Hindawi
Mathematical Problems in Engineering
Volume 2022, Article ID 3723630, 14 pages
https://doi.org/10.1155/2022/3723630

Research Article

Managing Peak-Hour Congestion in Urban Rail Transit with the Sub-Train Price Adjustment Strategy

Hui Liang[1], **Zhiqiang Tian**[1], **Renhua Liu**[1], **Guofeng Sun**[2] **and Fujing He**[1]

[1]*School of Traffic and Transportation, Lanzhou Jiaotong University, Lanzhou 730070, China*
[2]*School of Traffic and Transportation, Beijing Jiaotong University, Beijing 100044, China*

Correspondence should be addressed to Hui Liang; 12200958@stu.lzjtu.edu.cn

Received 24 November 2021; Revised 1 March 2022; Accepted 13 April 2022; Published 13 May 2022

Academic Editor: Yang Song

In urban rail transit, adjusting fares to satisfy passenger flow requirements is a new method to relieve urban congestion. A bilevel model is proposed herein to solve the congestion problem for an urban rail line. The upper level of the model determines the discount factor to minimize the total number of passengers exceeding the full-load rate, and the lower level of the model determines the distribution of passengers on the line, in which the cost-minimizing behavior of each passenger is considered using the allocation method based on the probability of selection. To achieve a more realistic model, the range of acceptable train numbers for each passenger is considered. A simulated annealing algorithm is introduced to solve the bilevel model. Based on an example, we obtain the specific fare and passenger flow distribution of each train after fare adjustment. The results show that the objective function is reduced by 17.5%, the congested section is reduced by 9.1% when the full-load rate is 90% of the train loading capacity, and the passenger flow shifts to both ends of the peak period. Finally, relevant parameters are discussed.

1. Introduction

In recent years, traffic congestion caused by the increasingly prominent contradiction between urban traffic demand and supply has become a social problem in countries worldwide. In this context, the development of public transportation has been prioritized to alleviate urban traffic problems. As the main tool to alleviate urban traffic congestion, the subway can transport passengers rapidly. In some large cities, peak and low periods are evident owing to the uneven distribution of daily passenger flow. In particular, during the peak period, the subway platform is crowded, which poses a severe safety hazard. The high degree of congestion in the section and the insufficient experience of passengers on the subway have significantly curbed the enthusiasm of urban residents in opting for the subway as a transport mode.

Currently, the passenger flow problem of urban rail transit during peak periods is primarily considered in terms of two aspects: traffic supply management and traffic demand management, which aim to improve the supply of transportation capacity through the construction of transportation infrastructure and optimization of transportation organization to satisfy the travel requirements of passengers. The primary methods include constructing new subway lines and optimizing train schedules. As a dynamic input, the train schedule should be changed with the change in passenger flow; however, the continued increase in subway passenger flow has resulted in a saturated train schedule, which prevents optimization. Currently, the minimum headway is approximately 1 min. From a technical perspective, continuing the reduction in headways poses high requirements in terms of both signals and vehicles. From a practical perspective, owing to the confusion of passengers boarding and alighting during peak hours and a few uncontrollable factors, certain risks are posed when continuing to reduce headways. We considered solving this problem from the perspective of transportation demand management by adjusting fares to change the travel time of passengers and reasonably loading the passenger flow to each train during the peak period to alleviate the problem of congestion during the peak period, balance the utilization rate of in-service trains, and improve the quality of urban rail transit services.

The fare adjustment method can be classified into incentive policy and direct adjustment of fares. An investigation by Ben-Elia and Ettcema [1, 2] showed that incentive measures effectively changed the travel time of passengers, where a few passengers opted to travel during off-peak hours. Zhang et al. [3] proposed an incentive policy to provide measures such as price reduction in fast-food restaurants for travelers who avoid traveling during peak periods. Yang and Tang [4] proposed a new incentive scheme to reduce the queue time of passengers at a station while ensuring that the operator's revenue remains unchanged. Tang and Jiang [5] proposed a premium fare incentive scheme that not only encourages passengers to change their travel time from peak to off-peak hours but also reduces passenger individual travel costs and total queuing time costs. Tang and Yang [6] proposed a hybrid fare scheme to ensure that the fare income remains unchanged. Lu and Zhang [7] proposed a fare scheme that alleviates congestion and reduces the cost of travel for passengers while ensuring that revenue is not reduced. Chen et al. [8] proposed a congestion pricing scheme that reduces the number of nonessential travel passengers during peak hours and provides road resources for commuters. Huang and Liu [9] proposed a pricing method determined by the distance between departure and terminal stations that allows passengers to select their travel routes. Zheng et al. [10] proposed a dynamic congestion pricing scheme that effectively reduces congestion and achieves savings for users. Wu and Qin [11] established a high-speed rail seat allocation model based on dynamic pricing to maximize the income of enterprises, which improves the revenue of railways.

In recent years, investigations pertaining to rail transit fares have primarily focused on the effect of fares on passenger travel behavior and adjustment methods of fares. Peer et al. [12] conducted a month-long experiment regarding the itinerary preferences of 1,000 Dutch citizens and then developed a departure time selection model. Kou and Tseng et al. [13, 14] investigated the effects of income level and time on passenger travel decisions. Thorhauge et al. [15] used a questionnaire survey to evaluate the psychological factors of travelers, and the results showed that the constructed selectivity model significantly affected people with fixed working hours. Anupriya et al. [16] used appropriate reasoning methods to assess the effects of discount policies on travelers' travel preferences; however, the mitigation of congestion by such policies is limited. Aboudina and Abdulhai [17] proposed a congestion pricing system that assesses the effect of charging on travelers' timing and path selections.

The automatic fare collection system (AFC) is developed to provide data support for the differentiated pricing of subways. To alleviate the problem of busy passenger flow during peak periods, researchers often adopt the peak-to-peak differentiated pricing method. Huan and Hess [18] used a bilevel planning model to consider pricing strategies for off-peak discounts and additional peak-period charges. Vuuren [19] confirmed that pricing during peak and nonpeak hours is primarily aimed at maximizing welfare and revenue, respectively. Whelan and John [20] established fare changes to accommodate the changing flow requirements of passengers throughout the day, which consequently solved the problem of overcrowding. De Palma et al. [21] derived the best dynamic pricing and seat share for the same type of origin-destination (OD) passengers.

Currently, various studies pertaining to fare schemes and comparisons have been conducted. Zhou and Li [22] used a simulation system to compare two fare incentive policies. Sun and Szeto [23] proposed a two-tier planning model to determine fares to improve the interests of operators and compared three different fare schemes. Huang [24] compared three pricing schemes and proposed an optimal combination that minimizes the total cost. Li and Guo [25] investigated the effect of congestion charging and incentive policies on car travelers, and the results showed that congestion pricing strategies affect the change in travel patterns of travelers more significantly than incentive policies. Lovrić and Raveau [26] investigated and evaluated two off-peak pricing strategies, and the results showed that the off-peak pricing strategy is vital for solving congestion, particularly during the afternoon peak period.

A summary of the recently developed fare adjustment models is presented in Table 1. Existing fare pricing strategies can be classified into hours or minutes, and the passenger flow division is not sufficiently precise. To better satisfy the actual requirements, we propose a strategy of implementing differentiated pricing within the scope of multiple trains to balance the utilization rate of each train, thereby alleviating the problem of congestion during peak periods. The main contributions of this study are summarized as follows:

(1) A method for determining fares, which is affected by the distribution of passenger flow during peak hours, is proposed

(2) The concept of the range of acceptable train numbers for each passenger (RATP) and allocating passenger flow during the peak period to achieve more realistic results are introduced

(3) A bilevel model with the smallest number of passengers exceeding the full-load rate (NEFR) is constructed, and a simulated annealing algorithm and logit model are used to solve the model

(4) The relationship between the value NEFR and the number of congestion sections is discussed, and RATP is analyzed

(5) A new subway fare and passenger flow distribution are obtained, which provide a reference for subway operating companies

The remainder of this paper is organized as follows. Section 2 presents the problem description, assumptions, and notations. Section 3 presents our model. Section 4 presents the procedures of the proposed algorithm for solving the price adjustment model of urban rail transit congestion. Numerical examples are presented in Section 5 to illustrate the performance of the proposed fare schemes. In Section 6, discussions as well as analyses of some parameters are presented. Finally, conclusions and future research directions are provided in Section 7.

