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Artificial Intelligence Assisted Intelligent Adjustment Method for Urban Rail Transit Train Operation

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Abstract. The operation of intercity rail transit has greatly relieved the pressure of urban traffic. In order to improve the operation quality and passenger carrying capacity, the scheduling strategy of urban rail needs to be timely adjusted according to the passenger flow and other disturbing factors, especially the traffic control problems brought by the outbreak of the epidemic. In this paper, according to the epidemic situation and the characteristics of peak passenger flow in the morning and evening, an optimization model is designed to minimize the travel cost of passengers and the daily cost of the urban rail operation company. The optimal solution of the model is found through the reinforcement learning algorithm. Finally, based on the parameters of Shijiazhuang Metro, the optimal train scheduling scheme is obtained through simulation, which verifies the effectiveness of the research method in this paper.

Keywords: train operation plan, reinforcement, q-learning

1 Introduction

The primary purpose of formulating subway operation plans is to meet the current passenger flow volume of the city. Therefore, dynamically and intelligently adjusting subway operation plans for different passenger flows can maximize the automation and intelligence level of train scheduling, and improve the efficiency of railway transportation and operation services. Since 2019, "COVID-19" has had a huge impact on people's travel. In the case of an outbreak, full consideration should be given to the impact of the outbreak on passenger flow, and various measures should be taken to meet the travel needs of passengers in the case of an outbreak.

(1) Design an algorithm optimization model with the goal of minimizing the comprehensive objective of passenger travel costs and enterprise operating costs, and consider various influencing factors as constraints to obtain the most reasonable optimization model.

(2) By combining the train operation environment with Q-learning, and through algorithm simulation and offline training, a real-time scheduling strategy that dynamically adjusts for the epidemic is obtained. Random search algorithms are used to improve convergence speed and avoid falling into local optima.

The second chapter mainly studies and compares the relevant research results of current scholars to determine the direction of this article. The third chapter designs and completes an optimization model based on the train operation status and factors that affect train operation. The fourth chapter implements model-free reinforcement learning algorithm to solve the optimal value. The fifth chapter verifies the effectiveness of the algorithm using the Shijiazhuang subway line and proposes the optimal adjustment plan in a real case. The sixth chapter is the conclusion part.

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2 Related Work

Regarding the dynamic adjustment of urban rail transit, relevant scholars have conducted relevant research. Krisanarach Nitisiri uses an improved genetic algorithm to solve the scheduling problem of urban trains, which can obtain the minimum waiting time for passengers and the minimum time for scheduling adjustment. However, it considers fewer model constraints [1]. Pengli Mo proposes an optimization model based on service quality and operating costs to address the current train scheduling problem, in order to meet the asymmetric demands of train operation direction and time changes, which is of reference significance [2]. Altazin Estelle adopts an iterative method that combines optimization and simulation, while considering multiple objectives of system performance and passenger service quality. The model solving process lacks intelligent means [3]. Rongsheng Wang et al. selected an improved variant of the elite preservation genetic algorithm to enhance the application of permutation coding and heuristic population initialization in response to station lockdowns caused by unexpected events, which improved the algorithm performance [4]. Xiaozhao Zhou considered the outage strategy of the intercity train operation plan adjustment bi level programming model, and designed a complete solution algorithm based on logical self mapping and variable scale chaotic Firefly algorithm algorithm [5]. Xuelei Meng analyzed the outbreak of the COVID-19, designed the calculation method of train arrival tracking interval and station departure time under the impact of the epidemic, and obtained the train operation adjustment method under the condition of sudden infectious epidemic [6].

3 Establishment and Solution of Optimization Model

As shown in Fig. 1, a certain urban rail transit line has a total of N stations, with a downward direction from station N+1 to station 2N, and an upward direction from station N+1 to station 2N. The distribution of passenger flow sections in general urban rail transit is uneven, and it is assumed to adopt a paired bidirectional operation scheme. In the figure, j and j’ represent the train numbers in the bidirectional passenger flow direction, respectively.

