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*Research Article*

# A Passenger-Oriented Model for Train Rescheduling on an Urban Rail Transit Line considering Train Capacity Constraint

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The major objective of this work is to present a train rescheduling model with train capacity constraint from a passenger-oriented standpoint for a subway line. The model expects to minimize the average generalized delay time (AGDT) of passengers. The generalized delay time is taken into consideration with two aspects: the delay time of alighting passengers and the penalty time of stranded passengers. Based on the abundant automatic fare collection (AFC) system records, the passenger arrival rate and the passenger alighting ratio are introduced to depict the short-term characteristics of passenger flow at each station, which can greatly reduce the computation complexity. In addition, an efficient genetic algorithm with adaptive mutation rate and elite strategy is used to solve the large-scale problem. Finally, Beijing Subway Line 13 is taken as a case study to validate the method. The results show that the proposed model does help neutralize the effect of train delay, with a 9.47% drop in the AGDT in comparison with the train-oriented model.

## 1. Introduction

The train rescheduling problem is one of the most crucial problems in rail transit operation and management. During the course of daily operation, trains are inevitably affected by unexpected accidents or technical problems, which leads to the deviations from the original timetable as well as delays. If dispatchers can not handle it immediately, the delay may propagate to other trains, which will do great harm to the normal operation and disturb passengers' trips seriously. Many researchers devoted themselves to studying the train rescheduling problem, which has become a research focus currently.

In order to achieve the real-time and intelligent train rescheduling, a lot of studies have been carried out in proposing regulation rules, presenting rescheduling models, and designing solution algorithms. Among so many studies, most proposed models were built from a train-oriented point of view with minimizing the delay time of trains, the number of delayed trains or deviations from the original timetable, and so on [1]. Zhou and Zhong [2] studied the train timetabling problem to minimize the total train travel time for single-track railways. A branch-and-bound program with some lower and upper bound heuristics to reduce the solution space was proposed to find the solutions efficiently. D'Ariano et al. [3] modelled the scheduling problem expecting to minimize the deviation from the original timetable with an Alternative Graph model, which was first introduced by Mascis and Pacciarelli [4] for no-store job shop scheduling. They developed a branch-and-bound algorithm which contains implication rules enabling speeding up the computation. Acuna-Agost et al. [5] studied the same problem in [6] and developed an approach named SAPI. This approach was used to reduce the size of the search space of the mixed integer program for rescheduling problems in order to obtain near-optimal solutions in reasonable durations. Šemrov et al. [7] introduced a reinforcement learning method including a learning agent for train rescheduling on a single-track railway. The solutions can be obtained within reasonable computational time. Sato et al. [8] considered that the inconvenience of traveling by train consisted of the traveling time on board, the waiting time at platforms, and the number of transfers. They presented a MIP-based timetable rescheduling formulation to minimize further inconvenience to passengers.

In addition, many researchers focus on heuristic algorithms to accelerate the speed of computation. Meng et al. [9] built a rescheduling model with minimizing the total delay time at the destination and proposed an improved particle swarm algorithm, which was proved to have real-time adjusting ability and high convergence speed. Törnquist Krasemann [10] developed a depth-first greedy algorithm to obtain good-enough schedules quickly in disturbed situations, working as a complement to the previously designed rescheduling approach in Törnquist and Persson [11], which minimized the total final delay of the traffic and the total cost when trains arrived at their final destination or the last stop considered. Dündar and Şahin [12] developed a genetic algorithm for conflict resolutions, which was evaluated against the dispatchers' and the exact solutions. Artificial neural networks were developed to mimic the decision behavior of train dispatchers so as to reproduce dispatchers' conflict resolutions. Kanai et al. [13] developed an algorithm seeking for minimizing passengers' dissatisfaction. The algorithm consisted of both simulation and optimization and tabu search algorithm was used in the optimization part.

To sum up, most researchers conceived the train rescheduling problem from a train-oriented viewpoint, and few works paid attention to passengers' interests. As for this problem in an urban rail transit system, considering the actual characteristics of urban rail transit lines: being shorter in length, high passenger flow volume, and high service frequency, a train rescheduling model for an urban rail transit line should be presented from a passenger-oriented perspective rather than a train-oriented point of view. Currently, during the actual operation process, train rescheduling mainly depends on dispatchers' dispatching orders, which are based on their experience and craftsmanship without intelligent decision support. But, with passengers' rising requirements for the level of service (LOS) of a rail transit system, train rescheduling should be more precise and scientific, which is what this work is expected to do. The main contributions of this work are summarized as follows:

(1) A train rescheduling model is proposed from a passenger-oriented viewpoint. In this model, the train capacity and stranded passengers are taken into consideration, which make the model more practicable. In addition, the prediction of stranded passengers will remind the corresponding stations to take timely measures of passenger flow control.

