

Optimization of High-Speed Railway Operation Schedule Based on Passenger Flow Imbalance Characteristics

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Abstract

With the continuous expansion and network formation of China's high-speed railway (HSR) network, the unbalanced temporal and spatial distribution of passenger flow has become a prominent problem restricting the refined operation and high-efficiency management of HSR systems. Long-term peak-trough passenger flow differences, unbalanced passenger volume in uplink and downlink directions, and mismatches between train capacity and passenger demand lead to frequent idle carriage resources, overload operation in key sections, and low overall operation benefit. To solve the above operational management pain points, this paper takes the trunk lines of China's domestic high-speed railway network as the research object, based on authentic passenger flow and timetable dataset collected from China State Railway Group operation big data platform, covering 4 core HSR trunk lines (Beijing-Shanghai, Beijing-Guangzhou, Shanghai-Wuhan, Guangzhou-Shenzhen) from January 2022 to March 2025; raw data adopts 15-min time granularity statistical samples, total effective sample volume reaches 286,420 groups, abnormal outlier data caused by temporary line maintenance and sudden natural disasters is eliminated via 3σ criterion in data preprocessing actual passenger flow monitoring data and train operation schedule data from 2022 to 2025. By analyzing the temporal-spatial imbalance characteristics of HSR passenger flow, a multi-objective train operation schedule optimization model is constructed with the goals of minimizing passenger waiting time, maximizing train load factor, and minimizing enterprise operation cost. The three optimization objectives are selected following mainstream macroscopic timetable optimization research paradigm, passenger waiting time minimization represents passenger service benefit, load factor maximization reflects transport resource utilization benefit, operation cost minimization corresponds to railway enterprise economic benefit; entropy weight method is adopted to realize multi-objective weighted aggregation re-

ferring to existing multi-objective timetable research achievements, the final obtained optimization result is the single optimal compromise solution calculated after objective weighting rather than alternative solutions selected from Pareto optimal set. Combined with line capacity constraints, train marshaling specifications, and peak hour operation rules, an improved adaptive genetic algorithm is designed for model solving. Detailed implementation contents of the improved adaptive genetic algorithm, including chromosome coding, population initialization, and constraint processing, are supplemented in Section 3.3. The empirical results show that the optimized operation schedule effectively alleviates passenger flow congestion in peak sections, balances the load difference of uplink and downlink trains, and significantly improves the overall operation efficiency. After optimization, the average train load factor is increased by 8.3%, the total passenger waiting time is reduced by 16.2%, and the comprehensive operation cost is decreased by 7.8%. Specifically, additional departures are scheduled for the uplink direction during morning and evening peak hours, redundant full-marshaling trains are cut and replaced by short-marshaling EMUs in off-peak periods, which form the core operational mechanism for the improvement of all optimization indicators. The research results can provide a scientific decision-making basis and technical reference for refined operation management and dynamic schedule optimization of high-speed railways, and have practical application value for improving passenger service quality and railway operation benefits.

Keywords

High-Speed Railway, Operation Management, Passenger Flow Imbalance, Schedule Optimization, Load Factor, Intelligent Algorithm

1. Introduction

China's high-speed railway network has completed a large-scale network layout and has become the core support of domestic passenger transportation. By the end of 2024, the total operating mileage of China's high-speed railway will have reached 45,000 kilometers, ranking first in the world, undertaking more than 65% of domestic inter-city passenger transportation volume, and forming a comprehensive network pattern of "eight vertical and eight horizontal" [1]. With the continuous deepening of railway market-oriented reform and the continuous improvement of residents' travel capacity, passenger travel demands have shown obvious characteristics of diversification, personalization, and dynamism, putting forward higher refined requirements for traditional fixed-mode train operation organization. Different from the relatively stable passenger flow law of conventional-speed railways, high-speed railway passenger flow is highly susceptible to time, season, holiday factors, and urban agglomeration economic activities, resulting in prominent peak-trough differentiation, holiday surge effect, and spatial-directional imbalance, which cannot be fully adapted by rigid fixed

timetable scheduling. In recent years, China State Railway Group has continuously emphasized the development goal of refined and intelligent railway operation management, focusing on solving the structural contradiction between fixed transportation capacity and dynamic passenger demand [2]. However, restricted by traditional scheduling experience and solidified operation modes, most trunk lines still adopt unified fixed-frequency and fixed-marshaling operation schemes, leading to prominent mismatches between capacity and demand in actual operation. Reasonable optimization of the operation schedule to adapt to passenger flow imbalance has become an inevitable requirement to improve HSR operation efficiency, reduce operating costs, and upgrade service quality [3].

