037$, is calculated using Equation (11). Although this does not exceed the trigger fluctuation threshold, there are still 1980 stranded passengers, accounting for 0.9% of the total. This suggests that the reference train line planning requires adjustment and optimization.

3.2.2. Optimization Results Analysis

The SAA was programmed using C# language, with the computational environment being a dual-core CPU, Intel i7 2.4 GHz, 16 GB RAM, and the total running time was approximately 900 s. Figure 5 shows the convergence curve of the objective function value. As observed, the objective function decreases from 2.52×10^8 to 2.17×10^8, representing an optimization of 13.89%, indicating a good convergence effect.

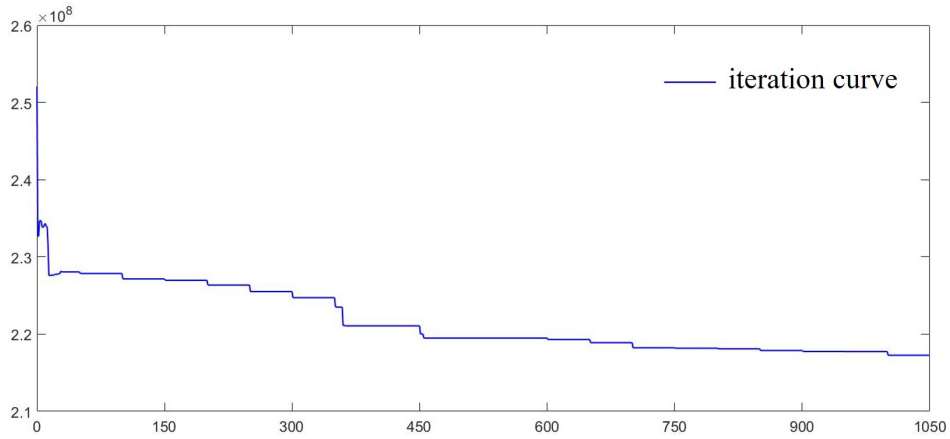


Figure 5. Convergence graph of objective function value systemic cost analysis.

Figure 6 compares the various cost components before and after the adjustment and optimization process. As shown, all cost components—except for passenger service fees at stations—decreased following the optimization. This overall cost reduction is attributed to adjustments in key operational factors, including train formations, vehicle types, station stops, and service frequencies. These modifications led to a more efficient alignment between capacity allocation and passenger travel demand. The results indicate that the optimized plan not only reduces the consumption of capacity-related resources but also enhances overall passenger service levels.

As a result of the re-optimization of capacity configuration, supply and demand were more effectively aligned, thereby reducing unnecessary train idling. This optimization led to a decrease in both the overall capacity and total weight of train routes, which in turn reduced line usage fees, catenary network usage fees, and station water supply service fees. Consequently, the total train operating cost decreased from CNY 76.1 million to CNY

75.1 million. The improved coordination between supply and demand also mitigated issues such as passenger backtracking and transfers, resulting in a 9.2% reduction in total passenger travel costs. This improvement, however, also contributed to a slight decline in ticket revenue and associated ticket service fees.

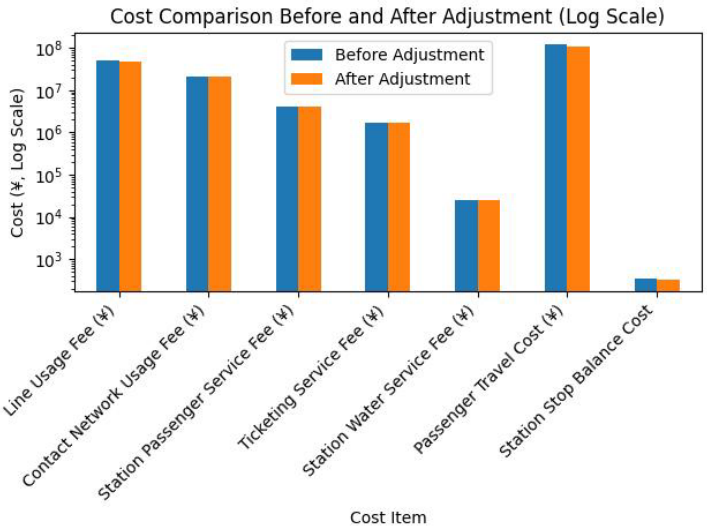


Figure 6. Comparison of systemic cost items before and after adjustment.

As passenger congestion decreased and the volume of dispatched passengers increased, station passenger service fees rose accordingly. Moreover, adjustments to train station stop patterns led to a more balanced distribution of stops in both temporal and spatial dimensions, resulting in a reduction in the stop balance index.

