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Adjust train schedules to minimize passenger waiting times during disruptions

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Abstract

Purpose – The interruption event will seriously affect the normal operation of urban rail transit lines, causing a large number of passengers to be stranded in the station and even making the train stranded in the interval between stations. This study aims to reduce the impact of interrupt events and improve service levels.

Design/methodology/approach – To address this issue, this paper considers the constraints of train operation safety, capacity and dynamic passenger flow demand. It proposes a method for adjusting small loops during interruption events and constructs a train operation adjustment model with the objective of minimizing the total passenger waiting time. This model enables the rapid development of train operation plans in interruption scenarios, coordinating train scheduling and line resources to minimize passenger travel time and mitigate the impact of interruptions. Regarding the proposed train operation adjustment model, an improved genetic algorithm (GA) is designed to solve it.

Findings – The model and algorithm are applied to a case study of interruption events on Beijing Subway Line 5. The results indicate that after solving the constructed model, the train departure intervals can be maintained between 1.5 min and 3 min. This ensures both the safety of train operations on the line and a good match with passengers' travel demands, effectively reducing the total passenger waiting time and improving the service level of the urban rail transit system during interruptions. Compared to the GA algorithm, the algorithm proposed in this paper demonstrates faster convergence speed and better computational results.

Originality/value – This study explicitly outlines the adjustment method of using short-turn operation during operational interruptions, with train departure times and station stop times as decision variables. It takes into full consideration safety constraints on train operations, train capacity constraints and dynamic passenger demand. It has constructed a train schedule optimization model with the goal of minimizing the total waiting time for all passengers in the system.

Keywords Teaching, Leadership, Transformational learning, Bibliometric, Urban rail transit, Interruption, Improved genetic algorithm, Passenger waiting time, Train operation adjustment, Short-turn operation

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1. Introduction

Urban rail transit is essential for providing residents with fast, efficient and environmentally friendly transportation. However, interruptions in its operation can lead to significant delays and lower service quality. To address this, it is crucial to develop practical and reliable train operation adjustment strategies using scientific decision models. These strategies are vital for effectively managing interruptions and minimizing train delays, ensuring smooth and efficient rail transit operations.

Train operation adjustment studies under delay conditions primarily focus on constructing optimization models based on real fault scenarios. These models are used to optimize train schedules by incorporating relevant train scheduling strategies. Canca *et al.* (2016) considered the impact of transfer connections and developed a network-level train timetable optimization model based on short-turning operations. Zhou *et al.* (2022) considered the impact of transfer connections, a network-level train timetable optimization model is constructed based on interlacing route operations. Jia *et al.* (2022) considered the stochastic nature of passenger flow and proposed a coordinated optimization model. It integrates short-turning plans, passenger flow control strategies and train timetable adjustments based on the dynamic relationship between passenger flow evolution and train operations. Zhu *et al.* (2020a) addressed the uncertainty in the duration of interruptions by formulating the train timetable rescheduling problem as a deterministic equivalent form of a rolling time-space two-stage stochastic programming problem. They calculate the optimal timetable solution for interruption scenarios based on the probabilities associated with the interruption duration. Binder *et al.* (2021) designed a train timetable adjustment algorithm considering train capacity. It aims to achieve a user equilibrium between timetables and passengers by optimizing objectives, including operating costs, deviation from the original timetable and passenger convenience. Zhang *et al.* (2021) considered cancellation, delay and speed reduction strategies and developed a mixed integer nonlinear model for adjusting train speeds and timetables. Ghaemi *et al.* (2016) created a macroscopic train scheduling model using mixed integer linear programming to obtain the optimal turnaround time for trains in the event of complete line disruptions. Zhu *et al.* (2020b) developed a model using mixed integer linear programming to minimize generalized travel time for passengers during interruptions. The model considers passenger reactions, decision-making behavior and station capacity, aiming to minimize onboard time, waiting time at origin and transfer stations and the number of transfers. Lin *et al.* (2018) established an optimization model for train operations, considering constraints such as the number of train units and passenger travel time. The objective of the model is to optimize the train schedule, prioritizing the rapid evacuation of stranded passengers. Yang *et al.* (2021) proposed a coordinated optimization method for train adjustment and passenger flow control to improve train operation order and passenger travel experience. Their approach involves a two-level linear programming model that includes skip-stop scheduling and multi-station passenger flow control.

Most of the above literature only makes quantitative analysis of train operation adjustment models in urban rail transit during disruption scenarios; the considered passenger flow data is typically fixed and does not account for dynamic changes. Therefore, based on the discussion of the above literature, this paper adopts a train operation adjustment method using short-turning operations. The objective function is to minimize the total waiting time for all passengers. It involves reconfiguring the train timetable during disruption scenarios and dynamically adjusting train departure and stopping times. Meanwhile, an improved genetic algorithm (IGA) is proposed and applied to an actual disruption event on Beijing Metro Line 5 to supplement the research on train operation adjustment under disruption scenarios.

2. Adjustment objectives and problem analysis

2.1 Adjustment objectives

When the urban rail transit system experiences a disruption event, the train operation adjustment needs to quickly formulate a train operation organization plan under the disruption scenario according to the passenger demand, taking into account a series of condition constraints such as line conditions, train numbers, headways and dwell times. The purpose is to reduce the travel time of passengers on the line by coordinating train and line resources, and to achieve that the train can resume the planned timetable operation as soon as possible after the disruption ends. Based on existing results, the objectives of train operation adjustment can generally be constructed from various optimization objectives from the perspectives of passengers and operators.

2.1.1 Passenger demand. From the perspective of passenger demand, the objectives of train operation adjustment can be divided into three aspects: first, to reduce the total travel time of all passengers; second, to reduce the total waiting time of all passengers; and third, to reduce the in-vehicle congestion cost. The reduction of total travel time is the time difference from when passengers enter the platform to wait until they get off at the destination station, including platform waiting time, section running time and train dwell time; the reduction of total waiting time includes platform waiting time and in-vehicle passenger waiting time; the in-vehicle congestion cost is to make the train load factor as close as possible to the range that passengers can tolerate. The three are interrelated and are important factors that affect passenger travel choice, which are related to passenger satisfaction with the service level of the urban rail transit system.