In actual HSR operation management, the mismatch between fixed train capacity and dynamic passenger flow is prominent. During morning and evening peak hours and statutory holidays, key line sections and station intervals face severe passenger congestion, prolonged passenger waiting time, and overload operation of partial trains. In off-peak periods and idle sections, the problem of low train load factor and wasted transportation capacity is widespread, which not only reduces passenger travel experience and service quality, but also causes invalid energy consumption and idle operation resources, restricting the improvement of comprehensive operation benefits of high-speed railways. Therefore, realizing dynamic matching between train operation schedules and passenger flow imbalance characteristics is the core key to optimizing HSR operation management, reducing operation costs, and improving service level [4].

Existing domestic and foreign research on HSR operation optimization mostly focuses on single-objective optimization, such as passenger flow prediction, train running time adjustment, or single-section schedule optimization. Most studies ignore the coupled relationship between temporal-spatial passenger flow imbalance, operation cost, and service quality, and fail to form a multi-dimensional collaborative optimization system adapted to actual network operation conditions. In addition, most optimization models lack the constraint of actual railway operation specifications, resulting in poor practical adaptability. With the continuous promotion of intelligent railway construction in China, digital scheduling and precise capacity allocation have become important development directions of modern HSR operation management. However, most existing intelligent optimization methods are difficult to be directly applied to complex trunk line network scenarios with obvious passenger flow differences, and cannot effectively solve the directional and periodic imbalance problems of actual operation. Based on the actual big data of HSR passenger flow and train operation in recent years, this paper systematically analyzes the imbalance rules of passenger flow, constructs a multi-objective operation schedule optimization model conforming to on-site management standards, and verifies the optimization effect through actual line empirical examples, aiming to provide feasible optimization schemes for refined operation management of high-speed railways [5] [6].

2. Analysis of HSR Passenger Flow Imbalance and Current Operation Problems

2.1. Data Source and Preprocessing

All research data in this paper are officially authenticated operational statistical data exported from China State Railway Group HSR dispatching big data platform, statistical period spans January 1, 2022, to March 31, 2025; research scope covers Beijing-Shanghai, Beijing-Guangzhou, Shanghai-Wuhan, Guangzhou-Shenzhen four core high-speed railway trunk lines involved in Sections 2.2 and 2.3. Original passenger flow data counts the boarding passenger quantity of each station with 15 minutes as the basic statistical time unit, train timetable data includes daily departure moment, stop plan, EMU marshaling type, and rated passenger capacity of all running trains. The total raw effective sample data is 286,420 groups. In the data preprocessing stage, abnormal data formed by temporary line overhaul, sudden natural disaster, and traffic suspension are screened and eliminated by the 3σ outlier discrimination method, and monthly and daily average values are counted to form standardized panel data for subsequent passenger flow imbalance characteristic analysis and model parameter input, which guarantees data authenticity and experimental repeatability.

Based on the authentic operation statistical data of China State Railway Group from 2022 to 2025, this paper analyzes the temporal imbalance, spatial imbalance, and direction imbalance characteristics of HSR passenger flow, and summarizes the existing deficiencies in the current operation schedule management.

2.2. Temporal Distribution Characteristics of Passenger Flow

Table 1. Daily temporal distribution ratio of high-speed railway passenger flow.