(2) The passenger arrival rate and the passenger alighting ratio of each station are introduced to capture the different short-term passenger flow characteristics of each station [14]. Then, the number of arrival passengers and the number of alighting passengers at each station can be simply obtained by computation, which can greatly reduce the solution time and improve the model's applicability.

(3) An efficient genetic algorithm with adaptive mutation rate and elite strategy is designed to obtain a good-enough solution of a practical problem within acceptable duration, which is a key factor for real-time application.

(4) A real-world case study of Beijing Subway Line 13 is carried out to test the method proposed in this work. The results show that the performance of the passenger-oriented model is much better than the train-oriented model's.

## 2. Train Rescheduling Model

A passenger-oriented model for train rescheduling is presented in this part. For presentation simplicity, the necessary symbols and notations are listed as follows:

$S$: the station set of an urban rail transit line, $S = (s \mid s = 1, 2, \ldots, m)$, where $m$ is the total number of stations on the line.

$V$: the train set of an urban rail transit line, $V = (v \mid v = 1, 2, \ldots, n)$, where $n$ is the total number of trains that need to be rescheduled.

$P_{v,s}$: the number of passengers on board when train $v$ arrives at station $s$.

$P^A_{v,s}$: the number of alighting passengers during the dwell time of train $v$ at station $s$.

$P^B_{v,s}$: the number of boarding passengers during the dwell time of train $v$ at station $s$.

$P^C_{v,s}$: the number of arrival passengers at station $s$ during the departure headway between train $v-1$ and train $v$ at station $s$.

$P^S_{v,s}$: the number of stranded passengers after train $v$ departing from station $s$.

$T^a_{v,s}$: the actual arrival time of train $v$ at station $s$.

$\overline{T}^a_{v,s}$: the planned arrival time of train $v$ at station $s$.

$T^d_{v,s}$: the actual departure time of train $v$ at station $s$.

$\overline{T}^d_{v,s}$: the planned departure time of train $v$ at station $s$.

$T^R_{s,s+1}$: the minimum running time for trains from station $s$ to station $s+1$.

$T^{\text{stop}}_s$: the minimum dwell time for trains at station $s$.

$C_T$: the capacity of an urban rail transit train.

*2.1. Short-Term Characteristics of Passenger Flow.* In an urban rail transit system, the passenger flow characteristics of a station can be captured by abundant historical AFC records. Each AFC record includes the accurate time of a passenger entering and leaving a station. As for transfer passengers, the accurate time of entering and leaving their transfer stations can be obtained by an assignment model [15, 16]. In the long term (e.g., a day), there are usually obvious changes in the passenger flow characteristics of a station (e.g., peak hour and non-peak hour). But, in the short term (e.g., an hour), a statistical method can be easily used to capture the passenger flow characteristics of a station [14]. The average time for passengers walking from turnstiles to the platform can be obtained by a practical survey. Then, the time of the passenger reaching the platform equals the time of a passenger entering

a station plus the average walking time, and we can count the number of passengers who reached the platform during a period of time (e.g., 8:30 am to 9:30 am).

In order to depict the passenger flow characteristics of a station, the arrival rate $\lambda_s$ is introduced to indicate the number of passengers reaching the platform at station $s$ within one minute. Meanwhile, the alighting ratio $\theta_s$ is introduced to represent the proportion of alighting passengers ($P^A_{v,s}$) to passengers on board ($P_{v,s}$). With the introduction of the two parameters, the computation complexity can be reduced greatly.

*2.2. Mathematical Relationship between Different Kinds of Passengers.* In this work, passengers fall into five categories: passenger on board ($P_{v,s}$), alighting passenger ($P^A_{v,s}$), boarding passenger ($P^B_{v,s}$), arrival passenger ($P^C_{v,s}$), and stranded passenger ($P^S_{v,s}$). The mathematical expressions of the five kinds of passengers are as follows. Equations (3) and (5) indicate the constraints of train capacity. The number of stranded passengers can be obtained by (5).