- Operating Indicator Analysis

  (1) Comparison of Operating Indicators Before and After Adjustment

Figure 7 presents a comparison of operational indicators before and after optimization. As shown, adjustments to train route composition, train models, and other operational factors have resulted in reductions in total train-kilometers, the number of trains, and the number of routes, thereby lowering overall operating costs. Under the optimized plan, a total of 191 train routes and 557 train services are operated. The longest running time is 1373 min, corresponding to Route 0: G6981–G6980–G343–G344.

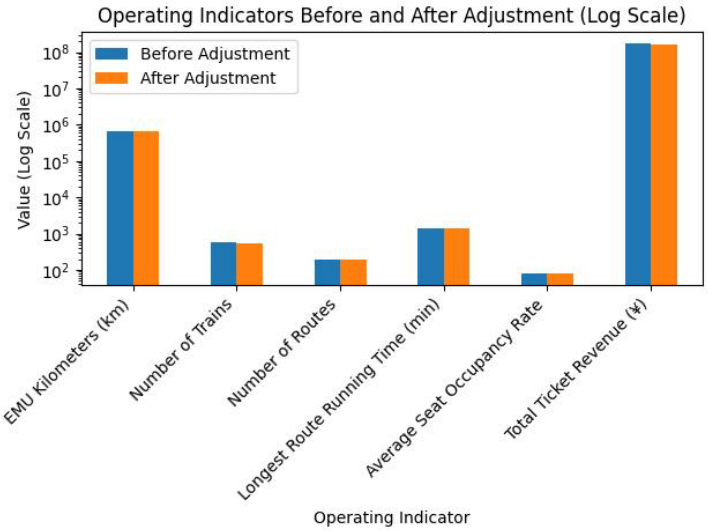


Figure 7. Comparison of operating indicators before and after adjustment.

Considering the connectivity among train routes, the overall adjustment required modifications across all routes, which resulted in slight overcapacity for a small number of trains. As a consequence, the average seat occupancy rate experienced a marginal decline compared to the reference line planning scheme. In addition, total ticket revenue—including that from both in-line and cross-line trains—decreased. This reduction is primarily attributed to the optimized plan's improvement in passengers' direct travel rate, which effectively minimized backtracking and transfers, thereby reducing overall fare expenditures.

(2) Train Seat Occupancy Rate

Figure 8 presents a comparison of train seat occupancy distribution before and after optimization. It can be observed that the number of trains with low occupancy rates (below 30%) remains unchanged. However, the optimized plan leads to an increase in the number of trains with moderate occupancy rates (30–70%), accompanied by a slight decrease in the number of trains with high occupancy rates. This shift is primarily due to the overall adjustment of train routes, which introduced overcapacity in certain services and redistributed seat occupancy more evenly across the network. As a result, seat occupancy levels became more balanced, contributing to an overall improvement in service quality.

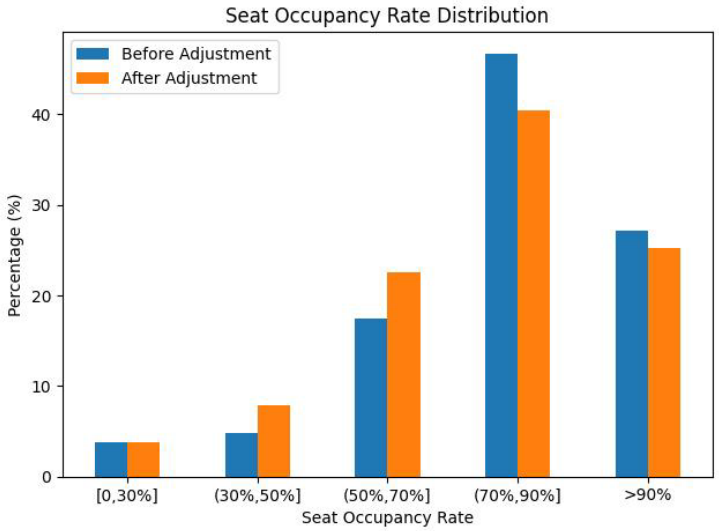


Figure 8. Comparison of train seat occupancy distribution before and after adjustment.

(3) Train Composition

Figure 9 presents a comparison of train composition distribution before and after optimization. The results indicate that the optimized plan increases the proportion of long trains and multiple-unit (MU) trains, while the proportion of short trains decreases. This shift is primarily driven by the more balanced distribution of passenger flow and the consistently high demand along the Beijing–Shanghai high-speed rail corridor, which make long trains and MU trains more suitable for operation. Additionally, given the constraints of the basic operational timetable and the limited availability of high-speed trainsets, the deployment of long or MU trains proves to be more efficient. As a result of the overall route adjustments, the number of long trains and MU trains has further increased.