Table 1: A summary of models.

References	Objective function	Solving algorithm
Tang et al.	The total equilibrium costs	Sequential iterative solution algorithm
Huan et al.	Max the sum of the operator and com-muter surplus and min the peak ridership	Genetic algorithms
Huang et al.	Maximization of the social welfare	Hybrid artificial bee colony algorithm
Wu et al.	Maximize the total ticket revenue	A two-stage algorithm
Sun et al.	Maximize transit operator's profit	Sensitivity-based descent search method
This paper	Minimize the total number of passengers exceeding the full-load rate (NEFR)	Simulated annealing algorithm

2. Problem Description, Assumption, and Notation

2.1. Problem Description. Owing to the continuous improvement in the division of urban functional areas, the distribution of urban citizens in the city has become unbalanced. Passenger and congestion sections are not necessarily the same in the upward and downward directions of a subway line. In this study, we considered only the problem of morning peak congestion in one direction, with station numbers 1, 2, . . ., $s \in S$, and the corresponding section numbers 1, 2, . . ., $s+1 \in M$.

Our price adjustment strategy is as follows: the period before and after the morning peak period is specified as the trough period, which encourages passengers to change their travel time via price adjustment such that the passenger demand for the morning peak hour is transferred in time and space. We believe that the total passenger flow remains the same before and after the fare adjustment; i.e., $S_G = S_{\mathrm{DL}} + S_{\mathrm{DR}}$.

Figure 1 shows an example of a station, where T_D^{XO} and T_D^{XE} denote the start and end times of the research period, respectively, and t_s^l and t_s^r denote the start and end time and end times of the morning peak hour at station s, respectively. During the morning peak hours, the dynamic passenger demand at the station is satisfied by the normal distribution of time [27]. Therefore, we used the midpoint of each station's peak hour (superpeak hour) to indicate the most congested state of this station. In Figure 1, t_s^m represents the superpeak hours of stations.

During the morning peak hours, the main purpose of travel by passengers is for work. For fixed working hours, the RATP is required before and after fare adjustment; it is not an unlimited number of waiting trains with the least travel resistance.

As shown in Figure 2, we believe that for each peak-hour passenger, an acceptable earliest and latest departure train exists, which is set as the previous train and the next train adjacent to the ideal departure train in this study.

2.2. Model Assumptions. Based on a model of fare adjustment with differentiated pricing across multiple trains, the relationship between passenger flow and the fare was considered and optimized in this study. The following assumptions were introduced for some factors in the urban rail transit service process:

(1) The train is under a long-term optimized configuration, all operating services are at full load, the train is operating in accordance with the determined timetable, and the headway is equal

(2) Considering the effect of price adjustment explicitly, we assume that after fare adjustment, all passengers will still opt to travel without changing the origin and destination stations

(3) Passenger travel behavior is determined by the passengers themselves, who always opt to travel on the train with the least travel resistance

2.3. Variable Definitions. We first list all the notations and parameters used in this study in Table 2.

3. Bilevel Model Establishment

3.1. Determination of Price. Before building the model, we must first provide a method for determining the price during peak hours. As shown in Figure 3, we assume that 11 stations (labeled from A to K) and 10 trains (numbered from 1 to 10) exist. The time span of our study is $[T_{\mathrm{start}}, T_{\mathrm{end}}]$, which reduces the passenger flow by the length of the headway. The colored regions of the figure represent the congestion periods for each section; $t_A^1, t_A^2, \ldots, t_A^{10}$ indicates the arrival time of trains $1, 2, \ldots, 10$ at station A (if station A is the origin station, it can be regarded as the departure time); t_A^l and t_A^r represent the start and end times of peak hours in section A, respectively; t_A^m is the midpoint time during the peak period of section A. We believe that the passenger flow is the most active on the platform at this time, and we define this moment as the superpeak hour.

In summary, we believe that two primary scenarios exist. In the first scenario, train k is in the off-peak period at station s (the train represented by the blue line in Figure 3), which can be determined as follows:

$$\left[\frac{1}{2}\left(t_s^l + t_s^r\right) - \left|t_s^k - t_s^m\right|\right] < 0. \tag{1}$$

In the second scenario, train k is in the peak period at station s (the train represented by the black line in Figure 3), which can be determined as follows:

$$\left[\frac{1}{2}\left(t_s^l + t_s^r\right) - \left|t_s^k - t_s^m\right|\right] > 0. \tag{2}$$

In essence, the two formulas above express the time difference between the arrival time of train k at station s and the superpeak time of station s. To express this time difference, we introduce a new variable, Δt_s^k. Subsequently, the following conditions specify the scenario of the train:

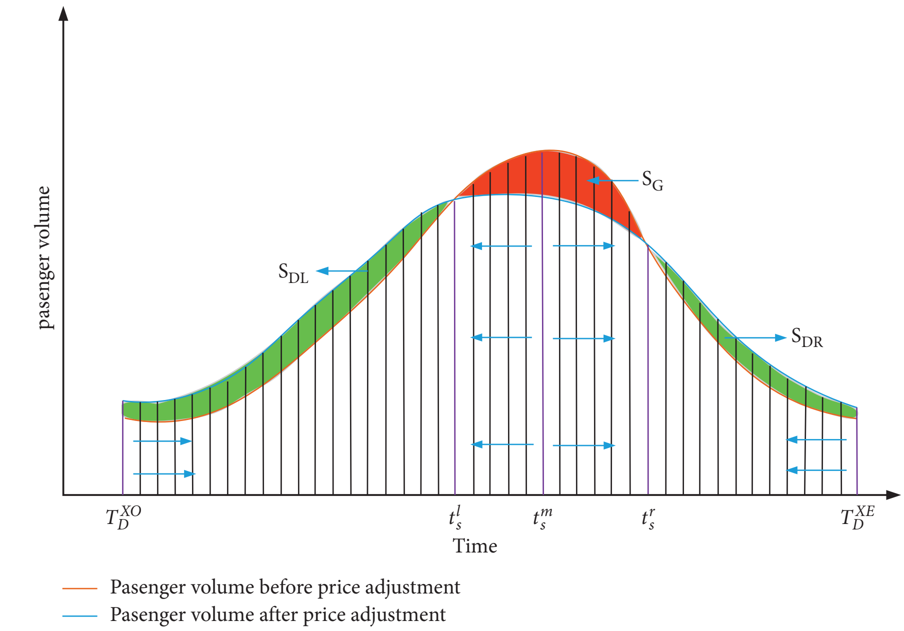


FIGURE 1: Passenger flow transfer diagram.

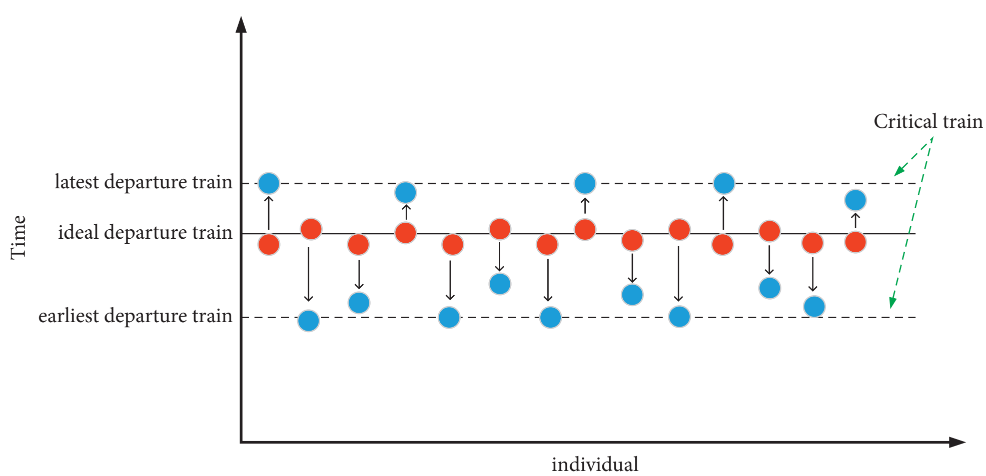


FIGURE 2: RATP diagram.

TABLE 2: Notations and parameters in this problem.