2.1.2 Operator demand. From the perspective of operator demand, the objectives of train operation adjustment can be divided into three aspects: first, to reduce the total delay time of trains; second, to ensure the balance of train arrivals and departures; and third, to reduce the number of people gathering on the station platforms. The reduction of total delay time of trains is to minimize the deviation between the actual timetable and the planned timetable of all affected trains; the balance of train arrivals and departures is to avoid the situation that the arrival interval of two adjacent trains is too small, resulting in a large difference in train load factor between the two trains; the reduction of the number of people gathering on the station platforms is to ensure that the platform waiting population is within the safe capacity range, and to avoid the occurrence of large passenger flow events at the station. The three are closely related and are important factors that operators consider for disruption scenarios.

The above-mentioned adjustment objectives are interrelated and contradictory; therefore, different degrees of adjustment need to be made according to the actual scenario in the process of formulating the optimization objectives of train operation adjustment.

2.2 Problem analysis

Large passenger flow is the decisive factor for subway failures. The morning and evening peak periods increase the frequency of vehicle use, vehicle wear and tear and failure frequency. According to the official Weibo announcement of Beijing Subway, signal failure is the most frequent and common failure event in subway operations, which often causes bidirectional delay and interruption of the line. Therefore, this paper takes a subway line that suffers from a signal failure event causing bidirectional interruption as the research object and uses the line passenger flow demand, train operation data, etc., as inputs to construct an optimization model of train timetable under the interruption event, so as to quickly and accurately replan the train timetable under the interruption event, and thus guarantee the capacity and passenger travel of the urban rail transit system to a certain extent.

In the abstracted line operation scenario depicted in Figure 1, when there is an interruption event in the N-3 interval of a bidirectional line, both directions are affected and normal operations are disrupted. If the interruption persists without resolution, timely emergency adjustment methods are required to ensure the transportation capacity of the line. This paper adopts the short-turn operation adjustment method, which allows for flexible modifications to train departure times and station dwell times.

Solution approach: Assuming Station N-3 or nearby stations can accommodate short-turning operations, trains can be organized to perform early turnarounds at Station N-3. This maintains segment operations between Station 1 and Station N-3, aiming to preserve service levels, minimize passenger waiting time, reduce station crowding and ensure passenger travel and safety.

3. Train schedule optimization model based on passenger waiting time

3.1 Model assumptions and symbol meanings

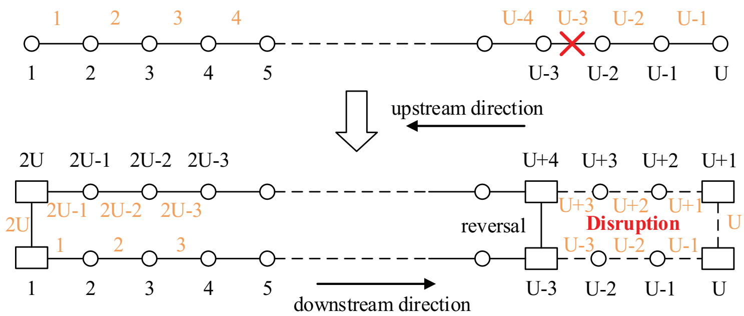
To facilitate research and modeling, the following assumptions are made in this study:

- The stations where train reversal operations can be conducted are not used for train storage.
- The railway line does not have the conditions for overtaking.
- The location of the interruption is known, and the duration of the interruption can be predicted.
- The passenger arrival rate and alighting rate at each station are calculated based on actual card-swiping data.
- During the boarding and alighting process, the "alight before boarding" and "first-come, first-serve" principles are followed, and the incoming passenger flow at each station is considered to be uniformly distributed.
- At any given time, only one train is allowed to stop at the platform of each station in both directions. All trains follow a station-to-station stopping pattern during operation.

Model parameters and symbol definitions as shown in Table 1.

3.2 Objective function

This paper focuses on passenger demand and operational considerations, aiming to optimize train operation adjustments based on the smoothness of passenger flow. The



Source: Authors' work

Figure 1. Illustration of train operation organization during interruption

Table 1. Model-related parameters and symbol definitions

Parameters	Symbol definitions	Parameters	Symbol definitions
$\|K\|$	Service train set, m, k are train indices	WT_1	Total waiting time of passengers on board
$\|U\|$	Set of stations on the line, u, v are train indices	WT_2	Total waiting time of passengers arriving within the interval between adjacent service trains
Cap	Train capacity	WT_3	Total waiting time of passengers stranded on the platform
H_1	Minimum time interval between the departures of two consecutive trains from the same station	$\lambda_u(t)$	The arrival rate of passengers at station u at time t
H_2	The minimum time interval between the arrival of two consecutive trains at the same station	λ_u^n	The arrival rate of passengers at station u during the nth time period
H_3	The minimum time interval between the arrival and departure of two consecutive trains at the same station	$\rho_u(t)$	The alighting rate of passengers at station u at time t
$t_{k,u}^{\text{dep}}$	The departure time of train k at station u	$D_{k,u}^{\text{al}}$	The number of passengers alighting from train k at station u
$t_{k,u}^{\text{dwell}}$	The station dwell time of train k at station u	T	The minimum total waiting time for all passengers
$t_{\min}^{\text{dwell}}$	Minimum station dwell time of the train	$t_{k,u}^{\text{arr}}$	The arrival time of train k at station u
$t_{\max}^{\text{dwell}}$	Maximum station dwell time of the train	δ_z	Train reversal time
$t_{k,u}^{\text{run}}$	The travel time of train k between stations u and $u+1$	$A_{k,u,v}^{\text{on}}$	The actual number of passengers boarding train k at station u when train k departs from station u to station v
$P_{k,u,v}^{\text{wait}}$	The number of passengers waiting to board train k at station u, planning to travel to station v, when train k arrives at station u	$A_{k,u}^{\text{on}}$	The actual number of passengers boarding train k at station u when train k departs from station u
$P_{k,u}^{\text{wait}}$	The number of passengers waiting to board train k at station u when train k arrives at station u	$W_{k,u,v}^{\text{hall}}$	The number of passengers who were unable to board train k at station u before its departure to station u when train k departs from station u
$E_{k,u,v}$	The number of passengers traveling from station u to station v, who arrived at station u within the departure interval of adjacent service trains k and $k-1$	$W_{k,u}^{\text{hall}}$	The number of passengers who were unable to board train k at station u when train k departs from station u
$Q_{k,u}^{\text{in}}$	The number of passengers on board train k when it departs from station u		

