Optimization of High-speed Rail Train Service Plan Considering Dynamic Formation in the Context of Carbon Peak Initiative

Siyu Cao, Xuelei Meng, Xiaoqing Chen, Ruhu Gao, and Qianyu Wang

Abstract—**To address the carbon reduction mandates for high-speed rail under emissions policies, this study analyzes inefficiencies in resource utilization and operational limitations caused by fixed train formation. Focusing on optimizing high-speed rail train service plan within the context of carbon peak initiative, we introduce a grid-based carbon emissions factor to quantify emissions for various train formation types. Moreover, we design the carbon emissions incentives that consider the impact of carbon emissions quota and allocation fairness on train service plan, incorporating carbon emissions credit points and carbon trading price. The dynamic formation plan adjusts 8-car and 16-car train formation and service frequency based on passenger demand on specific segments. We develop a mixed-integer programming (MIP) model to minimize total costs, including train operation, passenger travel time, and carbon emissions. The model is solved using the GUROBI solver and validated through a case study on the Nanjing-Shanghai intercity railway. Results show that dynamic train formation significantly reduces total costs and improves efficiency compared to existing train service plan. The operational cost and passenger travel time cost decrease by 24.14% and 23.08%, respectively, while carbon emissions costs decrease by 11.75% under the policy-driven reduction targets. Notably, 8-car trains demonstrate superior performance in emissions reduction. Sensitivity analyses confirm the robustness of the model. The proposed optimization model could provide decision support for achieving efficient and low-carbon operation in high-speed rail under diverse policies and market conditions.**

Index Terms—**High-speed rail, Train service plan, Carbon peak, Dynamic formation plan, GUROBI, Carbon emissions incentives**

Manuscript received March 9, 2025; revised May 15, 2025.

This work was supported in part by the Gansu Provincial Science and Technology Plan Project (24JRRA865), the National Natural Science Foundation of China (72361020) and the Gansu Province Central Government Guided Local Science and Technology Development Fund Project (25ZYJA015).

Siyu Cao is a postgraduate student at the School of Traffic and Transportation, Lanzhou Jiaotong University, Lanzhou 730070, China (e-mail: 11230018@stu.lzjtu.edu.cn).

Xuelei Meng is a professor of Traffic and Transportation School, Lanzhou Jiaotong University, Lanzhou 730070, China (corresponding author, phone: +86-15117071015; fax: 86-0931-4938025; e-mail: mxl@mail.lzjtu.cn).

Xiaoqing Cheng is an associate professor of Traffic and Transportation School, Beijing Jiaotong University, Beijing 100000, China (e-mail: xqcheng@bjtu.edu.cn).

Ruhu Gao is an associate professor of Traffic and Transportation School, Lanzhou Jiaotong University, Houston, Lanzhou 730070, China (e-mail: grh@mail.lzjtu.cn).

Qianyu Wang is a postgraduate student at the School of Traffic and Transportation, Lanzhou Jiaotong University, Lanzhou 730070, China (e-mail: 12231050@stu.lzjtu.edu.cn).

I. INTRODUCTION

THE transportation industry accounts for approximately 21% of global greenhouse gas emissions [1], making it a major contributor to climate change. Among various transport modes, high-speed rail holds significant potential for emissions reduction due to its high energy efficiency and lower carbon footprint. However, the rapid expansion of high-speed rail networks has led to a considerable increase in electricity consumption, highlighting the need for improved energy management strategies to maintain its environmental advantages. In the context of carbon peak initiative and sustainability policies, railway operators are now required to incorporate carbon emissions into train service plan. This shift requires an accurate balance between operational efficiency and environmental goals to achieve economic viability and ecological sustainability [2,3].

Existing research has examined the characteristics of carbon emissions, potential of emissions reduction, and optimization strategies in rail transport. Li Xiang et al. [4] proposed extending operational costs include trading expense for the carbon emissions allowance and developed a fuzzy multi-objective optimization model to minimize energy consumption and emissions costs. At the policy level, Li Lin et al. [5] analyzed the effects of demand-side carbon taxes and supply-side subsidies, and proposed the freight price adjustments to incentivize rail transport adoption, thereby reducing emissions while expanding the market share of rail transport. Zhu Xuesong et al. [6] introduced a fleet plan for the airline industry under the carbon emissions quota. Dai Yanze et al. [7] considered passenger transfer behavior and choice preferences into a multi-objective nonlinear model, with carbon emissions as a central consideration.

Recent studies have begun incorporating carbon emissions considerations into train service plan. For instance, Yin Chuanzhong et al. [8] developed an integer programming model for express train service plan under dual-carbon goals, designing a service plan that prioritizes rail transport as the primary and road transport as an auxiliary option. Similarly, Lin Li et al. [9] addressed inefficiencies in urban rail by optimizing multi-route and multi-formation mode to balance passenger comfort and carbon emissions. While these studies emphasize the low-carbon benefits of rail transport, they inadequately addressed the coordination between train operation and emissions limitations. Critical gaps remain in modeling dynamic formation, adjusting service frequency, and fully integrating carbon policies into train service plan under sustainability mandates.

In terms of dynamic train formation, relevant research has contributed to optimizing train service plan [10]. Cao Yuan et al. [11] proposed a scheduling strategy based on virtual formation and established a dynamic train formation model guided by passenger flow distribution. On this basis, Zhong Linhuan et al. [12] introduced a demand-responsive flexible train formation approach to resolve fluctuating passenger flow, demonstrating significant improvements in resource utilization efficiency. Xiao Jie et al. [13] examined the rail freight train formation plan and analyzed the operational benefits of replacing single-formation trains with double-formation. In addition, Li Zhengyang et al. [14] addressed the coordination of train formation and passenger flow allocation, optimizing urban train service plan by aligning service frequency with train formation to improve operational efficiency.

Research on optimizing passenger flow demand and train service plan has progressed through various methods. Fu Huiling et al. [15] developed a demand-responsive train service plan by classifying trains and stations into different types based on predicted passenger flow volume and demand characteristics. Meng Lingyun et al. [16] considered dynamic choice behaviors of passengers into a variable-demand optimization model, integrating train service plan, timetable, and rolling stock capacity to address passenger travel demand and limits of rolling stock resources. To enhance passenger satisfaction, Liu Pei et al. [17] aligned intercity rail train service plan with passenger preferences by quantifying the disparities between perceived and actual service quality. Yang Yuxiang et al. [18] optimized high-speed rail train service plan under capacity constraints using spatiotemporal passenger preferences and dispatching strategies. Zhang Xin et al. [19] proposed a train service plan with timetable, balancing operational efficiency and passenger demand through flexible stop patterns, passenger managements, and frequency adjustments to enhance efficiency and while satisfying passenger demand.

Additionally, researchers have proposed various strategies to optimize train service plan, aiming to improve rail resource utilization and passenger service quality [20]. Several studies have focused on aligning service plan with passenger demand under line capacity constraints [21]. Yang Wenbin et al. [22] addressed the complexity interactions of the mutual influence of passenger flow across different service plan, and proposed an optimization model for adjusting train service plan based on passenger flow allocation. To address cross-line interconnection issues, Wang Xiaochao et al. [23] designed an intercity rail train service plan that combines train route and service frequency. Wang Qing et al. [24] separated train service plan into route plan and stop plan, identifying the intersection points of trains and passenger flow to develop a multi-objective optimization model. Li Lin et al. [25] focused on integration and connection issues in multi-modal rail transport, developing a train service plan to mitigate transfer frequency and correct spatial imbalances of passenger demand and service availability.

Existing research on train formation and passenger demand responsiveness has advanced operational efficiency. However, most studies neglect the influence of carbon emissions on train formation. In particular, there is a lack of systematic analysis and strategic-level optimization that jointly considers operational costs and carbon emissions. To address these gaps, this paper proposes an optimized high-speed rail train service plan with the following innovations:

1) Considering passenger flow demand fluctuation, we design a dynamic train formation plan by assigning appropriate train types for specific service segments.

2) Designing carbon emissions quota and allocation fairness constraints to ensure an equitable distribution of emissions responsibilities across the railway line while maintaining policy compliance.