(4) Train Operation Distance

Figure 10 illustrates the distribution of train operation distances before and after the adjustment. As shown, the number of trains across all distance ranges has decreased in the optimized plan. This reduction is primarily attributed to adjustments in train composition and capacity, which have improved the alignment between supply and demand. For routes with lower adaptability or insufficient demand, certain services were discontinued. The

post-adjustment distribution reveals that trains on the Beijing–Shanghai high-speed rail line predominantly operate on medium- and short-distance routes, with a relatively large share of cross-line trains. In contrast, mainline trains mainly serve medium- and long-distance passenger flows along the corridor. This operational pattern reflects the relatively balanced passenger demand across the entire Beijing–Shanghai HSR, making it well-suited for long-distance train operations.

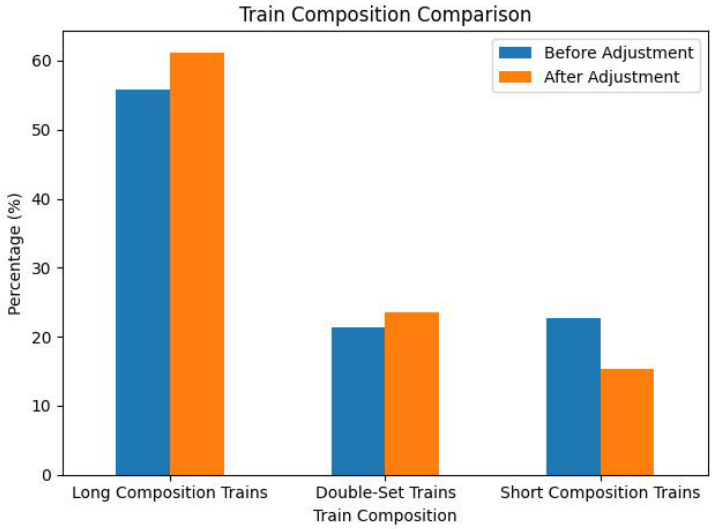


Figure 9. Comparison of train composition distribution before and after adjustment.

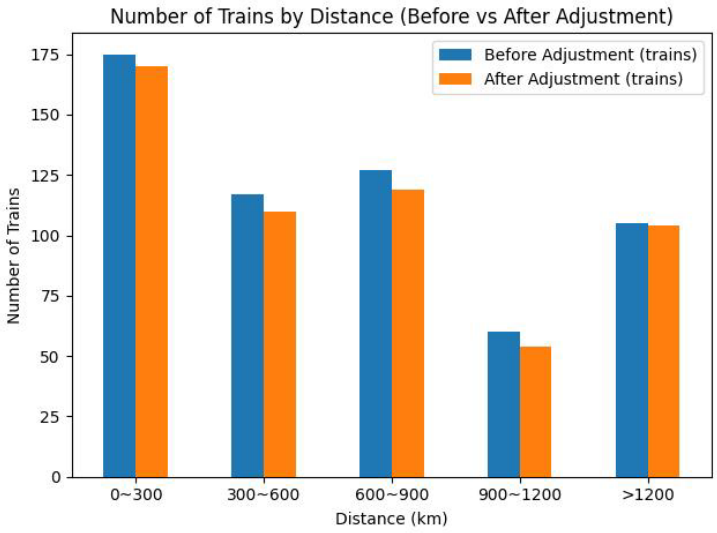


Figure 10. Distribution of train operating distances before and after adjustment.

- Service Indicators Analysis

  (1) Service Indicator Comparison Before and After Adjustment

Figure 11 presents a comparison of service indicators before and after the adjustment. Based on the reference line planning, the optimized passenger flow distribution for the target day resulted in 1980 delayed passengers, with a total of 2.26×10^6 passenger-kilometers of delay. The total passenger demand for the day was 218,765, with the network's total passenger-kilometers approximately 1.3×10^8. The delayed passenger flow and delayed passenger-kilometers accounted for 0.91% and 1.74%, respectively, indicating that medium- and long-distance passenger flows comprised a significant portion of the delayed flow. In the optimized plan, the number of delayed passengers decreased to 152, and

the delayed passenger-kilometers dropped to 1.3×10^5, with their respective proportions reduced to 0.07% and 0.1%. These improvements suggest that the optimized plan better addresses the travel demand for the day.