Source: Authors' work

objective is to minimize the total waiting time for passengers. The model takes into account onboard time, waiting time for passengers between consecutive train arrivals, and secondary waiting time for stranded passengers. To ensure timely emergency decision-making during disruption events, the calculation of waiting time between consecutive train arrivals is simplified for improved computational speed. The objective function is calculated as follows:

$$\min\ T = WT_1 + WT_2 + WT_3 \tag{1}$$

3.2.1 Total waiting time of passengers on board. The in-vehicle time of passengers is the product of the number of remaining passengers in the vehicle after the train arrives at the station and the actual dwell time. The number of remaining passengers in the vehicle after the train arrives at the station is obtained by calculating the difference between the number of passengers in the vehicle when the train arrives at the station and the number of passengers getting off when the train arrives at the station. Then, the calculation is performed by adding up all the stations and trains on the line. The calculation formula is as follows:

$$WT_1 = \sum_{k=1}^{|K|} \sum_{u=2}^{|U-1|} \left(Q^{\text{in}}_{k,u-1} - D^{\text{al}}_{k,u}\right)\left(t^{\text{dep}}_{k,u} - t^{\text{arr}}_{k,u}\right) \tag{2}$$

3.2.2 Total waiting time of passengers arriving within the interval between adjacent service trains. The waiting time of passengers arriving at the station within the departure interval of two adjacent trains is the integral of the product of the passenger arrival rate at the station and the passenger waiting time for departure within the departure interval of two adjacent trains, and then the calculation is performed by adding up all the stations and trains on the line. The calculation formula is as follows:

$$WT_2 = \sum_{k=1}^{|K|} \sum_{u=1}^{|U-1|} \int_{t^{\text{dep}}_{k-1,u}}^{t^{\text{dep}}_{k,u}} \lambda_u(t)\left(t^{\text{dep}}_{k,u} - t\right) dt \tag{3}$$

Based on the above analysis, to improve the speed of model iteration calculation, the above formula is simplified. The calculation formula is as follows:

$$WT_2 = \sum_{k=1}^{|K|} \sum_{u=1}^{|U-1|} \left[\lambda^n_u \frac{\left(t^{\text{dep}}_{k,u} - t^{\text{dep}}_{k-1,u}\right)^2}{2}\right] \tag{4}$$

3.2.3 Total waiting time of passengers stranded on the platform. The secondary waiting time of passengers who cannot leave the station by the current train and are stranded at the station is the product of the number of platform stranded passengers when the train leaves the station and the time difference between the departures of two adjacent trains, and then the calculation is performed by adding up all the stations and trains on the line. The calculation formula is as follows:

$$WT_3 = \sum_{k=1}^{|K|} \sum_{u=1}^{|U-1|} \left(W^{\text{hall}}_{k,u}\left(t^{\text{dep}}_{k+1,u} - t^{\text{dep}}_{k,u}\right)\right) \tag{5}$$

3.3 Constraints related to train operation safety

- Interval running time constraint:

$$t^{\text{arr}}_{k,u+1} - t^{\text{dep}}_{k,u} = t^{\text{run}}_{k,u} \tag{6}$$

The model assumes that the interval running time for trains is a fixed value:

- The constraints on train dwell time at stations:

$$t_{k,u}^{\mathrm{dep}} - t_{k,u}^{\mathrm{arr}} = t_{k,u}^{\mathrm{dwell}} \tag{7}$$

$$t_{\min}^{\mathrm{dwell}} \le t_{k,u}^{\mathrm{dwell}} \le t_{\max}^{\mathrm{dwell}} \tag{8}$$

The dwell time in this paper is a variable value. Equation (8) ensures that the train dwell time at stations satisfies the actual operational requirements, with the dwell time being a variable value:

- Train tracking interval constraint:

$$t_{k+1,u}^{\mathrm{dep}} - t_{k,u}^{\mathrm{dep}} \ge H_1 \tag{9}$$

$$t_{k+1,u}^{\mathrm{arr}} - t_{k,u}^{\mathrm{arr}} \ge H_2 \tag{10}$$

$$t_{k+1,u}^{\mathrm{arr}} - t_{k,u}^{\mathrm{dep}} \ge H_3 \tag{11}$$

In the model assumption, it is assumed that no overtaking will occur during the train operation process. Then, equations (9)–(11) are to ensure that the difference between the arrival and departure times of two adjacent trains at station u is within the range of the minimum safe driving interval so as to ensure the safety of the line operation.