Notations	Detailed definition
S	Set of involved stations
M	Set of involved stations
K	Set of in-service trains
t_s^k	Arrival time of train k at station s on the line
t_s^l	Start time of the peak hour at station s
t_s^m	Superpeak hour at the station s
t_s^r	End time of the peak hour at station s
p_{ij}^{ko}	Fare of passengers who take the train k at station i heading to station j before the price adjustment
p_{ij}^k	Fare of passengers who take the train k at station i heading to station j after the price adjustment
Δt_s^k	Time difference between the train k at the station s and the super-peak time of station s
q_{ij}^{ko}	The volume of passengers who take the train k at station i heading to station j before the price adjustment
q_{ij}^k	The volume of passengers who take the train k at station i heading to station j after the price adjustment
C	In-service train loading capacity
q_m^k	The volume of the passenger on the train k passing through the section m
flr	Value of full-load rate
q_m^{crowd}	The number of passengers in the section m larger than $flr \cdot C$
λ_s^k	The discount factor for the train k in the section s

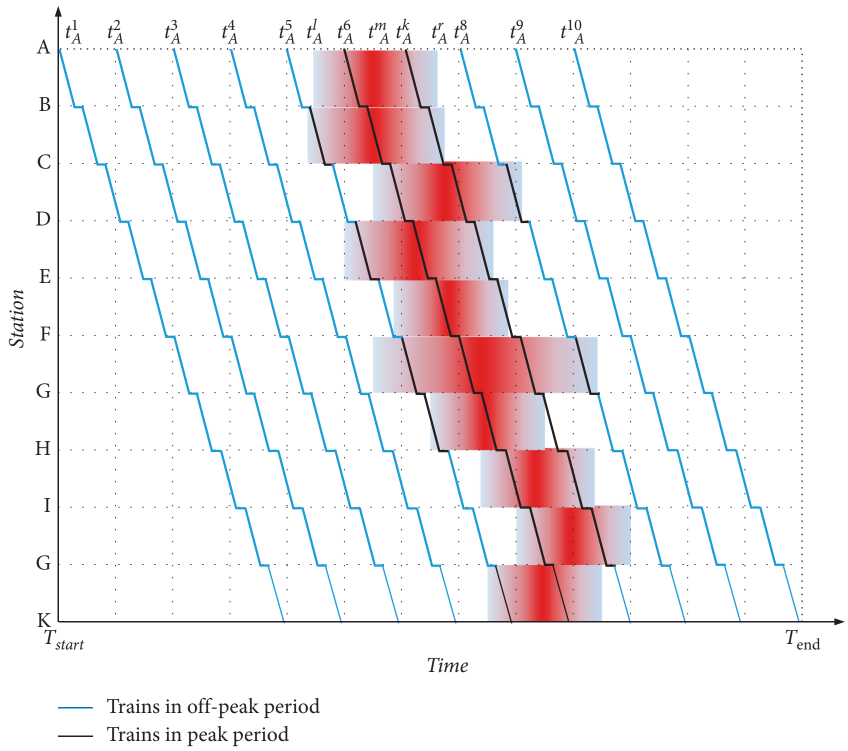


FIGURE 3: Diagram depicting passenger accumulation.

$$\Delta t_s^k \begin{cases} < 0, & k - th \text{ train is in off} - \text{peak period at the } s - th \text{ station}, \\ > 0, & k - th \text{ train is in peak period at the } s - th \text{ station}. \end{cases} \tag{3}$$

In this study, the time difference and discount factor were used jointly to determine the price. As multiple OD streams exist for each train, the variable parameters in the problem will be difficult to address if a discount factor is specified for each OD. To simplify this problem, we introduce a new variable λ_s $(0 < \lambda_s < 1)$, which represents the discount factor in section s and use the discount combination of each section to express the discount factor of the entire train. We believe that the closer it is to the peak hours, the greater the value of the discount factor is and that a linear relationship exists between both parameters. Considering the factors described above, we use the following formula to express the adjusted fare:

$$p_{ij}^k = p_{ij}^{ko} + \sum_{s=i}^{j} \left(\lambda_s \cdot \Delta t_s^k \right). \tag{4}$$

3.2. Passenger Flow Loading Instructions

3.2.1. Path Flow. The sum of passenger flows allocated to each path (train) for any OD pair should be equal to the passenger flow demand. For example, in Figure 3, the passenger flow between OD pair (A, C) is allocated to train $k = 3$, $k = 4$, and $k = 5$, whose flow is denoted as f_{AC}^3, f_{AC}^4, and f_{AC}^5, respectively, and satisfies $f_{\mathrm{AC}}^3 + f_{\mathrm{AC}}^4 + f_{\mathrm{AC}}^5 = q_{\mathrm{AC}}$.

3.2.2. Section Flow. The flow of any section is equal to the sum of the passenger flows of all the paths passing through the section. For example, in Figure 3, suppose that train $k = 3$ loads the passenger flow of OD pairs (A, C), (A, D), and (A, E); subsequently, $q_{\mathrm{BC}}^3 = f_{\mathrm{AC}}^3 + f_{\mathrm{AD}}^3 + f_{\mathrm{AE}}^3$. We introduce a 0-1 variable to represent the relationship between the path (train) and section. If train k passes through section m, then $\delta_{ij}^{k,m} = 1$; otherwise, $\delta_{ij}^{k,m} = 0$.

3.3. Passenger Travel Impedance. Passengers select the transportation mode based on a decision-making process, in which they expect to select the travel mode with the lowest cost. Fare is the most intuitive factor in this context. Owing to the improvement in living standards and changes in consumption concepts, convenience (transfer distance and transfer queue time), comfort (degree of congestion), safety, reliability (on-time rate), and other factors will affect the choice of transportation mode; therefore, travel impedance should be included as a factor. Based on an analysis of the travel requirements of citizens, it can be concluded that the main influencing factors of citizens' travel behavior are time, economy, and comfort. Citizens comprehensively consider the effect of the generalized travel cost and typically select the method with the lowest generalized travel cost.

3.3.1. Economy. The total cost of a passenger completing a trip includes the basic fare and various connection and transfer fees, such as the cost of passengers from the departure point to the subway station and from the origin station to the destination station. Herein, we consider only the process of passengers traveling via the subway and directly use the fare to reflect the economic indicators. The average annual national product [27] is used to convert the fare $D = 7.4$ min/yuan, as follows:

$$p_{ij}^{k'} = D \cdot p_{ij}^{k}. \tag{5}$$

3.3.2. Convenience. Travel time impedance can be categorized into section and station impedances. In an urban rail transit system, the section impedance is represented by the operating time of the train, and the station impedance is represented by the dwelling time of the train, as follows:

$$W_m^k = t_m + t_s, \tag{6}$$

where t_m is the operating time of the train in section m, and t_s is the dwelling time of the train at station s (including the acceleration and deceleration times of the train).

3.3.3. Comfort. Passenger well-being, time-saving value, and fares are affected by congestion [28] and future comfort improvements that increase the possibility of working, reading a book, watching a movie, and communicating during a trip [29]. For railway transportation, passenger comfort depends primarily on the train travel time and hardware/software service facilities. Comfort is an indicator that depends on the travel time, which can be quantified by the time required for passengers to recover from fatigue. For the urban rail transit, we use the congestion of the section to reflect comfort.

First, when the number of passengers on the train is less than the number of seats, i.e., when each passenger has a seat, the passengers will not feel any discomfort. When the number of passengers is greater than the number of seats, the additional time cost caused by discomfort is 0. At this time, because the passengers must stand or endure an overcrowded environment, the additional time caused by congestion per unit of travel time can be expressed as follows:

$$Y_m^k\left(q_m^k\right) = \begin{cases} 0, & q_m^k < Zm, \\ \dfrac{q_m^k - Z}{Z} A, & Z < q_m^k \le C, \\ \dfrac{q_m^k - Z}{Z} A + \dfrac{q_m^k - C}{Z} B, & q_m^k > C, \end{cases}$$
$$T_m^k = t_m \cdot Y_m^k\left(q_m^k\right), \tag{7}$$

where Z is the number of seats in the train, A is the additional time cost coefficient for general crowding, B is the additional time cost coefficient for overcrowding, and T_m^k is the weighted comfort cost.