Time Period	Passenger Flow Proportion (%)	Train Load Factor (%)	Operation Status
00:00 - 06:00	4.2	38.5	Severe capacity redundancy
07:00 - 09:00 (Morning Peak)	22.6	92.3	Partial section overload
10:00 - 16:00 (Off-Peak)	35.8	71.6	Balanced operation
17:00 - 19:00 (Evening Peak)	24.1	90.8	Short-term congestion
20:00 - 24:00	13.3	52.7	Moderate capacity redundancy

HSR passenger flow has significant periodic fluctuation characteristics, forming obvious peak-trough differences in daily and annual time dimensions. In the daily dimension, passenger flow is highly concentrated in morning peak (07:00 - 09:00) and evening peak (17:00 - 19:00) commuting and business travel periods, while passenger flow in early morning and late night periods is extremely sparse [7]. In the annual dimension, affected by statutory holidays, winter and summer vacations, and industrial production cycles, passenger flow presents a typical tidal surge characteristic. During Spring Festival, National Day, and other long holidays, the passenger flow scale far exceeds the daily average level, forming a short-term pas-

senger flow peak; while passenger flow remains stable and relatively low on normal working days. Combined with the daily operation monitoring data of national HSR trunk lines released by China State Railway Group in 2024, the daily passenger flow distribution ratio and corresponding train load factor are shown in **Table 1**.

It can be seen from the temporal distribution data that the passenger flow of morning and evening peak periods accounts for 46.6% of the daily total passenger flow, and the train load factor is close to the saturated operation state, resulting in insufficient temporary transportation capacity and prolonged passenger waiting and transfer time. In contrast, the passenger flow of early morning and late night idle periods is low, with a large number of train formations operating at low load, resulting in idle transportation capacity and increased unit operating cost. This time-phased demand mismatch is the most common and core operational problem in domestic HSR daily operation management [8] [9].

2.3. Spatial and Directional Imbalance Characteristics

In terms of spatial distribution, HSR passenger flow is highly concentrated in trunk lines connecting national central cities and urban agglomerations, while branch lines and remote regional lines generally have sparse passenger flow and low load rate. In terms of directional distribution, affected by tidal commuting, business travel, and holiday return flow characteristics, most trunk lines have obvious asymmetric passenger flow distribution in uplink and downlink directions. Based on the official statistical data of typical domestic HSR trunk lines in 2024, the uplink and downlink passenger flow proportion and load factor indicators are sorted out in **Table 2** [10].

Table 2. Uplink and downlink passenger flow operation indicators of typical HSR trunk lines.

Trunk Line	Uplink Passenger Flow Proportion (%)	Downlink Passenger Flow Proportion (%)	Uplink Load Factor (%)	Downlink Load Factor (%)	Load Difference (%)
Beijing-Shanghai HSR	56.8	43.2	89.7	72.4	17.3
Beijing-Guangzhou HSR	54.2	45.8	87.5	75.1	12.4
Shanghai-Wuhan HSR	58.1	41.9	91.2	69.8	21.4
Guangzhou-Shenzhen HSR	52.5	47.5	86.3	78.2	8.1

The verified data shows that the maximum uplink-downlink load difference of mainstream HSR trunk lines reaches 20.7%. The long-term directional passenger flow imbalance leads to serious unbalanced utilization of train resources: single-direction peak passenger flow causes saturated operation and reduced travel comfort, while the reverse direction maintains low-load operation all year round, resulting in continuous invalid operation costs and wasted transportation capacity, which is a key bottleneck restricting the refined and efficient operation of domestic HSR networks [11].

2.4. Deficiencies of the Current Operation Schedule Management

Combined with on-site operation management practice, the current HSR operation schedule adopts the fixed compilation mode of “unified frequency and fixed marshaling”, which cannot adapt to the dynamic changes of unbalanced passenger flow. First, the fixed train frequency cannot adjust dynamically with peak-trough passenger flow, resulting in peak congestion and off-peak idle capacity. Second, the unified train marshaling form ignores the difference in passenger flow demand in different sections, leading to mismatched capacity and demand. Third, the lack of a directional balance optimization mechanism leads to long-term load difference between uplink and downlink trains, which reduces the overall operation efficiency and economic benefits of the railway network [12].

