

Article

Integrated Optimization of Train Diagrams and Rolling Stock Circulation with Full-Length and Short-Turn Routes of Virtual Coupling Trains in Urban Rail Transit

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Abstract: The advancement of virtual coupling technology in urban rail transit has facilitated the online coupling and decoupling of trains, enabling a range of flexible transportation configurations, including various route types and adjustable formations. This study targets the fluctuating passenger demands on urban rail lines, aiming to minimize both passenger travel and operational costs. The model integrates constraints associated with virtual coupling, train operations, rolling stock circulation, and the interaction between virtually coupled trains and passenger arrivals. New decision variables are introduced to depict the train formation state under virtual coupling scenarios. An integrated optimization model for train diagrams and rolling stock circulation under virtual coupling conditions is developed, employing a genetic-simulated annealing algorithm informed by train operation simulations. A case study on an urban rail line during the morning peak examines the optimization of train diagrams for full-length and short-turn routes. Findings confirm that virtual coupling technology effectively adapts to lines with uneven passenger flow distribution, significantly enhancing the match between supply and demand, equalizing spatial and temporal traffic variations, and harmonizing the quality of passenger services with operational efficiency.

Keywords: urban rail transit; virtual coupling; full-length and short-turn routes; train diagrams; genetic-simulated annealing algorithm



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1. Introduction

As urbanization accelerates, urban rail transit networks face increasing imbalances in passenger flows, particularly during peak periods. Current strategies to enhance train headway reduction are often costly and lead to under-utilization during off-peak hours. A more efficient approach integrates both full-length and short-turn routes with variable train formations to align capacity with demand, reducing wait times and maintaining service regularity.

However, implementing variable train formations demands substantial modifications to signaling systems, yard facilities, and equipment conditions, which may result in extended adjustment periods and temporarily reduced line capacities. Adopting virtual coupling addresses these challenges by enabling real-time, train-to-train wireless communications. This system shares operational data such as speed, position, and status, allowing dynamic, site-independent train coupling and uncoupling based on passenger demand. This method enhances operational efficiency and mitigates issues like wear on mechanical parts and compatibility with different train couplings.

This study focuses on the integrated optimization of train diagrams and rolling stock circulation in urban rail transit, incorporating both full-length and short-turn routes for trains utilizing virtual coupling technology. By considering time-varying passenger flow

demand as the input, we dynamically simulate the passenger boarding and alighting process. This simulation aims to optimize the scheduling of trains to match the dynamically varying passenger flows [1]. We introduce a virtual coupling decision variable in the model, allowing consecutive trains to determine whether to engage in virtual coupling at stations.

The rest of this paper is organized as follows: Section 2 presents a literature review; Section 3 describes the establishment of the mathematical model and the design of solution algorithm; Section 4 discusses a case analysis; Conclusions are presented in Section 5.

2. Literature Review

2.1. Research on Operation Optimization of Full-Length and Short-Turn Routes

Operation plans for full-length and short-turn routes primarily focus on determining operating frequency and the number of trains for different routes. Tailoring the timetable to various train route modes enhances overall line transportation efficiency and improves passenger services, as discussed by Ceder [2], Zhu et al. [3], and Blanco et al. [4]. During service interruptions, Louwerse et al. [5] and Canca et al. [6] have addressed the need for timetable adjustments, proposing models that rely on short-turn route strategies to maintain service continuity. Building upon this work, Veelentur et al. [7] incorporated capacity constraints for all stations into their analysis, offering a more comprehensive approach to managing disruptions. Li et al. [8] introduced an optimization strategy for integrating short turning and heterogeneous headways to alleviate congestion on urban rail transit lines.

The circulation of rolling stock and the train diagrams are interdependent, influencing specific train tasks, continuity plans, etc. Scholars like Cadarso et al. [9] and Zhang [10] focus on the issue of rolling stock circulation across various train routes. Some scholars have proposed an integrated optimization method for both full-length and short-turn route train diagrams and rolling stock circulation, such as Zhang et al. [11], Jin et al. [12]. Ran et al. [13] aimed to minimize traction energy consumption and passenger waiting time, considering relevant constraints of full-length and short-turn routes and empty trains in their train diagram optimization model. Tan et al. [14] addressed return organization processes, comprehensively optimizing return route arrangements and full-length/short-turn route train diagrams, thereby enhancing train return efficiency.

2.2. Research on Virtual Coupling

To enhance railway freight transportation capacity, Bock et al. [15] introduced the concept of virtual coupling in 1999. Mitchell et al. [16] highlighted the primary application challenges of virtual coupling, including technical feasibility, safety, and capacity impact. Schumann et al. [17], Liu et al. [18], Ying et al. [19], and Quaglietta et al. [20] developed virtual coupling train optimized models, emphasizing the significant capacity improvement potential of virtual coupling technology. Meo et al. [21] and Flammini et al. [22] utilized the Petri net model to simulate virtual coupling, demonstrating a fivefold increase in throughput capacity compared to conventional methods. Virtual coupling necessitates close tracking and cooperative operation of trains at tight intervals. Goikoetxea et al. [23], Stander et al. [24], Zhang et al. [25], Yong et al. [26], and others have extensively investigated enhancing the safety of virtual coupling systems using diverse calculation and analysis methods.

In exploring railway transportation organization under virtual coupling technology, You et al. [27], Yang et al. [28] and Han et al. [29] investigated the flexible capacity adjustment strategy for urban rail transit, demonstrating its effectiveness in enhancing service levels and reducing operating costs through practical examples. Liu et al. [30] employed virtual coupling technology on the Beijing–Shanghai high-speed railway to minimize empty seats and mileage, demonstrating the adaptability of virtual coupling technology to the uneven distribution of passenger flow. Bai et al. [31] examined the organization modes of express/local trains under virtual coupling and evaluated their impact on reducing per capita travel time. Zhou et al. [32] presented a bi-level programming model

to optimize the operation plan of virtual coupling in full-length and short-turn routes, adjusting the number of couplings in overlapping sections. Muniandi et al. [33] introduced blockchain-based traffic conflict predictions and suggested seven virtual coupling strategies for conflict control. Lee et al. [34] proposed a train operation scheme using virtual coupling technology but overlooked passenger flow differences at various stations. Gallo et al. [35] presented an optimization model for the number of virtual couplings on passenger lines, showcasing improvements in train utilization. Additionally, Gallo et al. [36] introduced more intricate Y-shaped subway lines to enhance the routing scheme and departure times of virtual coupling trains.

2.3. Summary of Literature Review

Existing research primarily concentrates on optimizing operational plans for full-length and short-turn routes, including departure intervals, frequency, and the number of formations. Studies combining virtual coupling with full-length and short-turn routes, incorporating varying coupling numbers during operations, and decisions on coupling and uncoupling times and locations, are rare in train diagram optimizations. Current research on optimizing train operation plans with virtual coupling technology typically relies on processed static passenger flow demand data like line section passenger flow, utilizing departure intervals and frequency to calculate passenger waiting times. The portrayal of passenger travel is somewhat rudimentary, lacking a detailed analysis of rolling stock circulation. Therefore, the integrated optimization method of virtual coupling train diagrams and rolling stock circulation in this paper is proposed.