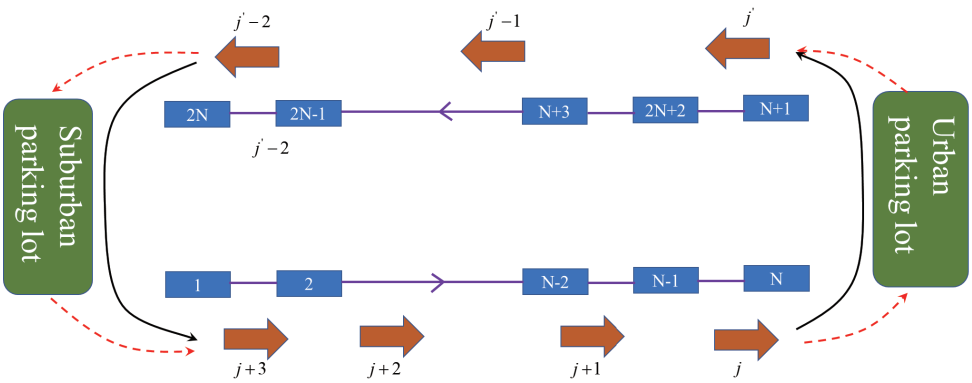


Fig. 1. Schematic diagram of train operation plan

3.1 Model Assumption

Basic assumption:

(1) All passengers choose to take the direct train, and queue up when the number of waiting passengers is large.

(2) Passengers shall not have secondary detention.

(3) The operation mode of the Train bottom is not fixed, and the connection is carried out according to the principle of proximity.

(4) Organize express trains at major stations in non-main passenger flow directions without considering the overrunning of fast and slow trains.

(5) Interval running time, stop time and start-stop additional time are all fixed.

(6) Trains started at the beginning and end of the study period [7].

3.2 Parameter and Variable Definition

The model parameters during train operation are shown in Table 1, the intermediate variables are shown in Table 2, and the decision variables are shown in Table 3.

Table 1. Model parameter table

Parameter	Definition and description	Parameter	Definition and description
$[0,T]$	Train study period	J_ρ	Train assembly in direction ρ during the period
K	Train capacity	S_ρ	Meet at the ρ station
J	Collection of running trains in the study period	J^*	Express assembly
S	Station assembly	L	A collection of alternative stopping plans for the express train
s,n	Station number	l	Stop plan serial number
ρ	Passenger flow direction variable, the value is 1 and 2, depending on the direction of passenger flow	δ_l^s	If the train stops at station s under the first stopping mode l, the value is 1; otherwise, it is 0
τ_s^P	The stopping time of the train at Station s	I_{dt}, I_{da}, I_{ta}	Time between sending, sending and arriving
τ^A	Extra time for starting and stopping trains	μ^W, μ^V	The cost per unit of passenger time spent waiting and riding
$\tau_{s,s+1}^r$	$[s,s+1]$ Pure running time	m^n	Unit operating cost of train
$\tau_\rho^{R,\max}$	The maximum and minimum reentry continuous time of the terminal in direction	m^r, m^o	Unit cost of vehicle bottom reentry and entry section
m_ρ	The number of cars under ρ direction can be used	M_T	Travel cost
λ_{sk}	Passenger arrival rate of OD pairs from stations s to k	M_O	Train operating cost
$I_{\max}, I_{\min}$	Maximum and minimum departure time intervals		