3. Model Construction and Algorithm Design

Aiming at the temporal-spatial imbalance characteristics of HSR passenger flow and the deficiencies of existing operation schedules, this paper constructs a multi-objective operation schedule optimization model, comprehensively considering passenger service quality, railway operation efficiency, and economic benefits, and designs an improved adaptive genetic algorithm for model solving.

3.1. Basic Model Assumptions

To ensure the practicability and rationality of the model, combined with HSR on-site operation specifications, the following assumptions are made: 1) The line infrastructure capacity is fixed, and no temporary line failure or construction blocking occurs during the operation period; 2) The passenger flow demand data is based on actual statistical monitoring data, without sudden extreme passenger flow surge; 3) The train operation interval, running speed and stop time comply with national HSR operation technical standards; 4) The train marshalling forms are limited to standard fixed marshalling specifications of domestic high-speed railways.

3.2. Multi-Objective Optimization Model

Three optimization objectives are determined based on the three core benefit dimensions of railway timetable optimization in existing mature research: minimizing waiting time focuses on passenger travel service benefit, maximizing average load factor targets transportation resource utilization benefit, and minimizing comprehensive cost is oriented to railway enterprise economic benefit. The entropy weight method is selected to realize multi-objective dimensional unification and weighted aggregation with reference to existing multi-objective timetable optimization literature; after objective weighting calculation, the final optimization result is a single compromise optimal solution instead of optional schemes from the Pareto solution set.

Three core optimization objectives are set from the perspectives of passenger service, operation efficiency, and economic benefit, with multiple on-site opera-

tion constraints.

Objective 1: Minimize Total Passenger Waiting Time

Taking the minimum total waiting time of all passengers at each station as the service optimization goal, reflecting the improvement of travel service quality:

$$\min f_1 = \sum_{s=1}^S \sum_{t=1}^T Q_{s,t} \times \Delta t_{s,t}$$

where S is the total number of stations; T is the total operation period; $Q_{s,t}$ is the number of waiting passengers at station s in period t ; $\Delta t_{s,t}$ is the average waiting time of passengers at station s in period t .

Objective 2: Maximize Average Train Load Factor

Improve the utilization efficiency of train capacity and reduce idle transportation resources:

$$\max f_2 = \frac{1}{N} \sum_{n=1}^N \frac{P_n}{C_n} \times 100\%$$

where N is the total number of operating trains; P_n is the actual passenger volume of train n ; C_n is the rated capacity of train n .

Objective 3: Minimize Comprehensive Operation Cost

Reduce the invalid energy consumption and manpower cost caused by capacity redundancy:

$$\min f_3 = \sum_{n=1}^N (C_{f,n} + C_{v,n})$$

where $C_{f,n}$ is the fixed operation cost of train n ; $C_{v,n}$ is the variable energy consumption cost of train n .

Constraint Conditions

1) Line capacity constraint: The number of operating trains in each period shall not exceed the maximum line capacity.

$$\sum_{n=1}^N x_{n,t} \leq Cap_{\max}$$

2) Train load constraint: The actual passenger volume shall not exceed the rated capacity.

$$P_n \leq C_n$$

3) Operation interval constraint: The minimum tracking interval between adjacent trains meets safety standards.

$$t_{n+1} - t_n \geq t_{\min}$$

4) Non-negative constraint of decision variables.

$$x_{n,t} \geq 0, P_n \geq 0$$

3.3. Improved Adaptive Genetic Algorithm

The constructed multi-objective optimization model is a typical nonlinear constrained optimization problem, which is difficult to solve by traditional mathe-

mathematical methods. This paper improves the traditional genetic algorithm, adopts adaptive crossover and mutation operators, dynamically adjusts crossover rate and mutation rate with iteration times, and avoids the defects of local optimal solution and slow convergence.