3. Mathematical Model and Solution Algorithm

3.1. Problem Description

3.1.1. Problem Analysis

Consider an urban rail transit line with N stations, each end of the line being connected to a depot. The set of up stations is $S^{(u)} = \{1, 2, \dots, N\}$ and the set of down station is $S^{(d)} = \{N + 1, N + 2, \dots, 2N\}$. The full-length route trains use the stations at both ends of the line as the originating and final stations. The short-turn route trains operate in certain sections, and the locations of the return stations are known. The up short-turn route trains run from station 1 to station m and returns, and the down train originates from station $2N + 1 - m$ and ends at station $2N$, as shown in Figure 1. After the rolling stock departs from the depot, it performs various train tasks before returning to the depot. The depot to which each rolling stock belongs is not fixed; hence, the departure and return depots may vary. This flexibility allows the rolling stock to operate regularly on different routes.

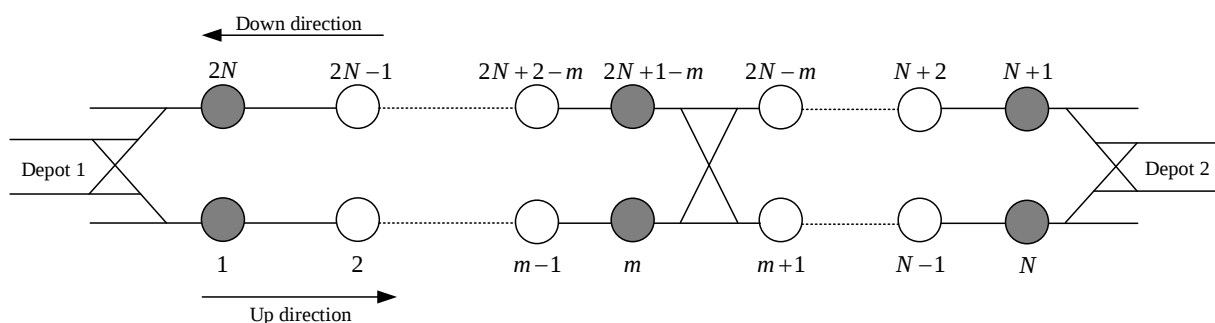


Figure 1. Schematic Diagram of the Urban Rail Transit Line.

3.1.2. Basic Assumptions

Assumption 1. Up to two unit trains can be virtually coupled at the station, and all stations can accommodate large formation trains after virtual coupling;

Assumption 2. The train's section running time and stop time are fixed, and the train stops at every station;

Assumption 3. Train overtaking is not allowed at both stations and sections;

Assumption 4. The departure time of the final train is known, marking the end of passenger flow. Passengers arriving after this time will not be served;

Assumption 5. Passengers entering the station follow the principle of “first come, first served” and will only choose direct trains;

Assumption 6. The turn back line capacity constraints are not considered.

3.1.3. Symbol Definition

The sets, indexes, parameters, intermediate variables, and decision variables defined in the model are shown in Tables 1–4.

Table 1. Set and Index Description.

Symbol	Definition
i, j	Train index
s, s', m, k	Station index
t	Time index
$I^{(u)}$	Set of up train number
$I^{(d)}$	Set of down train number
$S^{(u)}$	Set of up station
$S^{(d)}$	Set of down station
T	Research time frame

Table 2. Parameters Description.

Symbol	Definition
$P_{s,s'}(t)$	Passenger flow demand from station s to station s' at time t
T_{start}	Operation start time
T_{end}	Operation end time
T_s	The cut-off time for passenger flow to arrive at station s . This time is equal to the departure time of the given last train at station s . Passengers arriving after the cut-off time will not be served.
$r_{i,s}$	Train running time from station s to station $s + 1$
$e_{i,s}$	The stop time of the train at station s
h_{min}	Minimum departure interval between adjacent trains
h_{max}	Maximum departure interval between adjacent trains
δ_{min}	Minimum turnaround time
δ_{max}	Maximum turnaround time
RS	Total number of rolling stock
C	Train capacity
M	A large enough positive number
θ	Spare train ratio
c_1	Passenger unit waiting time value
c_2	Average train acquisition cost per unit time
c_3	Train cost per kilometer

Table 3. Intermediate Variables Description.

Symbol	Definition
$\lambda_{i,s}$	0–1 variable, if train i serves station s , then $\lambda_{i,s} = 1$, otherwise 0
$a_{i,s}$	Integer variable, the arrival time of the train i at station s
$Num_{i,s}$	Integer variable, the number of passengers in the train after the train i departs from station s

Table 4. Decision Variables Description.

Symbol	Definition
$x_{i,i',s}$	0–1 variable, if train i and i' are in a virtual coupling state when leaving station s , then $x_{i,i',s} = 1$, otherwise 0
T_i	0–1 variable, if train i chooses to operate, then $T_i = 1$, otherwise 0
θ_i	0–1 variable, if train i is full – length route, then $\theta_i = 1$, otherwise 0
$d_{i,s}$	Integer variable, the departure time of the train i at station s
$Y_{i,j}$	0–1 variable, if the rolling stock of train i is turned back to continue train j , then $Y_{i,j} = 1$, otherwise 0
α_i	0–1 variable, if the rolling stock of train i is sent from the depot, then $\alpha_i = 1$, otherwise 0
β_i	0–1 variable, if the rolling stock of train i ends its operation and directly returns to the depot, then $\beta_i = 1$, otherwise 0
$z_i^s(t)$	0–1 variable, whether passengers arriving at station s in the t –th time interval have the chance to get on the train i , if so, then $z_i^s(t) = 1$, otherwise 0
$L_i^{s,s'}(t)$	0–1 variable, whether passengers arriving at station s and go to station s' in the t –th time interval choose to board train i , if so, then $L_i^{s,s'}(t) = 1$, otherwise 0

3.2. Model Construction

3.2.1. Objective Function

This study aims to minimize both passenger travel costs and enterprise operating costs. Using the linear weighting method, the weight coefficient of passenger travel time cost is set to μ , transforming it into a single-objective problem, as shown in Equation (1).

$$\min Z = \mu Z_1 + (1 - \mu)(Z_2 + Z_3) \quad (1)$$

(1) Passenger travel costs

In this study, we assume passengers opt solely for direct trains, eliminating any transfer behavior (i.e., transfer time is 0). Furthermore, the train follows an all-stop plan with fixed stop and section running times, ensuring passengers' travel times remains constant. Consequently, the passenger's travel cost only encompasses the waiting time cost, as illustrated in Equation (2).

$$Z_1 = c_1 \cdot \sum_{i=1}^{I^{(u)}} \sum_{s=1}^{S-1} \sum_{s'=S+1}^N \sum_{t=1}^T L_i^{s,s'}(t) \cdot \lambda_{i,s} \cdot \lambda_{i,s'} \cdot T_i \cdot P^{s,s'}(t) \cdot (d_{i,s} - t) + c_1 \cdot \sum_{i=1}^{I^{(d)}} \sum_{s=N+1}^{S-1} \sum_{s'=S+1}^{2N} \sum_{t=1}^T L_i^{s,s'}(t) \cdot \lambda_{i,s} \cdot \lambda_{i,s'} \cdot T_i \cdot P^{s,s'}(t) \cdot (d_{i,s} - t) \quad (2)$$

(2) Enterprise operating costs

Enterprise operating costs mainly consider train purchase costs and travel kilometer costs. To ensure comparability with other cost components, the purchase cost of urban rail transit trains, with an average service life of 30 years, is evenly spread over the research period. This cost is determined by factors such as the actual number of train units in operation, the average purchase cost per unit time, and the spare train ratio, as shown in Equation (3). Additionally, the cost per kilometer of operation is contingent upon the total distance covered by all trains throughout the research period, as shown in Equation (4).

$$Z_2 = \vartheta \cdot c_2 \cdot T \left(\sum T_i - \sum Y_{j,i} + \sum T_j - \sum Y_{i,j} \right), \forall i \in I^{(u)}, j \in I^{(d)} \quad (3)$$

$$Z_3 = c_3 \cdot \left(\left(\sum \theta_i + \sum \theta_j \right) \cdot L_1 + \left(\sum T_i - \sum \theta_i + \sum T_j - \sum \theta_j \right) \right), \forall i \in I^{(u)}, j \in I^{(d)} \quad (4)$$

3.2.2. Constraints

The operating lines for the two unit trains in virtual coupling can be merged, altering the train operation constraints. Additionally, an extra virtual coupling constraint must be introduced to limit the number of coupled train formations.