3) Developing the model based on carbon emissions credit points and carbon emissions incentive factor, capturing the interaction of emissions impacts and passenger economic benefits. This ensures that train service plan complies with carbon emissions reduction mandates, improves operational efficiency and supports a low-carbon solution pathway for high-speed rail.

II. Problem Analysis

A. Dynamic Train Formation

Traditional fixed train formation struggle to accommodate uneven passenger demand, resulting in capacity shortages during peak periods and underutilized resources during off-peak periods. These imbalances in resource allocation lead to increased operational costs and carbon emissions. In contrast, dynamic train formation plan adjusts train types and service frequency based on passenger demand. This approach enhances transport capacity utilization, lowers operational costs, and reduces carbon emissions by avoiding unnecessary energy consumption.

The train service plan integrates train formation plan and stop plan, this study prioritizes three core factors for optimization: cost control, carbon emissions reduction, and passenger satisfaction. As illustrated in Figure 1, which depicts a cost-optimized service plan. k_i represents the stop plan, where solid black dots indicate train stops at this station, solid lines represent 8-car, and dashed lines denote 16-car.

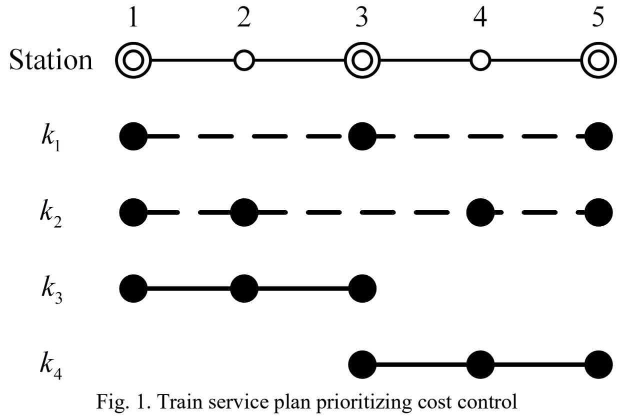

Fig. 1. Train service plan prioritizing cost control

The key features of this strategy include: k_1 stops at Stations 1, 3, and 5, by minimizing unnecessary stops, 16-car trains could provide sufficient capacity on high-demand segments, reducing dwelling time and operational costs associated with frequent halts. k_2 does not stop at Station 3, aiming to streamline passenger flow and improve transport efficiency through intermediate stations. k_3 stops at Stations 1, 2, and 3, utilizing 8-car trains to prevent overcapacity and resource waste occurred with 16-car. k_4 stops at Stations 3, 4, and 5. Reasonable stop plan enables precise alignment of transport capacity with passenger demand, improving service flexibility while lowering operational costs.

Figure 2 presents the optimization for carbon emissions reduction. The key strategies include: k_1 stops at Stations 1, 3, and 5, focusing on high-demand segments, especially at the departure and arrival stations, reducing dwelling time and emissions. k_2 stops at Stations 1, 2, and 5, differentiated service strategies based on line requirements at specific stations, avoiding overcapacity and excess emissions. k_3 stops at Stations 1 and 3, serving low-demand segments with minimal stops to further reduce carbon emissions. k_4 stops at Stations 3, 4, and 5, ensuring service coverage at critical stations while maintaining emissions efficiency.

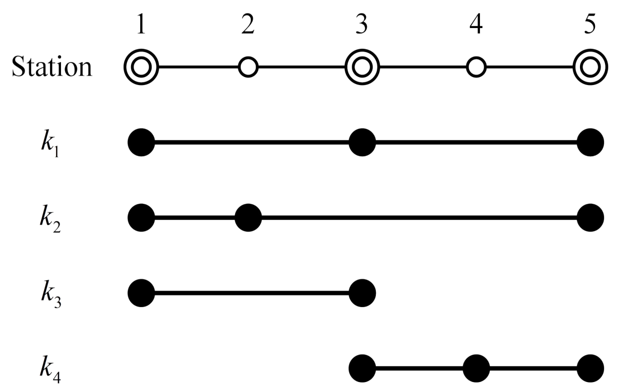

Fig. 2. Train service plan prioritizing carbon emissions reduction

Figure 3 illustrates the optimization for passenger satisfaction through the following strategies: k_1 stops at all stations, utilizing 16-car trains to accommodate diverse passenger demand along the route. k_2 stops at Stations 1 and 5, minimizing travel time for long-distance passenger and enhancing comfort by reducing intermediate stops. k_3 stops at Stations 1, 2, 3, and 5, serving dispersed medium-short distance demand. with dispersed station coverage, balancing operational efficiency and accessibility. k_4 stops at Stations 1, 3, 4, and 5, focusing on high-demand stations (Stations 3 and 4) during peak periods to reduce dwelling time, thereby improving service reliability.

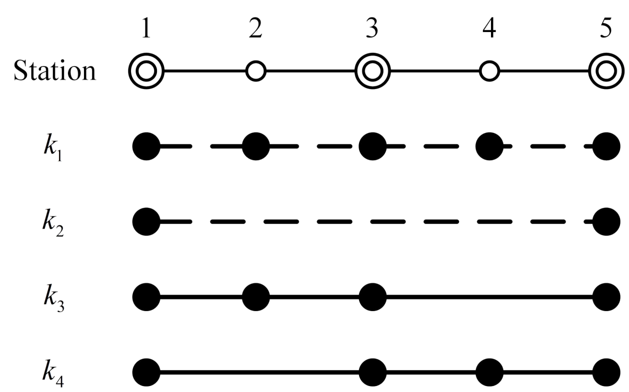

Fig. 3. Train service plan prioritizing passenger satisfaction

B. Carbon Emissions Measurement

The carbon peak represents a critical inflection point, denoting the stage at which cumulative emissions reach the maximum before transitioning into a phase of sustained decline. Achieving this milestone signifies that the high-speed rail industry has initiated measurable carbon reduction efforts, representing a pivotal stage toward carbon neutrality.

Within the high-speed rail lifecycle, the operational phase accounts for 84.97% of total carbon emissions. Therefore, optimizing train formation and service frequency during this stage offers significant potential for emissions reduction and improves environmental efficiency.

Train carbon emissions are influenced by several factors, including vehicle design parameters, energy efficiency, and operational speed. For instance, comparative analyses of CRH and CR series electric multiple units (EMUs) reveal notable differences in technical specifications, directly influence carbon emissions profiles. These differences introduce added complexity to the optimization of dynamic formation plan.

The per kilometer energy consumption of the train is defined as:

$$En^h = \frac{P^h}{v^h} \tag{1}$$

En^h is the per kilometer energy consumption of train h, P^h is the rated power of train h, v^h is the design speed of train h.

The per kilometer carbon emissions of the train can be defined as:

$$C_t^h = En^h \cdot \Theta \tag{2}$$

C_t^h is the per kilometer carbon emissions of train h, Θ is the grid-based carbon emissions factor.

The per kilometer capita carbon emissions of the train can be defined as:

$$C_r^h = \frac{En \cdot \Theta}{Cap^h} \tag{3}$$

C_r^h is the per kilometer capita carbon emissions of train h, Cap^h is the passenger capacity of train h.

To simplify the model and improve computational feasibility, the following assumptions are made.

1)The train operates on a single route, excluding passenger transfer behavior.

2)The train operates on a single track, without considering cross-line operations.

3)The difference between passenger expected and actual departure time is not considered.

III. Model Development

A. Symbol Definition

Table I presents the definitions and explanations of the symbols used in this paper.

B. Objective Function

This study considers three key stakeholders: railway enterprises, passengers, and government. A multi-objective optimization model is developed to minimize the cost of train operations, passenger travel time, and carbon emissions.