In summary, the generalized cost (path impedance) of the OD pair passenger's selection of route (train) travel is expressed as follows:

$$gc_{ij}^k = \left[\alpha_1 \sum_i \sum_j P_{ij}^{k'} + \alpha_2 \sum_m W_m^k + \alpha_3 \sum_m T_m^k\right] \cdot \delta_{ij}^{k,m}. \tag{8}$$

In the formula above, $\alpha_i\,(i = 1, 2, 3)$ represents the weighting coefficient, i.e., the degree to which passengers traveling on different trains attach importance to each travel cost; in this study, $\alpha_1 = 0.5$, $\alpha_2 = 0.1$, and $\alpha_3 = 0.4$.

3.4. Upper-Level Model. The core purpose of the price adjustment model used in this study is to change the arrival time of passengers to alleviate the problem of busy passenger flow during the peak period, thereby rendering the utilization rate of trains during peak periods as balanced as possible and improving the overall service level of rail transit. Hence, the minimum NEFR was used as the optimization goal in this study, as shown in (9): if flr is 90%, then the objective function represents the function of any adjacent section, thereby resulting in the minimum number of passengers exceeding 90% of the train capacity, as follows:

$$\min \sqrt{\sum \left| q_m^{\text{crowd}} - flr \cdot C \right|}. \tag{9}$$

3.4.1. Revenue Constraints. The income of subway operators is an important factor that must be considered. When the revenue from inducing passenger flow cannot compensate for the loss in peak passenger flow transfer, the fare inevitably results in reduced total operating revenue. Herein, we use only the fare revenue to represent the overall revenue of the operator; in other words, the total revenue after the price adjustment must not be less than the total revenue before the price adjustment.

$$\sum_i \sum_j \sum_k p_{ij}^k \cdot q_{ij}^k \ge \sum_i \sum_j \sum_k p_{ij}^{ko} \cdot q_{ij}^{ko}. \tag{10}$$

3.5. Lower-Level Model. The lower-level model is a passenger distribution model that considers the passenger departure time. The multipath probability selection problem in the urban rail transit network is explained by behavioral science, which is a decision-making problem, i.e., the manner by which passengers select the travel path during urban rail travel; furthermore, the travel impedance of the path can be used as a basis for passengers to select the path. The objective function of lower-level planning is to minimize the travel impedance of the passengers, as shown in (8).

3.5.1. Passenger Flow Constraints. We believe that the purpose of implementing fare adjustment is to divert passenger flow rather than to eliminate passenger flow. In this process, the total passenger flow remains unchanged; i.e.,

$$\sum_{k=1}^{K} q_{ij}^{ko} = \sum_{k=1}^{K} q_{ij}^{k}, \ (i, j) \in S. \tag{11}$$

3.5.2. Capacity Constraints. The passenger flow of each train during peak hours should be controlled under the corresponding train loading capacity as follows:

$$\sum_i \sum_j q_{ij}^k \cdot \delta_{ij}^{km} \leq C, \forall k, m. \tag{12}$$

4. Algorithm Solution

In this study, the simulated annealing algorithm and allocation method based on selection probability were used to solve the model above. The idea of the algorithm solution is as follows: the decision variable λ_s of the upper model is encoded and input to the lower model as a known condition, and the lower model obtains the distribution of passengers on the train through the distribution method based on the selection probability and then returns the result to the upper model. The upper model uses the simulated annealing algorithm to obtain the corresponding fitness function value and finally obtains the optimal solution iteratively.

4.1. Passenger Flow Allocation Model Based on Selection Probability. An improved logit model was used as the probability model to solve the lower model. The specific procedures are as follows:

Step 1. The effective path for each OD pair is determined. For each OD pair, the optional path includes the ideal departure train and the previous train, and the next train deviates from the ideal departure train among the three optional paths (trains). The set of optional paths is represented by l.

Step 2. Calculate the generalized cost of each path gc_{ij}^k in the optional paths set and obtain the minimum generalized cost between OD pairs, which is denoted as $gc_{ij}^{\min}$;

Step 3. According to the improved logit model (13) used to calculate the selection ratio of each alternative route, θ is an index that measures the overall familiarity of passengers with the road network.

$$\text{prob}_{ij}^k = \frac{\exp\left(-\theta gc_{ij}^k / gc_{ij}^{\min}\right)}{\sum_l \exp\left(-\theta gc_{ij}^l / gc_{ij}^{\min}\right)}. \tag{13}$$

Step 4. According to prob_{ij}^k, the passenger flow distribution of each path is calculated as follows:

$$f_{ij}^k = q_{ij}\text{prob}_{ij}^k, \quad \forall k, i, j. \tag{14}$$

Step 5. The passenger flow of each section in the alternative path is calculated as follows:

$$q_m^k = \sum_i \sum_j \sum_{k \in K} f_{ij}^k \delta_{ij}^{k,m}. \tag{15}$$

4.2. Simulated Annealing Algorithm Critical Step Design. The main procedures of the algorithm are as follows:

Step 1. Initialization of parameters: the parameters are set as follows: initial temperature temperature = 1000, cooling_rate = 0.94, number of internal and external cycles LK = 100, *and* maxgen = 500.

Step 2. The passenger flow distribution of platforms and sections under the existing operating organization is calculated. The fitness function value, which is denoted by previous_fitness, is calculated using (9).

Step 3. Generate the initial solution λ_s, and calculate the fare revenue. If the fare revenue satisfies Equation (10), then proceed to the next step; otherwise, regenerate the solution.

Step 4. Use the passenger flow allocation model based on the selection probability to obtain the passenger flow distribution; if the passenger flow satisfies (11) and (12), then proceed to the next step; otherwise, return to Step 4.

Step 5. Based on the new passenger flow distribution, calculate the fitness function value using (9), which is denoted as current_fitness. Record the solution and its corresponding platform and section population distribution.

Step 6. Calculate the increment diff = current_fitness −previous_fitness,

$$\begin{cases} 1, & \text{diff} < 0, \\ \exp\left(\dfrac{\text{diff}}{\text{temperature}}\right), & \text{diff} \geq 0. \end{cases} \tag{16}$$

If diff < 0, the new solution is accepted with 100% probability, and if diff ≥ 0, the new solution is accepted with probability exp (diff/temperature). If the new solution is accepted, then the new fitness function value is also accepted, i.e., previous_fitness = current_fitness.

Step 7. Determine whether the number of inner loops is satisfied. If it is satisfied, perform the cooling operation, i.e., temperature = cooling_rate × temperature; otherwise, return to Step 3.

Step 8. Determine whether the number of outer loops is satisfied. If it is satisfied, then the algorithm terminates, and the optimal solution is output. Otherwise, it returns to Step 3.

5. Numerical Experiments

This study is based on the passenger flow data on a subway line. We number each station by numbers 1–26 and number the corresponding sections by numbers 1–25. The parameters used in this study and their values are shown in Table 3.

To facilitate the calculation of the example, we set the fare for all adjacent sections to 1 yuan. We define the departure time of the first bus as 6 a.m., based on the passenger flow information provided by the AFC. Passengers on trains 12–31 were selected as the research objects in this study (hereinafter collectively referred to as trains 1–20). MATLAB programming calculations were used to obtain the

Table 3: Values of main parameters.

Parameter	Value
t_m	5 min
t_s	1 min
Z	360
C	1440
A	1
B	2
flr	90%
θ	1
H	5 min

convergence curve, as shown in Figure 4. As shown in Figure 4, the initial value of the objective function is 114, and the objective function decreases with the decrease in temperature. When iterating around 230 generations, the optimal solution and objective function remain stable, and the model reaches a state of convergence. The optimal objective function is 94, which is reduced by 17.5%. The number of congested sections (the congested section is defined as more than 90% of the train's loading capacity) changes from 55 to 50, which is a reduction of 9.1%.

The price-added value of the section is listed in Table 4. The price of the relatively congested section increases, and the price of the adjacent relatively idle section decreases. For example, passengers who board the 9th train and pass through the 10th section will be charged an additional 2.1 yuan fare in this section, whereas passengers passing through the 18th section are entitled to a 1 yuan fare subsidy in this section. This encourages the passengers to select the fare subsidized section as well as change their travel time. The fare revenue before the price adjustment was 94146 yuan, and the fare revenue after the price adjustment was 107,700 yuan, which is an increase of 13,554 yuan to satisfy the revenue of the operator. We applied the section price adjustment amount to the in-world subway fare table. Table 5 shows the subway fare table for the 9th train. The OD pair (1,11) in the table is 4/6.1, which represents the price before the price adjustment. The fare was 4 yuan, and the adjusted fare was 6.1 yuan. After calculation, the total fare revenue before the price adjustment was 40236 yuan, and the total fare revenue after the price adjustment was 44243 yuan, which translates to an increase of 4007 yuan and a growth rate of 10%. The fare for the other train is shown in the supplemental file.