(1) Station service constraints

The decision variables of the model encompass the train's operational status, denoted as T_i , and the type of route, denoted as θ_i . As running sections vary across routes, a 0–1 variable $\lambda_{i,s}$, is introduced to signify the train's service scope.

$$\lambda_{i,s} \leq T_i, \forall i \in I^{(u)} \quad (5)$$

$$\lambda_{i,s} \leq T_i, \forall i \in I^{(d)} \quad (6)$$

The up short-turn route trains operate between station 1 and turnaround station m , while the down short-turn route trains run between station $2N$ and $2N + 1 - m$, avoiding non-operating sections.

$$\sum_{s \leq m} \lambda_{i,s} \geq m - M(1 - T_i + \theta_i), \forall i \in I^{(u)}, s \in S^{(u)} \quad (7)$$

$$\sum_{s \leq m} \lambda_{i,s} \geq m - M(1 - T_i + \theta_i), \forall i \in I^{(d)}, s \in S^{(d)} \quad (8)$$

$$\sum_{s \leq m} \lambda_{i,s} \leq M \cdot \theta_i, \forall i \in I^{(u)}, s \in S^{(u)} \quad (9)$$

$$\sum_{s \leq m} \lambda_{i,s} \leq M \cdot \theta_i, \forall i \in I^{(d)}, s \in S^{(d)} \quad (10)$$

Up and down full-length routes trains serve all stations.

$$\lambda_{i,s} \geq 1 - M(2 - T_i - \theta_i), \forall i \in I^{(u)}, s \in S^{(u)} \quad (11)$$

$$\lambda_{i,s} \geq 1 - M(2 - T_i - \theta_i), \forall i \in I^{(d)}, s \in S^{(d)} \quad (12)$$

(2) Train operation constraints

The time gap between train arrivals and departures at two consecutive stations equals the duration of travel for that section, with adherence to the following constraints:

$$a_{i,s} - d_{i,s} = r_{i,s}, \forall i \in I^{(u)}, s \in S^{(u)} / \{S\} \quad (13)$$

$$a_{i,s+1} - d_{i,s} = r_{i,s}, \forall i \in I^{(d)}, s \in S^{(d)} / \{S\} \quad (14)$$

When the train halts at a station, it must adhere to the following constraints:

$$d_{i,s} - a_{i,s} = e_{i,s}, \forall i \in I^{(u)}, s \in S^{(u)} \quad (15)$$

$$d_{i,s} - a_{i,s} = e_{i,s}, \forall i \in I^{(d)}, s \in S^{(d)} \quad (16)$$

The departure time of the train needs to be within the operating hours:

$$T_{start} \leq d_{i,s} \leq T_{end}, \forall i \in I^{(u)}, s \in S^{(u)} \quad (17)$$

$$T_{start} \leq d_{i,s} \leq T_{end}, \forall i \in I^{(d)}, s \in S^{(d)} \quad (18)$$

The introduction of the virtual coupling decision variable reflects the coupling status of adjacent trains at the station. If trains i and $i + 1$ are in a coupled state at the station s , their departure times are synchronized. Otherwise, they must adhere to the minimum and maximum departure interval constraints. When train $i + 1$ is not in operation, the departure interval between it and the preceding train i is set to 0. The linearization process for the aforementioned condition is outlined as follows:

$$d_{i+1,s} - d_{i,s} \geq -M(1 - x_{i,i+1,s}), \forall i \in I^{(u)} / \{I\}, s \in S^{(u)} \quad (19)$$

$$d_{i+1,s} - d_{i,s} \leq M(1 - x_{i,i+1,s}), \forall i \in I^{(u)} / \{I\}, s \in S^{(u)} \quad (20)$$

$$d_{i+1,s} - d_{i,s} \geq h_{min} \cdot T_{i+1} - M \cdot x_{i,i+1,s}, \forall i \in I^{(u)} / \{I\}, s \in S^{(u)} \quad (21)$$

$$d_{i+1,s} - d_{i,s} \leq h_{max} \cdot T_{i+1} + M \cdot x_{i,i+1,s}, \forall i \in I^{(u)} / \{I\}, s \in S^{(u)} \quad (22)$$

(3) Virtual coupling constraint

To ensure that virtual coupling trains stop simultaneously at the platform, a train can only engage in virtual coupling with its preceding or succeeding train.

$$x_{i-1,i,s} + x_{i,i+1,s} \leq 1, \forall i \in I^{(u)} / \{1, I\}, s \in S^{(u)} \quad (23)$$

$$x_{i-1,i,s} + x_{i,i+1,s} \leq 1, \forall i \in I^{(d)} / \{1, I\}, s \in S^{(d)} \quad (24)$$

When either train i or $i + 1$ is not in operation, virtual coupling between the two trains will not take place.

$$x_{i,i+1,s} \leq T_i, \forall i \in I^{(u)} / \{I\}, s \in S^{(u)} \quad (25)$$

$$x_{i,i+1,s} \leq T_{i+1}, \forall i \in I^{(u)} / \{I\}, s \in S^{(u)} \quad (26)$$

$$x_{i,i+1,s} \leq T_i, \forall i \in I^{(d)} / \{I\}, s \in S^{(d)} \quad (27)$$

$$x_{i,i+1,s} \leq T_{i+1}, \forall i \in I^{(d)} / \{I\}, s \in S^{(d)} \quad (28)$$

(4) Rolling stock circulation constraints

(1) Rolling stock continuation unique constraint

When the full-length route train reaches the terminal, it has the option to reverse direction and operate in the opposite direction or return to depot 2. This also applies to the full-length route trains in the down direction. Up short-turn route trains must undergo turnaround operations upon reaching station m .

Train i may start from the depot or be returned from a specific opposite train j .

$$\sum_{j \in I^{(d)}} Y_{j,i} + \alpha_i = T_i, \forall i \in I^{(u)} \quad (29)$$

$$\sum_{j \in I^{(u)}} Y_{j,i} + \alpha_i = T_i, \forall i \in I^{(d)} \quad (30)$$

After completing the task, train i has the option to either return to the depot or proceed to undertake another transportation assignment for opposite train j .

$$\sum_{j \in I^{(d)}} Y_{j,i} + \beta_i = T_i, \forall i \in I^{(u)} \quad (31)$$

$$\sum_{j \in I^{(u)}} Y_{j,i} + \beta_i = T_i, \forall i \in I^{(d)} \quad (32)$$

The short-turn route's turnaround station m is disconnected from the depot, requiring all short-turn route trains to turn back.

$$\beta_i \leq \theta_i, \forall i \in I^{(u)} \quad (33)$$

$$\alpha_i \leq \theta_i, \forall i \in I^{(d)} \quad (34)$$

Based on the starting and ending stations of various routes, it is evident that, when the up train i reverses to connect with the down train j , both trains must share the same route type.

$$Y_{i,j} \leq 1 - \theta_i + \theta_j, \forall i \in I^{(u)}, \forall j \in I^{(d)} \quad (35)$$

$$Y_{i,j} \leq 1 - \theta_j + \theta_i, \forall i \in I^{(u)}, \forall j \in I^{(d)} \quad (36)$$

(2) Rolling stock connection time constraints

The train has connection problems at station 1 ($2N$), station $N(N+1)$, and station $m(2N+1-m)$, and it needs to meet the turnaround operation time constraints.