(1) Passenger on board ($P_{v,s}$) is

$$P_{v,s+1} = P_{v,s} - P^A_{v,s} + P^B_{v,s}. \tag{1}$$

(2) Alighting passenger ($P^A_{v,s}$) is

$$P^A_{v,s} = P_{v,s} \times \theta_s. \tag{2}$$

(3) Boarding passenger ($P^B_{v,s}$) is

$$P^B_{v,s} = \min \quad \left\{C_T - \left(P_{v,s} - P^A_{v,s}\right), P^C_{v,s} + P^S_{v-1,s}\right\}. \tag{3}$$

(4) Arrival passenger ($P^C_{v,s}$) is

$$P^C_{v,s} = \lambda_s \times \frac{\left(T^d_{v,s} - T^d_{v-1,s}\right)}{60}. \tag{4}$$

(5) Stranded passenger ($P^S_{v,s}$) is

$$P^S_{v,s} = \max \quad \left\{0, P^C_{v,s} + P^S_{v-1,s} - \left(C_T - \left(P_{v,s} - P^A_{v,s}\right)\right)\right\}. \tag{5}$$

*2.3. Model Constraints.* The model is mainly subject to some operational requirements to ensure the safety of the operation and the feasibility of the timetable optimized by the proposed model.

*2.3.1. Section Running Time.* Under the limitation of traction and brake performance of trains, the length of each section, safety requirements, and so on, the actual running time of trains in each section must be longer than the minimum running time [17]; see

$$T^a_{v,s+1} - T^d_{v,s} \geq T^R_{s,s+1}. \tag{6}$$

*2.3.2. Dwell Time.* Similar to section running time, the actual dwell time of trains at each section must be longer than the minimum dwell time [18]; see (7). It should be pointed out that dwell times are affected by the number of alighting passengers and boarding passengers, which may extend dwell times. Meanwhile, in the rescheduling process, station staff will guide passengers alighting or boarding a train quickly to shorten dwell times and to recover the timetable.

$$T^d_{v,s} - T^a_{v,s} \geq T^{\text{stop}}_s. \tag{7}$$

*2.3.3. Headway.* Regarding all trains running on the subway line, they should meet the requirements of the minimum arrival and departure headway of the line, as shown in (8) and (9), where $H_{\min}$ represents the minimum headway.

$$T^a_{v+1,s} - T^a_{v,s} \geq H_{\min} \tag{8}$$

$$T^d_{v+1,s} - T^d_{v,s} \geq H_{\min}. \tag{9}$$

*2.3.4. Variable.* Obviously, the rescheduled timetable cannot be earlier than the planned timetable and all variables in this practical problem must be integers, as shown in formulas (10), (11), and (12), where $N$ represents the set of nonnegative integers.

$$T^a_{v,s} \geq \overline{T}^a_{v,s}, \quad T^a_{v,s} \in N \tag{10}$$

$$T^d_{v,s} \geq \overline{T}^d_{v,s}, \quad T^d_{v,s} \in N \tag{11}$$

$$P_{v,s}, P^A_{v,s}, P^B_{v,s}, P^C_{v,s}, P^S_{v,s} \in N. \tag{12}$$

*2.4. Train Rescheduling Objective.* For most previous studies about train rescheduling problem, their optimal objectives tend to be designed from a train-oriented point of view. For instance, a train-oriented objective can be calculated by (13). Formula (13) and constraints (6)–(11) constitute a complete and train-oriented model of train rescheduling.

$$\min \quad \sum_{v\in V}\sum_{s\in S}\left(T^a_{v,s} - \overline{T}^a_{v,s}\right). \tag{13}$$

However, in this work, the train rescheduling problem is considered from a passenger-oriented perspective with two aspects: the delay time of alighting passengers and the penalty time of stranded passengers. The delay time of each alighting passenger equals the delay time of the train arriving at his or her destination station. The total delay time of alighting passengers can be calculated by

$$\sum_{v\in V}\sum_{s\in S}\left(P^A_{v,s} \times \left(T^a_{v,s} - \overline{T}^a_{v,s}\right)\right). \tag{14}$$

As for stranded passengers, they have to spend extra time, at least a headway, waiting for the next train. The penalty factor $T_{\text{pen}}$ is introduced to depict this situation. The total penalty time of stranded passengers can be calculated by (15). As a result, the total generalized delay time of passengers equals (14) plus the following equation:

$$\sum_{v\in V}\sum_{s\in S}\left(P^S_{v,s} \times T_{\text{pen}}\right). \tag{15}$$