(1) Train operational costs:

Comprising fixed cost, operating cost, and stopping expenditure.

$$minZ_1 = \sum_{h \in H} \mu_h \cdot f^h \cdot \left(\gamma_1 + \gamma_2 \cdot p^h + \sum_{i \in S} \gamma_3 \cdot x_i^h \right) \quad (4)$$

(2) Train carbon emissions cost:

The external environmental cost of train operation is quantified by converting carbon emissions into economic value using carbon trading price. Train carbon emissions are calculated based on service frequency, train type, and per kilometer emissions, following industry-standard carbon emissions measurement methods.

$$minZ_2 = \sum_{h \in H} pr \cdot f^h \cdot p^h \cdot C_t^h \quad (5)$$

(3) Passenger travel time cost:

Passenger behavioral in response to time-related service attributes is modeled by integrating passenger flow demand, travel time, and the value of travel time, thereby capturing differences in decision-making under different stop plan.

$$minZ_3 = \sum_{h \in H} \sum_{i \in S} \sum_{j \in S} \omega \cdot q_{ij}^h \cdot t_{ij}^h \quad (6)$$

Total passenger travel time consists of the train running time, dwelling time, and additional time of acceleration and braking phases.

$$t_{ij}^h = \sum_{e \in E_{ij}^h} \frac{l_e}{v_e^h} + t_1^h + \sum_{i \in S_{ij}^h} x_i^h \cdot (t_1^h + t_2^h + t_3^h) + t_3^h \quad (7)$$

(4) Passenger carbon emissions incentive cost:

This study proposes the passenger carbon emissions incentives. A demand-responsive incentive factor, adjusted based on passenger flow fluctuation, is designed to amplify the influence of carbon emissions cost through scale effects. Passenger selecting different types of trains incur a dynamic fare surcharge proportional to their capita emissions. Conversely, passengers choose trains with emissions below the predefined benchmark receive carbon emissions credit points. These dual incentives discourage the intensive operation high-emissions trains, and reward passenger for their low-carbon travel behavior.

$$K = \frac{1}{1 + \theta \cdot \left(\sum_{i \in S} \sum_{j \in S} q_{ij}^h / Cap^h \right)} \quad (8)$$

$$\Phi = \frac{Q}{P} \quad (9)$$

$$minZ_4 = \sum_{h \in H} \sum_{i \in S} \sum_{j \in S} q_{ij}^h \cdot \mu_h \cdot \left[pr \cdot K \cdot C_r^h \cdot p_{ij} - \sigma \cdot \left(\Phi - C_r^h \right) \cdot 10^5 \right] \quad (10)$$

C. Constraints

(1) Passenger flow conservation constraint:

Total passenger flow remains constant across operational plan. This ensures that regardless of adjustments to stop plan, the aggregate number of passengers across all segments remain unchanged, thereby fully accommodating passenger demand while preserving reliability of the train service plan.

$$q_{ij} = \sum_{h \in H} q_{ij}^h \quad \forall i, j \in S, i < j \quad (11)$$

(2) Passenger flow transport capacity constraint:

The actual passenger assigned to each train should not exceed its maximum capacity.

$$\sum_{m<i} \sum_{n>i} q_{mn}^h \le f^h \cdot Cap^h \quad \forall h \in H \quad (12)$$

(3) Load rate constraint:

A minimum passenger load rate is imposed to ensure transport efficiency and economic sustainability of operation. Lower load factor leads to insufficient revenue to offset operational costs while declining capita passenger emissions.

$$\frac{\sum_{i \in S} \sum_{j \in S} \alpha \cdot p_{ij} \cdot q_{ij}^h}{Cap^h \cdot p^h \cdot f^h} \ge \beta \quad \forall h \in H \quad (13)$$

TABLE I
SYMBOL DEFINITIONS AND EXPLANATIONS

Symbol	Explanation	Symbol	Explanation
Sets		Φ	Carbon emissions benchmark
E	Sets of intervals, $e \in E$	Q	Total carbon emissions
S	Set of stations, $i, j \in S, i \ne j$	P	Transport turnover
E^h	Sets of intervals by train h	p_{ij}	Mileage between the station i and j
S^h	Set of stations by train h	σ	Carbon emissions benchmark exchange value
E_{ij}^h	Sets of intervals from the station i to j by train h	τ	Decline ratio of comprehensive energy consumption
S_{ij}^h	Set of stations from the station i to j by train h	t^h	Total passenger travel time of train h
Parameters		δ	Reward coefficient
γ_1	Fixed cost of the train	q_{ij}	Passenger demand from the station i to j
γ_2	Operating cost of the train	α	Fluctuation coefficient of passenger flow
γ_3	Stopping cost of the train	β	Load factor of the train
p^h	Operation mileage of train h	M	An infinite positive integer
t_{ij}^h	Total travel time from the station i to j by train h	$T_{\max}$	Maximum number of stops allowed for train h
l_e	Mileage of interval e	η	Carbon emissions allocation ratio
v_e^h	Operation speed of train h in interval e	Variables	
t_1^h	Additional time of train h to start	μ_h	Formation type of train h, 1 is 8-car, 2 is 16-car
t_2^h	Stopping time at the station of train h	f^h	Service frequency of train h
t_3^h	Additional time of train h to brake	x_i^h	=1 if train h stops at station i ;=0, otherwise
K	Carbon emissions incentive factor	q_{ij}^h	Passenger demand from the station i to j by train h
θ	Incentive intensity	z_{ij}^h	Auxiliary decision variable, $z_{ij}^h = x_i^h \cdot x_j^h$

(4) Passenger services and stops consistency constraint:

Trains operating between stations i and j are designed to align with passenger demand within this segment, ensuring service coverage and accessibility for passengers traveling between these stations.

$$q_{ij}^{h} \le M \cdot x_i^h \cdot x_j^h \quad \forall i, j \in S, h \in H \tag{14}$$

Given the proposed model is a nonlinear mixed-integer programming model, the auxiliary decision variable z_{ij}^h is introduced to linearize the constraint (14), and denoted as $z_{ij}^h = x_i^h \cdot x_j^h$. The nonlinear equation can be reformulated by linear constraints as follows:

$$z_{ij}^h \le x_i^h \tag{15}$$

$$z_{ij}^h \le x_j^h \tag{16}$$

$$z_{ij}^h \ge x_i^h + x_j^h - 1 \tag{17}$$

$$z_{ij}^h \ge 0 \tag{18}$$

(5) Train stops constraint:

Excessive stops at intermediate station increase total travel time and influence operational efficiency by increasing dwelling time and energy consumption. To balance passenger demand with service quality, stop plan must be strategically regulated. This involves constraining the maximum number of stops permitted in each service plan to ensure an optimal allocation of train resources while maintaining service effectiveness.

$$\sum_{h\in H}\sum_{i\in S} x_i^h \le T_{\max} \quad \forall h \in H \tag{19}$$

(6) Carbon emissions quota constraint:

Chinese rail industry is committed to achieving carbon peak by 2030 and carbon neutrality by 2060, with an interim target of reducing the comprehensive energy consumption of rail transport by 10% by 2025, relative to 2020 level [26]. To implement this goal, carbon emissions mitigation has been institutionalized as a binding policy. Carbon emissions quota is allocated to rail lines based on transport turnover and energy efficiency, ensuring compliance with sectoral carbon budgets and legally mandated emissions cap. Additionally, surplus quota can be traded via national carbon trading market, incentivizing innovation in low-carbon operation.

$$\left[\sum_{h\in H} C_t^h \cdot f^h \cdot p^h + \sum_{h\in H}\sum_{i\in S}\sum_{j\in S} K \cdot C_r^h \cdot q_{ij}^h \cdot p_{ij}\right] \le \Theta \cdot \Phi \tag{20}$$

(7) Carbon emissions allocation fairness constraint:

To prevent certain types of trains from being excluded from operation due to their higher carbon emissions, this constraint is defined based on train type and passenger demand, ensuring an efficient utilization of trains.

$$\frac{\sum_{h\in 1,2} C_t^h \cdot f^h \cdot p^h}{\sum_{h\in 1,2} q_{ij}^h} \cdot \eta \le \frac{\sum_{h\in 3,4} C_t^h \cdot f^h \cdot p^h}{\sum_{h\in 3,4} q_{ij}^h} \quad \forall i, j \in S \tag{21}$$

(8) Service frequency constraint:

The service frequency of the train is a positive integer.

$$f^h \in Z^* \quad \forall h \in H \tag{22}$$

(9) Decision variable constraint:

The decision variables must be within their domain.

$$x_i^h \in \{0,1\} \quad \forall i \in s, h \in H \tag{23}$$

$$q_{ij}^h \in Z \quad \forall i, j \in s, h \in H \tag{24}$$

This study employs the ε -constraint method to solve the multi-objective optimization problem. In this approach, one objective function is selected as the primary goal, while the remaining objectives are reformulated as parameterized inequality constraints. By iteratively adjusting ε , the model generates a discrete set of non-dominated solutions, each representing a trade-off among conflicting objectives. These solutions are used to construct the Pareto frontier, which serves as a decision-making aid for identifying balanced solutions that optimize operational efficiency while meeting emissions reduction target.