During peak hours, in addition to the balanced train utilization rate, the congestion problem should be considered. Figure 5 shows the distribution of the crowded section before and after the price adjustment. We consider a section with 1440 or more passengers as an overcrowded section, a section with 1296–1440 passengers as a crowded section, and a section with less than 1296 as a safe section [30]. Comparing the number of congested sections before and after the price adjustment, it was discovered that the total number of congested sections reduced from 55 to 50, which is a reduction of 9.1%, whereas the total numbers of overcrowded and congested sections reduced from 31 to 27 and 24 to 23, respectively.

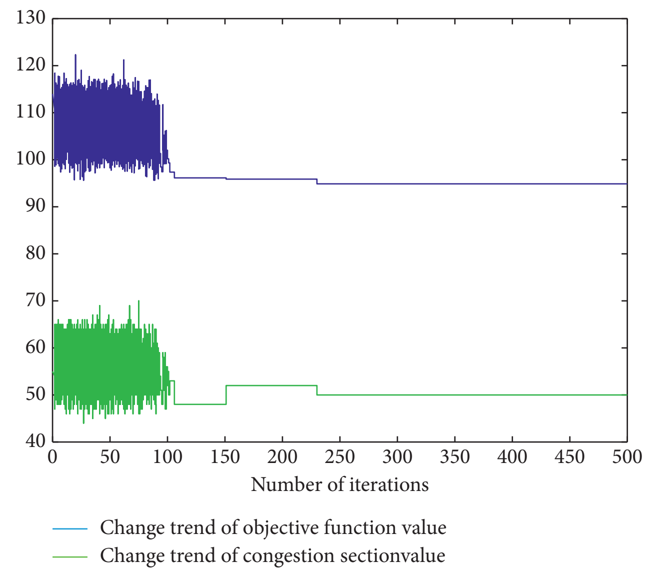


Figure 4: Convergence curve of the objective function.

To better reflect the congestion section and passenger flow changes in the congestion section during peak hours, we use PS to denote the set of congested sections before the price adjustment, NS to the set of congested sections after the price adjustment, and $PS \cup NS = 65$ to represent the total set of congested sections. As shown in Table 6, the sections marked in yellow are the congestion sections that coexist before and after the price adjustment (40 in total); the sections marked in blue are the unique congestion sections before the price adjustment (15 in total); the sections marked in red are the unique congestion sections after the price adjustment (10 in total); the congestion section changed from 55 (40 + 15) before the price adjustment to 50 (40 + 10) after the price adjustment.

We numbered the 65 congestion sections based on the following numbering rules. In general, the sections were numbered in the increasing order, and the same sections were numbered in the increasing order of train number. Figure 6 shows the passenger flow fluctuations in the congested section before and after the price adjustment. The solid green line indicates passenger flow fluctuations in crowded sections before the price adjustment, the solid blue line indicates passenger flow fluctuations in crowded sections after the price adjustment, and the dotted pink line indicates the number of passengers at a loading capacity of 90%. Compared with before the price adjustment, the number of congested sections was 65, of which 42 sections had fewer people, primarily between the 8th and 13th trains; after the price adjustment, the number of people increased in 23 trains, primarily between the 6th–7th and 15th–20th trains. The passenger flow distribution was more balanced, and the fluctuation decelerated.

6. Parametric Analysis

In the proposed model, it is assumed that three alternative routes exist for passengers: the ideal departure train, the

Table 4: The price-added value of the section.

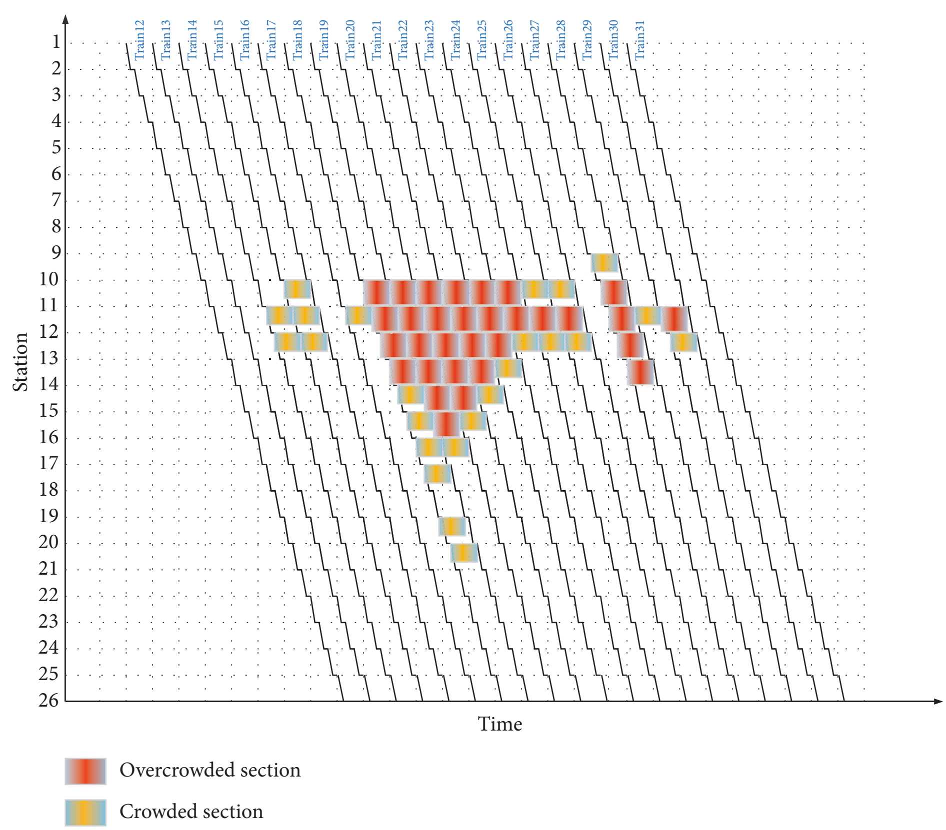
Section	Train 1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
3	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
5	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
8	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
9	0.0	0.0	0.0	0.0	0.0	0.0	0.0	−0.1	0.0	0.0	0.0	0.0	−0.1	0.0	−0.1	0.0	0.0	−0.1	0.0	0.0
10	0.0	−1.0	0.0	0.5	0.0	−1.0	0.0	1.0	2.1	3.1	2.1	1.0	0.0	1.0	0.0	0.0	0.0	0.0	0.0	−1.0
11	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.0	2.1	3.1	4.2	3.1	2.1	1.0	0.0	0.0	0.0	0.0	0.0
12	0.0	0.0	0.0	0.0	0.0	0.0	0.0	1.6	3.2	3.2	1.6	0.0	0.0	0.0	−1.6	0.0	0.0	−1.6	0.0	0.0
13	0.0	0.0	0.0	0.0	0.0	−0.2	0.0	0.2	0.4	0.2	0.0	−0.2	0.0	0.0	−0.2	0.0	0.0	−0.2	0.0	0.0
14	0.0	0.0	−1.5	0.0	0.0	−1.5	−1.5	0.0	1.5	0.0	−1.5	0.0	−1.5	0.0	0.0	0.0	0.0	0.0	0.0	0.0
15	0.0	−0.2	0.0	0.0	−0.2	0.0	−0.2	0.0	0.0	−0.2	0.0	−0.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
16	0.0	0.0	0.0	0.0	0.0	−3.2	0.0	3.2	3.2	0.0	−3.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
17	0.0	0.0	0.0	0.0	0.0	−4.0	0.0	4.0	0.0	−4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
18	0.0	0.0	0.0	0.0	0.0	−1.0	0.0	0.0	−1.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
19	0.0	0.0	0.0	0.0	−4.0	0.0	4.0	0.0	−4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
20	0.0	0.0	−2.0	0.0	2.0	4.0	2.0	0.0	−2.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
21	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
22	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
23	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
24	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
25	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

Table 5: The 9th train subway fare table.

