Research on Collaborative Optimization of Train Line Planning and Train Timetabling Considering Multidimensional Travel Demands of Passengers

Zhiqiang Tian, Maowu Zhu, Guofeng Sun, Xinni Jin

***Abstract* - A collaborative optimization model has been proposed to enhance the service quality of express rail link passenger transportation, addressing the diverse travel demands of passengers. The model incorporates decision variables such as train departure and arrival stations, train numbers, stop and train formation planning, and train timetables. It optimizes these variables while considering passenger demand and variable coupling constraints. The main goal of the model are to minimize the cost of train operation and passenger travel costs. The model was reformulated as a single-objective optimization problem and solved using the adaptive large-scale neighborhood search algorithm. A case study on the Yinchuan-Xi'an high-speed railway was conducted to validate the model and algorithm, including sensitivity analysis. The results demonstrate that co-optimization of train route planning and timetabling effectively meets the diverse travel demands of passengers. Moreover, the adaptive large-scale neighborhood (ALSN) search algorithm achieved superior solution quality compared to the variable neighborhood search and simulated annealing algorithms.**

***Index Terms* - high-speed railway; train line planning; train timetabling; multi-dimensional travel demand; adaptive large-scale neighborhood search algorithm**

I. INTRODUCTION

Since the early twenty-first century, the global railway industry has seen significant development, driven by its numerous advantages such as fast, safe, on time, high capacity. Railroads are considered by many countries as crucial for accelerating economic growth and meeting increasing demands. However, due to the complexity of railroad planning, which typically involves multiple stages including line planning, train scheduling, vehicle management, and crew scheduling (as shown in Figure 1, Lusby et al., 2011) [1], several unresolved issues persist. At both strategic and tactical levels within railway systems, two fundamental and interconnected challenges are the line planning problem (LPP) and train timetabling problem (TTP).

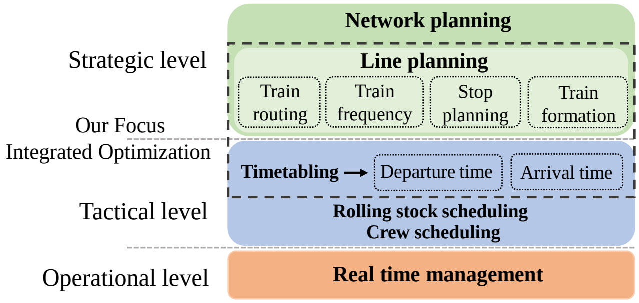

Fig. 1. The railway planning process

Train line planning encompasses crucial aspects such as train routing, frequency, stop scheduling, and train formation (Lusby et al. (2011) [1], Yan and Goverde [2]). Once the train route planning is established, the train timetable is optimized using these parameters as inputs. This optimization determines the departure and arrival times at stations served by each train (Tian et al. (2020) [3]). Employing a staged decision-making process has proven effective in simplifying problem-solving complexities. However, this approach typically yields only the current optimal solution at each stage of optimization and may not adequately address the multidimensional travel demands of passengers.

In recent years, the personalized travel demands of railway passengers have become increasingly diverse, encompassing factors such as departure times, travel durations, and ticket prices (Sun et al. (2021)). The departure times and stopping patterns of trains directly influence passenger preferences for departure times and ticket costs, while stop planning and train routes impact passenger preferences for travel times. Additionally, train frequency directly affects overall passenger flow demands. Consequently, the decision-making factors involved in train line planning and timetabling significantly influence passenger travel demands.

To effectively meet the multidimensional travel demands of passengers and simultaneously reduce operational costs, train route planning and timetabling processes must be integrated and optimized.

This study presents a methodology aimed at optimizing the integrated problem of train route planning and

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timetabling, while satisfying the different needs of passengers. The results of this study are summarized as follows:

(1) This paper presents a mixed integer nonlinear programming model for integrating and optimizing train route planning and schedule preparation. The objective is to minimize both passenger travel costs and operational expenses for enterprises, considering constraints such as train capacity, number of stops of trains, and operational logistics.

(2) Development of an ALSN search algorithm to solve nonlinear mixed-integer programming models. Additionally, a passenger flow allocation algorithm based on utility functions is proposed. This allocation method effectively assists passengers in selecting optimal departure times and seat classes. From the passengers' perspective, it reduces travel costs, while from the enterprises' perspective, it lowers overall operational expenses.

(3) Application of the method and algorithm in the high-speed railroad line from Yinchuan to Xi'an North. This application serves to validate the efficacy of the algorithms developed in this study. In addition, a comparative analysis was performed to compare the capability of the ALSN search algorithm with that of simulated annealing and variable neighborhood search algorithms.

II. Literature review

In practice, both route planning and train timetables are integral to the development of a coherent train operating plan. Line planning involves crucial decisions such as determination of the optimal number of trains to run, selection of the appropriate train type and determination of the schedule of stops for each train. These decisions are pivotal as they form part of the strategic decision-making process at the operational level.

Extensive research has been conducted over the past few decades on the topic of line planning, focusing traditionally on two primary objectives that cater to both operators and passengers. These objectives involve minimizing operational costs and maximizing passenger satisfaction. Early studies often addressed these objectives separately. Claessens et al. (1998) introduced a mathematical calculation model aimed at minimization of operating expenses by optimizing parameters such as type of line and train length [4]. Bussieck et al. (2004) developed a rapid algorithm to handle the nonlinear mixed-integer programs associated with cost-optimized line planning problems [5]. Goossens et al. (2006) presented alternative formulations of integer programming to address variations in stopping patterns across different lines [6]. Canca et al. (2016, 2019) focused on profit maximization in their line planning research, exploring network design integration and route planning to maximize net profitability within the planning horizon, especially in the context of competing transportation modes [7]. Customer-oriented line planning models typically prioritize minimizing travel time for passengers and maximizing direct travel options. Scholl (2006) concentrated on time required for travel for each passengers, proposing a integer planning models with details to achieve this objective [8]. Schiewe et al. (2019) approached the LPP by framing passengers as participants in the process, aiming to optimize factors such as travel time, transit fines and cost-sharing [9]. Addressing the inherent conflict between cost-oriented and customer-oriented objectives, researchers have explored integrated approaches. Borndörfer et al. constructed a multi-commodity flow model using a column generation algorithm to minimize operating costs and passenger time of travelling [10]. Similarly, Goerigk and Schmidt (2017) addressed both passenger time of travelling and the operation costs [11]. They devised a model that prioritized passengers completing their journeys via the shortest routes, balancing benefits for both customers and railroad operating sector. Fu et al. also tackled this issue with an integrated grading line planning methodology [12], focusing on mutual benefits for customers and railway companies. They developed a bi-level programming model and crafted heuristic algorithms to efficiently tackle the problem.