Consequently, the passenger-oriented objective of minimizing the AGDT of passengers is presented by (16), where $\sum_{v\in V}\sum_{s\in S}P^{C}_{v,s}$ represents the total number of passengers who enter the subway line and look for service. The complete passenger-oriented model for train rescheduling is as follows:

$$\min \quad \frac{\sum_{v\in V}\sum_{s\in S}\left(P^{A}_{v,s}\times\left(T^{a}_{v,s}-\overline{T}^{a}_{v,s}\right)+P^{S}_{v,s}\times T_{\text{pen}}\right)}{\sum_{v\in V}\sum_{s\in S}P^{C}_{v,s}} \tag{16}$$

$$\begin{aligned}
\text{Subject to:}\quad & T^{a}_{v,s+1}-T^{d}_{v,s}\geq T^{R}_{s,s+1}\\
& T^{d}_{v,s}-T^{a}_{v,s}\geq T^{\text{stop}}_{s}\\
& T^{a}_{v+1,s}-T^{a}_{v,s}\geq H_{\min}\\
& T^{d}_{v+1,s}-T^{d}_{v,s}\geq H_{\min}\\
& P_{v,s+1}=P_{v,s}-P^{A}_{v,s}+P^{B}_{v,s}\\
& P^{A}_{v,s}=P_{v,s}\times\theta_{s}\\
& P^{B}_{v,s}=\min\left\{C_{T}-\left(P_{v,s}-P^{A}_{v,s}\right),P^{C}_{v,s}+P^{S}_{v-1,s}\right\}\\
& P^{C}_{v,s}=\lambda_{s}\times\frac{\left(T^{d}_{v,s}-T^{d}_{v-1,s}\right)}{60}\\
& P^{S}_{v,s}=\max\left\{0,P^{C}_{v,s}+P^{S}_{v-1,s}-\left(C_{T}-\left(P_{v,s}-P^{A}_{v,s}\right)\right)\right\}\\
& T^{a}_{v,s}\geq\overline{T}^{a}_{v,s},\quad T^{a}_{v,s}\in N\\
& T^{d}_{v,s}\geq\overline{T}^{d}_{v,s},\quad T^{d}_{v,s}\in N\\
& P_{v,s},P^{A}_{v,s},P^{B}_{v,s},P^{C}_{v,s},P^{S}_{v,s}\in N.
\end{aligned} \tag{17}$$

## 3. Solution Algorithm

The train rescheduling problem is considered as one of the most intractable problems in the operation and management of rail transit system [19]. With the rising scale of the problem, exact algorithms usually take a very long time to output the optimal solution, which can not meet the real-time requirement for the actual operation. Fan et al. [20] compared eight different algorithms and found that simple scenarios can be managed efficiently using exact algorithms. But, for complex scenarios, heuristic algorithms are more appropriate, such as ant colony optimization and genetic algorithm. In this work, an efficient genetic algorithm is designed to solve this problem.

*3.1. Chromosome Structure.* A chromosome represents a solution in the genetic algorithm. Each train's actual arrival time $T^{a}_{v,s}$ and departure time $T^{d}_{v,s}$ are chosen as genes to form the chromosome. A chromosome is divided into two parts and each part consists of $n$ (the total number of rescheduled trains) subparts. The subpart sequencing is according to the serial number of trains, as shown in Figure 1.

Each number in a rectangle in Figure 1 represents the serial number of a station. For example, the number in the red circle is $s$, which means that the gene in this position is the actual arrival time of train $v$ at station $s$. Similarly, the number in the pink circle is $s$ too, which means that the gene in this position is the actual departure time of train $v$ at station $s$. For the purpose of calculation simplification, all genes are encoded by real type method [21].