OD	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
1	2/2.0	2/2.0	2/2.0	2/2.0	3/3.0	3/3.0	3/3.0	3/3.0	3/3.0	4/6.1	4/5.5	4/7.1	4/5.6	4/5.6	4/5.6	5/6.9	5/6.9	5/6.5	5/5.7	5/5.5	5/5.5	6/6.5	6/6.5	6/6.5	6/6.5
2		2/2.0	2/2.0	2/2.0	2/2.0	3/3.0	3/3.0	3/3.0	3/3.0	3/5.1	4/5.5	4/7.1	4/5.6	4/5.6	4/5.6	4/5.9	5/6.9	5/6.5	5/5.7	5/5.5	5/5.5	5/5.5	6/6.5	6/6.5	6/6.5
3			2/2.0	2/2.0	2/2.0	2/2.0	3/3.0	3/3.0	3/3.0	3/5.1	3/4.5	4/7.1	4/5.6	4/5.6	4/5.6	4/5.9	4/5.9	5/6.5	5/5.7	5/5.5	5/5.5	5/5.5	5/5.5	6/6.5	6/6.5
4				2/2.0	2/2.0	2/2.0	2/2.0	3/3.0	3/3.0	3/5.1	3/4.5	3/6.1	4/5.6	4/5.6	4/5.6	4/5.9	4/5.9	4/5.5	5/5.7	5/5.5	5/5.5	5/5.5	5/5.5	5/5.5	6/6.5
5					2/2.0	2/2.0	2/2.0	2/2.0	3/3.0	3/5.1	3/4.5	3/6.1	3/4.6	4/5.6	4/5.6	4/5.9	4/5.9	4/5.5	4/4.7	5/5.5	5/5.5	5/5.5	5/5.5	5/5.5	5/5.5
6						2/2.0	2/2.0	2/2.0	2/2.0	3/5.1	3/4.5	3/6.1	3/4.6	3/4.6	4/5.6	4/5.9	4/5.9	4/5.5	4/4.7	4/4.5	5/5.5	5/5.5	5/5.5	5/5.5	5/5.5
7							2/2.0	2/2.0	2/2.0	2/4.1	3/4.5	3/6.1	3/4.6	3/4.6	3/4.6	4/5.9	4/5.9	4/5.5	4/4.7	4/4.5	4/4.5	5/5.5	5/5.5	5/5.5	5/5.5
8								2/2.0	2/2.0	2/4.1	2/3.5	3/6.1	3/4.6	3/4.6	3/4.6	3/4.9	4/5.9	4/5.5	4/4.7	4/4.5	4/4.5	4/4.5	5/5.5	5/5.5	5/5.5
9									2/2.0	2/4.1	2/3.5	2/5.1	3/4.6	3/4.6	3/4.6	3/4.9	3/4.9	4/5.5	4/4.7	4/4.5	4/4.5	4/4.5	4/4.5	5/5.5	5/5.5
10										2/4.1	2/3.5	2/5.1	2/3.6	3/4.6	3/4.6	3/4.9	3/4.9	3/4.5	4/4.7	4/4.5	4/4.5	4/4.5	4/4.5	4/4.5	5/5.5
11											2/3.0	2/4.1	2/3.5	2/3.5	3/4.5	3/4.8	3/4.8	3/4.3	3/3.6	4/4.3	4/4.3	4/4.3	4/4.3	4/4.3	4/4.3
12												2/5.2	2/3.8	2/3.7	2/3.7	3/5.0	3/5.0	3/4.4	3/3.5	3/3.2	4/4.2	4/4.2	4/4.2	4/4.2	4/4.2
13													2/2.4	2/3	2/3.0	2/3.7	3/4.7	3/4.0	3/2.8	3/2.5	3/2.5	4/3.5	4/3.5	4/3.5	4/3.5
14														2/3.5	2/3.5	2/4.3	2/4.3	3/4.2	3/2.6	3/0.0	3/0.0	3/0.0	4/0.3	4/0.3	4/0.3

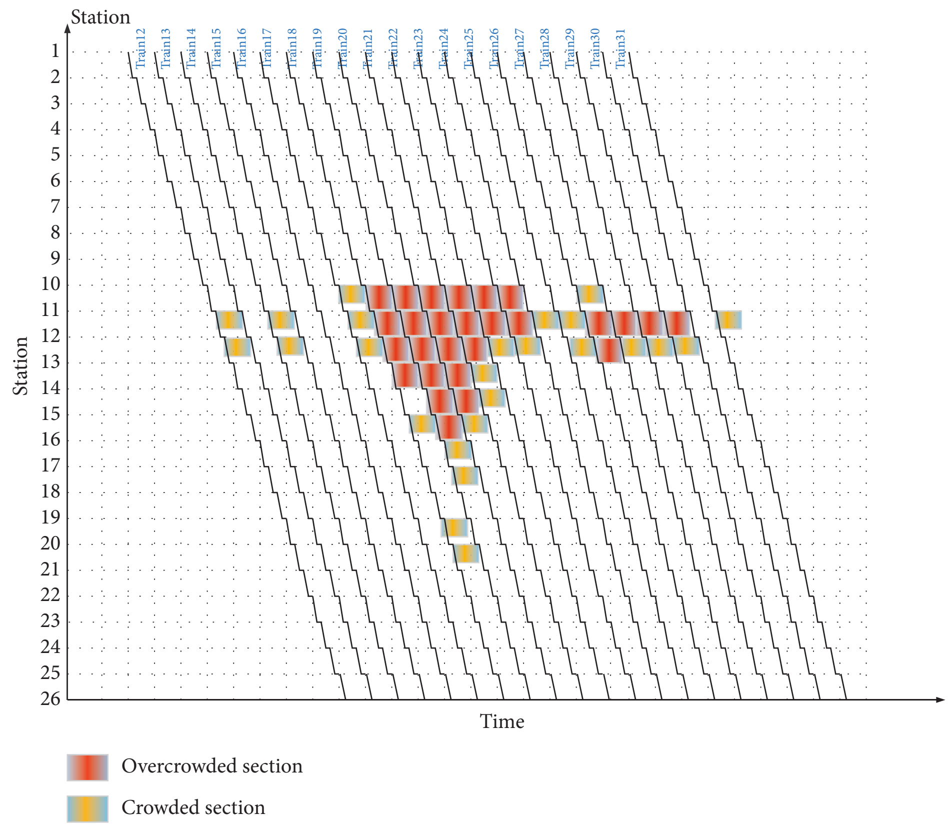
Table 5: Continued.

OD	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26
15															2/2.0	2/5.2	2/5.2	2/3.1	3/2.3	3/2.0	3/2.0	3/2.0	3/2.0	4/3.0	4/3.0
16																2/5.2	2/5.2	2/3.1	2/1.3	3/2.0	3/2.0	3/2.0	3/2.0	3/2.0	4/3.0
17																	2/2.0	2/1.0	2/0.0	2/0.0	3/1.0	3/1.0	3/1.0	3/1.0	3/1.0
18																		2/1.0	2/0.0	2/0.0	2/0.0	3/1.0	3/1.0	3/1.0	3/1.0
19																			2/0.0	2/2.0	2/2.0	2/2.0	3/3.0	3/3.0	3/3.0
20																				2/0.0	2/0.0	2/0.0	2/0.0	3/1.0	3/1.0
21																					2/2.0	2/2.0	2/2.0	2/2.0	3/3.0
22																						2/2.0	2/2.0	2/2.0	2/2.0
23																							2/2.0	2/2.0	2/2.0
24																								2/2.0	2/2.0
25																									2/2.0



(a)

Figure 5: Continued.



(b)

Figure 5: Congestion section distribution before and after the price adjustment. (a) Congestion section distribution before the price adjustment. (b) Congestion section distribution after the price adjustment.

Table 6: Distribution of congestion sections.

Section	Train																			
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
9																1/0				
10				1/0		0/1	1/1	1/1	1/1	1/1	1/1	1/1	1/0	1/0	0/1	1/0				
11	0/1		1/1	1/0		1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/1	1/1	0/1	1/1	1/1	1/1		0/1
12	0/1		1/1	1/0		0/1	1/1	1/1	1/1	1/1	1/1	1/1	1/0	1/1	0/1	1/1	0/1	1/1		
13							1/1	1/1	1/1	1/1	1/0					1/0				
14							1/1	1/1	1/1	1/0										
15						0/1	1/1	1/1	1/0											
16							1/1	1/0												
17							1/1													
18																				
19							1/0													
20							1/0													

Note. 1/1 indicates the coexisting congestion section before and after the price adjustment. 1/0 indicates the unique congestion section before the price adjustment. 0/1 indicates the unique congestion section after the price adjustment.

previous train adjacent to the ideal departure train, and the next train adjacent to the ideal departure train. Next, consider the case involving five alternative routes for passengers: the ideal departure train, the first two trains adjacent to the ideal departure train, and the final two trains adjacent to the ideal departure.