- Train turnaround operation constraint:

$$t_{k,u+1}^{\mathrm{arr}} - t_{k,u}^{\mathrm{dep}} = \delta_z \tag{12}$$

This paper proposes to adopt the adjustment method of short-turn operation to ensure the service level under system operation interruption. To ensure the safety of train operation, equation (12) is the difference between the arrival time of the down train after the up train completes the turnback operation at the turnback station and the departure time of the up train at the turnback station, which is the turnback operation time of the train:

3.4 Constraints related to passenger flow control

- Actual number of passengers boarding the train:

$$A_{k,u,v}^{\mathrm{on}} = \begin{cases} \min\left\{P_{k,u,v}^{\mathrm{wait}}, Cap\right\}, \text{if } u = 1 \\ \min\left\{P_{k,u,v}^{\mathrm{wait}}, Cap - Q_{k,u-1}^{\mathrm{in}} + D_{k,u}^{\mathrm{al}}\right\}, \text{if } 1 < u \le |U| \end{cases} \tag{13}$$

$$A_{k,u}^{\mathrm{on}} = \sum_{v=u+1}^{|U|-1} A_{k,u,v}^{\mathrm{on}} \tag{14}$$

- Number of passengers alighting from the train:

$$D^{al}_{k,u} = \begin{cases} 0, & \text{if } u = 1 \\ \sum_{v=1}^{u-1} A^{on}_{k,v} \cdot \rho_u(t), & \text{if } 1 < \text{u} \leq |U| \end{cases} \tag{15}$$

- Number of passengers waiting to board the train:

$$P^{wait}_{k,u,v} = W^{hall}_{k-1,u,v} + E_{k,u,v} \tag{16}$$

$$P^{wait}_{k,u} = \sum_{v=u+1}^{|U|-1} P^{wait}_{k,u,v} = \sum_{v=u+1}^{|U|-1} \left(W^{hall}_{k-1,u,v} + E_{k,u,v} \right) \tag{17}$$

- Number of passengers stranded at the station:

$$W^{hall}_{k,u,v} = P^{wait}_{k,u,v} - A^{on}_{k,u,v} \tag{18}$$

$$W^{hall}_{k,u} = P^{wait}_{k,u} - A^{on}_{k,u} = \sum_{v=u+1}^{|U|-1} \left(P^{wait}_{k,u,v} - A^{on}_{k,u,v} \right) \tag{19}$$

- Number of passengers on board the train:

$$Q^{in}_{k,u} = \begin{cases} A^{on}_{k,u}, & \text{if } u = 1 \\ Q^{in}_{k-1,u} - D^{al}_{k,u} + A^{on}_{k,u}, & \text{if } 1 < \text{u} < |U| \end{cases} \tag{20}$$

- Train capacity constraint:

$$Q^{in}_{k,u} \leq Cap \tag{21}$$

3.5 Constraint linearization

In the above-mentioned constraints related to passenger flow control, equation (20) represents a nonlinear expression. According to linearization theory, the constraints can be linearized by introducing two binary variables, $\alpha,\varepsilon \in [0,1]$, to transform the nonlinear relationships into linear inequalities. The specific linearization process is as follows: if $P^{wait}_{k,u,v} > Cap$ is true, then $\alpha = 0$; otherwise, $\alpha = 1$. Similarly, the comparison between $P^{wait}_{k,u,v}$ and $Cap - Q^{in}_{k,u-1} + D^{al}_{k,u}$ is linearized in the same manner:

$$\text{if } u = 1: \begin{cases} A^{on}_{k,u,v} \leq P^{wait}_{k,u,v} \\ A^{on}_{k,u,v} \geq P^{wait}_{k,u,v} - M(1-\alpha) \\ A^{on}_{k,u,v} \leq Cap \\ A^{on}_{k,u,v} \geq Cap - M\alpha \end{cases} \tag{22}$$

$$\text{if } 1 < u \leq |U| : \begin{cases} A^{\text{on}}_{k,u,v} \leq P^{\text{wait}}_{k,u,v} \\ A^{\text{on}}_{k,u,v} \geq P^{\text{wait}}_{k,u,v} - M(1-\varepsilon) \\ A^{\text{on}}_{k,u,v} \leq Cap - Q^{\text{in}}_{k,u-1} + D^{\text{al}}_{k,u} \\ A^{\text{on}}_{k,u,v} \geq Cap - Q^{\text{in}}_{k,u-1} + D^{\text{al}}_{k,u} - M\varepsilon \end{cases} \quad (23)$$

4. Solving algorithm

4.1 Algorithm principle

This paper presents a train operation adjustment model for urban rail transit based on fault interruption events, with the objective of minimizing passenger waiting time. The model involves a large number of stations and train services, and the iterative process of solving the model is complex. In emergency scenarios with unexpected interruptions, the response time is crucial. However, precise solution algorithms can be time-consuming for large-scale problems. Therefore, this article adopts an IGA to solve the model. The genetic algorithm (GA) is modified and designed to solve the model, building upon traditional GAs.

This paper proposes an IGA based on the GA, as shown in Figure 2. The improvements are as follows:

- To adjust the crossover rate and mutation rate adaptively according to the number of iterations and to realize the nonlinearity of the adaptive adjustment curve of the crossover rate and mutation rate so as to improve the global search ability and convergence speed of the algorithm. At the same time, in the adjustment process, the sigmoid function, which is a smoother neuron activation function in neural networks, is used as the adaptive adjustment curve so as to retain the excellent individuals as much as possible.

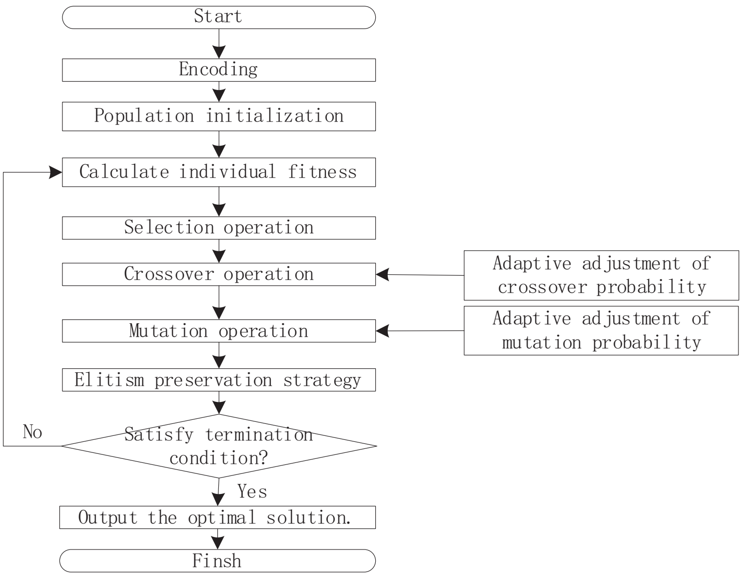


Figure 2. Steps for solving with improved genetic algorithm

Source: Authors' work

- To adopt the elitist strategy, there is a problem in the IGA that it can adjust the crossover rate and mutation rate adaptively, but their values may gradually increase, resulting in the elimination of good individuals. Therefore, the elitist strategy is adopted to avoid eliminating the individual with the highest fitness value in the previous generation and to ensure that the algorithm can converge better.