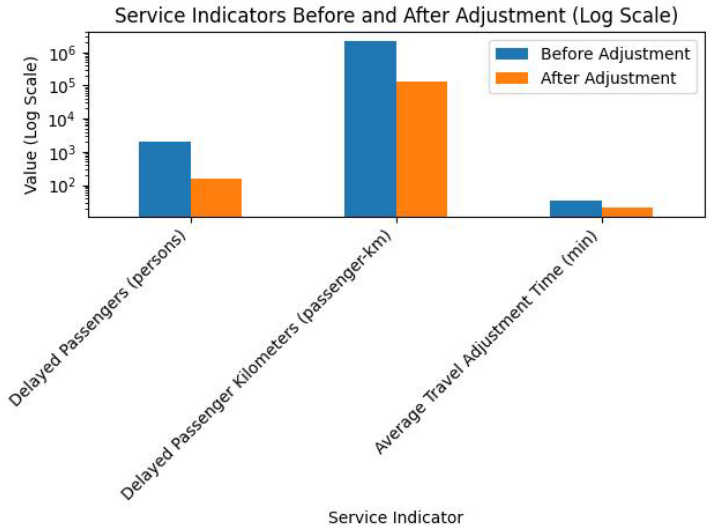


Figure 11. Comparison of service indicators before and after adjustment.

Regarding passenger travel adjustments, the average travel adjustment time per passenger decreased from 32.87 min to 20.43 min. This reduction indicates that the adjustments to train routes' capacity and station service times align more effectively with the spatial and temporal distribution of the target day's travel demand, enhancing the supply-demand match.

(2) Delayed Passenger Flow

Figure 12 presents the mileage distribution of delayed passenger flow before and after the adjustment. As shown in Figure 12, prior to the adjustment, the delayed passengers were predominantly long-distance travelers. After the adjustment, the proportion of medium- and short-distance delayed passengers increased, while the proportion of long-distance passengers decreased. This suggests that the optimized plan is more responsive to the travel needs of medium- and short-distance passengers, which helps improve the utilization of long-distance train capacity on the main line.

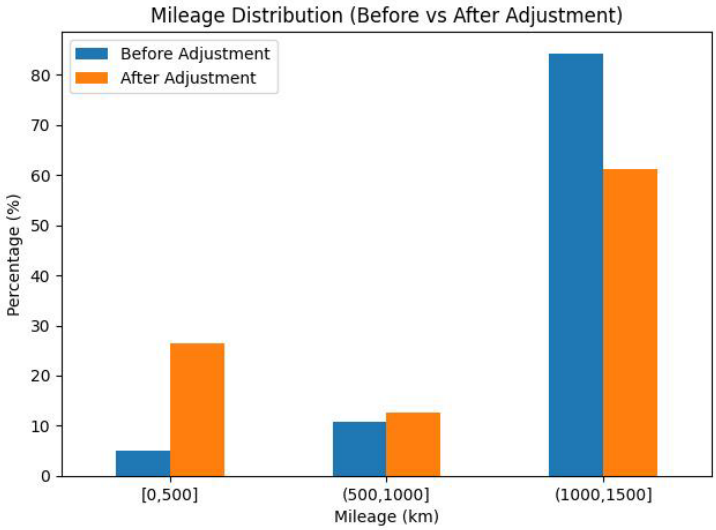


Figure 12. Distribution of delayed passenger flow mileage before and after adjustment.

The O–D pairs with a significant proportion of delayed passenger flow in the optimized plan include Changzhou North—Beijing South, Changzhou North—Qufu East, and Nanjing South—Shanghai Hongqiao, among others. The primary reason for the delays is that, due to the overall adjustment of train service routes, it is necessary to modify the operating elements of the train routes according to the objective function. This comprehensive adjustment does not guarantee the service level for specific O–D pairs or stations, leading to insufficient capacity and stop configurations for certain O–Ds.

(3) Travel Adjustment Time

Figure 13 shows the distribution of average passenger travel adjustment time before and after optimization. Before optimization, the majority of passenger travel adjustments were completed within one hour, with an average adjustment time of approximately 33 min, suggesting that train services on the Beijing–Shanghai high-speed rail generally accommodated fluctuations in passenger travel demand. After optimization, over 90% of passenger travel demands were adjusted within 30 min, and all passengers were able to secure a travel solution within 1.5 h of their desired departure time. The average travel adjustment time decreased to about 20 min, indicating that the optimized plan, through adjustments in train composition, capacity, and station services, better aligned with passenger demand distribution.

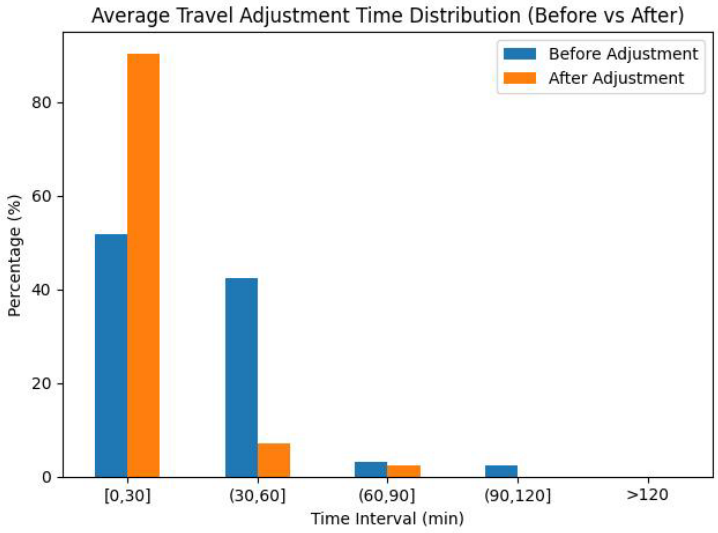


Figure 13. Distribution of average passenger travel adjustment time before and after adjustment.