Specifically, we select Z_1 as the primary objective, while the remaining objectives are converted into constraints with upper bounds controlled by ε , By incorporating these upper limits along with the defined constraints and objective functions, we construct the optimization model.

$$\min f = \min Z_1$$

$$s.t. \begin{cases} Z_2 \le \varepsilon_2 \\ Z_3 \le \varepsilon_3 \\ Z_4 \le \varepsilon_4 \\ \text{constraints(11)-(13),(15)-(24)} \end{cases} \tag{25}$$

The parameters ε_2 , ε_3 , and ε_4 are determined using a payoff matrix. First, the optimal solution $f_i\left(x_i^*\right)$ of the *i*-th objective function is obtained by solving it independently, yielding the corresponding optimal solution x_i^* . This solution is then substituted into the remaining objective functions to get $\left\{f_1\left(x_i^*\right), f_2\left(x_i^*\right), f_3\left(x_i^*\right), f_4\left(x_i^*\right)\right\}$. Then repeating this process for each objective function yields the complete payoff matrix, as shown below:

$$\begin{bmatrix} f_1\left(x_1^*\right) & f_2\left(x_1^*\right) & f_3\left(x_1^*\right) & f_4\left(x_1^*\right) \\ f_1\left(x_2^*\right) & f_2\left(x_2^*\right) & f_3\left(x_2^*\right) & f_4\left(x_2^*\right) \\ f_1\left(x_3^*\right) & f_2\left(x_3^*\right) & f_3\left(x_3^*\right) & f_4\left(x_3^*\right) \\ f_1\left(x_4^*\right) & f_2\left(x_4^*\right) & f_3\left(x_4^*\right) & f_4\left(x_4^*\right) \end{bmatrix}$$

After constructing the payoff matrix, the optimal value $f_i^o = f_i\left(x_i^*\right)$ and worst value $f_i^w = f_i\left(x_j^*\right)$ of each objective can be determined. A gridding score $q_{ij} \in \left\{1, 2, ..., q_{i,\max}\right\}$ is then assigned to each secondary objective function. The ε constraints for the remaining objective functions are calculated as follows:

$$\varepsilon_{ij} = f_i^{sn} - \frac{\left(f_i^w - f_i^o\right)}{q_{ij}} \cdot j \quad j = 1, 2, ..., q_{i,\max} \tag{26}$$

D. Solving tool

The model developed in this study is a linearized mixed-integer programming problem, incorporating constraints such as passenger flow conservation, service capacity, load rate limitation, and carbon emissions quota requirement. The integration of fluctuating passenger demand and carbon emissions incentives adds structural complexity, making it computationally challenging to obtain optimal solutions.

While heuristic and decomposition algorithms can provide faster solutions for large-scale optimization problems, they typically do not guarantee global optimality. In fact, the core challenge of this study lies in jointly optimizing train formation plan and stop plan in response to passenger flow demand on specific segment, carbon emissions quota and carbon allocation fairness. Given the complexity of the proposed model and characteristics of the research problem, in order to ensure computational efficiency and solution accuracy, this study utilizes the GUROBI solver to precisely solve the problem.

IV. CASE STUDY

A. Experimental data

A.1. Data Sources

This study employs the Nanjing-Shanghai intercity railway as a case study for empirical analysis. The corridor spans approximately 301 km and is primarily served by CRH series EMUs. Figure 4 illustrates the route layout and interstation distances. The departure and arrival stations include Nanjing Station, Changzhou Station, Wuxi Station, Suzhou Station, and Shanghai Station.

Passenger flow data are collected from a representative weekday in 2024 as shown in Figure 5, aligned with the corresponding train schedule and operational records. Carbon emissions are calculated from two primary sources: emissions measurement methods issued by the Chinese Ministry of Ecology and Environment and manufacturer-published performance data for CRH series EMUs. A detailed list of parameters and corresponding values is calculated in Table II.

A.2. Parameters setting

The fixed cost γ_1 of the train is 4.2×10^4 CNY/train, the operating cost γ_2 is 2000/(train·km), the stopping cost γ_3 of the train is 100 CNY /(train·time), the carbon trading price pr is 68.15 CNY/t, the passenger travel time value ω is 0.8 CNY/min, the additional time to start t_1^h of train h is 2 min, the additional time to brake t_3^h of train h is 1 min, the incentive intensity θ is 1.5, the total carbon emissions Q of Shanghai Railway Administration are 1.03×10^4 tons, the transport turnover P is 1.1×10^6 person-kilometer, the benchmark exchange value σ is 5 CNY/point, the grid-based carbon emissions factor Θ is 0.65×10^{-3} t/kWh, the reward coefficient δ is 500 CNY/t. The maximum number of stops allowed $T_{\max}$ is 10, the carbon emissions allocation ratio η is 1.3, α and β are set 0.1 and 0.8, respectively.

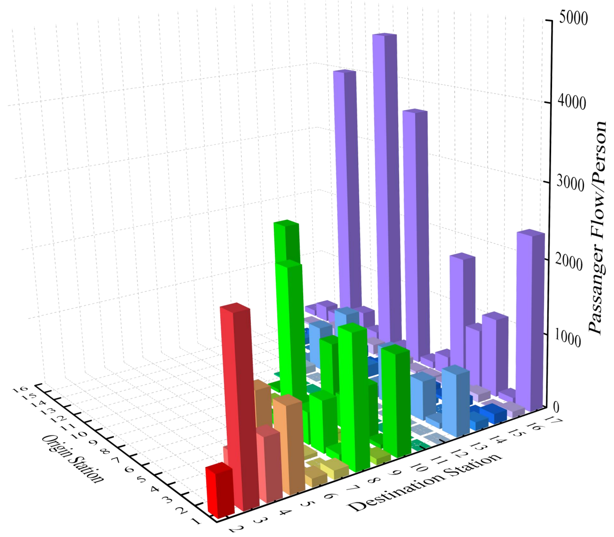

Fig. 5. Route OD passenger flow

B. Dynamic Train Formation Plan

The optimization model evaluates total costs under different train formation plan, with the results shown in Figure 6. No feasible solutions exist in the diagonal region of the solution space (former half), where insufficient train formation is unable to satisfy the baseline passenger demand, thereby rendering the problem infeasible. In contrast, feasible solutions are found near the diagonal. However, in the latter half of the space, the capacity has tended to be saturated, further increasement in number of trains do not result in significant costs reduction due to diminishing marginal returns. Consequently, the algorithm terminates the search once additional trains no longer improve costs efficiency.

Within the feasible solution range, operating 8-car trains for 11 and 16-car trains for 17 results in the total costs of approximately 4.12 million CNY. Adjusting the number of 8-car trains to 15 while reducing 16-car trains to 14 reduces the total costs to 3.97 million CNY. The most cost-effective formation plan, as determined by the optimization model, operates 8-car trains for 18 and 16-car trains for 12, minimizing the total costs to 3.90 million CNY. This progression demonstrates that strategically increasing the use of 8-car trains enhances transport capacity utilization and energy efficiency.