*3.2. Fitness Function.* The fitness of an individual in the population represents that the individual is good or bad. Meanwhile, it determines the possibility that the individual can be selected to generate the new individual. The passenger-oriented model is a model with a minimizing objective, so the objective function with some relatively minor modifications is the fitness function; see (18), where $M$ is a big enough positive integer.

$$F=M-\frac{\sum_{v\in V}\sum_{s\in S}\left(P^{A}_{v,s}\times\left(T^{a}_{v,s}-\overline{T}^{a}_{v,s}\right)+P^{S}_{v,s}\times T_{\text{pen}}\right)}{\sum_{v\in V}\sum_{s\in S}P^{C}_{v,s}}. \tag{18}$$

The other main operations in the genetic algorithm are summarized as follows. The method of roulette is adopted

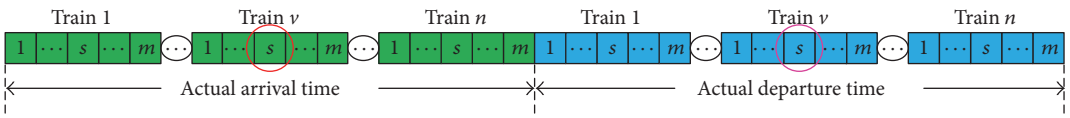


Figure 1: Chromosome representation.

in selecting operation and the single-point crossover is used in crossover operation. As for mutation operation, the value of each gene on the chromosome can change within the determined lower and upper bound according to the adaptive mutation rate, which can be determined by (19). When the number of iterations reaches the maximum value, the algorithm is terminated and outputs the optimal solution [22].

$$R_i^m = R_{\min}^m + \left(R_{\max}^m - R_{\min}^m\right) \times \frac{\left(F_i - F_{\min}\right)}{\left(F_{\max} - F_{\min}\right)}, \qquad (19)$$

where $R_i^m$ represents the mutation rate of individual $i$. $F_i$ represents the fitness value of individual $i$. $R_{\max}^m$ and $R_{\min}^m$ indicate the maximum and minimum mutation rate, respectively, which are determined in advance. $F_{\max}$ and $F_{\min}$ indicate the maximum and minimum fitness value in the current population, respectively.

*3.3. Algorithm Procedure.* The detailed algorithmic steps are depicted as follows.

*Step 1* (initialization). This step is as follows:

(1) Set the initial parameters: population size $N$, initial generation $g = 0$, the maximum number of generations $G$, crossover rate $R^c$, and mutation rates $R_{\max}^m$ and $R_{\min}^m$.

(2) Input the initial data: $\overline{T}_{v,s}^a$, $\overline{T}_{v,s}^d$, $T_{s,s+1}^R$, $T_s^{\text{stop}}$, $C_T$, $\lambda_s$, $\theta_s$, and $H_{\min}$.

(3) Input the serial number of the delayed train, the delay position, and the delay time.

(4) Generate the initial population $P(g)$ according to the given upper and lower bound of each variable and check whether each individual is feasible. If an individual is infeasible, then delete this individual and reproduce a new individual which meets all constraints.

(5) Calculate the fitness $F_i$ of each individual in the initial population $P(g)$.

*Step 2* (selection, crossover, and mutation). This step is as follows:

(1) Calculate the selecting probability $p_i = F_i / \sum_{i=1}^N F_j$ of each individual and the method of roulette is adopted to select individuals in $P(g)$ to form the new population $NP(g)$ according to the selecting possibility $p_i$.

(2) Make crossover operation in $NP(g)$ according to the crossover rate $R^c$.

(3) Make mutation operation in $NP(g)$ according to the adaptive mutation rate $R_i^m$ calculated by (19).

(4) Calculate the fitness $NF_i$ of each individual in $NP(g)$.

(5) Select individuals in $NP(g)$ based on $NF_i$ to replace those worse individuals in $P(g)$ and reproduce the new $P(g)$.

(6) Calculate the objective value of (16) and the fitness $F_i$ of each individual in the new $P(g)$.

(7) Elite strategy: replace the worst individual with the best individual in $P(g)$.

*Step 3* (stop or not). This step is as follows:

(1) Update $g = g + 1$.

(2) If $g = G$, the algorithm is terminated and outputs the optimal solution. Otherwise, return to Step 2(1).

## 4. Case Study

*4.1. Line Description.* The performance of the passenger-oriented model for train rescheduling and the genetic algorithm is tested by a real-world case of Beijing Subway Line 13. Beijing Subway Line 13 is a semiloop line with 16 stations in total, as shown in Figure 2. The down-direction of Line 13 starts from XiZhiMen station and terminates at DongZhiMen station, and the up-direction is opposite. The total length of this line is 40.9 km, and the train in operation has a capacity of 1356 passengers. The length and the minimum train running time of each section are given in Table 1.