As shown in Figure 7, the passenger flows shown in Figure 7(a) are primarily concentrated in Sections 10–15 on trains 6–12. Meanwhile, the passenger flows shown in Figure 7(b) are primarily concentrated in Sections 10–13 on trains 7–16, where the passenger flow is more evenly shared by the trains and is not as dense as that shown in Figure 7(a).

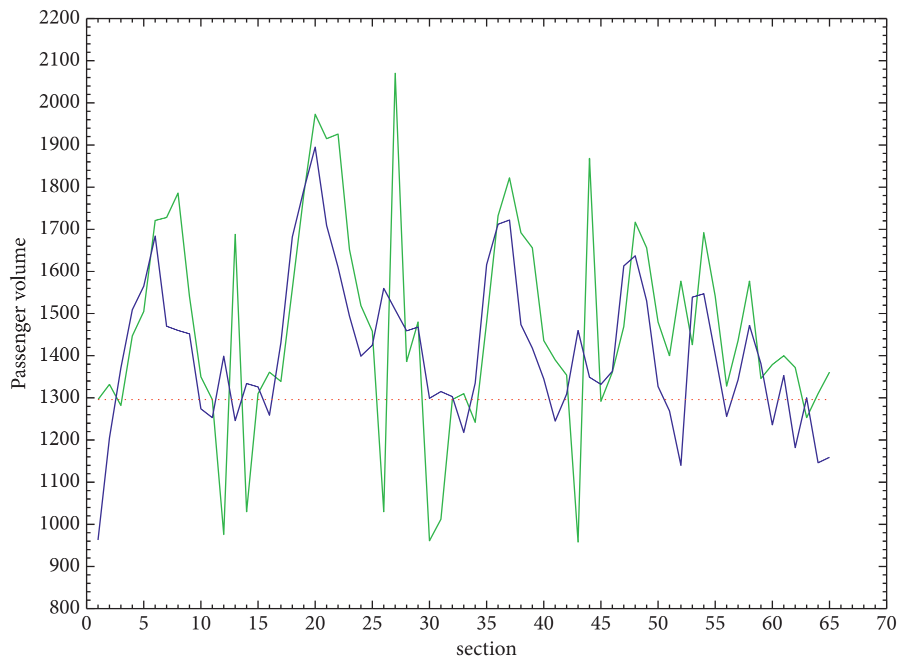


Figure 6: Passenger flow fluctuations in crowded sections.

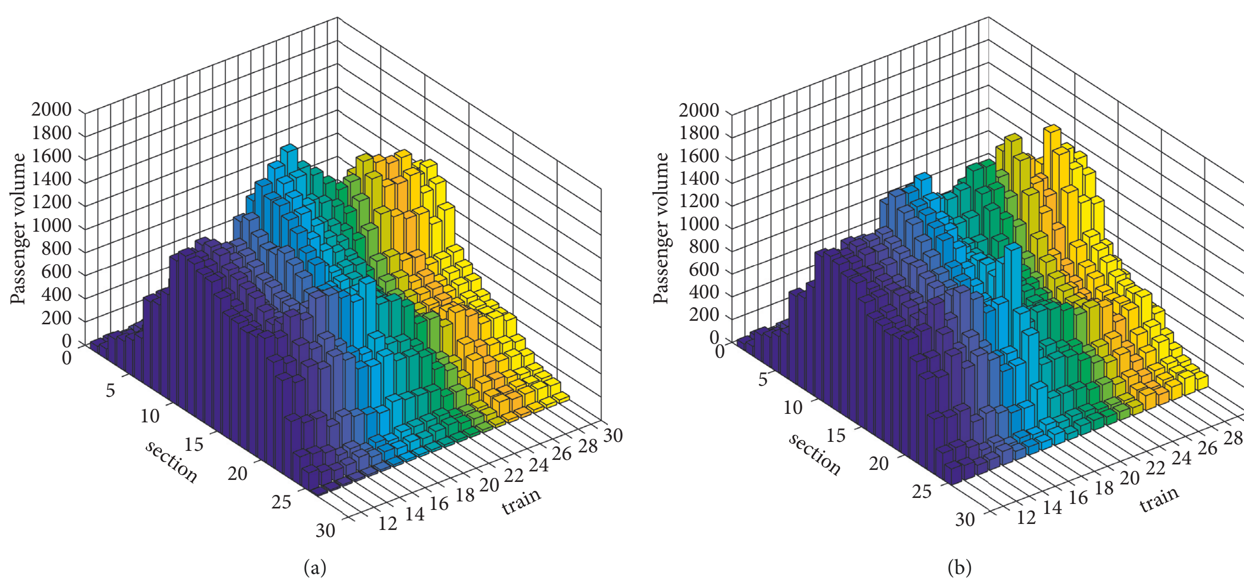


Figure 7: Passenger flow distribution for different RATPs. (a) RATP = 3. (b) RATP = 5.

Figure 8 shows a comparison of the distribution of passenger flows before and after the price adjustment. The solid blue line indicates passenger flow fluctuations in crowded sections under the three alternative routes for passengers, the solid brown line indicates passenger flow fluctuations in crowded sections under the five alternative routes for passengers, and the dotted pink line indicates the number of passengers at a full-load rate of 90%. As shown in the figure, 70 congestion sections exist in the two abovementioned situations. Five alternative routes exist for the passengers instead of three routes: in 34 sections, the number of people decreases, primarily between trains 7 and 11, whereas in 36 sections, the number of people increases, primarily between trains 4–6 and 12–20. It can be observed that when the RATP increases, the distribution becomes balanced.

The value of the full-load rate affects the value of the objective function. To ensure that the objective function is valid, the number of congested sections is reduced by only five to minimize the number of congested sections during peak hours. Next, we discuss the relationship between the full-load rate, NEFR, and the number of congested sections based on Table 7.

In Table 7, Situation 1 indicates that the minimum NEFR is the objective function; we calculated only the

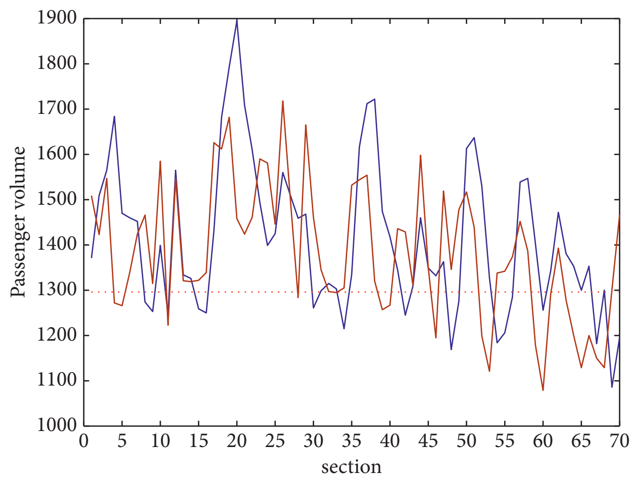


Figure 8: Passenger flow fluctuations for different RATPs.

Table 7: Change of objective function under different full-load rate values.

Flr	Situation 1				Situation 2			
	NEFR		Number of congestion sections		NEFR		Number of congestion sections	
	Before price adjustment	After price adjustment	Before price adjustment	After price adjustment	Before price adjustment	After price adjustment	Before price adjustment	After price adjustment
100	84	62	31	33	84	69	31	23
90	114	95	55	50	114	98	55	45
80	152	139	88	92	152	161	88	77
70	197	190	129	141	197	199	129	118
60	248	244	189	188	248	249	189	167

section where the full-load rate is greater than the specified full-load rate, and the other sections are not discussed. Situation 2 indicates that the minimum number of congested sections is the objective function. It is believed that when congestion in the peak period is high, the optimization objective should be to reduce the number of congested sections. When congestion in the peak period is low, the NEFR can be considered the optimization objective.