When the up and down full-length route train i and train j connect at return station N , the time difference between train j 's arrival at station $N+1$ and train i 's departure at station N must fall within the minimum and maximum turnaround time range.

$$a_{j,N+1} - d_{i,N} \geq \delta_{min} + M(\theta_i + Y_{i,j} - 2), \forall i \in I^{(u)}, \forall j \in I^{(d)} \quad (37)$$

$$a_{j,N+1} - d_{i,N} \leq \delta_{max} - M(\theta_i + Y_{i,j} - 2), \forall i \in I^{(u)}, \forall j \in I^{(d)} \quad (38)$$

When the up and down short-turn rout trains connect at the return station m , the following constraints need to be met:

$$a_{j,2N+1-m} - d_{i,m} \geq \delta_{min} + M(Y_{i,j} - \theta_i - 1), \forall i \in I^{(u)}, \forall j \in I^{(d)} \quad (39)$$

$$a_{j,2N+1-m} - d_{i,m} \leq \delta_{max} - M(Y_{i,j} - \theta_i - 1), \forall i \in I^{(u)}, \forall j \in I^{(d)} \quad (40)$$

When the down train i connects to the up train j at return station $2N$, both trains may be full-length or short-turn route trains. Connection time constraints are as follows:

$$a_{j,1} - d_{i,2N} \geq \delta_{min} + M(Y_{i,j} - 1), \forall i \in I^{(d)}, \forall j \in I^{(u)} \quad (41)$$

$$a_{j,1} - d_{i,2N} \leq \delta_{max} - M(Y_{i,j} - 1), \forall i \in I^{(d)}, \forall j \in I^{(u)} \quad (42)$$

(3) Rolling stock quantity constraints

The number of rolling stock departing from the depot must not exceed the total number of rolling stock available.

$$\sum_{i \in I^{(u)}} \alpha_i + \sum_{i \in I^{(d)}} \alpha_i \leq RS \quad (43)$$

(5) Passenger ride selection constraints

Passengers' decision to board the train is primarily influenced by factors such as the train's operational status, route type, arrival time, and available passenger capacity. To illustrate, take the up direction as an example for discussion.

(1) Constraints on passenger boarding opportunities.

The passengers' opportunity to board train i is contingent upon their arrival time at station s and the departure time of train i . If passengers arriving within the t -th time interval can board train i , then those who arrived in the preceding moment must also have the same boarding opportunity.

$$z_i^s(t-1) \geq z_i^s(t), \forall i \in I^{(u)}, \forall s \in S^{(u)} \quad (44)$$

(2) Constraints on the relationship between passenger boarding opportunities and train departure times.

If train i departs at the end of time t , the disparity in the variables indicating passengers' boarding opportunities between time t and time $t+1$ is 1, while the difference in these variables between the other two adjacent times remains 0.

$$d_{i,s} = \sum_{t=1}^{T_s-1} t \cdot [z_{i,s}(t) - z_{i,s}(t+1)], \forall i \in I^{(u)}, \forall s \in S^{(u)} \quad (45)$$

(3) Constraints on the relationship between passenger boarding decisions and boarding opportunities.

A passenger's decision to board a train depends not only on the availability of boarding opportunities but also on the train's service provision at the station and its remaining

capacity. Thus, passengers arriving at station s within the t -th time interval may have the chance to board train i , but it is not obligatory. Opting to board becomes a sufficient condition for the opportunity to do so.

$$L_i^{s,s'}(t) \leq z_i^s(t), \forall i \in I^{(u)}, s, s' \in S^{(u)}, s < s' \quad (46)$$

(4) Constraints on passenger boarding decisions.

Passengers arriving at station s at time t can only select one train to travel to station s' , provided that the chosen train is operational and offers direct service.

$$\sum_{i=1}^I L_i^{s,s'}(t) \cdot \lambda_{i,s} \cdot \lambda_{i,s'} \cdot T_i = 1, \forall i \in I^{(u)}, s, s' \in S^{(u)}, s < s' \quad (47)$$

(5) Constraints on the relationship between passenger boarding decisions and train capacity.

After train i departs from station s , the occupancy of the train must not exceed its capacity.

$$Num_{i,s} = \sum_{s=1}^a \sum_{s'=a+1}^s \sum_{t=1}^T \lambda_{i,s} \cdot \lambda_{i,s'} \cdot T_i \cdot P^{s,s'}(t) \cdot L_i^{s,s'}(t), \forall i \in I^{(u)}, s, s' \in S^{(u)}, s < s' \quad (48)$$

$$Num_{i,s} \leq C, \forall i \in I^{(u)}, s \in S^{(u)} / \{S\} \quad (49)$$

3.3. Model Solving Algorithm Design

3.3.1. Simulation-Based Genetic-Simulated Annealing Algorithm

The integrated optimization model presented in this study is an NP-Hard problem, often addressed using heuristic algorithms to obtain an approximate optimal solution. Hence, we propose a genetic-simulated annealing algorithm. The objective function reveals that passenger waiting time at station s upon arrival of train i comprises waiting time of remaining passengers from train $i - 1$ and new arrivals. Since this is challenging to express mathematically, we embed passenger flow distribution simulation into the genetic-simulated annealing algorithm.

3.3.2. Algorithm Steps

(1) Parameter initialization

Initially, we set the relevant parameters. The input data include five main categories: (1) passenger flow OD data with a granularity of 1 min during the study period; (2) line parameters such as the number of stations, configuration of turnaround stations, depot settings, and the quantity of available rolling stock; (3) technical parameters for trains, including capacity, dwell time at stations, running times, maximum and minimum departure intervals, as well as maximum and minimum turnaround times; (4) genetic algorithm parameters: population size pop_size , crossover probability p_c , mutation probability p_m , Iteration number max_gen ; (5) simulated annealing algorithm parameters: the initial temperature t_{max} , cooling coefficient ε , termination temperature t_{min} .

(2) Chromosomal coding

The chromosome coding consists of two components: One part is the sequence for up train solutions, comprising three segments. The first segment utilizes binary coding to indicate train departures, the second segment employs natural number coding to denote the train's route type and destination at the terminal station, while the third segment utilizes real number encoding to signify the departure time from the originating station. The other part is the sequence for down trains the same as the up trains. When a train departs from its originating station at a specific time, the departure operator corresponding to that time is assigned a value of 1; otherwise, it is 0, with the departure time code representing the

respective time. If a full-length route train proceeds to the terminal and opts to enter the depot, the value is 0; if it chooses to reverse, it is 1. For short-turn route trains required to reverse, the value is 2. Concatenating these two parts forms the chromosome code for this algorithm, illustrated in Figure 2.