(4) Train Stop Ratio

Figure 14 presents the distribution of train stop ratios before and after optimization. The change in train stop ratio is relatively minor, with the majority of ratios concentrated between 0.25 and 0.75. A small number of flagship trains exhibit relatively low stop ratios, as they serve longer travel distances and high-level stations. In contrast, other trains make stops at county-level stations along the route to serve local passenger demand.

For long-distance trains (over 1000 km), the stop ratio generally remains below 0.6, as these trains primarily cater to long-distance direct passenger flows across regions. For medium-distance trains (500–1000 km), the stop ratio increases, typically ranging from 0.4 to 0.75, reflecting more frequent stops at county-level stations. Short-distance trains tend to have a higher stop ratio to improve service frequency for regional passenger flows. Both before and after optimization, the number of stations served by trains remains at 56, primarily serving short-distance regional trains or cross-line train segments.

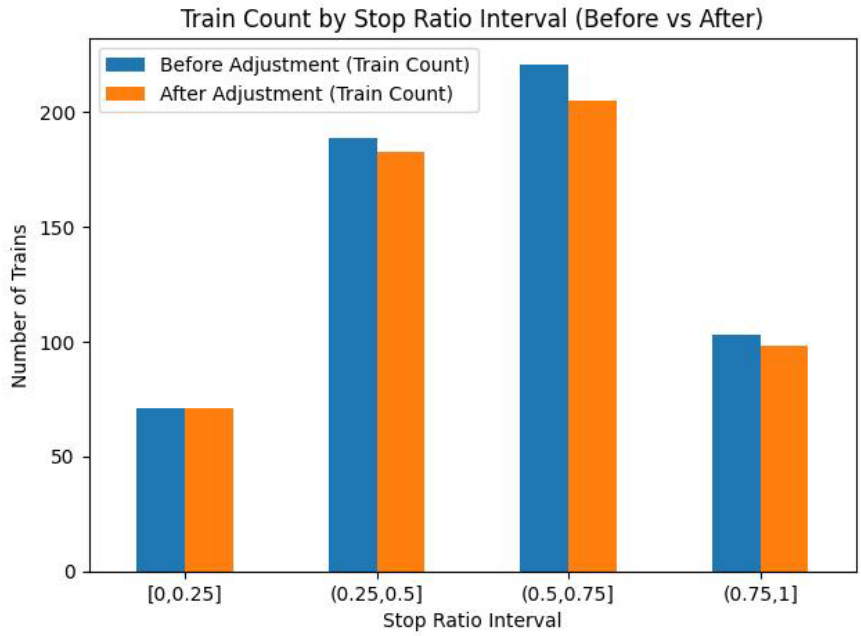


Figure 14. Distribution of train stop ratio before and after adjustment.

(5) Station Service Frequency

The service frequency of each station before and after optimization meets the lower bound of the service frequency constraint. Table 4 presents the service frequency and stop ratio of stations before and after optimization. As observed, the service frequency and stop ratio before and after optimization are similar, with a slight decrease after optimization. The overall stop ratio is approximately 0.5. As station grade decreases, both service frequency and stop ratio gradually decrease.

Table 4. Service frequency at stations before and after adjustment.

Indicator	Before Adjustment			After Adjustment		
	Service Frequency	Number of Passing Trains	Stop Ratio	Service Frequency	Number of Passing Trains	Stop Ratio
Overall	3365	6726	0.5003	3202	6439	0.4973
Provincial-Level Stations	1379	1590	0.8673	1321	1521	0.8685
Prefectural-Level Stations	1679	3773	0.445	1589	3611	0.44
County-Level Stations	307	1363	0.2252	292	1307	0.2234

At the provincial-level stations, the passing trains primarily consist of direct mainline trains and a few cross-line trains, resulting in the highest stop ratio, exceeding 0.86. Due to the influence of cross-line trains, prefecture-level stations have the highest number of passing trains and service frequency, although the stop ratio remains around 0.44. At the county-level stations, the number of passing trains and service frequency are the lowest, with the stop ratio also being the lowest, at around 0.22. These variations in stop services at different station levels reflect the passenger flow structure, passenger volume, and the train connection and transfer situation at each station. By adjusting train stop arrangements, service can be better aligned with passenger demand distribution characteristics, thereby meeting passenger travel needs.