7. Conclusion

In this study, a scheme with differentiated pricing across multiple trains was formulated, an integer programming model with NEFR was built, and a simulated annealing algorithm was used to solve the model based on the selection probability; subsequently, the distribution of passenger flow after fare adjustment was obtained.

A method for determining the fare during peak hours using the concept of graphical time difference is proposed herein to reflect the position of the train during peak hours. The results of the calculation example show that the objective function and number of congested sections were reduced, and the passenger flow shifted to the trains at both ends of the study period, achieving the effect of cutting peaks and filling valleys.

In a parametric analysis, we discovered that the trends of the NEFR and congestion sections differed when different full-load rates were used. When the requirements for the two situations were different, the distribution of passenger flow after optimization differed as well. This provides a reference for formulating fare policies during peak periods based on the conditions and demands of urban rail transit.

The method for determining fares in this study is not fully developed and was investigated for only one line. In the future, multiple lines and transfers should be investigated to develop more reasonable section fare strategies and obtain more balanced passenger flow allocation results.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest.

Acknowledgments

The research described in this paper was supported by grants from the National Natural Science Foundation of China (Grant no. 71761023), the National Natural Science Foundation of China (Grant no. 72161023), and "Double-First Class" Major Research Programs, Educational Department of Gansu Province (No. GSSYLXM-04).

Supplementary Materials

Refer to the fares of other trains: (PDF) Fares for each of the 20 trains (researchgate.net) (DOI: http://doi.org/10.13140/RG.2.2.11997.54244). (*Supplementary Materials*)

References

[1] E. Ben-Elia and D. Ettema, "Changing commuters' behavior using rewards: a study of rush-hour avoidance," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 14, no. 5, pp. 354–368, 2011.

[2] E. Ben-Elia and D. Ettema, "Rewarding rush-hour avoidance: a study of commuters' travel behavior," *Transportation Research Part A: Policy and Practice*, vol. 45, no. 7, pp. 567–582, 2011.

[3] Z. Zhang, H. Fujii, and S. Managi, "How does commuting behavior change due to incentives? An empirical study of the Beijing Subway System," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 24, pp. 17–26, 2014.

[4] H. Yang and Y. Tang, "Managing rail transit peak-hour congestion with a fare-reward scheme," *Transportation Research Part B: Methodological*, vol. 110, pp. 122–136, 2018.

[5] Y. Tang and Y. H. O. A. Jiang, "Modeling and optimizing a fare incentive strategy to manage queuing and crowding in mass transit systems," *Transportation Research Part B: Methodological*, vol. 138, pp. 247–267, 2020.

[6] Y. Tang and H. B. J. Y. Yang, "A Pareto-improving and revenue-neutral scheme to manage mass transit congestion with heterogeneous commuters," *Transportation Research Part C: Emerging Technologies*, vol. 113, pp. 245–259, 2020.

[7] X.-S. Lu and X. J. Y. Zhang, "Managing rail transit peak-hour congestion with step fare schemes," *Transportmetrica: Transportation Science*, vol. 16, no. 3, pp. 1490–1511, 2020.

[8] Y. Chen, N. Zheng, and H. L. Vu, "A novel urban congestion pricing scheme considering travel cost perception and level of service," *Transportation Research Part C: Emerging Technologies*, vol. 125, Article ID 103042, 2021.

[9] D. Huang and Z. P. J. Liu, "Optimal transit fare and service frequency of a nonlinear origin-destination based fare structure," *Transportation Research Part E: Logistics and Transportation Review*, vol. 96, pp. 1–19, 2016.

[10] N. Zheng, G. Rérat, and N. Geroliminis, "Time-dependent area-based pricing for multimodal systems with heterogeneous users in an agent-based environment," *Transportation Research Part C: Emerging Technologies*, vol. 62, pp. 133–148, 2016.

[11] X. Wu and J. W. Y. X. Qin, "Collaborative optimization of dynamic pricing and seat allocation for high-speed railways: an empirical study from China," *IEEE Access*, vol. 7, Article ID 139409, 2019.

[12] S. Peer, J. Knockaert, and E. T. Verhoef, "Train commuters' scheduling preferences: e," *Transportation Research Part B: Methodological*, vol. 83, pp. 314–333, 2016.

[13] W. Kou and X. L. Y. Y. Chen, "Urban commuters' valuation of travel time reliability based on stated preference survey: a case study of Beijing," *Transportation Research Part A: Policy and Practice*, vol. 95, pp. 372–380, 2017.

[14] Y. Y. Tseng and E. T. Verhoef, "Value of time by time of day: a stated-preference study," *Transportation Research Part B: Methodological*, vol. 42, no. 7-8, pp. 7-8, 2008.

[15] M. Thorhauge, S. Haustein, and E. Cherchi, "Accounting for the theory of planned behaviour in departure time choice," *Transportation Research Part F: Traffic Psychology and Behaviour*, vol. 38, pp. 94–105, 2016.

[16] D. J. Anupriya, D. J. Graham, D. Hörcher, R. J. Anderson, and P. Bansal, "Quantifying the ex-post causal impact of differential pricing on commuter trip scheduling in Hong Kong," *Transportation Research Part A: Policy and Practice*, vol. 141, pp. 16–34, 2020.

[17] A. Aboudina and B. Abdulhai, "A bi-level distributed approach for optimizing time-dependent congestion pricing in large networks: a simulation-based case study in the Greater Toronto Area," *Transportation Research Part C: Emerging Technologies*, vol. 85, pp. 684–710, 2017.

[18] N. Huan and S. E. W. Hess, "Time-dependent pricing strategies for metro lines considering peak avoidance behaviour of commuters," *Transportmetrica: Transportation Science*, pp. 1–25, 2021.

[19] D. V. Vuuren, "Optimal pricing in railway passenger transport: theory and practice in The Netherlands," *Transport Policy*, vol. 9, no. 2, pp. 95–106, 2002.

[20] D. Johnson and G. Whelan, *Modelling the Impact of Alternative Fare Structures*, Institute of Transport Studies, University of Leeds, Leedes, United Kingdom, 2003.

[21] A. De Palma, M. Kilani, and S. Proost, "Discomfort in mass transit and its implication for scheduling and pricing," *Transportation Research Part B: Methodological*, vol. 71, pp. 1–18, 2015.

[22] F. Zhou and C. Z. R. W. Li, "Fare incentive strategies for managing peak-hour congestion in urban rail transit networks," *Transportmetrica: Transportation Science*, vol. 18, no. 1, pp. 166–187, 2020.

[23] S. Sun and W. Y. Szeto, "Optimal sectional fare and frequency settings for transit networks with elastic demand," *Transportation Research Part B: Methodological*, vol. 127, pp. 147–177, 2019.

[24] H.-J. Huang, "Fares and tolls in a competitive system with transit and highway: the case with two groups of commuters," *Transportation Research Part E: Logistics and Transportation Review*, vol. 36, no. 4, pp. 267–284, 2000.

[25] Y. Li and Y. J. S. Guo, "Impacts of congestion pricing and reward strategies on automobile travelers' morning commute mode shift decisions," *Transportation Research Part A: Policy and Practice*, vol. 125, pp. 72–88, 2019.

[26] M. Lovrić and S. Raveau, "Evaluating off-peak pricing strategies in public transportation with an activity-based approach," *Transportation Research Record: Journal of the Transportation Research Board*, vol. 2544, no. 1, pp. 10–19, 2016.

[27] S. Q. Ni, H. N. Yang, and Q. Peng, "Passenger flow distribution of regional multi-standard rail transit based on passenger route selection," *Journal of Transportation Systems Engineering and Information Technology*, vol. 21, no. 1, pp. 108–115, 2021.

[28] A. Tirachini, D. A. Hensher, and J. M. Rose, "Crowding in public transport systems: effects on users, operation and implications for the estimation of demand," *Transportation Research Part A: Policy and Practice*, vol. 53, pp. 36–52, 2013.

[29] M. Kouwenhoven, "Value of travel time as a function of comfort," *Journal of Choice Modelling*, vol. 28, pp. 97–107, 2018.

[30] J. Shi, L. Yang, J. Yang, and F. Z. Zhou, "Cooperative passenger flow control in an oversaturated metro network with operational risk thresholds," *Transportation Research Part C: Emerging Technologies*, vol. 107, pp. 301–336, 2019.