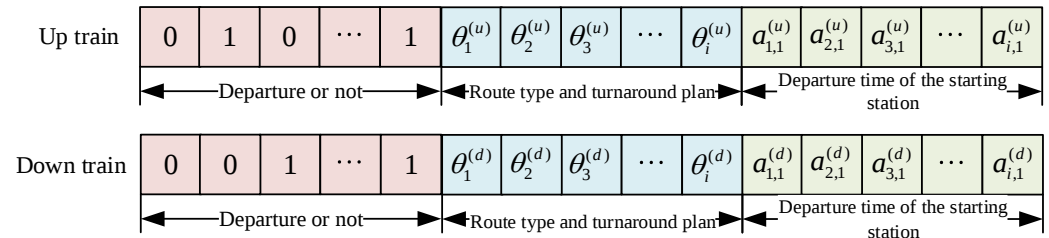


Figure 2. Schematic Diagram of Chromosome Coding.

(3) Initialize the population

We randomly generate running trains and route types, ensuring that the departure time from the first station is a feasible solution, and assign departure times for the last train at each station.

First, we randomly generate the departure time for the first train at the first station in the range of $[0, h_{max}]$. Subsequently, we generate an integer $h_1 \in [h_{min}, h_{max}]$. The departure interval between two consecutive trains at the first station is h_1 (for non-coupling sending) or 0 (for coupling sending), allowing for the computation of departure times for all trains at the first station.

(4) Fitness function construction

Building upon the initial feasible solution, the passenger flow distribution is simulated using train operation simulation, shown in Figure 3.

The specific steps are outlined below.

Step 1: Initial data input involves entering model parameter values, such as time-varying passenger flow demand, turnaround stations, dwell time at each station, running time, train capacity, unit waiting cost, average train acquisition cost per unit time, unit travel kilometer cost, etc. We utilize a dictionary within the data structure to store attributes related to passengers and trains. Train attributes primarily encompass train route type and return plan, current train location, train arrival time, and passenger capacity; while passenger attributes include passenger OD, arrival time for each passenger, passenger's train selection behavior, and waiting time.

Step 2: Simulation initialization begins by initializing each parameter value and setting the station where the train is located, along with the number of people getting off the train, to zero. Then, the simulation process commences. As the simulation clock progresses, updates are made to passengers' boarding and alighting statuses, on-board status, and waiting status. Concurrently, the number of passengers waiting at each station and the relevant train attributes are updated until the system reaches a stable state and halts.

Step 3: Simulation process design. The simulation step is determined by the shortest time between passenger arrival and train arrival. Time variables and parameters are updated gradually. When the simulation time equals the length of the research period, the process halts, and each parameter is outputted. A train dynamic simulation primarily consists of three stages: departure from the first station, arrival at intermediate stations, and reaching the terminal station with the option to turn back or enter the depot. Passenger dynamic simulation comprises three processes: passenger arrival at the station, passenger alighting from the train, and passenger boarding the train.

Through the above steps, the waiting time for all passengers, train mileage, and the count of rolling stocks are determined. Each metric is then multiplied by its corresponding unit cost input, culminating in the model's objective function through weighted summation.

Subsequently, the objective function value serves as the fitness function value, enabling the assessment of individual quality within the population.

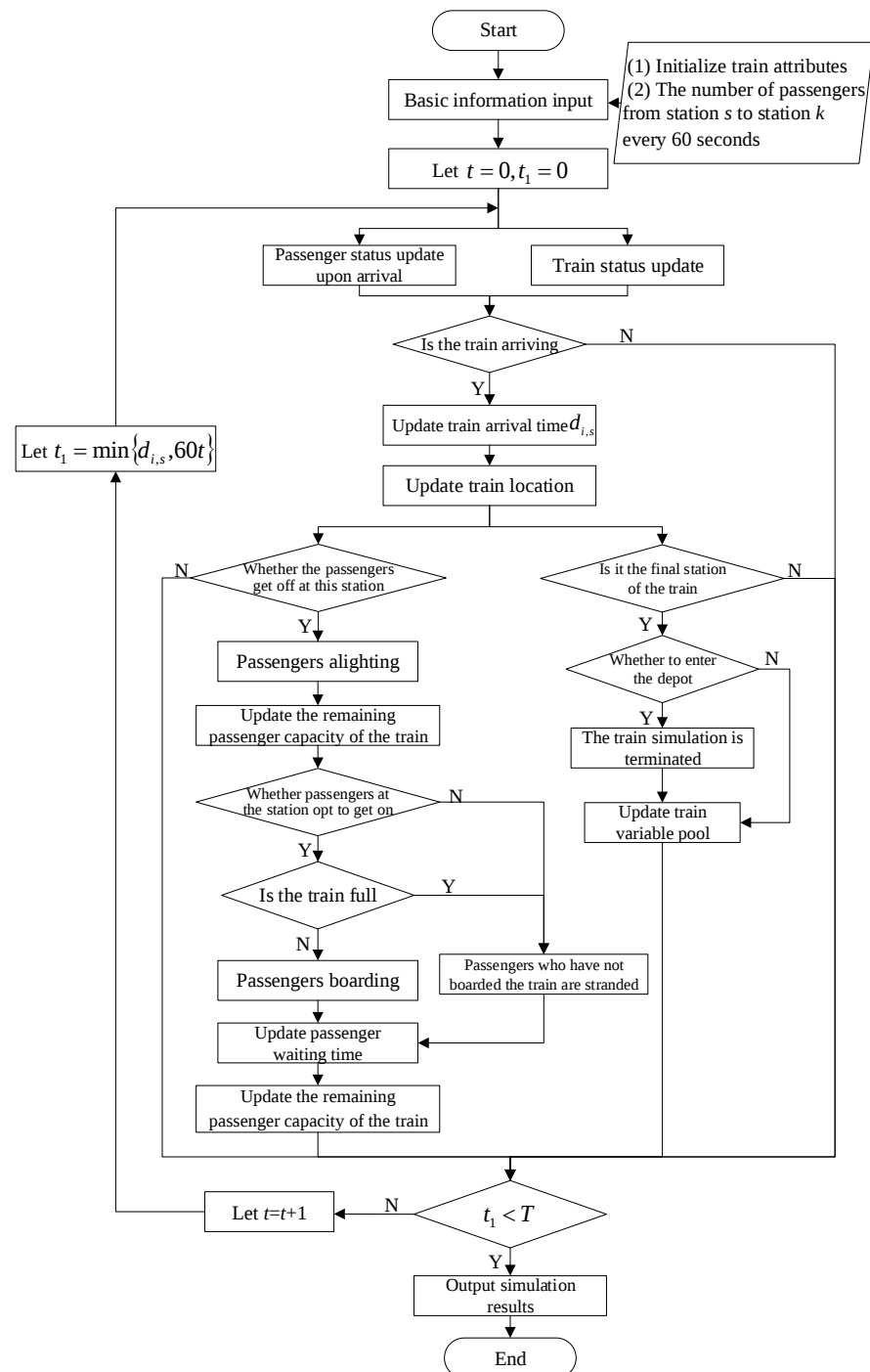


Figure 3. Simulation Flowchart of Passenger Flow Distribution.

(5) Genetic manipulation

(1) Selection

Selection is conducted utilizing the roulette operator, with this study opting for the minimum cost as the objective function. Consequently, the reciprocal of the fitness function

value is denoted as $f(x_i)$, and the probability, along with the cumulative probability, of each chromosome's selection is computed. The calculation formula is as follows:

$$p(x_i) = \frac{f(x_i)}{\sum_{j=1}^{pop_size} f(x_j)} \quad (50)$$

$$q(x_i) = \sum_{j=1}^i p(x_j) \quad (51)$$

A random number, denoted as r , is generated within the interval $(0, 1)$. If $r < q(x_i)$, chromosome x_i is selected; otherwise, it is eliminated.