*4.2. Train Delay Scenario and Optimization.* According to the planned timetable of Line 13 down-direction, the planned train diagram for trains whose departure times are between 8:30 am and 9:30 am is obtained in Figure 3. There are 11 trains in operation in total and for the 6th train it is assumed that its departure time at Huilongguan station is late for five minutes due to some accidents.

Based on abundant historical AFC records of Beijing Subway Line 13, the passenger arrival rate $\lambda_s$ and the passenger alighting ratio $\theta_s$ of Line 13 down-direction are obtained by statistical methods, which are listed in Table 2.

Using the passenger-oriented model and the genetic algorithm proposed in this work, the practical problem is solved within 30 seconds by programing in MATLAB R2014b on an Intel Pentium dual-core CPU 3.1 GHz and 8 GB RAM desktop computer. Meanwhile, the problem is also solved by the train-oriented model mentioned above, using Lingo. The necessary parameters are given in Table 3. Table 4 shows the detailed solution results. Compared to the train-oriented model, there is a 9.47% decrease in the AGDT by the passenger-oriented

Table 1: The length and the minimum train running time of each section.

| Section | Length/m | $T^R_{s,s+1}$/s | Section | Length/m | $T^R_{s,s+1}$/s |
|---|---|---|---|---|---|
| Xizhimen–Dazhongsi | 2839 | 215 | Huoying–Lishuiqiao | 4785 | 275 |
| Dazhongsi–Zhichunlu | 1206 | 95 | Lishuiqiao–Beiyuan | 2272 | 135 |
| Zhichunlu–Wudaokou | 1829 | 125 | Beiyuan–Wangjingxi | 6720 | 385 |
| Wudaokou–Shangdi | 4866 | 285 | Wangjingxi–Shaoyaoju | 2152 | 135 |
| Shangdi–Xierqi | 2538 | 185 | Shaoyaoju–Guangximen | 1110 | 85 |
| Xierqi–Longze | 3623 | 265 | Guangximen–Liufang | 1135 | 85 |
| Longze–Huilongguan | 1423 | 95 | Liufang–Dongzhimen | 1769 | 125 |
| Huilongguan–Huoying | 2110 | 135 | | | |

Table 2: $\lambda_s$ and $\theta_s$ of each station.

| Station | $\lambda_s$ (persons/min) | $\theta_s$ | Station | $\lambda_s$ (persons/min) | $\theta_s$ |
|---|---|---|---|---|---|
| Xizhimen | 166 | 0 | Huoying | 38 | 0.25 |
| Dazhongsi | 93 | 0.01 | Lishuiqiao | 32 | 0.23 |
| Zhichunlu | 95 | 0.03 | Beiyuan | 12 | 0.08 |
| Wudaokou | 132 | 0.06 | Wangjingxi | 9 | 0.27 |
| Shangdi | 38 | 0.13 | Shaoyaoju | 11 | 0.13 |
| Xierqi | 130 | 0.19 | Guangximen | 6 | 0.13 |
| Longze | 50 | 0.24 | Liufang | 3 | 0.3 |
| Huilongguan | 50 | 0.29 | Dongzhimen | 0 | 1 |

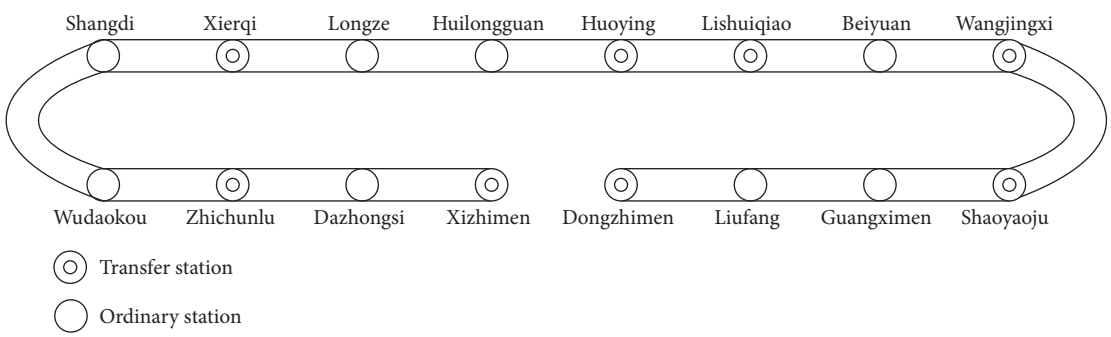


Figure 2: Beijing Subway Line 13.