- Analysis of Capacity Resource Utilization

  (1) Utilization of Station Departure and Arrival Capacity

For the local rail network of the Beijing–Shanghai high-speed railway examined in this study, the departure and arrival capacities at all stations remained within their respective constraints both before and after optimization. Table 5 presents the number of departing and arriving trains at key stations, including cross-line services at their respective entry and exit points along the Beijing–Shanghai corridor. Due to adjustment strategies such as the addition or suspension of certain train routes, the number of departures and arrivals in the optimized plan has been slightly modified.

Table 5. Statistics of train departures and arrivals at major stations before and after adjustment.

Station	Departure Train Statistics		Arrival Train Statistics	
	Before Adjustment	After Adjustment	Before Adjustment	After Adjustment
Beijing South	131	128	135	132
Langfang	3	3	3	3
Tianjin South	1	1	0	0
Cangzhou West	2	2	2	2
Dezhou East	25	23	25	23
Jinan West	43	40	43	40
Tai'an	17	17	16	16
Xuzhou East	60	55	60	55
Bengbu South	32	30	33	30
Nanjing South	79	76	77	75
Wuxi East	2	2	1	1
Suzhou North	1	1	0	0
Shanghai Hongqiao	116	111	121	117
Tianjin West	37	33	34	29
Shanghai	10	10	10	10

The main stations with departure and arrival capacity in the local rail network include high-level stations, such as Beijing South, Shanghai Hongqiao, Nanjing South, and Jinan West, which have large departure and arrival capacities. Additionally, stations where multiple lines intersect, such as Xuzhou East and Bengbu South, play key roles in serving cross-line trains within the local network.

(2) Utilization of Section Throughput Capacity

The number of trains passing through each unidirectional section in the local rail network meets the section throughput capacity constraints. Figure 15 illustrates the distribution of bidirectional train traffic through each section before and after the adjustment. As shown in Figure 15, train operations along the Beijing–Shanghai high-speed railway are relatively balanced. The number of trains passing through each section ranges between 128 and 140 pairs. However, sections experiencing higher capacity strain include Tianjin South to Dezhou East (approximately 154 pairs before adjustment and 146 pairs after), Tai'an to Qufu East (around 160 pairs before adjustment and 155 pairs after), and Xuzhou East to Bengbu South (approximately 155 pairs before adjustment and 148 pairs after). Other sections outside the main line, such as Tianjin South to Tianjin West, Shanghai Hongqiao to Shanghai, and Shanghai West, see fewer passing trains. Following the adjustment, the number of trains passing through each section has slightly decreased, largely due to the suspension of certain train routes.

(3) Utilization of EMU Fleet Resources

The base diagram involved in this case includes 24 types of EMU models, consisting of 14 long composition models and 10 short composition models. Both before and after the adjustment, the number of vehicles for each model meets the fleet size constraint. Table 6 shows the utilization of EMU fleet resources before and after the adjustment.