(2) Crossover

Using the method of two-point crossover and random numbers, the crossover probability is p_c . Initially, we identify the crossover point's location of the gene fragment, specifically regarding the train departure. Subsequently, we intercept it at the corresponding position denoting the train type and departure time, ensuring equivalence in chromosome lengths across the three segments. Figure 4 illustrates the crossover process of up-train gene segments.

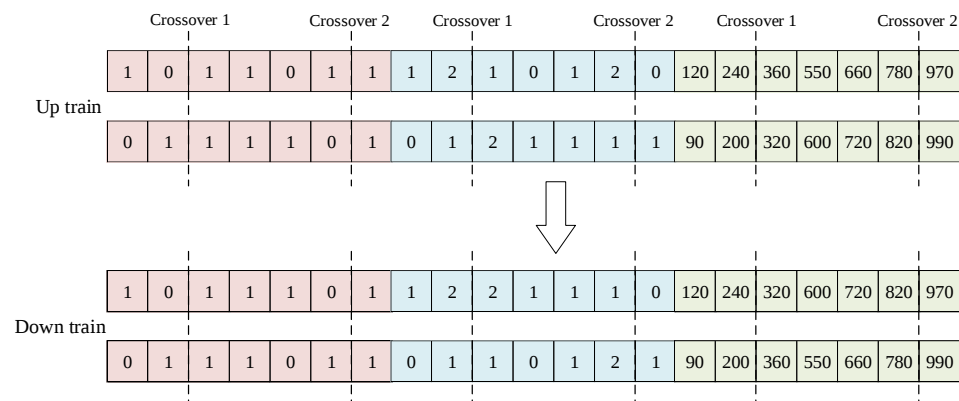


Figure 4. Crossover Operation.

(3) Mutation

Utilizing the designated mutation probability, denoted as p_m , specific genes on the chromosomes within the population undergo random selection for mutation. The mutation process, illustrated in Figure 5, focuses on the departure time at the first station, with a variation range of $[-90, 90]$. Post-mutation, chromosome modifications adhere to model constraints, ensuring compliance with departure interval constraints for adjacent trains.

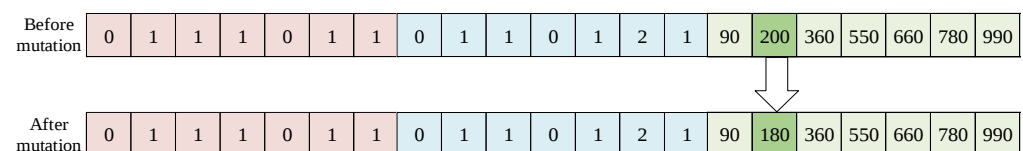


Figure 5. Mutation Operation.

(6) Simulated annealing operation

After the genetic algorithm generates new individuals, a local search optimization proceeds via the simulated annealing algorithm. Randomly select a chromosome in the offspring population to generate its neighborhood solution x_{i+1} . The algorithm then assesses whether the new individual satisfies constraint conditions, computes its fitness function value if applicable, and applies the Metropolis criterion to decide on acceptance. Subsequently, the corresponding fitness function value increment, denoted as

$\Delta f = f(x_{i+1}) - f(x_i)$, is calculated. If $\Delta f < 0$, then $x_i = x_{i+1}$; if $\Delta f \geq 0$, a random number between 0 and 1 is generated. Acceptance of x_i as the new solution occurs when $\exp(\Delta f/T) > \text{random}(0,1)$, signaling completion of an annealing cycle. Iteration termination is determined by evaluating whether the current temperature falls below t_{min} . If so, the loop concludes; otherwise, annealing operations persist.

The provided steps outline a single iteration cycle within the algorithm design of this study. Following the completion of each operation, the fitness function value for the new population is recalculated, and the process is repeated until reaching the specified iteration number determined by the genetic algorithm.

4. Case Study

4.1. Case route Overview

4.1.1. Line Operation Data

A specific urban rail transit line, operating during the morning peak hours from 7:00 to 9:00 a.m., with the last train departing from the first station at 9:00 a.m., is selected for analysis. This line extends over 26.65 km and encompasses 23 stations, which are numbered from 1 to 23 for up trains and from 24 to 46 for down trains. Depots are located at each end of the line. Short-turn route trains turn back at station 15, covering a section of 17.13 km, as depicted in Figure 6. The line utilizes 4-car B-type trains as the standard operating unit, with each car having with a capacity of 250 passengers. All platforms are capable of accommodating larger train formations after coupling. Parameter values are provided in Table 5.

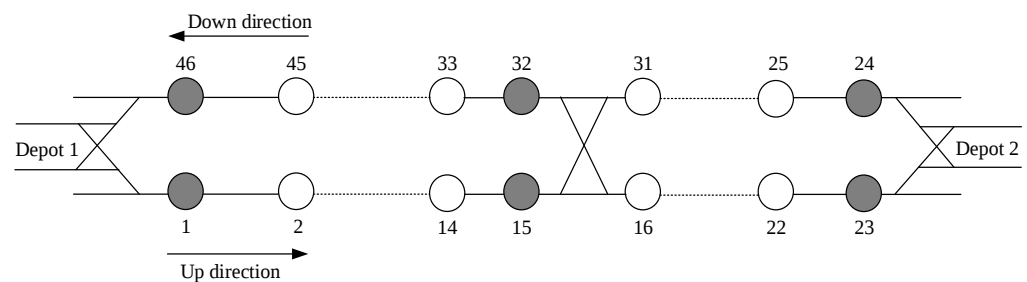


Figure 6. Schematic Diagram of the Case Line.

Table 5. Parameters in Numerical Case.

Parameter Symbols	Description	Parameter Value	Unit
h_{min}	Minimum departure interval	90	s
h_{max}	Maximum departure interval	600	s
δ_{min}	Minimum turnaround time	90	s
δ_{max}	Maximum turnaround time	360	s
RS	Number of rolling stock	50	Group
C	Train capacity	1000	People
θ	Spare train ratio	1.2	-
c_1	Passenger unit time value	0.5	Yuan/min
c_2	Average train purchase cost per unit time	200	Yuan/a train·h
c_3	Train cost per kilometer traveled	40	Yuan/a train·km
μ	Passenger waiting cost weight	0.5	-
T	Research time frame	2	h

4.1.2. Passenger Flow Demand Data

Given the passenger flow demand at a granularity of 1 min from 7:00 to 9:00, taking Station 1 as an example, the arrival situation of passengers is shown in Figure 7. The arrival pattern of passengers changes over time, so it is necessary to adopt differentiated departure intervals to dynamically match the passenger flow demands.