4.2 Algorithm flow

Step 1: Input parameter initialization. Load passenger flow data, timetable data, interval running time, planned stop time and other initial data, set train capacity, population size, number of iterations, crossover rate, mutation rate and calculation times and other related parameters.

Step 2: Encoding. The decision variables of the model in this paper are the departure time and dwell time of the trains at each station on the line, which is a continuous parameter optimization problem. Therefore, real number encoding is used to encode the departure time and dwell time. Because the running time between stations is a fixed value, it is only necessary to determine the departure time of the train at the origin station, and then determine the dwell time at each station, and then the departure time of the train at the subsequent stations can be calculated.

Step 3: Generate the initial population. Considering the safety of train operation, use a random method to generate an initial array X within the range of [0, 1] according to the number of iterations. Under the condition of meeting the departure interval constraint and dwell time constraint, determine the departure time t of the first train within the range of [1, $h_{\min}$], determine the dwell time t of the first train within the range of $\left[t_{\min}^{\text{dwell}}, t_{\max}^{\text{dwell}}\right]$, determine the departure time of subsequent trains according to $T = X\,(h_{\max} - h_{\min}) + h_{\min}$ and determine the dwell time of subsequent trains in the same way. This generates an initial population of N chromosomes.

Step 4: Calculate the fitness of each individual in the population. Individual fitness is the evaluation criterion of the individual's superiority or inferiority in the population, so it is also called the evaluation function, which mainly judges the individual's fitness by the characteristics of the population individuals. The objective function of the model in this paper is to minimize the total waiting time of passengers, and the smaller the objective function is, the better the individual solution is. Therefore, the algorithm selects the objective function as the calculation formula of the fitness function:

$$\text{Fitness} = \min(T) \tag{24}$$

Step 5: Selection operation. Selection operation is also called replication operation, which is to use a method to select a certain number of excellent individuals from the current population as parents, and start breeding the next generation. It should be noted that the probability of being selected is determined by the individual fitness. This paper adopts the most commonly used roulette wheel selection method. The detailed calculation steps are as follows:

- First, calculate the fitness function value fitness (v_i) of each individual $v_i =$ ($i = 1, 2 \ldots$ popsize) in the population.
- Then, calculate the total fitness value of the population: Fitness $= \sum_{i=1}^{\text{popsize}} \text{fitness}(v_i)$.

- Then calculate the probability p_i = fitness(v_i)/fitness and cumulative probability $q_i = \Sigma p_i$ of each individual $v_i = (i = 1, 2...\text{popsize})$ in the population being selected.
- Generate a random number z within the range of [0,1]; if $z < q_i$, then select the first chromosome; otherwise, select the ith chromosome v_i (i=2...popsize) that makes q_i−1$< z < q_i$ true.

Step 6: Crossover operation. Crossover is the process of producing new individuals by selecting and exchanging genes from both chromosomes of two individuals. This paper adopts the simulated binary crossover method, which divides the parent individuals into two parts, performs crossover N/2 times, selects two individuals for crossover, uses the minimum departure interval $h_{\min}$ as the judgment condition and considers the number of iterations to use the neural network activation function to improve and adjust the crossover probability P_c, thus obtaining a new population:

$$\mathrm{P_c} = k_1 + \log\mathrm{sig}[k_2 \times (\mathrm{iter}/\mathrm{iterations} - k_3)] \times k_4 \tag{25}$$

$$\log\mathrm{sig}(x) = \frac{1}{1 + e^{-x}} \tag{26}$$

Step 7: Mutation operation. Mutation is the process of randomly changing the individual gene characteristics in the population with a very small mutation probability. Generally, the mutation probability is set to a very small value. This paper considers the number of iterations to use the neural network activation function to improve and adjust the mutation probability P_m and adopts the polynomial mutation method to generate a new population:

$$\mathrm{P_m} = h_1 + \log\mathrm{sig}[h_2 \times (\mathrm{iter}/\mathrm{iterations} - h_3)] \times h_4 \tag{27}$$

The mutation form $x_k = c_k + \delta \times$(popmax-popmin) of the polynomial mutation method, then the process of generating new individuals by mutating the parent individuals is: first, randomly generate a random number ψ, $\psi \in$ [0,1], select the chromosome position where the random number is less than the mutation probability, and then calculated according to the following formula:

$$\delta = \begin{cases} \left[2u + (1 - 2u)(1 - \delta_1)^{\eta m+1}\right]^{1/(\eta m+1)} - 1, & u \leq 0.5 \\ 1 - \left[2(1 - u) + 2(u - 0.5)(1 - \delta_2)^{\eta m+1}\right]^{1/(\eta m+1)}, & u > 0.5 \end{cases} \tag{28}$$

Where, $\delta_1 = \frac{c_k - \mathrm{popmin}}{\mathrm{popmax} - \mathrm{popmin}}$, $\delta_2 = \frac{\mathrm{popmax} - c_k}{\mathrm{popmax} - \mathrm{popmin}}$, $u \in [0,1]$.

Step 8: Elite preservation strategy. The algorithm is prone to eliminate excellent individuals in the iterative calculation process of crossover and mutation, so the elite preservation strategy is adopted to prevent the elimination of excellent individuals. The main idea of the elite preservation strategy is that when the calculation iterates to the nth generation, the optimal individual in the population is c (n), and if there is no individual better than c (n) in the next generation population, then c (n) individual is taken as the optimal individual of the next generation population.