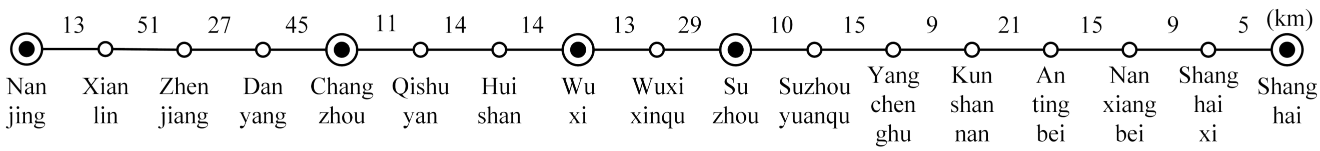

Fig. 4. Route of Nanjing-Shanghai intercity railway

TABLE II
DATA OF CARBON EMISSIONS MEASUREMENT

Train type	Design speed /(km·h^{-1})	Train formation/car	Rated power /(kW)	Train capacity /person	Carbon emissions per kilometer of train /t	Carbon emissions per kilometer of passenger /t
CRH2C	310	8	8760	610	1.61×10^{-2}	2.64×10^{-5}
CRH380D	310	8	10080	554	1.64×10^{-2}	2.96×10^{-5}
CRH380BL	350	16	18752	1015	3.45×10^{-2}	3.40×10^{-5}
CRH380CL	350	16	19680	1015	3.21×10^{-2}	3.16×10^{-5}

Increasing the proportion of 8-car trains effectively reduces operational and carbon emissions cost. This reduction is primarily attributed to the higher capacity flexibility and energy efficiency of 8-car trains, which are well-suited for routes with significant temporal and spatial variations in passenger demand. Furthermore, implementing dynamic train formation could timely adjust service frequency and train type, ensuring a closer alignment between capacity and actual demand. The optimized train service plan minimizes total costs while enhancing service quality and the utilization of transport resources.

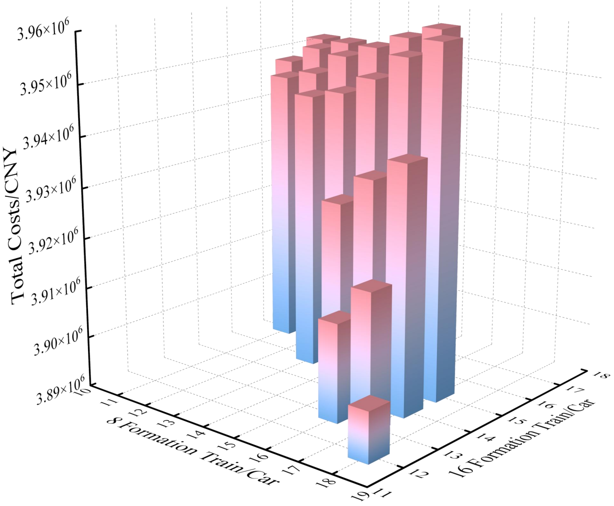

Fig. 6. Dynamic formation experiment

C. Optimization Results

The model is solved using the commercial optimization software GUROBI solver. The operating environment is a personal computer with i5-8250U CPU @ 1.60GHz, 16GB of RAM, with Microsoft Windows 11 (64-bit) as the operating system. The optimal solution is obtained within 47 minutes. As summarized in Table III, the optimized train service plan significantly enhances the transport efficiency and reduces total cost by 23.03%. Specifically, operational cost decreases by 24.14%, while passenger travel time cost drops by 21.89%. In addition, due to the optimization of train formation and the adjustment of service frequency, the train carbon emissions cost and passenger carbon emissions incentive cost decline by 23.08% and 8.77%, respectively.

Additionally, the total number of train operation decrease by 6.67%, with the number of 8-car trains increasing by 38.46% and 16-car trains decreasing by 36.84%, as shown in Figure 7. These adjustments improve operational flexibility, e as 8-car trains are better suited to accommodate fluctuations in segment-specific passenger demand. This precise capacity matching contributes to reduced carbon emissions and improved service efficiency.

Comparison of the exiting and optimized train service plan is presented in Figures 8 and 9. The total number of train stops is reduced by 1.02%, primarily by strategically decreasing stop frequencies at stations with low passenger demand. This adjustment shortens overall travel time and improves operational efficiency. Moreover, service quality at major hub stations remains is maintained through the reallocation of train resources. The optimization results in a reduction in operational cost and carbon emissions while enhancing capacity utilization, demonstrating that service quality is preserved even as operational efficiency increases.

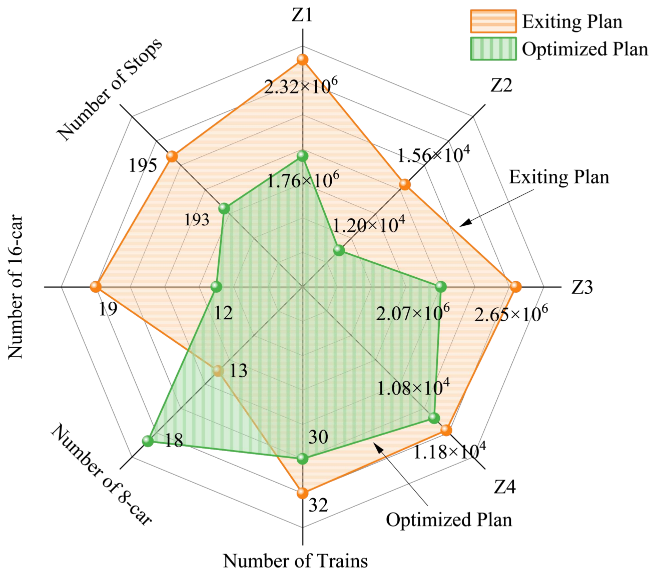

Fig. 7. Comparison of indicators

To further assess the effectiveness of transport capacity matching under dynamic formation plan and flexible stop plan, passenger flow data is analyzed in Figure 10. The results show notable improvements in transport capacity allocation and segment-level load rates. Compared to the actual service plan, the optimized strategy reduces segment transport capacity by an average of 18.5%, streamlining resources to better align with actual demand. The mismatch between passenger demand and actual available capacity is significantly mitigated, with the average deviation dropping from 36.9% to 22.2%, indicating a substantial reduction in transport resources. Additionally, the average load rate across the line increase by 14.6%, highlighting the effectiveness of dynamic formation plan and flexible stop plan in maximizing resource utilization.

Table IV presents the changes in train service frequency across different departure and arrival stations. The number of trains between Nanjing and Shanghai Station decreased by 4, and those between Suzhou and Shanghai Station decreased by 1. In contrast, service frequency between Changzhou and Shanghai Station increased by 2, and the number of trains between Wuxi and Shanghai Station increased by 1. These adjustments enhance the flexibility and responsiveness of the train service plan, enabling it to better accommodate various passenger demand along different segments of the line.

TABLE III
INDICATOR COMPARISON

	Z_1	Z_2	Z_3	Z_4	Total number of trains	Number of 8-car trains	Number of 16-car trains	Total number of stops
Exiting	2.32×10^6	1.56×10^4	2.65×10^6	5.93×10^4	32	11	21	195
Optimized	1.76×10^6	1.20×10^4	2.07×10^6	5.41×10^4	30	18	12	193
Change rate	24.14%	23.08%	21.89%	8.77%	6.67%	38.46%	36.84%	1.02%