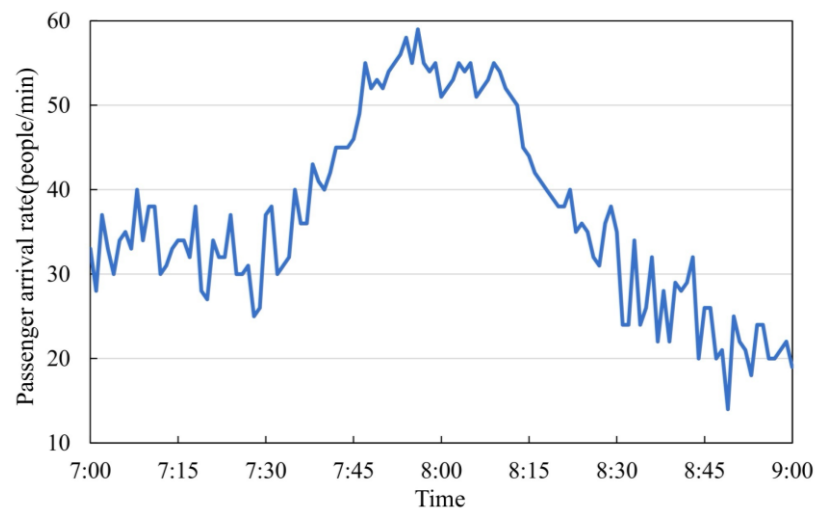


Figure 7. Passenger Arrival Rate of Station 1.

Cross-sectional passenger flows between 7:00~8:00 and 8:00~9:00 are depicted in Figure 8. Notably, passenger flows in the up and down directions primarily concentrate between stations 6 and 12. Imbalance coefficients for both directions exceed 1.9, highlighting significant disparities in passenger flow distribution.

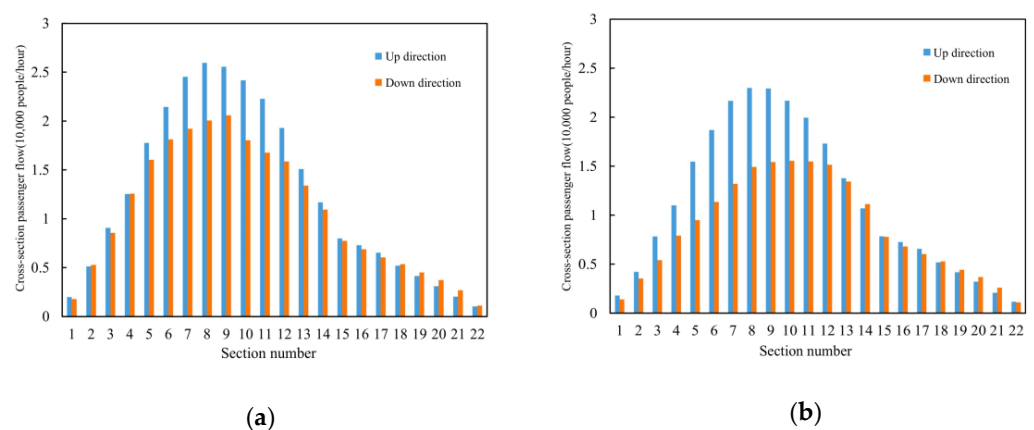


Figure 8. (a) Section Passenger Flow(7:00 to 8:00); (b) Section Passenger Flow(8:00 to 9:00).

4.2. Virtual Coupling Train Diagram Analysis

Utilize the genetic-simulated annealing algorithm to solve the case and obtain the theoretical optimal train diagram under virtual coupling. Relevant parameters are detailed in Table 6. The algorithm starts converging after 90 iterations, with the convergence of the fitness function value depicted in Figure 9.

Table 6. Parameter Values Used in GA-SA.

Parameter Symbol	Description	Value
pop_size	Population size	100
p_c	Crossover probability	0.9
p_m	Mutation probability	0.1
max_gen	The maximum number of iterations	150
t_{max}	The initial temperature	100
ε	Cooling coefficient	0.9
t_{min}	Termination temperature	1

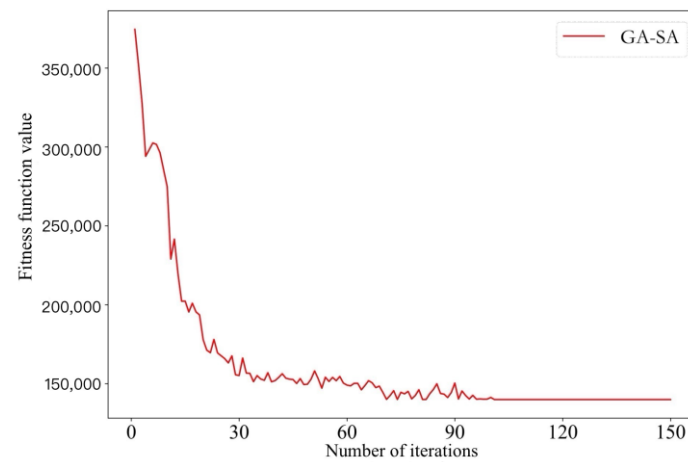


Figure 9. Convergence Curve of GA-SA.

We assign a value of 0 or 1 to the gene segment representing the route type in the initial chromosome. Then, we set the departure interval between adjacent trains at the starting station to $h_1 \in [h_{min}, h_{max}]$, thereby generating a traditional single-route train diagram. We add the short-turn route train to the gene fragment, initialize $h_1 \in [h_{min}, h_{max}]$, and obtain the traditional full-length and short-turn route train diagram. The theoretical optimal train diagram under virtual coupling is shown in Figure 10. The cost values for the three operation plans are shown in Table 7.

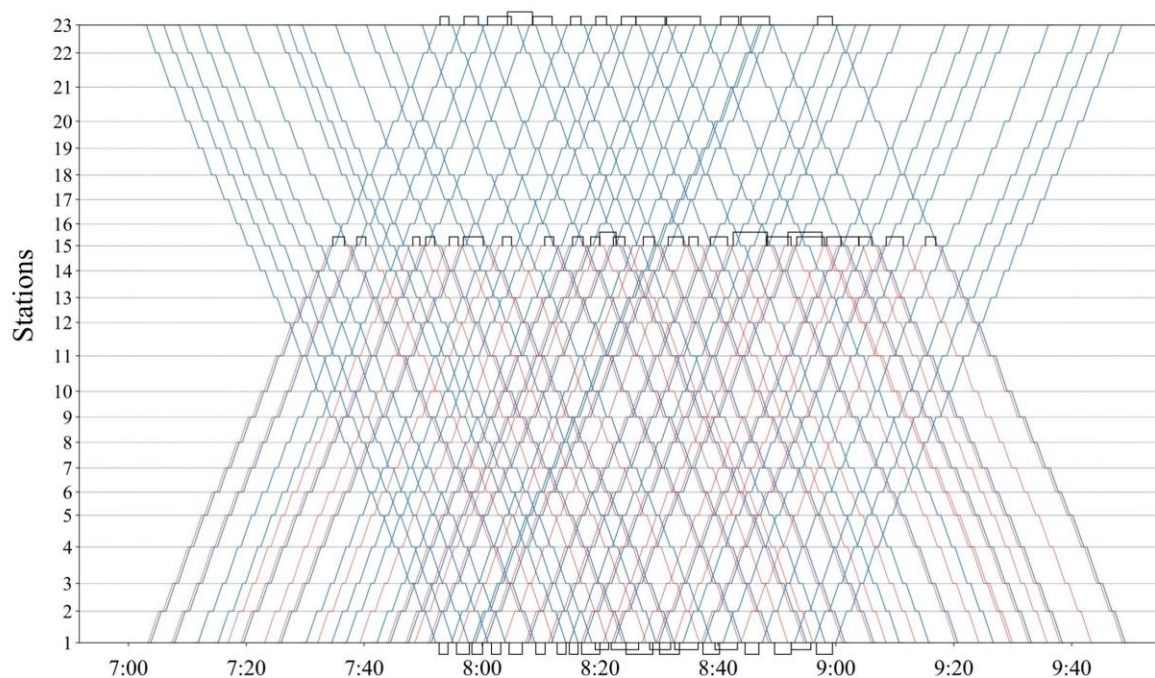


Figure 10. Optimized Train Diagram under Virtual Coupling Technology.