Using the provided line plan, a train schedule can be meticulously structured to oversee the details of the operation of various trains on the railroad. Implementing an efficient train timetable is crucial for optimizing the utilization of railway infrastructure resources within a network or specific line. Extensive research has been conducted by numerous scholars focusing on the train operational issues from the perspective of railway operators. They have developed diverse optimization models aimed at minimizing overall travel time across the system. Studies in this field have investigated two primary types of timetables: cyclic and noncyclic. Cyclic train scheduling is the focus of the study and is mainly modeled by the periodic event scheduling problem proposed by Serafini and Ukovichc. Additionally, researchers have adapted and refined this model into the "cycle periodicity formulation" model, proposed by Peeters and Kroon in 2003 [13].

This modification aims to simplify the scheduling process by reducing the number of constraints and variables involved. Kroon et al. introduced a stochastic optimization model aimed at enhancing the robustness of cyclic schedules through the allocation of time supplements and buffer periods [14]. This approach optimizes the allocation of these resources to enhance the reliability and resilience of the timetable. While a cyclic train timetable offers passengers convenience with consistent arrival and departure times, it can be insensitive to fluctuations in passenger demand. This lack of flexibility may lead to prolonged waiting time for a train during low-frequency periods and inefficiency in the utilization of seats during peak hours.

When addressing noncyclic train timetabling, significant research has been conducted over the years. Szpigel et al. led the way in optimizing train scheduling for single-line tracks by introducing a linear programming model based on job-shop scheduling principles, aimed at reducing overall travel time. [15]. Subsequent work by Cai and Gho (1994) established the NP-hardness of the timetabling problem, underscoring the difficulty in obtaining optimal solutions, especially for increasing case sizes [16]. Higgins et al. contributed a lower value that enhances the branch and bound algorithm's efficiency in discovering optimal solutions within feasible timeframes for complex scenarios [17]. This lower bound is instrumental in refining the branch and bound algorithm's effectiveness when applied to timetabling problems characterized by intricate constraints. In the realm of train scheduling, Zhou et al. (2005) introduced a bi-criteria model considering time consumed by the train in acceleration and deceleration [18]. They devised a branch-and-bound algorithm incorporating the rule of dominance and a beam search algorithm that can evaluate utility, aimed at identifying to effectively identify sub-optimal solutions. Zhou and Zhong further focused on single-track schedule development, aiming to minimize total travel time by proposing constrained lower bounds and heuristic methods for finding upper bounds to improve computational efficiency [19].Beyond train scheduling, Hou and Zhao (year) applied the improved NSGA-II algorithm to solve multi-objective school bus routing problems, enhancing algorithm-model alignment and overall solution efficiency [20]

In recent times, there has been a noticeable surge in passenger demand for improved service quality, coupled with an expansion in the operational capacity of rail service providers. In response to these developments, researchers have increasingly focused on understanding and meeting dynamic passenger demands. They have put forth various methodologies aimed at maximizing passenger satisfaction and benefits, recognizing the crucial need to align rail operations with evolving passenger expectations.

Niu et al. (2013) examined the time-sensitive nature of the issue by developing a specialized timetabling model for oversaturated conditions [21]. Their goal was to avoid reducing excessive passenger wait times by optimizing schedules using local boosting algorithms. Additionally, they proposed a genetic algorithm to tackle the broader challenge of optimizing timetables across entire rail lines. These approaches effectively addressed passenger wait times and enhanced overall timetabling processes. Sun et al. introduced the concept of equivalent time to balance train schedules with passenger requirements [22]. They further advanced this idea with an integer mixture model that add the limitations on the train seats number and thus improves the degree of service of the subway service schedule. Metro service schedule issues with capacity was efficiently resolved using CPLEX optimization software, offering a robust solution to timetabling challenges in metro systems. Canca et al. introduced an integer nonlinear model to handle the fluctuating nature of passenger demand [23]. Notably, earlier studies predominantly focused on minimizing passenger wait times at stations, often overlooking in-vehicle travel times.

Some researchers have recently underscored the significance of integration of train preparation plans and timetables to improve overall system efficiency and effectiveness. Liebchen et al. successfully integrated network planning, vehicle scheduling and timetabling process. They emphasized the critical nature of this integration, which maximized the flexibility provided by the Periodic Event Scheduling Problem without excessively complicating the overall system. In a similar vein, Kaspi and Raviv (2013) designed an integrated model aimed at minimizing costs and passengers' total time in travelling. To tackle this challenge, they introduced a cross-entropy metaheuristic method capable of optimizing the model, which employed a dual-objective approach to optimization. Their goal was to find an efficient and cohesive solution that would simultaneously reduce operational costs and enhance passengers' overall travel experience. Yan and Goverde adopted a holistic strategy that combines the LPP and TTP to address multiple aspects such as reliability of the train schedules, and time of passenger travelling. Initially, they developed a multi-targeting mixed-integer linear programming model for the Multi-Frequency Line Planning Problem (MF-LPP) utilizing a predefined route library. Subsequently, they proposed a Multi-Period Train Timetabling Problem (MP-TTP) model is iteratively optimized by incorporating constraints to customize robust rail operations solutions. This integrated method aimed to concurrently address various factors, thereby improving the reliability of the operation. Cacchiani et al. (2020) conducted an extensive investigation into the complex problem of stop planning and timetables of trains, consider the randomness of traveler behavior. They designed three robust optimal models, combining light robust techniques, specifically designed for addressing the challenges of robust stop planning and timetables of trains. They conducted several numerical experiments on the Wuhan-Guangzhou express rail link to evaluate the proposed method. These experiments aimed to validate the effectiveness of the developed approaches in enhancing the robustness and reliability of stop planning and timetables of trains processes. Dong and Gao (year) modeled and studied the minimum safe distance of high-speed trains for train control.

In our view, there is little research on two important areas in integrating the optimization of train route planning and timetabling problems. Firstly, existing studies typically use passengers' Origin-Destination (OD) demands as inputs in the optimization process, often neglecting passengers' multidimensional preferences such as desired departure slots, travel durations, and fares. Secondly, few studies from the perspective of passenger demand incorporate the cost associated with deviations from desired departure times into the optimization objective. Building upon prior research, this paper considers passengers' diverse and personalized travel needs to develop an optimization model that integrates diverse requirements for train route planning and train timetables. The purpose of this is to develop timetables to control rail operator costs and meet passenger requirements.