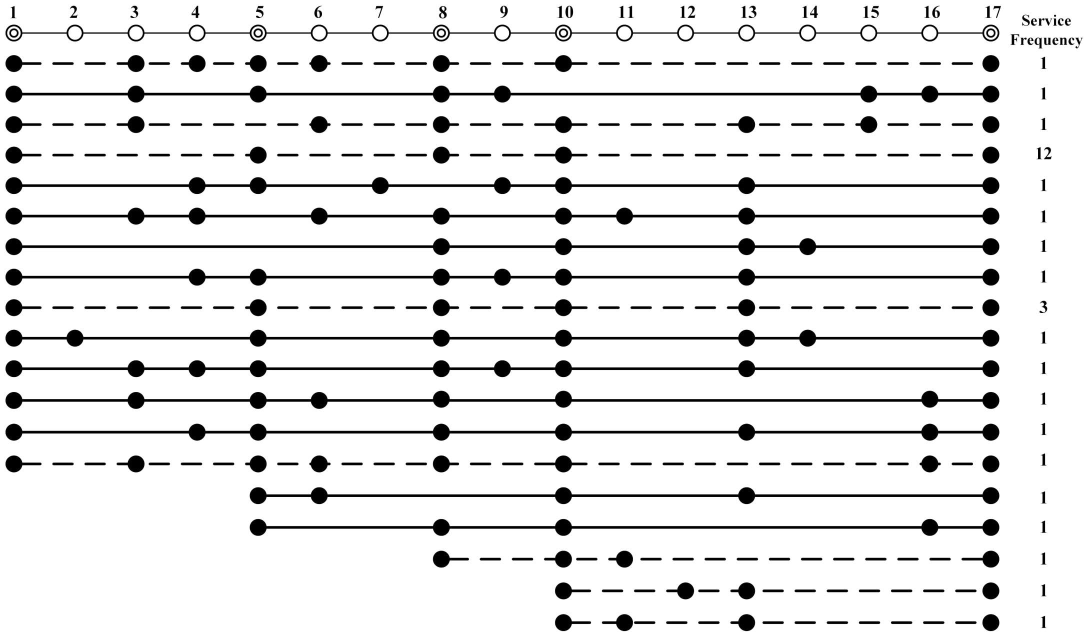

Fig. 8. Exiting train service plan

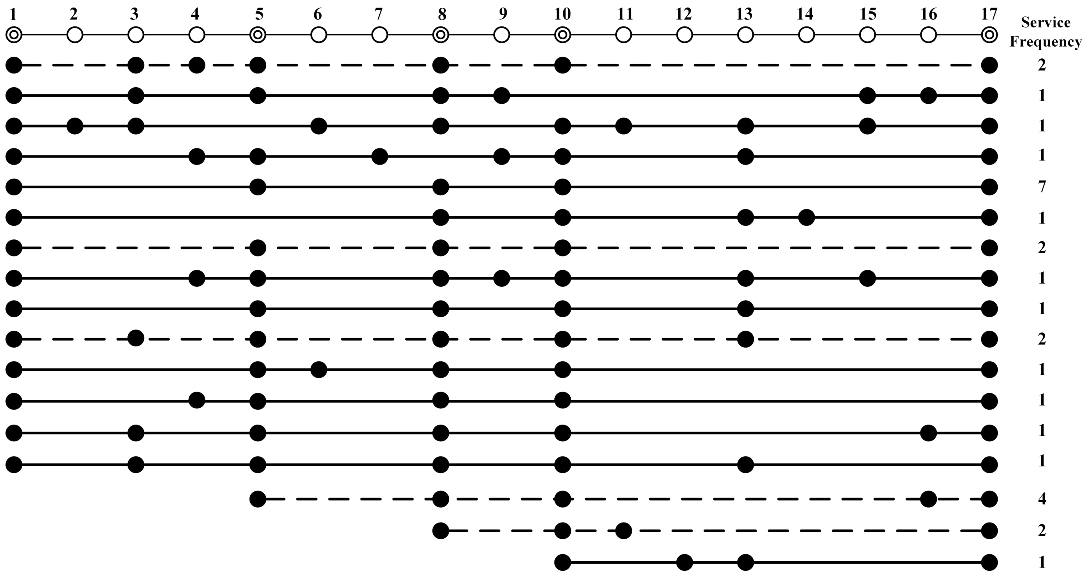

Fig. 9. Optimized train service plan

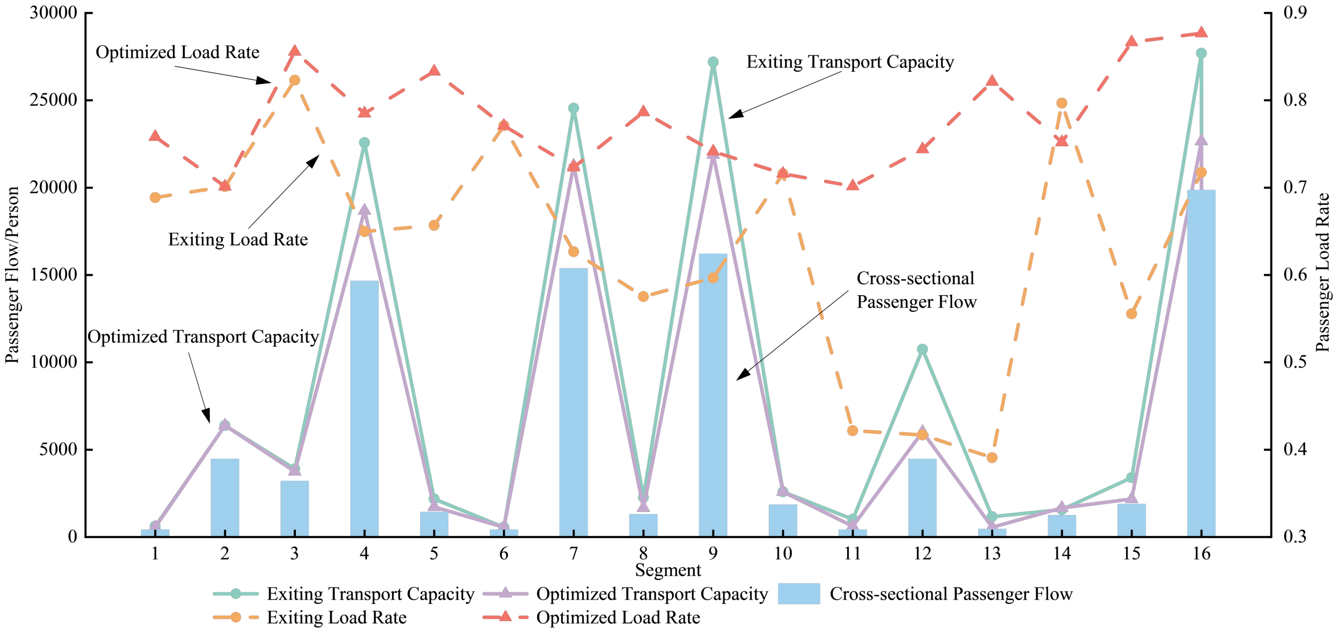

Fig. 10. Comparison of passenger load rate on segments

TABLE IV
TRAINS OPERATE FROM DEPARTURE TO ARRIVAL STATIONS

Stations	Distance/km	Actual	Optimized	Change
Nanjing-Shanghai	301	27	23	-4
Changzhou-Shanghai	165	2	4	+2
Wuxi-Shanghai	126	1	2	+1
Suzhou-Shanghai	84	2	1	-1

To validate the synergistic effects of dynamic formation and carbon emission incentives, this study conducts a comparative analysis of three scenarios, with key performance indicators summarized in Table V. Scenario 1 employs a fixed train formation, in which 16-car trains account for 59.38% of operation. The inflexible capacity and low resource utilization result in carbon emissions that are 12.80% higher than those of optimized plan. Scenario 2 introduces dynamic formation but excludes carbon emissions incentives. Although the formation flexibility enhances operational efficiency, the lack of emission reduction incentives limits further reductions in carbon emissions. Scenario 3 represents the proposed optimized plan, integrates dynamic formation plan with carbon emissions incentives.

This dual strategy not only improves operational efficiency but also encourages passenger participation in low-carbon travel, resulting in significant reductions in both total costs and carbon emissions.

TABLE V
COMPARISON OF INDICATORS UNDER DIFFERENT STRATEGIES

Strategies	Total cost/CNY	Total emissions cost/CNY	8-car	16-car
No Dynamic Formation	4.73×10^6	7.58×10^4	13	19
No Emissions Incentives	4.21×10^6	6.93×10^4	15	16
Optimized	3.90×10^6	6.61×10^4	18	12

Figure 11 illustrates the train stop situation. The optimized train service plan adjusts the stop ratio with actual passenger demand. Specifically, it increases the stop ratio at secondary stations (e.g., Zhenjiang Station and Nanxiangbei Station) to better serve the dispersed passenger flow along the route. Conversely, it reduces the stop ratio at major hubs (e.g., Kunshannan Station and Suzhou Station) to avoid excessive dwelling time at high-traffic stations and improve overall operational efficiency.

Additionally, Figure 12 compares the total carbon emissions of each train. The optimized train service plan achieves a notable reduction in carbon emissions, primarily due to the strategic deployment of 8-car trains. These type of trains exhibit superior operational flexibility, making them well-suited for short-distance and high-frequency routes. Their improved capacity matching reduces empty load rate and enhances energy efficiency, thereby resulting in significant carbon mitigation. Overall, the optimized train service plan substantially improves emissions performance while maintaining service quality.