Table 7. Cost Comparison under Different Transportation Organization Modes.

Diagrams	Objective Function (yuan)	Passenger Waiting Costs (yuan)	Rolling Stock Purchase Costs (yuan)	Train Travel Kilometer Costs (yuan)
single full-length route	155,986.26	181,372.52	24,000.00	106,600.00
Full-length and short-turn routes	151,109.83	183,570.46	22,560.00	96,089.20
Virtual coupling	139,942.03	164,808.05	21,120.00	93,956.00

Table 7 illustrates that introducing short-turn route trains increases passenger waiting costs but significantly reduces enterprise operating costs. Implementing virtual coupling technology further decreases various cost values.

In the traditional single-route mode, 50 full-length route trains operate in both directions. Station 1's depot uses 26 sets of rolling stock, and station 23's depot uses 24 sets. In the full-length and short-turn routes mode, 35 full-length route trains and 18 short-turn route trains operate in the up direction, while 32 full-length route trains and 18 short-turn route trains operate in the down direction. The inclusion of short-turn route trains expedites rolling stock circulation, utilizing 47 sets of rolling stock to complete 103 trains. Regarding rolling stock circulation, eight upbound short-turn route trains depart from depot 1, reverse at station 15, and continue as downbound short-turn route trains. After completing the downbound task, they continue to reverse. Thus, the same rolling stock continuously serves three operating lines.

After adopting virtual coupling technology, 44 groups of rolling stock left the depot and completed 106 train tasks. This included 30 full-length route trains and 25 short-turn route trains traveling upbound, as well as 26 full-length route trains and 25 short-turn route trains traveling downbound. The virtual coupling technology resulted in a reduction of 10.29% in the objective function, 9.13% in passenger waiting cost, 12% in train procurement cost, and 11.86% in train mileage cost compared to the traditional single-route mode. Moreover, when compared to the traditional full-length and short-turn routes mode, the reductions were 7.39%, 10.22%, 6.38%, and 2.22%, respectively.

Based on the virtual coupling time of trains, operations primarily occur between 7:45 and 8:30, demonstrating improved synchronization between dynamic passenger flow and train formation. In the up direction, 14 full-length and short-turn routes trains form large eight-group formations at the starting station to accommodate heavy passenger flow, uncoupling at the short-turn turnaround station. Short-turn trains then reverse to service down trains, while full-length trains continue to the terminal. Additionally, 12 up short-turn route trains virtually couple with full-length route trains at intermediate stations. Two short-turn route trains coupling at station 15 form a large formation to station 1. At 7:57:50, an eight-group virtual coupling train departs from depot 1, while remaining trains operate independently in four-group units. Virtual coupling technology surpasses multi-marshaling methods by allowing depot dispatch of both four-group units and eight-group virtual coupling trains, facilitating uncoupling at intermediate stations to better meet varying passenger flow demands.

The passenger flow demand outside the short-turn route area is calculated in 15 min intervals, as illustrated in Figure 11.

The x-axis in the figure denotes passenger starting points, while the z-axis represents total passenger flow at terminal stations from stations 16 to 23. A notable surge in passenger flow at these stations is observed between 7:45 and 8:15. To accommodate these passengers, seven full-length route unit trains and one virtual coupling full-length route train were dispatched from the starting station during this timeframe.

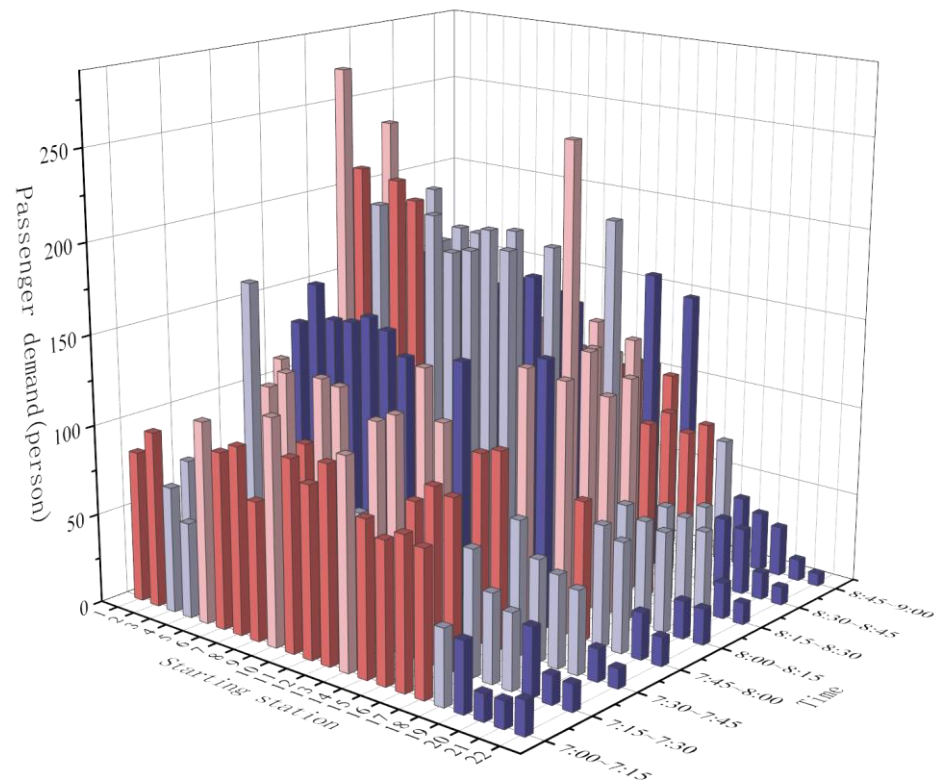


Figure 11. Passenger Demand outside the Short-turn Route.

5. Conclusions

This paper presents an operational strategy for optimizing both full-length and short-turn routes using virtual coupling technology. We have developed an integrated optimization model that minimizes passenger travel time and operational costs, taking into account the variability in passenger flow [37–40]. This model includes constraints related to station services, train operations, virtual coupling, rolling stock circulation, and passenger ride selection. Auxiliary variables are introduced to reformulate the model into a mixed integer linear programming model.

Given the complexities in accurately modeling passenger flow transitions—from new arrivals to those waiting for direct trains—we incorporated a train operation simulation into the genetic-simulated annealing algorithm. This integration allows for a more precise depiction of the dynamic passenger boarding and alighting processes, enhancing the model's effectiveness through the combined global and local search capabilities of the algorithm.

In our case study of an urban rail transit line during morning peak hours, we explored the benefits of virtual over traditional mechanical coupling. The findings demonstrate that virtual coupling technology offers significant adaptability to fluctuations in passenger flow across different sections of the line. By enabling flexible coupling and uncoupling of trains, the technology adapts transportation capacity dynamically, which helps alleviate congestion and meets the spatial and directional demands of the passenger flow. Furthermore, the dynamic allocation of train formations through virtual coupling significantly enhances rolling stock circulation efficiency, effectively balancing the trade-offs between passenger waiting times, rolling stock procurement costs, and per-kilometer train operation costs. Ultimately, this approach optimizes the balance between passenger service quality and operational efficiency.

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