III. PROBLEM DESCRIPTION

In the collaborative optimization of high-speed railway train line planning and train timetabling, it is crucial to consider multidimensional passenger attributes such as departure time, travel duration, and ticket prices. This optimization process goes beyond merely factoring in operational costs for enterprises; it requires determining aspects like train departure and arrival stations, number of operational trains, stop planning, train formation, and timetable configuration while accommodating passenger preferences for departure time, travel duration, and dynamic ticket pricing. Moreover, the optimization of train line planning and timetabling presents a complex challenge in combinatorial optimization. When approached collaboratively, the scale of the problem expands, intensifying the difficulty of finding solutions. Therefore, this paper focuses on addressing these challenges and proposes a viable algorithm to optimize both train line planning and timetabling effectively.

This paper focuses exclusively on optimizing the train route planning and timetabling for a specific operational direction of a double-track railway, as depicted in Fig 1. Each station along the route is part of the set $S = \{S_i | i = 1,2,\dots,N\}$, where N denotes the total number of stations. The line intervals are represented by $H =$

$\{1,2,\ldots,h,\ldots N-1\}$, with h indicating the section index; thus, the N stations form N-1 intervals sequentially. During the study period T in the aforementioned direction, the train operations are planned based on line capacity, denoted as L={L j |j=1,2,.... M}, where M represents the number of alternative trains. For each alternative train, predetermined departure times and departure-arrival stations are provided. This planning integrates China's current dynamic pricing strategy for high-speed railways, incorporating advanced ticket price information based on differences in operational times.

In the co-optimization of train route planning and schedule, it becomes essential to decide whether to operate these alternative trains and determine their specific operational times, all while ensuring adequate safety intervals between trains.

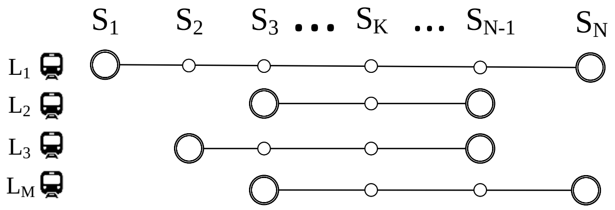

Fig. 2. Railway line and the origins and destinations of alternative train

The passenger flow demand considered in this paper encompasses the OD attributes of passengers, denoted by $P=\{1,2,3,\ldots,p,\ldots,N_p\}$, where P represents the set of all travelling passengers, and N_p represents the number of all passengers. For each passenger p, their departure station is o_p, and the corresponding arrival station is d_p. In addition, the expected departure time attribute $e_p=[l_{e_p},u_{e_p}]$ of each passenger p is all considered, where l_{e_p} represents the lower limit of the expected departure time, and u_{e_p} represents the upper limit of the expected departure time, which are used as input data for passenger flow demand.

This paper utilizes route data, alternative train data, and passenger flow demand data as inputs to establish a collaborative optimization model for train line planning and timetabling. It incorporates sophisticated solving algorithms designed to effectively determine the origin-destination pairs of trains, the number of operational trains, stop planning, train formation planning, as well as departure and arrival times. This approach aims to meet the diverse travel demands of passengers comprehensively while also optimizing operational costs for enterprises.

IV. METHODOLODY

A. Model assumption

In this paper, the following assumptions are made to design an optimization model for train route planning and timetabling and to satisfy different requirements:

- Assumption 1. Our model exclusively focuses on the second-class seats of Multiple Units and considers only these seats for determining the train ticket prices. This assumption is essential and commonly adopted in demand-oriented train timetable optimization.
- Assumption 2. Without loss of generality, similar to most operational high-speed railway lines, we assume that the arrival and departure tracks for up and down trains at each station are independent. This means up and down trains use separate arrival and departure tracks.
- Assumption 3. Passengers traveling on high-speed railway corridors select a single train to complete their entire journey, without considering transfers within the corridor.
- Assumption 4. All trains within the high-speed railway corridor operate at the same speed level. Hence, we do not account for train overtaking within sections.

B. Mathematical model

B.1 Model parameters and variables

The notations used in the optimization model are listed in TABLE I.

TABLE I
NOTATIONS AND PARAMETERS IN THIS PROBLEM

Notation	Definition
S	The set of station, $S=\{S_i\|i=1,2,\ldots,N\}$, N represents the number of stations
H	The set of intervals, $H=\{1,2,\ldots,h,\ldots N-1\}$, h represents the interval index, the N stations constitute $\mathrm{N}-1$ intervals in turn.
L	The set of alternative train, $L=\{L_j\|j=1,2,\ldots,M\}$, M represents the number of alternative trains
P	The set of passengers, $P=\{1,2,3,\ldots,p,\ldots,N_p\}$, N_p represents the number of passengers
C_{run}	Train operational cost
c_b	The operational cost of formation train in per kilometer
$Mile_{L_j}$	The operational mileage of train L_j
ω	The unit time value of the number of converted EMUs hours
t_{L_j}	The travel time of train L_j
η_{L_j}	The number of converted EMUs of train L_j
BPR_{L_j}	The base price rate of train L_j
$Mile_p$	The travel mileage of passenger p
$t_{L_j}^{d_p}$	The arrival time of passenger p arrives at the destination d_p by train L_j
$t_{L_j}^{o_p}$	The departure time of passenger p by train L_j from origin station o_p
l_{e_p}	The lower limit of the expected departure time of passenger p
u_{e_p}	The upper limit of the anticipated time of departure of passenger p
$t_{L_j}^{o_p}$	The departure time of passenger p by train L_j from origin station o_p
$y_{L_j}^{p}$	A decision variable that represents the passenger p assignment to the train $\mathrm{L_j}$
$Q_{o,d}$	The total passenger flow between any passenger flow OD
$z_{L_j}^{S_i}$	A decision variable that represents whether the train L_j stops at the station S_i, if it stops, equal to 1, otherwise equal to 0
S_o, S_d	The origin and destination station of train L_j respectively
Num_{L_j}	The maximum number of allowable stops for train L_j
$\varphi_{L_j}^{ph}$	It represents the relationship between train $\mathrm{L_j}$, section h, and passenger p. If train $\mathrm{L_j}$ serves p passing the section h, then $\varphi_{\mathrm{L_j}}^{ph}=1$,

	otherwise $\varphi_{L_j}^{ph} = 0$
Cap_{L_j}	The maximum passenger capacity of the train L_j
x_{L_j}	A decision variable that represents whether the train L_j is operating, if it is operating, then $x_{L_j} = 1$, otherwise $x_{L_j} = 0$
Num_{max}	The maximum number of trains allowed to operate
b_{L_j}	The formation number of the train L_j
$t_{L_j,O_{L_j}}^{d}$	The departure time of the train L_j at the origin station O_{L_j}
O_{L_j}	The origin station of the train L_j
T_{L_j}	The minimum departure time of the train L_j
ΔT_{L_j}	The range of departure time of the train L_j
t_{L_j,S_i}^{d}	A decision variable that represents the departure time of the train L_j at the station S_i
$t_{L_j,S_{i+1}}^{a}$	The time when the train L_j arrivals at the station S_{i+1}
$t_{L_j,h}^{run}$	The operational time of the train L_j in the section h, h consists of station S_i and S_{i+1}
t_{L_j,S_i}^{a}	A decision variable that represents the arrival time of the train L_j at the station S_i
$T_{S_i}^{a}$	The minimum safe interval time between two adjacent trains arriving at the station S_i
$T_{S_i}^{d}$	The minimum safe interval time between two adjacent trains departing from the station S_i
α_1、α_2	Weight coefficient, where $\alpha_1 + \alpha_2 = 1$