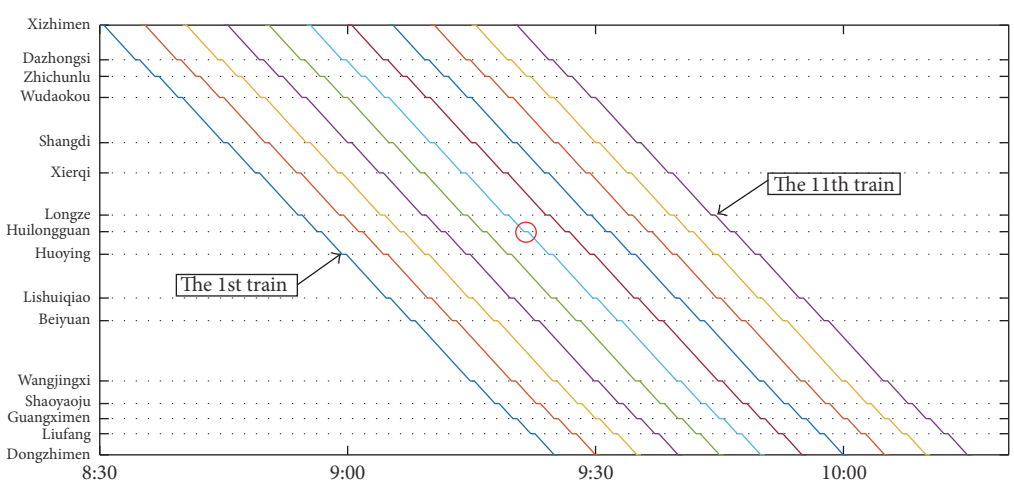


Figure 3: The planned train diagram of Beijing Subway Line 13 (8:30 am to 9:30 am).

Table 3: Necessary parameters.

| Parameter | Value |
|---|---|
| $N$ | 40 |
| $G$ | 800 |
| $R^c$ | 0.8 |
| $R^m_{\max}$ | 0.05 |
| $R^m_{\min}$ | 0.01 |
| $T_s^{\text{stop}}$/s | 20 |
| $C_T$/person | 1356 |
| $H_{\min}$/s | 160 |
| $T_{\text{pen}}$/s | 500 |

Table 4: Solution results.

| Model | AGDT/s |
|---|---|
| The train-oriented model | 65.07 |
| The passenger-oriented model | 58.91 |
| Improvement | −9.47% |

model. The proposed model has obviously optimal effects on passengers' generalized delay time. The convergence curve of the genetic algorithm is shown in Figure 4.

*4.3. Train Capacity and Stranded Passengers.* The highlight of this work is that the train capacity is taken into consideration. With this constraint, the number of passengers on board ($P_{v,s}$) cannot be greater than the train capacity. In this experiment, the passenger-oriented model with train capacity constraint is compared with the passenger-oriented model without train capacity constraint. Figure 5 shows the number of passengers on board of the 6th train (the delayed train) with or without the constraint of train capacity. Obviously, without the constraint of train capacity, there are more passengers on board compared to the capacity when the train arrives at Shangdi station and Longze station, which is inconsistent with the reality.

In addition, with the constraint of train capacity, there is a possibility that some passengers can not board the arriving train. In this experiment, it is found that there are stranded passengers ($P^S_{v,s}$) at Wudaokou station and Xierqi station, and the number of stranded passengers is increasing as trains go on, which is shown in Figure 6. The two stations are both of high arrival rate of passengers in practice. In case that there are too many passengers stranded in a station, which may lead to some unexpected incidents, efficient measures must be taken to control the flow of arrival passengers as well as reducing the arrival rate, in particular in Xierqi station, which is a key transfer station in reality. If control measures are taken at Xierqi station, for example, the arrival rate of passengers becomes 90% of the original; Figure 7 shows the drop in the number of stranded passengers at Xierqi station, with a 52.44% decrease on average.

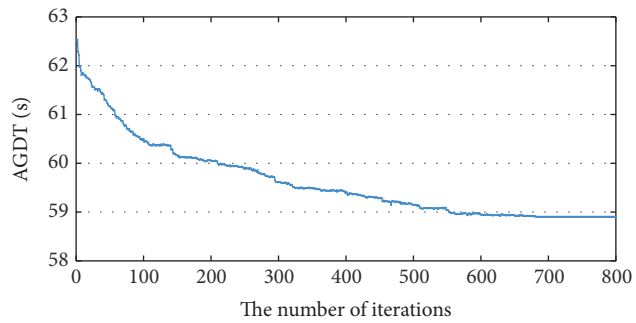


Figure 4: The convergence curve of the genetic algorithm.