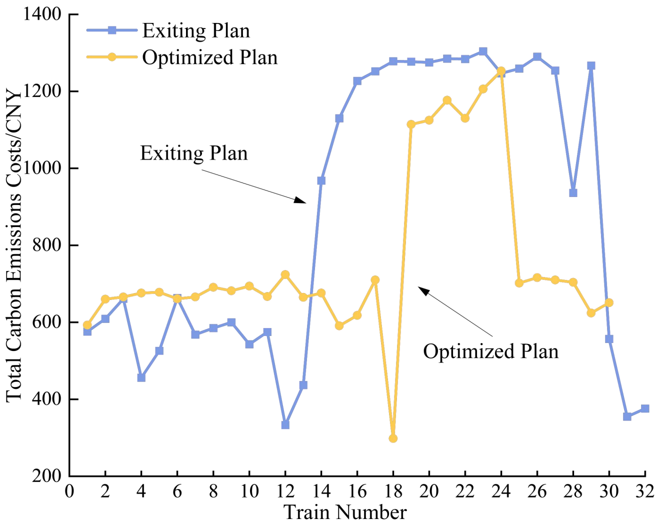

Fig. 12. Comparison of total carbon emissions of each train

V. SENSITIVITY ANALYSIS

We conduct a sensitivity analysis on three key parameters-passenger travel time value, carbon trading price, and load factor, to evaluate their impacts on optimization outcomes across specific objective functions.

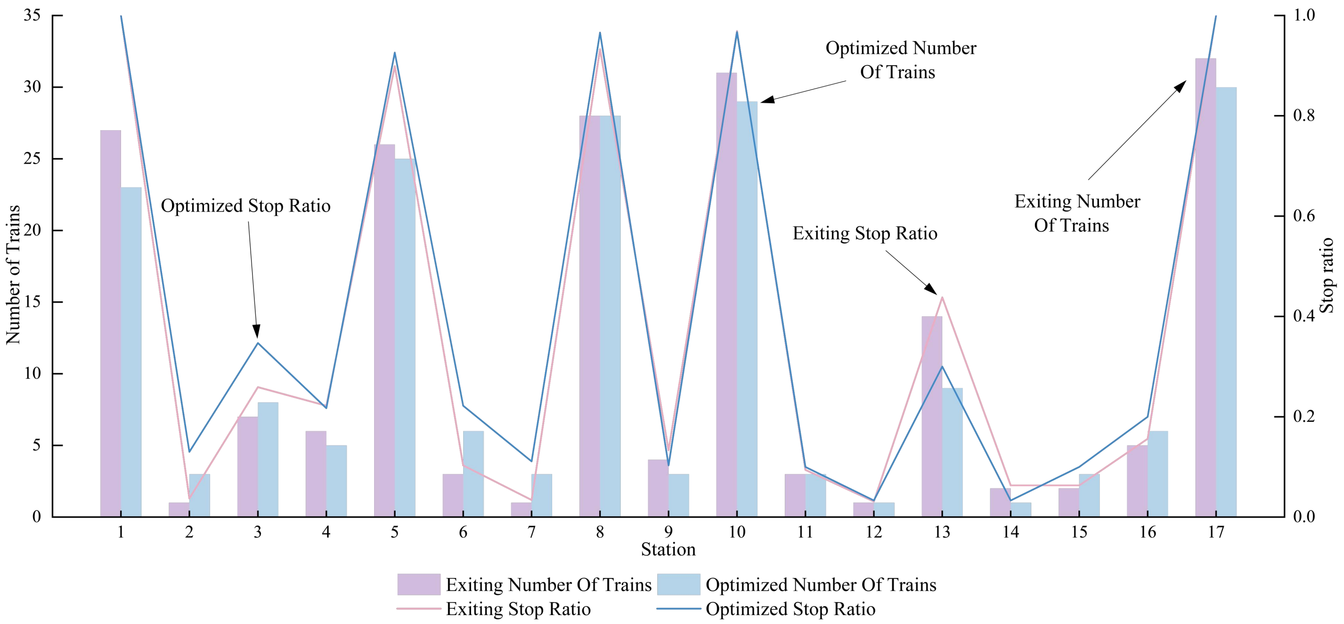

Fig. 11. Stops situation at each station

A. Passenger Travel Time Value

Passenger travel time value primarily influences functions Z_2 and Z_4. As shown in Figure 13, passenger travel time cost increases steadily in a linear pattern, and the train carbon emissions cost decreases slightly within the value range of 0.4 to 0.6. A higher time value drives passenger preference toward faster trains with fewer stops, prompting the need for additional direct services. However, this increased service frequency paradoxically leads to higher carbon emissions.

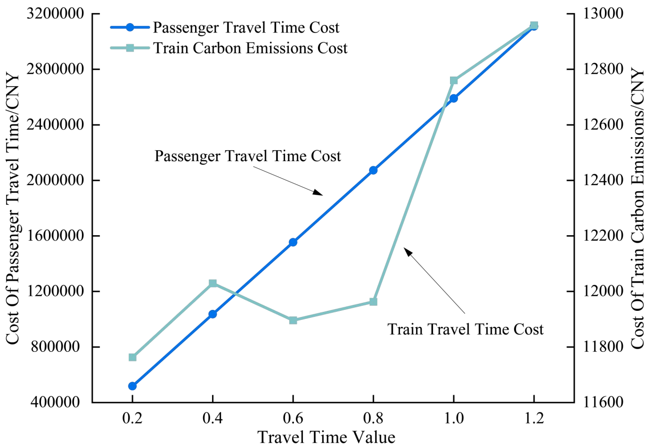

Fig. 13. Costs under the influence of travel time value

B. Carbon Trading Price

Carbon trading price primarily affects functions Z_2 and Z_6. As illustrated in Figure 14, variations in carbon trading price have a limited direct impact on emission costs under current low-market conditions. However, as carbon prices rise and quota regulations tighten, emission costs are expected to account for a larger share of total operating expenses. This economic pressure prompts operators to adopt low-carbon strategies, such as optimized train formation and stop plan, thereby reducing emissions intensity while controlling overall costs.

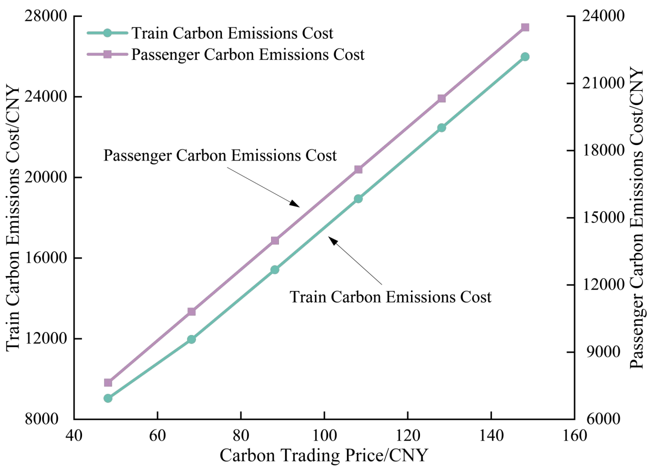

Fig. 14. Costs under the influence of carbon trading price

C. Load Rate

Passenger load rate critically impacts functions Z_2 and Z_6. As shown in Figure 15, an increase in load rate leads to reductions in both train carbon emissions and passenger-related emissions costs. Within the 0.8 to 0.9 range, these costs show fluctuations, indicating potential for optimization that balances service efficiency and environmental impact. A lower load factor results in underutilized seating, increasing per capita emissions per kilometer. In contrast, an optimized load rate minimizes unnecessary operations and reduces emissions. However, excessive optimization may compromise service availability during off-peak periods, negatively affecting passenger satisfaction. Therefore, coordinated strategies such as dynamic train formation are essential to balance emissions reduction with service quality.