B.2 Objective function

We have incorporated two objective functions into our analysis. Firstly, from the standpoint of express rail link enterprises, our objective is to minimize the operational costs associated with all trains. Secondly, from the perspective of passengers, we aim to minimize their travel expenses. By addressing these dual objectives, we effectively meet the multifaceted demands of passengers while simultaneously reducing the operating cost of the express rail link.

Below, we outline the detailed compositions of these two objective functions:

(1) Minimize the operating cost of enterprises of express rail link

The operating cost of enterprises of express rail link includes the cost of trains' operation and formation. The operation cost of enterprises of express rail link Z_1,which is formulated as:

$$\min Z_1 = C_{run} + C_{formation} \tag{1}$$

The train operation cost C_{run} can be expressed as the product of the operation trains number and their corresponding operation mileage. Among them, the train operating cost of per kilometer of trains refer to all transportation expenses allocated to each train running 1 km.

$$C_{run} = c_b \sum_{j=1}^{M} Mile_{L_j} \cdot x_{L_j} \tag{2}$$

The operating cost of express rail link trains is also relevant to the train formation number, and the hours of Multiple Unit represents the related cost of Multiple Unit trains formation (Shi et al.).

$$C_{formation} = \omega \sum_{j=1}^{M} t_{L_j} \eta_{L_j} \tag{3}$$

Where, η_{L_j} is the number of converted Multiple Units of the train L_j, and when the train formation $b_{L_j} = 8, \eta_{L_j} = 1$; When $b_{L_j} = 16, 1 < \eta_{L_j} < 2$.

(2) Minimize general travel costs for passengers

The passenger travel costs include the fare cost C_{fare}, travel time cost C_{travel}, and the departure time deviation cost in expected departure time $C_{deviation}$ of passengers. The generalized travel cost of passengers Z_2 , which is formulated as:

$$\min Z_2 = C_{fare} + C_{travel} + C_{deviation} \tag{4}$$

The passengers fare cost is the ticket expenditure of all passengers. Namely,

$$C_{fare} = \sum_{p=1}^{N_p} \sum_{j=1}^{M} BPR_{L_j} \cdot Mile_p \cdot y_{L_j}^{p} \tag{5}$$

The passengers travel time cost is the product of the total time of all passengers in travelling and the time value of passengers. Namely,

$$C_{travel} = \sum_{p=1}^{N_p} \sum_{j=1}^{M} \left(t_{L_j}^{d_p} - t_{L_j}^{o_p} \right) \cdot y_{L_j}^{p} \tag{6}$$

The departure time deviation cost in expected is the product of the deviation time of all passengers and the time value of passengers. Namely,

$$C_{deviation} = \sum_{p=1}^{N_p} \sum_{j=1}^{M} min\left(\left| l_{e_p} - t_{L_j}^{o_p} \right|, \left| u_{e_p} - t_{L_j}^{o_p} \right| \right) \cdot y_{L_j}^{p} \tag{7}$$

B.3 Constraint condition

Passengers demand constraint

The passenger flow demand in any OD section need to be served by the corresponding trains, that is, making sure that all passengers are served:

$$\sum_{p=1}^{N_p} \sum_{j=1}^{M} y_{L_j}^{p} = Q_{o,d}, \quad \forall o,d \in S, o < d \tag{8}$$

Train line planning constraint

(1) The departure-arrival stations constraint of train

In our research, trains are given in advance by an alternative set, and any train L_j in the alternative set has a stationary arrival-departure station:

$$z_{L_j}^{S_o} = z_{L_j}^{S_d} = 1 \qquad \forall L_j \in L \tag{9}$$

(2) The stop times constraint of train

In practice, having excessive stops for any train L_j results in the increased operation cost of trains from the perspective of operational enterprises of express rail link. Viewed from the perspective of the service quality, it increases the travel time and reduces the service quality. Therefore, constraining the train stops for any train L_j can achieve the purpose of reducing the operation cost of trains and improving the service quality for passengers:

$$\sum_{S_i \in S} z_{L_j}^{S_i} \le Num_{L_j}, \quad \forall L_j \in L \tag{10}$$

(3) The capacity constraint of train

For passenger flow allocating to the train, it is necessary to ensure that the number of passengers getting on the trains in each section is no more than the maximum passenger capacity of train. For this purpose, an auxiliary variable $\varphi_{L_j}^{ph}$ is introduced to represent the relationship between train L_j, section h, and passenger p. If train L_j serves passenger p

passing the section h, then $\varphi_{L_j}^{ph}=1$, otherwise $\varphi_{L_j}^{ph}=0$. Then the train capacity constraint is formulated as:

$$\sum_{p=1}^{N_p}\varphi_{L_j}^{ph}y_{L_j}^{p}\leq Cap_{L_j}\qquad \forall h\in H_{L_j},\forall L_j\in L \qquad (11)$$

(4) The number of train operation constraint

In fact, for the co-optimization of train route planning and train schedule, numerous trains will be operated with the aim of minimizing the passengers' travel cost. In order to control the operating cost of train within a reasonable range, we constrain the number of train operating to ensure that the operation cost of enterprises during the planning periods are controlled, while catering to the travel demand of passengers.

$$\sum_{j=1}^{M}x_{L_j}\leq Num_{max} \qquad (12)$$

(5) The train formation constraint

In the operational practice of high-speed railway in China, train formations are mainly divided into 8 or 16 units. Therefore, the constraint of formation b_{L_j} for train $L_j\in L$ is formulated as:

$$b_{L_j}\in\left\{\begin{matrix}\text{8 rolling stock units in formation},\\ \text{16 rolling stock units in formation}\end{matrix}\right\},\forall L_j\in L \qquad (13)$$