Step 9: Algorithm termination judgment. Judge whether the maximum number of iterations of the algorithm has met the preset number of iterations. If it is greater than the set number of iterations, the calculation stops and outputs the optimal solution in the iterative calculation process. Otherwise, return to Step 5 and perform the calculation again until the number of iterations is equal to the set number of iterations, and then output the optimal solution in the iterative calculation process.

5. Case studies

5.1 Basic data and parameters

The study focuses on Beijing Subway Line 5 as the research object. The line has a total of 23 stations, and all transfer stations on the line are equipped with crossover tracks. The direction of travel is from Songjiazhuang to Tiantongyuan North. The research period is set from 17:45 to 18:30 on February 19, 2019. During this time, a switch failure occurred at Datunlu East Station, resulting in a disruption of train operations in the section between Datunlu East Station and Tiantongyuan North Station.

Based on the above interruption event in the section between Songjiazhuang and Datunlu East, a short-turn operation is conducted, and the revised train timetable is developed using the train operation adjustment model proposed in this study. For ease of statistical analysis, the stations in the direction from Songjiazhuang to Tiantongyuan North are numbered as Station 1 to Station 23, as shown in Table 2. The dwelling time of trains during the research period is shown in Table 3, and the running time of intervals is shown in Table 4. The section numbers are numbered in sequence according to the station numbers. Table 5 lists the parameters in the model and algorithm.

5.2 Results analysis

This article uses two algorithms (GA and IGA) to solve the model. Figure 3 shows the change in fitness values with the number of iterations, and Table 6 presents the results of the objective function calculation for both algorithms. It can be observed that IGA can achieve the solution in fewer iterations compared to the GA algorithm, and the calculation results show a time saving of 1,830,741 s for passengers within the system. IGA exhibits faster convergence speed and better computational results, which can enhance the operational service quality of urban rail transit systems under interruption conditions to some extent.

Station name	Station no.	Station name	Station no.
Songjiazhuang	1	Hepingli Beijie	13
Liujiayao	2	Heping Xiqiao	14
Puhuangyu	3	Huixin Xijie Nankou	15
Temple of Heaven East Gate	4	Huixin Xijie Beikou	16
Ciqikou	5	Datunludong	17
Chongwenmen	6	Beiyuanlubei	18
Dongdan	7	Lishuiqiaonan	19
Dengshikou	8	Lishuiqiao	20
Dongsi	9	Tiantongyuannan	21
Zhangzizhong Lu	10	Tiantongyuan	22
Beixinqiao	11	Tiantongyuanbei	23
Yonghegong Lama Temple	12		

Source: Authors' work

Table 2.
Station number

Table 3.
Dwell time

Station	Dwell time (s)	Station	Dwell time (s)	Station	Dwell time (s)
1	30	9	40	17	30
2	40	10	35	18	40
3	40	11	35	19	45
4	35	12	60	20	40
5	45	13	30	21	45
6	50	14	30	22	40
7	50	15	40	23	40
8	35	16	60		

Source: Authors' work

Table 4.
Interval running time

Interval	Interval running time (s)	Interval	Interval running time (s)	Interval	Interval running time (s)
1	122	9	86	17	253
2	80	10	76	18	101
3	128	11	79	19	99
4	95	12	86	20	116
5	78	13	87	21	85
6	76	14	85	22	84
7	84	15	76		
8	78	16	122		

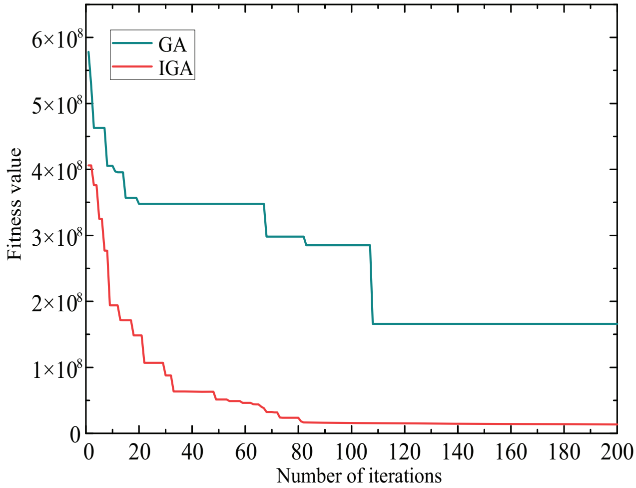
Source: Authors' work

Table 5.
Other related parameters of the model

Parameters	Value	Parameters	Value
Train capacity	1,440 people	Minimum departure interval	1.5 min
Reversal time	1.5 min	Maximum departure interval	3 min
Population size	80	Minimum station dwell time	45 s
Number of iterations	200	Maximum station dwell time	60 s
Crossover probability	0.5	h_1	0.1
Mutation probability	0.1	h_2	5
k_1	0.5	h_3	0.5
k_2	5	h_4	0.1
k_3	0.5	Popmax	1
k_4	0.3	Popmin	0
η	1	m	1

Source: Authors' work

The initial and adjusted train timetables are shown in Figures 4 and 5, respectively. The initial train timetable data was obtained from the official website of Beijing Subway for the study period. From Figure 5, it can be observed that there are 20 train services operating in the up direction at Station 17 as part of the short-turn operation. The dashed lines in the figure represent the canceled train services in the down direction toward Station 23, totaling 22 train services. Table 6 shows that the replanned train timetable significantly reduces the waiting time for passengers within the system. Once the interruption event is over, all subsequent trains will resume their planned timetable operations.