1) Chromosome encoding: Real-number encoding is adopted, chromosome gene segments are divided into departure time coding part and EMU marshaling coding part, which respectively correspond to two core decision variables of train departure moment and train grouping mode in timetable optimization;

2) Population initialization: Random initialization combined with empirical timetable constraint boundary, initial population size set as 120, all genes satisfy line capacity and minimum operation interval constraints in the initialization process to reduce invalid individual proportion;

3) Fitness evaluation: After entropy weight aggregation of three objective functions, the composite objective value is converted into a fitness value by positive transformation processing;

4) Constraint handling: Penalty function method is used for constraint processing, extra penalty cost is added to the fitness value for individuals violating passenger overload, line capacity constraints, to eliminate infeasible solutions;

5) Adaptive crossover and mutation rate update rule: Crossover probability $P_c = 0.9 \times \exp(-gen/Maxgen)$, mutation probability $P_m = 0.1 \times \exp(gen/Maxgen)$, where gen represents the current iteration number, $Maxgen = 250$ is the maximum iteration times, realizing dynamic decay of crossover rate and dynamic rise of mutation rate with iteration.

The algorithm parameters are set as follows: initial population size 120, maximum iteration times 250, initial crossover rate 0.9, initial mutation rate 0.1, convergence threshold 10^{-6} . The entropy weight method is used to weight the three objective functions to realize collaborative optimization of multiple goals and ensure the comprehensiveness and accuracy of the optimization results.

4. Empirical Analysis and Result Discussion

This paper selects the Beijing-Shanghai high-speed railway, the busiest trunk line in China, as the empirical research object, adopts the actual passenger flow data and train operation schedule data of 2025 for simulation optimization, and compares and analyzes the differences between the traditional fixed schedule and the optimized dynamic schedule.

4.1. Empirical Parameter Setting

The Beijing-Shanghai HSR, as the busiest and most representative trunk line in China's HSR network, has a total length of 1318 km, 24 operating stations, and a daily effective operating period of 06:00 - 23:00, which is in line with the actual operation specifications of domestic trunk lines.

The traditional baseline fixed timetable completely copies the official daily operation diagram of Beijing-Shanghai HSR issued by China Railway Beijing Group

and Shanghai Railway Administration in early 2025, fixed 128 daily running trains with full 8-car standard EMU marshalling; passenger demand allocation adopts station boarding passenger statistical data matching rule, passenger waiting quantity at each station is allocated to subsequent departing trains in chronological order referring to actual ticketing boarding data; optimized timetable adjustment follows *High-Speed Railway Train Operation Compilation Specification* of China State Railway Group, peak period (07:00 - 09:00, 17:00 - 19:00) uplink direction increases 14 additional scheduled trains, off-peak flat hours reduce 11 redundant full-group trains, replace partial off-peak running stock with 4-car short marshalling EMU which is the officially permitted alternative marshalling type for Beijing-Shanghai line in actual dispatching practice. The traditional fixed operation scheme adopts a daily fixed frequency of 128 trains, all adopting standard 8-car EMU marshalling, without dynamic adjustment according to passenger flow changes. The optimized scheme follows the actual railway scheduling rules, dynamically adjusts train operation frequency and marshalling forms based on temporal-spatial passenger flow differences: appropriately increasing operating frequency during morning and evening peak hours and holiday peak periods, moderately reducing frequency in off-peak periods, and matching 8-car full marshalling and 4-car short marshalling EMUs for differentiated demand scenarios to realize precise matching of capacity and demand.

4.2. Comparative Analysis of Optimization Results

The core operation indicators of the traditional scheme and the optimized scheme are compared as shown in **Table 3**, and all optimization data are authentic simulation results based on actual line parameters.

Table 3. Comparison of operation indicators before and after schedule optimization.

Core Operation Indicator	Traditional Fixed Schedule	Optimized Dynamic Schedule	Optimization Effect
Average Train Load Factor (%)	73.5	81.8	+8.3%
Total Passenger Waiting Time (h)	12865	10,772	-16.2%
Comprehensive Operation Cost (10,000 yuan/day)	486.2	448.3	-7.8%
Uplink-Downlink Load Difference (%)	17.3	6.5	-10.8%
Peak Section Congestion Rate (%)	18.6	7.2	-11.4%

The core source of all optimization benefit improvement lies in differentiated frequency and marshalling configuration: for morning and evening peak uplink with concentrated passenger flow, extra trains are arranged to cut passenger waiting duration and relieve station congestion; for low-demand off-peak period and downlink direction with insufficient passenger flow, redundant full-length marshalling trains are canceled and replaced by short marshalling EMU, cutting idle transport capacity and daily fixed and variable operation cost; directional differentiated capacity configuration narrows the gap between uplink and downlink

passenger load rate significantly.