Train timetable constraint

(1) Departure time range constraint

In general, multiple trains are required to operate in the corridor of railway during the planning period, so the preferred(expected) departure time of each train at the departure station is expected to be determined in advance, in order to ensure the service balance within the range of considered time.

$$T_{L_j}\leq t_{L_j,O_{L_j}}^{d}\leq T_{L_j}+\Delta T_{L_j},\quad \forall L_j\in L \qquad (14)$$

(2) The section operation time constraint

The travel time of train L_j from station S_i to station S_{i+1} equals to the time of train L_j arriving at station S_{i+1} minus the departure time from station S_i. That is the constraint of the travel time of inter-station is formulated as:

$$t_{L_j,S_{i+1}}^{a}-t_{L_j,S_i}^{d}=t_{L_j,h}^{run},\forall L_j\in L,\forall S_i\in S\backslash\{S_N\}\forall h\in H_{L_j} \qquad (15)$$

(3) Train safety interval constraint

In order to ensure the safety operation of trains, the departure and arrival of adjacent trains are required in a certain safety interval during the co-optimization process of train line planning and timetabling.

$$t_{L_{j+1},S_i}^{d}-t_{L_j,S_i}^{d}\geq T_{S_i}^{d},\quad \forall L_j\in L,S_i\in(S\backslash\{S_N\}) \qquad (16)$$

$$t_{L_{j+1},S_i}^{a}-t_{L_j,S_i}^{a}\geq T_{S_i}^{a},\quad \forall L_j\in L,S_i\in(S\backslash\{1\}) \qquad (17)$$

Coupling constraint of decision variables

(1) Coupling constraint between the passenger flow allocation variable $y_{L_j}^{p}$ and the train operation variable x_{L_j}

Only when the train L_j is operating, the passenger p allocates to the train L_j can be considered.

$$y_{L_j}^{p}\leq x_{L_j},\quad \forall p\in P,\forall L_j\in L \qquad (18)$$

(2) Coupling constraint between the stopping variable $z_{L_j}^{S_i}$ and the train operation variable x_{L_j}

Only when the train L_j is operating, the train L_j can be stopped at the station S_i.

$$z_{L_j}^{S_i}\leq x_{L_j},\quad \forall L_j\in L\ ,\forall S_i\in S \qquad (19)$$

Variable value constraint

$$x_{L_j}\in\{0,1\},\quad \forall L_j\in L \qquad (20)$$

$$y_{L_j}^{p}\in\{0,1\},\quad \forall p\in P,\forall L_j\in L \qquad (21)$$

$$z_{L_j}^{S_i}\in\{0,1\},\quad \forall L_j\in L,\forall S_i\in S \qquad (22)$$

$$t_{L_j,S_i}^{d}\in\mathbb{N},\quad \forall L_j\in L,\forall S_i\in S\backslash\left\{D_{L_j}\right\} \qquad (23)$$

$$t_{L_j,S_i}^{a}\in\mathbb{N},\quad \forall L_j\in L,\forall S_i\in S\backslash\left\{O_{L_j}\right\} \qquad (24)$$

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B.4 Transformation of multi-objective model

Z_1 and Z_2 are transformed into Z by using the liner weighting sum method. Considering the magnitude difference between Z_1 and Z_2, enpowering while enlarging Z_2 by φ times to achieve the unity of magnitude of Z_1 and Z_2.

$$minZ=\alpha_1\cdot Z_1+\alpha_2\cdot\varphi\cdot Z_2 \qquad (25)$$

In conclusion, the objective function of model is transformed into formulation (25), and the constraints are formulations (1)-(17).

V. Optimization Algorithm

A. *Algorithm introduction*

Adaptive Large Neighborhood Search (ALNS) is a heuristic method introduced by Ropke and Pisinger in 2006. It enhances traditional neighborhood search techniques by dynamically adjusting the effectiveness of operators, allowing for automated selection of operators that improve solutions through both destruction and repair phases. This approach increases the likelihood of finding improved solutions by balancing exploration and exploitation. ALNS effectively addresses limitations seen in other methods such as the lower probability of finding optimal solutions in simulated annealing or the lack of heuristic guidance in Variable Neighborhood Search (VNS), thereby yielding higher-quality solutions.

While ALNS has been extensively studied and applied in transportation and organizational contexts within railway systems, research specifically focusing on improvements in collaboration on train route planning and timetabling remain limited. Therefore, this paper designs an algorithm aimed at solving the co-optimization model for train line planning and timetabling. The adaptability and efficacy of ALNS in addressing this model are demonstrated through numerical examples.

B. *Initial solution generation*

The initial solution comprises four components: train departure times, stop planning, train formation, and passenger flow allocation. The solution for model LT is presented in formulation (26).

$$LT=\begin{bmatrix}TT_1 & SS_1 & TF_1 & PA_1\\ TT_2 & SS_2 & TF_2 & PA_2\\ \vdots & \vdots & \vdots & \vdots\\ TT_M & SS_M & TF_M & PA_M\end{bmatrix} \qquad (26)$$

In the above formulation, TT_M is the solution of departure time for M alternative train, SS_M is the solution of stop planning for M alternative train, TF_M is the solution of train formation for M alternative train, PA_M is the solution of allocated passenger flow for M alternative train.

Initially, guided by the constraint conditions specified in formulations (4), (7), and (9), the departure times for trains are randomly generated, incorporating the operational decisions x_{L_j} . Subsequently, the solutions for train stop planning and train formation are randomly generated while adhering to the constraints outlined in formulations (2), (3), (6), and (12). Finally, the algorithm detailed in Section 5.3 is used to generate the passenger flow allocation scheme.

C. Passenger flow allocation based on greedy algorithm

In this paper, the passenger flow allocation algorithm is an inner algorithm that needs to be executed after generating the solution of departure time, stopping planning and formation planning. The quality and efficiency of the solution of passenger flow allocation directly determine the solving quality and efficiency of algorithm. The strategy of passenger flow allocation according to the greedy algorithm in this paper is proposed to increase the quality of the solution of passenger flow allocation.

Traversing an array of passenger groups with a length of N_p, and allocating the passenger to the train with the smallest operation cost Z_2. If the passengers number allocated to each train dissatisfy the formulation (4), then the remaining passengers will be allocated to the train with the minor operation cost until all passengers are allocated to the train. The algorithm flow is as follows

Step1: Initialize the solution of passenger flow allocation. Generate an initial array of passenger flow allocation of M rows and N_p columns.

Step2: Determine the qualification train QT of each passenger based on their OD information and SS_M.

Step3: Calculate the travel cost of each passenger p for choosing the train with the corresponding qualification.