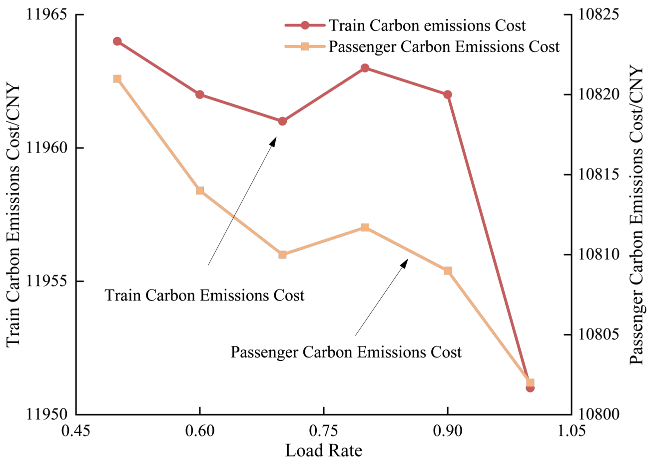

Fig. 15. Costs under the influence of passenger load rate

VI. Conclusion

This study proposes an optimized high-speed rail train service plan that integrates carbon emissions incentives and dynamic train formation plan. We develop a mixed-integer programming model to minimize three cost components: train operation, passenger travel time, and carbon emissions. Based on GUROBI solver, the model optimizes train formation and service frequency in accordance with actual passenger flow demand.

The carbon emissions measurement method utilizes the grid-based carbon emissions factor, addressing limitations of fossil fuel-based approaches in regions with diverse electricity sources. On the supply side, optimization focuses on train carbon emissions, while demand side strategies focus on passenger carbon emissions. These strategies incorporate carbon trading price, carbon quota, and carbon emissions incentive factor into the objective functions and constraints. Moreover, the introduction of the carbon emissions credit points converts low-carbon travel behavior into economic benefits, encouraging passenger to choose sustainable travel choices. This approach integrates carbon quota and allocation fairness constraint into train service plan, promoting equitable and efficient decarbonization across the high-speed rail network.

While this study advances the decarbonization of high-speed rail operation, the actual high-speed rail network is more complex. Further research will focus on passenger transfer behavior and cross-line operational coordination to enhance service optimization.

References

[1] IEA, Emissions Factors 2024. https://www.iea.org/data-and-statistics/data-product/emissions-factors-2024.

[2] Xinyu Sun, Sen Yan, Tao Liu, and Jianhan Wu, "High-speed rail development and urban environmental efficiency in China: A city-level examination," Transportation Research Part D: Transport and Environment, vol. 86, 2020.

[3] Kemei Yu, Jack Strauss, Shuli Liu, Hongchang Li, Xujuan Kuang, and Jianhong Wu, "Effects of railway speed on aviation demand and CO2 emissions in China," Transportation Research Part D: Transport and Environment, vol. 94, 2021.

[4] Xiang Li, Dechun Wang, Keping Li, and Ziyou Gao, "A green train scheduling model and fuzzy multi-objective optimization algorithm," Applied Mathematical Modelling, vol. 37, no.4, pp. 2063-2073, 2013.

[5] Lin Li, and Xiaoqiang Zhang, "Integrated optimization of railway freight operation planning and pricing based on carbon emission reduction policies," Journal of Cleaner Production, vol. 263, 2020.

[6] Xuesong Zhu, and Ken Chen, "Research on Cargo Fleet Planning for Competitive Routes under Carbon Emission Restrictions," Aeronautical Computing Technique, vol. 53, no.6, pp.6-10, 2023.

[7] Yanze Dai, and Shuguang Zhan, "Analysis of full-length and short-turn routing of urban rail transit considering carbon emission," Journal of Railway Science and Engineering, vol. 19, no.12, pp.3546-3556, 2022.

[8] Chuanzhogn Yin, Yueshan Li, and Zongze Tao, "An Operation Scheme for Regular Train Services for Transporting Containers Considering Carbon Emission Cost," Journal of Transport Information and Safety, vol. 41, no.03, pp. 128-137, 2023.

[9] Li Lin, Xuelei Meng, and Xiaoqing Cheng, "A Method for Developing Service Plan of Urban Rail Train Considering Carbon Emissions Impacts," Journal of Transport Information and Safety, vol. 41, no. 05, pp. 176-184, 2023.

[10] Guangming Xu, Yihan Liu, Yihan Gao, and Wei Liu, "Integrated optimization of train stopping plan and seat allocation scheme for railway systems under equilibrium travel choice and elastic demand," Transportation Research Part E: Logistics and Transportation Review, vol. 177, pp. 103231, 2023.

[11] Yuan Cao, Jiakun Wen, and Lianchuan Ma, "Dynamic marshalling and scheduling of trains in major epidemics," Journal of Traffic and Transportation Engineering, vol. 20, no. 3, pp. 120-128, 2020.

[12] Linhuan Zhong, Guangming Xu, Wei Liu, "Energy-efficient and demand-driven train timetable optimization with a flexible train composition mode," Energy, vol. 305, 2024.

[13] Jie Xiao, Boliang Lin, and Jiaxi Wang, "Solving the train formation plan network problem of the single-block train and two-block train using a hybrid algorithm of genetic algorithm and tabu search," Transportation Research Part C: Emerging Technologies, vol. 86, pp. 124-146, 2018.

[14] Zhengyang Li, Jun Zhao, and Qiyuan Peng, "Train service design in an urban rail transit line incorporating multiple service routes and multiple train compositions," Transportation Research Part C: Emerging Technologies, vol. 123, 2021.

[15] Huiling Fu, Lei Nie, Lingyun Meng, Benjamin R. Sperry, and Zhenhuan He, "A hierarchical line planning approach for a large-scale high speed rail network: The China case," Transportation Research Part A: Policy and Practice, vol. 75, pp. 61-83, 2015.

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

[17] Pei Liu, Bao Ming Han, and Qi Zhang, "Optimization Model of Passenger Train Service Plan Based on the Degree of Passenger Satisfaction," Applied Mechanics and Materials, vol. 505-506, pp. 577-582, 2014.

[18] Yuxiang Yang, Jie Li, Chao Wen, Ping Huang, Qiyuan Peng, and Javad Lessan, "A bi-level passenger preference-oriented line planning model for high-speed railway operations," Transportation Research Record, vol. 2672, no. 10, pp. 224-235, 2018.

[19] Xin Zhang, Huiling Fu, andLu Tong, "Optimizing the high speed train stop schedule using flexible stopping patterns combination," 17th IEEE International Conference on Intelligent Transportation Systems, vol. 2014, pp. 2398-2403, 2014.

[20] Jun Chen, Lei Nie, and Huiling Fu, "Comparative analysis of line plans of intercity railway using different train stopping patterns," 8th International Conference on Logistics, Informatics and Service Sciences (LISS), pp. 1-6, 2018.

[21] Huanyin Su, Wencong Tao, and Xinlei Hu, "A line planning approach for high-speed rail networks with time-dependent demand and capacity constraints," Mathematical Problems in Engineering, 2019.

[22] Wenbin Yang, Zhenhuan He, and Jing Yang, "Research on computer-aided adjustment and optimization of train service plan based on passenger flow assignment," Journal of Physics: Conference Series, vol. 2735, no. 1, 2024.

[23] Xiaochao Wang, Jingen Fu, and Lianbo Deng, "Optimization method for train operation plan between intercity railway lines based on interconnectivity," Journal of Railway Science and Engineering, 2024.

[24] Qing Wang, Lianbo Deng, Yuxin Chen, Wenliang Zhou, and Feng Niu, "Optimizing a high-speed railway operation plan based on train capacity and service frequency," Journal of Transportation Engineering Part A: Systems, vol. 146, no. 10, 2020.

[25] Li Lin, Xuelei Meng, Xiaoging Cheng, Yangyang Ma, and Shichao Xu, "Train service plan design under the condition of multimodal rail transit systems integration and interconnection," Journal of Advanced Transportation, vol. 2023, 2023.

[26] Hongqin Peng, and Guowu Zhang, "Strategies for high-quality development of air and high-speed rail transportation under goal of carbon peaking and carbon neutrality," Journal of Transportation Systems Engineering and Information Technology, vol. 23, no. 3, pp. 1-5, 2023.