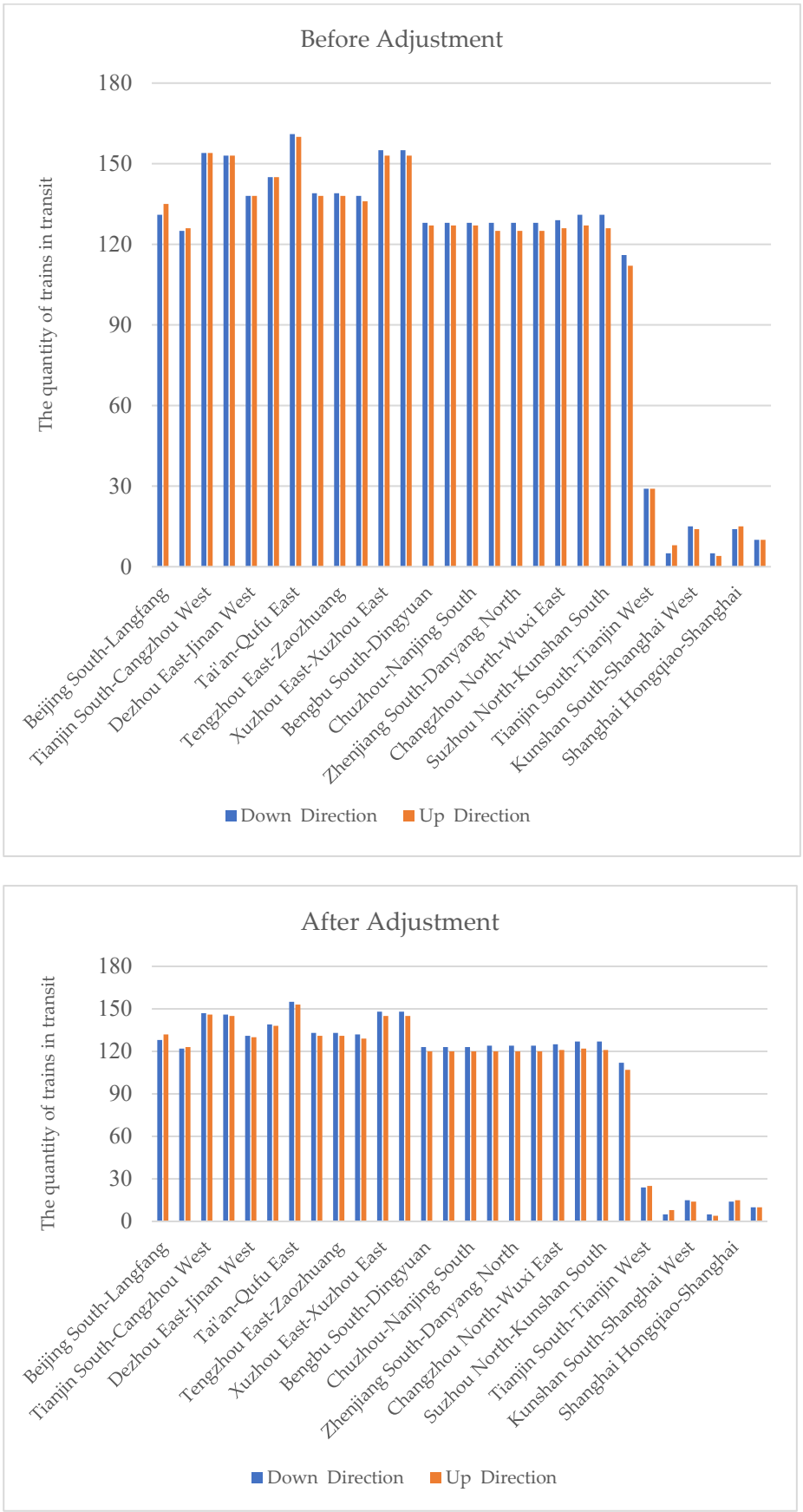


Figure 15. Distribution of bidirectional train passages across each section before and after adjustment.

Table 6. Utilization of EMU fleet resources before and after adjustment.

Train Type	Formation	Seating Capacity	Number of EMUs in Use (Before/After Adjustment)	Number of EMU Fleet
CRH2A_610	8	610	0/0	40
CRH2B_1230H	17	1230	0/0	40
CRH2B_1230	17	1230	0/17	40
CRH2E_110	16	890	0/32	40
CR400BF-BZ_1285	17	1285	17/17	40
CR400BF-A	16	1193	336/288	504
CR400BF	8	576	408/344	672
CRH380BL_1043	16	1005	384/592	744
CR400AF-B	17	1282	153/136	260
CR400BF-B	17	1283	68/68	104
CR400AF-A	16	1193	160/96	264
CRH380BL_1015	16	1015	304/304	456
CR400AF-Z_578	8	578	96/120	132
CR400BF_1285	17	1285	17/17	40
CRH380A_556	8	556	464/376	852
CRH380B_551	8	551	72/56	120
CRH380B_556	8	556	80/88	168
CRH380AL_1099	16	1061	80/96	120
CR400BF-AZ	16	1195	16/16	40
CRH380AL_1066	16	1028	32/16	48
CRH380D_556W	8	556	0/16	40
CRH2C2_610	8	610	24/24	40
CRH2C1_610	8	610	16/0	40
CR400AF_578	8	578	16/40	40

As seen from Table 6, the reference line planning primarily uses short composition models to operate short trains or double-set trains. In contrast, the optimized plan reduces the number of short composition models and replaces them with long composition models, which have smaller capacity, thereby replacing the double-set trains with those of larger capacity. Additionally, the optimized plan makes the utilization of EMU models more flexible and diverse, leading to a more balanced use of various fleet resources.

- Comparison with Actual Plan

In this study, the actual timetable of the selected day is used as the reference plan to evaluate the practical effectiveness of the proposed optimization approach. This reference represents conventional line planning practices based on operational experience, rather than systematic cost optimization. As such, it provides a realistic and meaningful benchmark against which the improvements achieved by the integrated optimization model can be assessed.

On the optimized day, a total of 585 trains were operated across 199 routes under the actual plan, which exceeds the number of trains and routes in the optimized plan. A comparison between the optimized and actual plans for that day is presented below. As detailed travel cost data for passenger demand under the actual plan is unavailable, the comparison focuses on train operating costs, the station stop balance index, and train occupancy rates. Table 7 summarizes the differences in key operational indicators between the optimized and actual plans.

Table 7. Comparison of operational indicators between optimized and actual plans.