Step4: When the formulation (12) is satisfied, the passenger groups are optimally allocated to the corresponding train according to their travel cost. If the passengers' number on each train after the current passenger allocation does not meet the train capacity constraint of formulation (12), the current passenger will be skipped and the next passenger will continue to be assigned.

Step5: If some passengers remain unallocated, increase the number of operation trains until all passenger flow have been allocated.

D. Executing operator operation

In the process of solving, the new solution LT_{new} is derived by applying operator operations to the current solution. This paper introduces deletion, addition, and adjustment operators. The deletion and addition operators are adopted from existing literature, while the adjustment operators for stop planning and formation planning are designed as follows:

(1) Adjusting operators on stopping planning

The adjustment operator is mainly used to adjust the stop planning of trains. The adjustment operator of OD information of unallocated passengers is used to judge the arrival-departure station of passenger p and randomly choose the train i for currently unallocated passengers p. If the train i does not stop at the departure or arrival station of the passenger p, the stop planning is changed from 0 to 1.

(2) Adjusting operators on formation planning

The adjustment operator here is used to adjust the formation planning of trains. It mainly adopts two kinds of adjustment operators that are random and average attendance. The random adjustment operator is randomly adjusting the formation planning of the operation train. If current formation planning of the train with the highest attendance rate is $b_{L_j} = 8$, the formation of adjustment train L_j is $b_{L_j} = 16$; On the contrary, if current formation planning of the train with the lowest attendance rate is $b_{L_j} = 16$, the formation of adjustment train L_j is $b_{L_j} = 8$.

E. The solving steps of algorithm

The steps for solving the algorithm are as follows, with the detailed process illustrated in Fig. 3.

Step1: Import the basic data, such as line date, alternative train data, passenger flow demand data, parameter values, etc.

Step2: Create the initial solution by utilizing the methods in Section 5.1, and calculate the objective function Z corresponding to the initial solution.

Step3: Generate the new optimum solution of train route planning and train timetabling by utilizing the execution operators, and calculate the objective function value Z_{new} corresponding to the new solution.

Step4: If the new solution $Z_{new} \leq Z$, then the current optimal solution Z_{opt} is updated to Z_{new}.

Step5: Update the optimal degree of the new solution, and score it.

Step6: Determine whether the algorithm satisfies the termination criterion. If it does, turn to Step 7; Otherwise, go to Step 3.

Step7: Output the optimal solution.

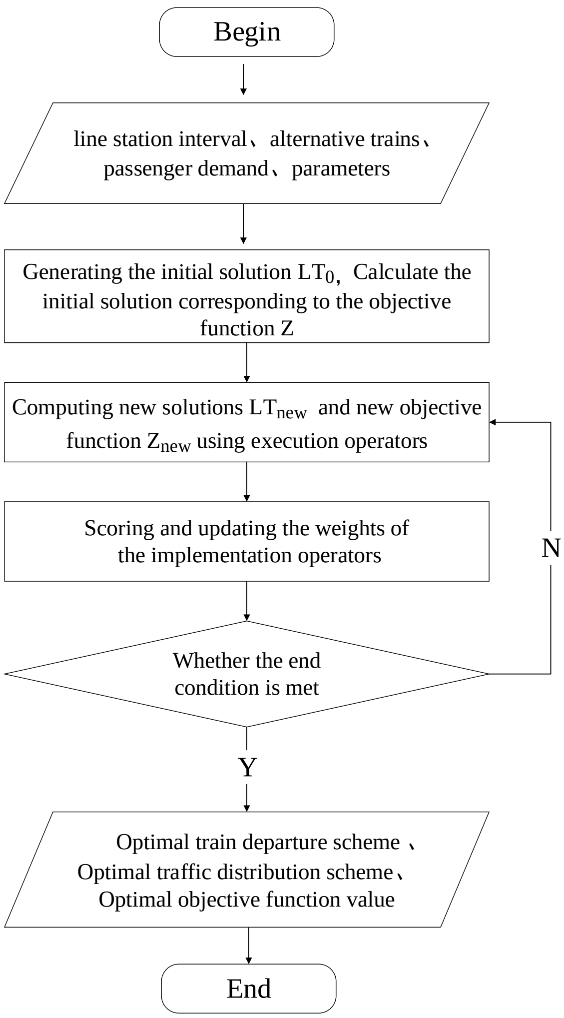

Fig. 3. Algorithm flowchart

VI. Numerical Experiments

A. *The basic data of example*

This study uses the Yinchuan-Xi'an high-speed railway as a case study. The route spans 617 km and includes 17 stations, as depicted in Figure 4. Detailed information regarding interval mileage, operational timings, and train types can be found in TABLE II.

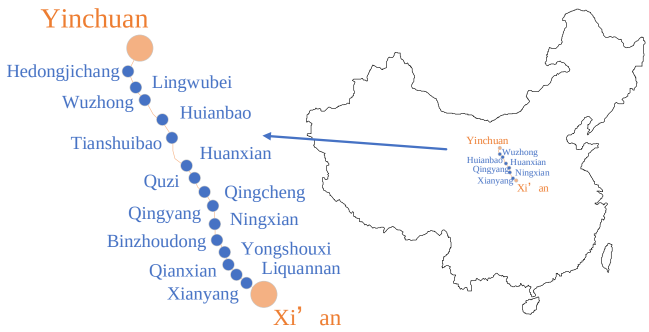

Fig. 4. The stations of Yin-Xi high-speed railway

TABLE II
The Information of Line Interval Mileage and Operational Time

Interval number	Station spacing /km	Interval operational time /min
1	33	17
2	22	11
3	19	10
4	68	22
5	40	12
6	89	27
7	24	11
8	39	14
9	50	18
10	41	15
11	59	19
12	38	13
13	29	12
14	13	8
15	25	11
16	28	14

A total of 180 alternative trains operate on this route, comprising 100 long-distance trains from Yinchuan to Xi'an North and 80 short-distance trains from Qingyang to Xi'an North. For this study, the passenger flow demand on a specific day in 2022 was analyzed. The total number of passengers was 11,016, with expected departure times within 2 hours before or after the scheduled departure times of existing trains. The distribution of passenger flow demand is visualized in Figure 5. It can be seen that there is significant variability in passenger demand on the route at all times of the day. Several of the peak points where passenger demand fluctuates are marked on Figure 5. Parameters used in the model and algorithm are detailed in TABLE III..