Source: Authors' work

Figure 3. Variation curve of fitness values with iteration count

	Objective function (s)	WT_1/(s)	WT_2/(s)	WT_3/(s)
Initial	16,157,070.64	2,781,076.80	3,931,921.70	9,444,072.14
GA	15,383,045.94	2,469,551.18	3,530,028.24	9,383,466.52
IGA	13,552,304.17	2,102,633.45	2,263,137.96	9,186,532.76

Source: Authors' work

Table 6. Comparison of calculation results

Figures 6–8 show that the number of passengers staying at the station is significantly reduced after optimization, reducing passenger aggregation and ensuring the travel safety of passengers. Figure 7 shows that the number of passengers in all trains leaving the station is significantly reduced after optimization, which can not only match the passenger flow and traffic well but also improve the travel experience of passengers. Figure 8 shows that the number of passengers getting off at each station when all trains arrive is reduced after optimization, indicating that the optimized train operation plan can further ensure the travel of passengers to a greater extent, thereby reducing passenger aggregation on the platform.

These three evaluation indicators all show that the train timetable after optimization can further demonstrate the effectiveness of the model in this paper, which can reduce the degree of passenger aggregation and improve the travel experience to a certain extent.

In the model, both departure time and station dwell time are decision variables. After solving the model using the algorithm and processing the results, a comparative analysis was conducted on the optimized departure intervals (Table 7) and the optimized station dwell times (Table 8) compared to their initial values. From Table 7, it can be observed that there are significant differences between the optimized departure intervals and the initial ones. The planned departure intervals were fixed at 2 min or 3 min, which provided a balanced distribution of departure times but did not align well with passenger travel demands. However, the model's solution allowed for departure intervals ranging from 1.5 min to 3 min, ensuring both safe train operations and better alignment with passengers'

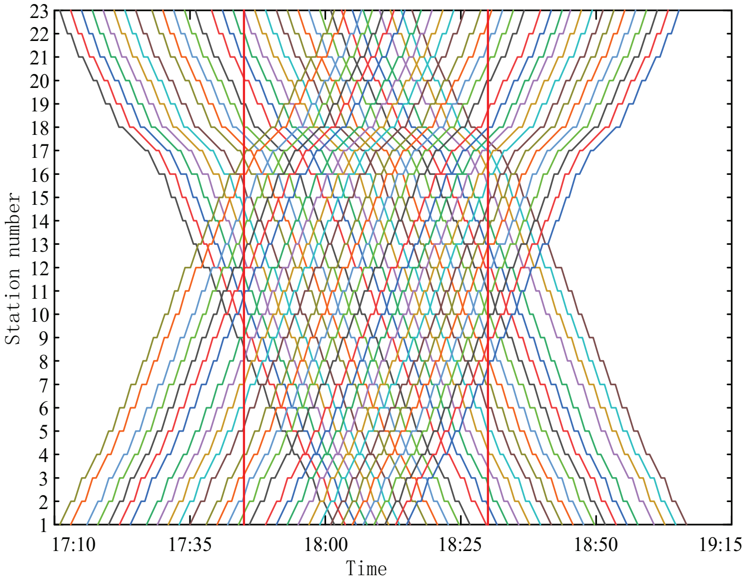


Figure 4.
Train schedule before model optimization adjustment

Source: Authors' work

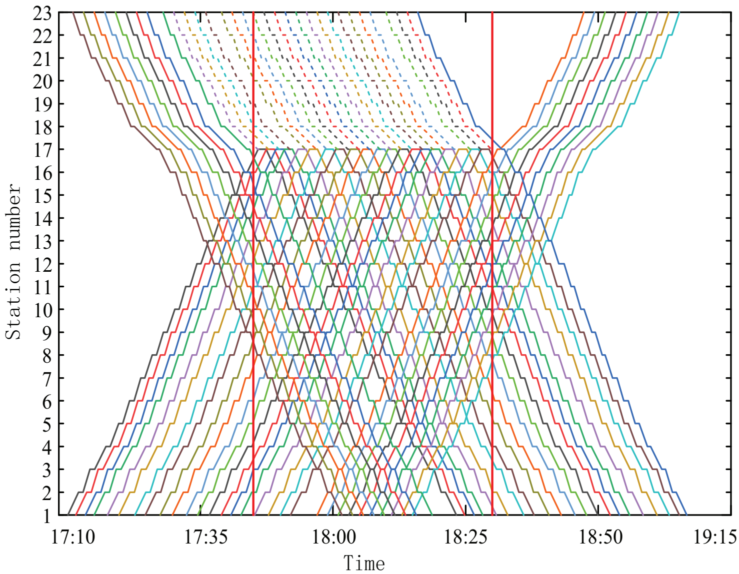
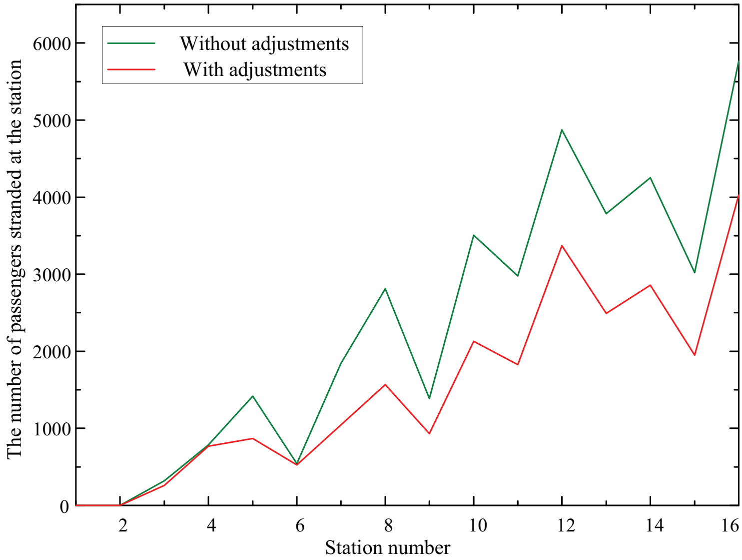