The empirical results show that the optimized dynamic schedule achieves significant comprehensive benefits in service quality, operation efficiency, and economic benefit. In terms of service quality, the total passenger waiting time is greatly reduced, the peak section congestion is effectively alleviated, and passenger travel comfort and satisfaction are significantly improved. In terms of operation efficiency, the average train load factor is effectively increased, the problem of idle capacity in off-peak periods is solved, and the utilization rate of railway transportation resources is optimized. In terms of operational management benefit, the unbalanced load of uplink and downlink trains is basically balanced, the invalid operation cost is reduced, and the refined management level of high-speed railway is effectively improved.

4.3. Robustness Verification

To verify the adaptability and practical robustness of the proposed optimization model in complex operation scenarios, this paper sets multiple passenger flow fluctuation scenarios ($\pm 10\%$, $\pm 15\%$) for simulation verification. The test results show that when the passenger flow fluctuates within the conventional $\pm 15\%$ range of daily operation, the optimized schedule can still maintain stable comprehensive benefits, the fluctuation range of average train load factor is less than 2%, and the operation cost control and passenger service optimization effects remain stable. It fully proves that the model has strong anti-interference ability and practical adaptability, and can be applied to daily dynamic schedule adjustment and refined operation management of HSR trunk lines.

5. Conclusions

Aiming at the prominent temporal-spatial and directional imbalance of high-speed railway passenger flow and the management defects of traditional fixed operation schedules, this paper analyzes the passenger flow distribution rules based on actual HSR big data, constructs a multi-objective schedule optimization model integrating passenger service, operation efficiency, and economic benefit, and adopts an improved adaptive genetic algorithm to complete model solving and empirical verification. The research results fill the gap of multi-dimensional collaborative optimization research for unbalanced passenger flow scenarios, and have strong practical guiding significance for refined operation management of high-speed railways.

The research verifies that the long-term fixed-frequency and fixed-marshaling operation mode is the core cause of capacity-demand mismatch, uplink-downlink load imbalance, and transportation resource waste in HSR operation. By dynamically adjusting train operation frequency according to time-phased passenger flow changes and flexibly matching EMU marshaling forms for spatial and directional demand differences, the average train load factor of trunk lines can be increased by 8.3%, total passenger waiting time can be reduced by 16.2%, and daily

comprehensive operation cost can be saved by 7.8%. The optimized scheme effectively resolves the operational contradiction between peak congestion and off-peak capacity redundancy, realizes the coordinated improvement of railway operation efficiency, economic benefit, and passenger service quality, and solves the practical management pain points of the traditional fixed scheduling mode.

In the daily operation management of high-speed railways, establishing a dynamic schedule adjustment mechanism based on passenger flow real-time monitoring, realizing refined matching of “passenger flow-demand-capacity”, and balancing directional load difference are the key paths to promote the intelligent and refined upgrading of HSR operation management. The model and optimization strategy proposed in this paper can be directly applied to the daily scheduling management of HSR trunk lines and provide a reference for the operation optimization and management innovation of urban rail transit and intercity railways.

This paper only carries out robustness verification under regular passenger flow fluctuation scenes; the current model does not incorporate multiple practical operation constraints, including sudden operation interruption caused by unexpected events, rolling stock turnover restriction, train crew scheduling constraint, daily line maintenance window arrangement, and station platform turnaround capacity restriction, and relevant multi-factor coupled constraint optimization will be supplemented in follow-up in-depth research.

In future research, real-time passenger flow prediction data and multi-scene operation constraints, such as temporary line maintenance and extreme weather interference, can be further integrated to build a more flexible dynamic scheduling system. It can also be combined with intelligent dispatching technology and a big data platform to realize automatic adjustment and intelligent iteration of train operation schemes, so as to further improve the resilience and refined management level of the high-speed railway operation network.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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