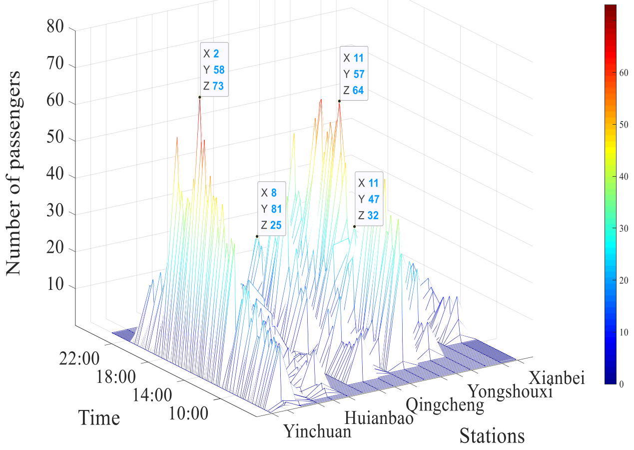

Fig. 5. The distribution of passenger flow demand

TABLE III
The Parameter Value of Model and Algorithm

parameter	definition	value
Num_{L_j}	The maximum number of allowable stops for train L_j/time	Long-distance train：10 Short-distance train：4
Cap_{L_j}	The maximum passenger capacity of the train L_j/people	613
Num_{max}	The maximum number of trains allowed to operate/train	15
ΔT_{L_j}	The range of departure time of the train L_j/min	5
$T^d_{S_i}$	The minimum safe interval time between two adjacent trains departing from the station S_i/min	5
$T^a_{S_i}$	The minimum safe interval time between two adjacent trains arriving at the station S_i/min	5
c_b	The operational cost per kilometer of train in b formation/(yuan/km)	8 trains in formation: 6.8 16 trains in formation: 13.6
ω	The unit time value of the number of converted EMUs hours/yuan	820
BPR_{L_j}	The base price rate of train L_j/(yuan/km)	0.2805
α_1	Weight coefficient	0.5
α_2	Weight coefficient	0.5
Γ_o	Original temperature	1000
Γ_{end}	End temperature	0.1
ϵ	Step size	0.98

B. *The analysis of solution results*

The algorithm implemented in this study utilized the C language on the Visual Studio 2019 platform. After 700 iterations, the objective function reached its minimum value of 982,643.33, as depicted in Figure 6. Detailed train line planning and timetabling information can be found in Table IV, with the final train line planning shown in Fig 6.

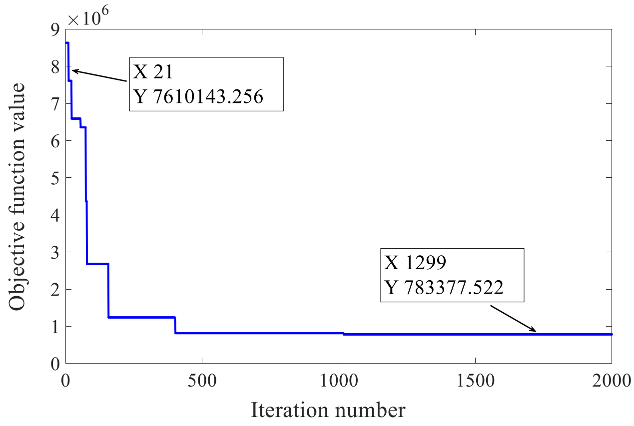

Fig. 6. Iterative process

TABLE IV
TRAIN LINE PLANNING AND TIMETABLING INFORMATION

Train number	Origin-Destination	Number of stops	Train formation	Departure time	Average attendance
1	1-17	8	16	8:36	0.90
2	1-17	6	8	8:46	0.79
3	1-17	7	8	9:19	0.46
4	1-17	7	8	9:34	0.40
5	1-17	8	8	11:32	0.40
6	1-17	8	16	11:42	0.76
7	1-17	7	8	13:03	0.74
8	10-17	6	8	13:31	0.80
9	1-17	6	8	16:15	0.85
10	1-17	7	8	16:24	0.79
11	1-17	3	8	17:02	0.97
12	1-17	7	8	17:22	0.75
13	1-17	8	8	17:56	0.79

Following optimization, there are now 12 long-distance trains operating from Yinchuan to Xi'an North and 1 short-distance train from Qingyang to Xi'an North. On average, long-distance trains make 7 stops while short-distance trains make 3 stops. The operational fleet includes 2 double-formation trains and 11 single-formation trains, achieving an average train attendance rate of 0.72, indicating balanced utilization.

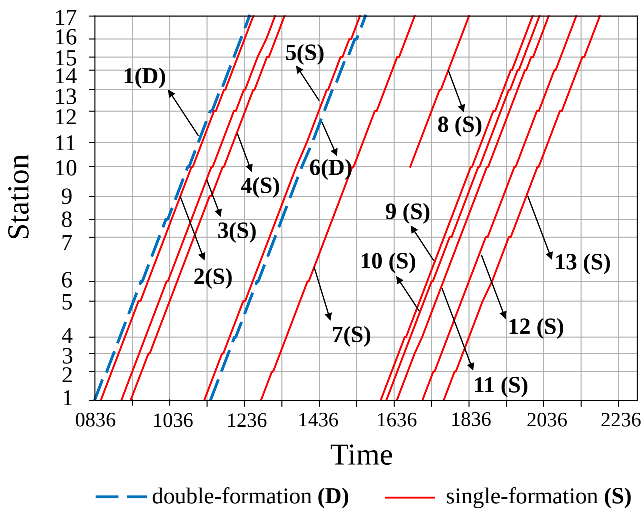

Fig. 7. Train timetable

Fig 7 displays the optimized train timetable, where dashed lines represent double-formation trains and solid lines represent single-formation trains. The first train departs Yinchuan station at 8:26, with the last departure scheduled for 17:56. Notably, no trains operate during 10:00-11:00, 12:00-13:00, and 14:00-16:00, aligning with passenger flow demand across multiple dimensions.

Table V compares various indicators before and after optimization. Despite an increase of 2 in total operating trains post-optimization, the number of double-formation units decreased by 11.76%, from 6 to 2. Similarly, although total stops increased by 7, the stops per double-formation unit decreased by 19.05%. Overall, the objective function value decreased by 1.00% after optimization, reflecting positive outcomes from the optimization process.

TABLE V
THE COMPARISION BEFORE AND AFTER OPTMAZATION

	Before optimization	After optimization	Rate of change
Number of operational train	11	13	-18.18%
Number of EMU unit	136	120	11.76%
Total stops	81	88	-8.64%
Number of stops of per EMU unit	1.68	1.36	19.05%
Train operation cost	20901.76	10160.47	51.39%
Passenger travel cost	971697.90	972482.86	-0.08%
Objective function value	992599.66	982643.33	1.00%

The attendance rate of the optimized train in each section are illustrated in Fig 8. The average attendance rate of the train is 68.85%. The seat availability of the train in each section appears relatively balanced, and the actual passenger flow satisfies the constraint of train capacity.