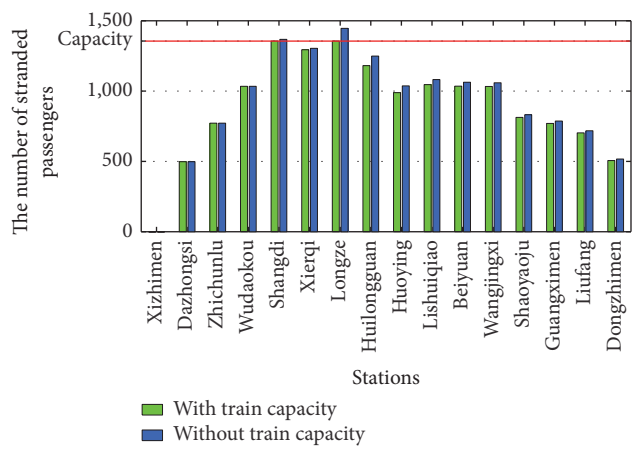


Figure 5: The number of passengers on board of the 6th train.

## 5. Conclusions

The train rescheduling problem is always a hot problem in rail transit operation and management. With passengers' rising requirements for the LOS of an urban rail transit system, a passenger-oriented model is much better than a train-oriented model. In this work, a passenger-oriented model with train capacity constraint is presented to minimize the AGDT of passengers, which consists of the delay time of alighting passengers and the penalty time of stranded passengers. In order to meet the real-time requirement, an efficient genetic algorithm is proposed to solve the practical and complex problem. Finally, the case study of Beijing Subway Line 13 is carried out to verify the method proposed in this work. The results show the following:

(1) Compared to the train-oriented model, the passenger-oriented model has obviously optimal effects on the generalized delay time of passengers, with a 9.47% decrease in the AGDT.

(2) In comparison with the passenger-oriented model without the constraint of train capacity, the model with train capacity constraint is more corresponding to the reality and the number of passengers on board cannot be greater than the train capacity.

(3) With the constraint of train capacity, the number of stranded passengers can be counted by the proposed

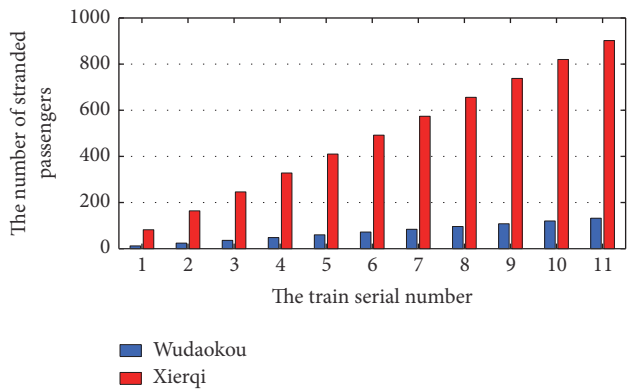


Figure 6: The number of stranded passengers at Wudaokou station and Xierqi station.

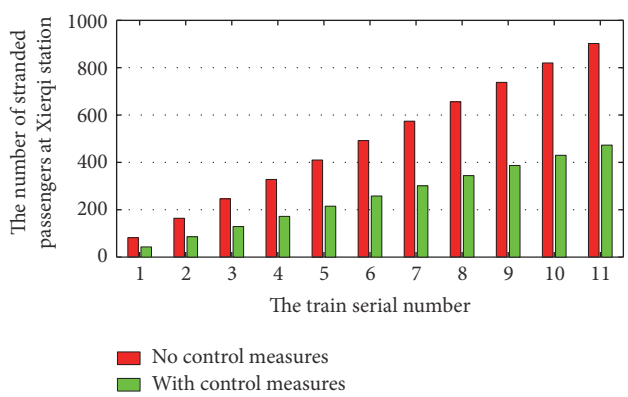


Figure 7: The changes in the number of stranded passengers at Xierqi station.

model so that the stations with increasing number of stranded passengers can be detected. Then, the corresponding stations are able to take preventive measures in time.

## Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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