Plan	Train Operation Cost (CNY)	Line Usage Fee (CNY)	Contact Network Usage Fee (CNY)	Station Passenger Service Fee (CNY)	Ticketing Service Fee (CNY)	Station Water Service Fee (CNY)	Average Occupancy Rate (%)
Actual Plan	7.56×10^7	4.92×10^7	2.07×10^7	4.1×10^6	1.64×10^6	2.45×10^4	79.17%
Optimized Plan	7.51×10^7	4.86×10^7	2.08×10^7	4.03×10^6	1.66×10^6	2.47×10^4	80.21%

As shown in Table 7, the total train operating cost, line usage fee, and station passenger service fees in the optimized plan are all lower than those in the actual plan. During the optimization process, adjustments to train composition led to the selection of some longer train formations, which resulted in increased contact network usage fees and station water service fees. Additionally, since the optimization aimed to minimize passenger travel costs, some travel paths involved slight backtracking, leading to a modest increase in ticketing service fees. Nevertheless, the average seat occupancy rate under the optimized plan is higher than that of the actual plan, indicating improved capacity utilization.

The station stop balance index for the actual plan is 340.99, which is higher than that of the optimized plan. This suggests that the optimized plan better accounted for the spatiotemporal balance of train stop services, making the stop services more efficient.

Although the total train operation cost and most individual cost components have decreased in the optimized plan, a slight increase in contact network usage fee and ticketing service fee is observed. This is primarily due to the adoption of longer train compositions and minor backtracking in travel paths aimed at reducing passenger adjustment costs. These increases reflect a deliberate trade-off, where enhanced passenger service quality and reduced delays are achieved at the expense of minor rises in operational components, demonstrating the model's balancing ability.

The proposed approach resulted in a 13.89% improvement in the overall objective function value, integrating both passenger and operational costs. This translates to an estimated CNY 3.5 million reduction in total systematic cost on the test day, with a 92% reduction in unserved passengers and an increase in seat utilization rate by 1.04%. These results indicate not only economic gains for railway operators, but also substantial enhancements in service quality, robustness, and passenger satisfaction.

3.2.3. Sensitivity Analysis

To further illustrate the capability of the model, we present the sensitivity analysis of the objective weights. Among the four objectives, we select the weight of the delayed passenger kilometers as the analyzed issue. The sensitivity analysis is presented in Table 8.

Table 8. Sensitivity analysis on objective weight w_4.

w_4	Z_1/CNY	Z_2/CNY	Z_3	Z_4/Person · km
1	7.46×10^7	1.08×10^8	332.94	1.43×10^5
10	7.51×10^7	1.08×10^8	332.43	1.3×10^5
100	7.54×10^7	1.08×10^8	332.1	1.25×10^5
1000	7.55×10^7	1.08×10^8	338.19	1.16×10^5

It can be seen from Table 8 that as w_4 increases, Z_4 gradually decreases while Z_1 increases. It indicates that the delayed passenger kilometer and the train cost have opposite trends when the weight changes, which is the same as the correlation between supply and demand. The balance index slightly changes because the stops would be adjusted to match the importance of Z_4 in the optimization. Passenger travel cost stays relatively stable

because of the stable travel choices of passengers, and the influence from change of Z_4 on Z_2 is little.

4. Conclusions

This study developed a Simulated Annealing Algorithm (SAA)-based optimization model to minimize systematic cost—which includes train operation costs, passenger travel costs, and hidden costs related to station-stop imbalances—by adjusting train routes, compositions, and capacity allocations. Applied to the Beijing–Shanghai high-speed railway network, the proposed approach achieved a 13.89% reduction in the objective function value, demonstrating improvements in both operational efficiency and passenger service quality. Specifically, the optimized plan reduced the number of trains and routes, lowered line usage and catenary network fees, and improved the distribution of train occupancy by increasing the proportion of trains operating within the moderate occupancy range (30–70%). Delayed passenger flows and total passenger-kilometers were significantly reduced, while the average travel adjustment time decreased from 32.87 to 20.43 min—reflecting a better alignment between supply and demand. Additionally, adjustments to train stop distributions enhanced service equity across different station levels. Resource utilization constraints—such as segment capacity and EMU fleet availability—were also effectively managed. Compared with the actual plan, the optimized solution not only reduced total operating costs and mitigated stop imbalances but also slightly improved the overall seat occupancy rate. These results validate the feasibility of using SAA to dynamically align train operations with fluctuating passenger demand, offering a flexible and scalable solution to optimize both service quality and operational performance.

Future research will focus on the following aspects. First, we plan to incorporate more practical factors into the systematic cost framework to enhance model accuracy. Second, we aim to develop new solution algorithms that better exploit the structural characteristics of the problem. Third, we will explore extending the proposed approach to cover the train scheduling stage for a more integrated optimization framework.

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