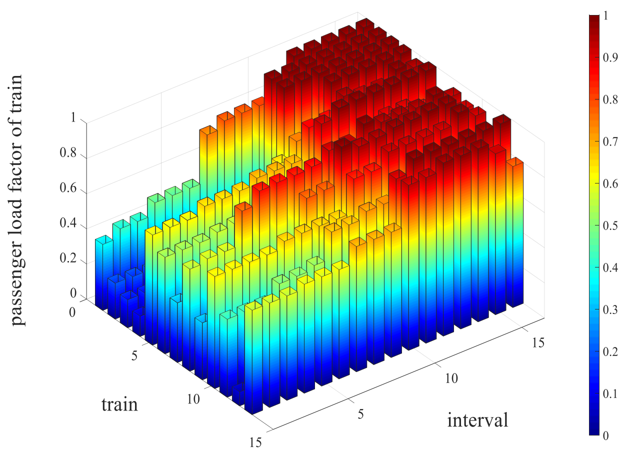

Fig. 8. The passenger load factor of train in each section

C. Comparative analysis of parameters

To examine the impact of α_1 and α_2 on the results, we varied these parameters based on the example above to assess the optimization outcomes. Setting $\alpha_1 = 1, \alpha_2 = 0$ implies that only the operational costs of enterprises are considered, excluding the travel costs of passengers. Conversely, setting $\alpha_1 = 0, \alpha_2 = 1$ means that only the travel costs of passengers are considered, without regard to the operational costs of enterprises.

Based on our optimization results with $\alpha_1 = 1, \alpha_2 = 0$, the train line planning and scheduling were optimized primarily from the perspective of enterprise operational costs. This approach yielded 12 operational trains, sufficient to meet the travel displacement demands of passengers. As α_1 decreases, both the operational costs for enterprises and the number of operational trains gradually increased, while passenger travel costs decreased. Additionally, various costs and total expenses for passengers decreased gradually, enhancing overall service quality for passengers.

In contrast, with $\alpha_1 = 0, \alpha_2 = 1$, optimization focused solely on passenger travel costs, disregarding enterprise operational costs. This configuration resulted in 15 operational trains, the maximum feasible under the operational train constraint value defined by Formula (5) in this paper. In this scenario, enterprise operational costs were highest, yet service quality for passengers was optimized.

TABLE VI
THE PARAMETER VALUE OF MODEL AND ALGORITHM

Parameter value	Z	Z_1	Z_2	Operation trains
$\alpha_1 = 1, \alpha_2 = 0$	148158	148158	0	12
$\alpha_1 = 0.8, \alpha_2 = 0.2$	590567	47452	543114	13
$\alpha_1 = 0.6, \alpha_2 = 0.4$	974802	24048	950754	13
$\alpha_1 = 0.4, \alpha_2 = 0.6$	989041	12389	976651	14
$\alpha_1 = 0.2, \alpha_2 = 0.8$	1003667	9145	994521	13
$\alpha_1 = 0, \alpha_2 = 1$	937326	0	937326	15

D. Comparison of results from different algorithms

Simulated Annealing (SA) and Variable Neighborhood Search (VNS) algorithms are employed as comparative approaches to solve the model in this paper, and their results are detailed in TABLE VII. Regarding convergence speed, SA demonstrated the fastest convergence, followed by VNS, while Adaptive Large Neighborhood Search (ALNS) exhibited the slowest convergence.

In terms of solution quality, ALNS achieved the highest quality solutions. Despite its slightly slower convergence compared to SA and VNS, ALNS is less prone to falling into local optima, resulting in significantly better optimal solutions compared to SA and VNS.

Regarding computational efficiency, both VNS and ALNS achieved optimal solutions within 3 minutes, whereas SA showed the lowest efficiency in finding solutions.

TABLE VII
COMPARATIVE ANALYSIS OF DIFFERENT ALGORITHMS

Algorithm	Number of iterations/times	Z	Calculation time/s
SA	273	1129438.52	321
VNS	547	1057481.27	165
ALNS	700	982643.33	172

Fig 9 illustrates the iterative convergence process of these algorithms during optimization. SA and VNS tended to reach local optimal solutions earlier in the iteration process, whereas ALNS, though slower to converge initially, consistently delivered higher-quality iterative solutions due to its adaptive mechanism leveraging historical solution information.

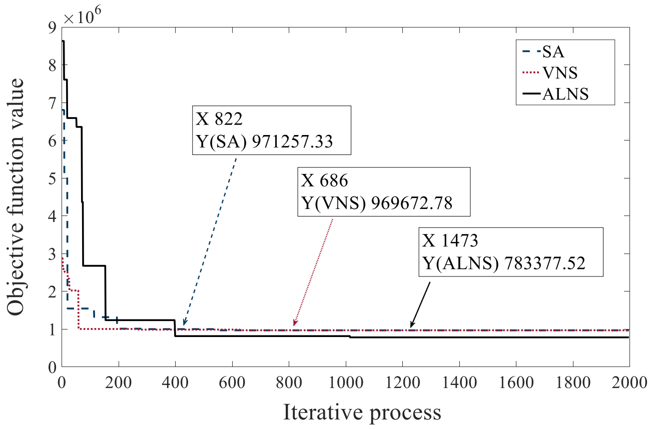

Fig. 9. Convergence curves of different algorithms

VII. CONCLUSION

To meet the travel demands of high-speed railway passengers while considering operational costs for both enterprises and passengers, we comprehensively integrated constraints such as passenger demand, train line planning, train timetabling, and variable coupling. This led to the establishment of a collaborative optimization model for train line planning and timetabling. Leveraging the model's characteristics, we designed an adaptive large-scale neighborhood search algorithm and validated both the model and algorithm using practical examples.

In optimizing train route planning and scheduling collaboratively, taking into account passengers desired departure times effectively and objectively reflects their real needs. This approach ensures that the resulting train line plans and timetables align better with passenger travel needs.

In comparison with traditional methods like SA and VNS, the ALNS algorithm proposed in this paper significantly improves solution quality and efficiency. ALNS effectively addresses the collaborative optimization challenges of train line planning and timetabling.

The model and algorithm introduced in this study provide theoretical and technical support for high-speed railway operators in formulating train timetables, thereby enhancing the transportation service level of high-speed railway enterprises.

This study focused solely on the collaborative optimization of train route planning and schedule for single-direction express rail link operations. Future research could expand this scope to include bidirectional operations or entire railway networks.

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