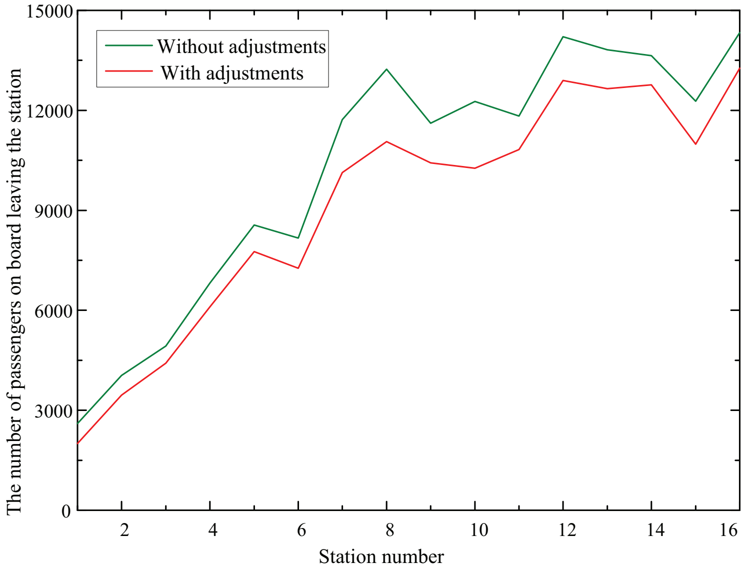
Figure 5.
Train schedule after model optimization adjustment

Source: Authors' work



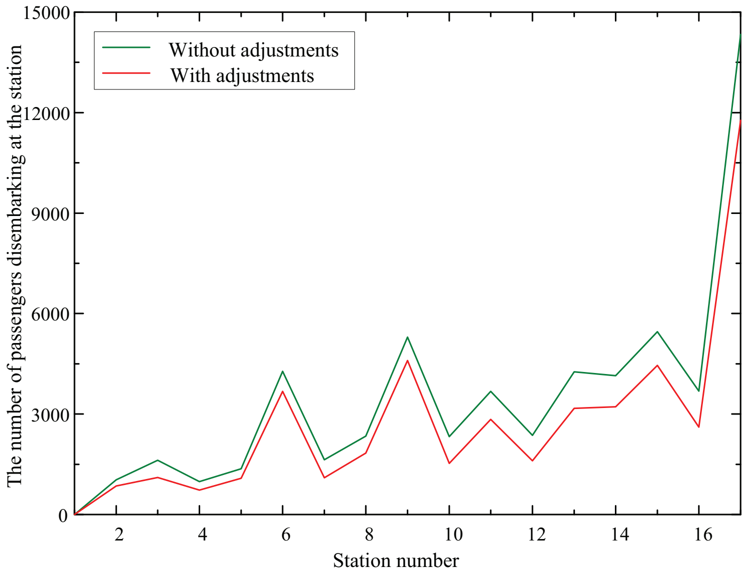
Source: Authors' work

Figure 6.
Comparison of the number of stranded passengers at different stations



Source: Authors' work

Figure 7.
The number of passengers on board all trains when departing from the station



Source: Authors' work

Figure 8. The number of passengers disembarking at each station when all trains arrive

Train	Before/(s)	After/(s)	Train	Before/(s)	After/(s)	Train	Before/(s)	After/(s)
1–2	120	93	8–9	120	168	15–16	120	114
2–3	180	108	9–10	120	139	16–17	120	153
3–4	120	97	10–11	120	158	17–18	180	158
4–5	120	153	11–12	120	127	18–19	120	136
5–6	120	129	12–13	180	131	19–20	120	115
6–7	120	180	13–14	120	137			
7–8	180	118	14–15	120	107			

Source: Authors' work

Table 7. Optimization results of departure intervals

Station	Before/(s)	After/(s)	Station	Before/(s)	After/(s)	Station	Before/(s)	After/(s)
1	30	56	7	50	47	12	30	45
2	40	47	8	35	46	14	30	45
3	40	47	9	40	47	15	40	48
4	35	46	10	35	48	16	60	47
5	45	46	11	35	45	17	30	52
6	50	46	12	60	46			

Source: Authors' work

Table 8. Comparison of optimization results for dwell time

travel demands. This effectively reduced the total waiting time for passengers. Table 8 shows that the optimized station dwell times differ significantly from the initial fixed values. Station 1 experienced the largest increase in dwell time, from 30 s to 56 s, whereas Station 12 experienced the largest decrease, from 60 s to 46 s. Other stations, such as Stations 2, 3 and 4, had some increases in dwell time, while Stations 6, 7 and 16 had some decreases. Overall, the total dwell time increased by 119 s, allowing more passengers to board the train and alleviating congestion on the platforms.

In conclusion, after the occurrence of an interruption event, the use of the small-loop operation adjustment method and the optimization model of train timetable based on passenger waiting can effectively reduce passenger waiting time and crowd congestion within the system, thereby improving the service level of the system under interruption events.

6. Conclusions

This study comprehensively considers the constraints of train operation safety, capacity and dynamic passenger demand. It adopts the small-loop operation adjustment method to handle disruption events and constructs a train timetable adjustment model with the objective of minimizing the total passenger waiting time. An IGA is proposed as the solving algorithm. The model and algorithm are applied to a real disruption event on Beijing Metro Line 5 for validation. The results demonstrate the following:

- After a disruption event occurs, implementing a small-loop operation plan allows for the continued operation of some trains, thereby reducing the impact of the disruption on the rail transit system. By limiting the scope of the disruption, its effects can be contained within a smaller area, allowing other stations to continue normal operations and avoiding a complete shutdown of the entire line. This approach contributes to improved overall operational reliability and passenger satisfaction by minimizing the extent of the disruption and its consequences.
- The proposed train operation adjustment model, as validated through practical examples, demonstrates that the initial departure intervals exhibit good balance but fail to align well with passenger travel demands. However, after optimization, the departure intervals range between 1.5 min and 3 min, ensuring both the safety of train operations and a better alignment with passengers' travel needs. This optimization effectively reduces the overall waiting time for passengers and enhances the service level of the urban rail transit system during disruptions.

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Further reading

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