Table 2. Intermediate variable

Parameter	Definition and description	Parameter	Definition and description
$t^a_{j,s}, t^d_{j,s}$	Are respectively the arrival time and departure time of train *j* at Station *s*	$t^w_{j,\rho}, t^v_{j,\rho}$	The waiting time of passengers waiting for train j in direction ρ and the total time of passengers waiting to board train j
y^s_j	Train *j* stops at station *s* as 1, otherwise as 0	$a_{j,N+1}$	If there is a replacement train *j* of the opposite train at the departure station (station *N + 1*) in the direction of the main passenger flow, the value is 0; otherwise, it is 1
$Q^a_{j,sn}$	The number of passengers waiting for train j and the number of stranded passengers waiting for train j	Y	Train issuing frequency
$Q^b_{j,sn}$	Is the number of passengers on board train j when OD pairs between stations *s* and *n*	$\beta_{j,2N}$	If there is train *j* in the main passenger flow direction terminus (station *2N*), the value is 0; otherwise, the value is 1
$Q^v_{j,s}, Q^g_{j,n}$	The number of passengers when train j leaves Station s and the number of passengers when train j disembarks at Station n.	$\gamma_{j,1}$	If there is a continuation train of opposite train *j* at the departure station (station *1*) in the direction of non-main passenger flow, the value is 0; otherwise, it is 1
$A^\tau_{j,s}$	Train residual capacity when train *j* leaves Station *s*	$\eta_{j,k}$	The value is 0 if there is train *j* replacing the opposite train at the terminal (station *k*) in the direction of non-main passenger flow; otherwise, the value is 1

Table 3. Intermediate variable

Parameter	Definition and description	Parameter	Definition and description
k_ρ	Number of rows and columns in the ρ direction	T^d_j	Train *j* departure time
ζ	Ratio of fast and slow trains in passenger flow direction	x^l_j	If express *j* chooses the *l* stopping mode, the value is 1; otherwise, the value is 0

3.3 Objective Function

The objective function includes the total travel cost of passengers and the operating cost of urban rail company, and the optimization result is the minimum objective function. The objective function is expressed as:

$$W = \min(M_T + M_O). \quad \textbf{(1)}$$

The total passenger travel cost is the product of the unit time cost and the total passenger travel time, and the total passenger travel time is composed of passenger waiting time and passenger time on the train:

$$M_T = \mu^W \sum_{\rho=1}^{2} \sum_{j=1}^{k_\rho} t^W_{j,\rho} + \mu^V \sum_{\rho=1}^{2} \sum_{j=1}^{k_\rho} t^V_{j,\rho}. \quad \textbf{(2)}$$

$$t^{W}_{j,\rho}\begin{cases}\sum_{s=N+1}^{2N-1}\left[\frac{1}{2}(t^{d}_{j,s}-t^{d}_{j-1,s})\sum_{n=s+1}^{2N}Q^{a}_{j,sn}+(t^{d}_{j,s}-t^{d}_{j-1,s})\sum_{n=s+1}^{2N}Q^{r}_{j-1,sn}\right], \rho=1\\ \sum_{s=1}^{N-1}\left[\frac{1}{2}(t^{d}_{j,s}-t^{d}_{j-1,s})\sum_{n=s+1}^{N}Q^{a}_{j,sn}+(t^{d}_{j,s}-t^{d}_{j-1,s})\sum_{n=s+1}^{N}Q^{r}_{j-1,sn}\right], \rho=2\end{cases}. \tag{3}$$

$$t^{V}_{j,\rho}\begin{cases}\sum_{s=N+1}^{2N-1}\left[Q^{v}_{j,s}(t^{a}_{j,s+1}-t^{d}_{j,s})+(Q^{v}_{j,s}-Q^{g}_{j,s})t^{p}_{s}\right], \rho=1\\ \sum_{s=1}^{N-1}\left[Q^{v}_{j,s}(t^{a}_{j,s+1}-t^{d}_{j,s})+y^{s}_{j}(Q^{v}_{j,s}-Q^{g}_{j,s})t^{p}_{s}\right], \rho=2\end{cases}. \tag{4}$$

The operating costs of urban rail companies include the operating costs of trains and the costs generated by the turnover of train bottoms. The train operating cost is the product of the unit operating cost and the number of trains running in both directions; The turnover cost of the vehicle bottom includes the cost of turning back and the cost of entering and exiting the section, which are the product of the unit turning back and entering section cost and the corresponding number of turning back and entering section operations.

$$\begin{aligned}M_{O}&=c^{n}\sum_{\rho=1}^{2}k_{\rho}+c^{t}(\sum_{\rho=1}^{2}k_{\rho}-\sum_{j'=1}^{k_2}\eta_{j',N}-\sum_{j=1}^{k_1}\beta_{j,2N})+\\ &c^{o}(\sum_{j=1}^{k_1}a_{j,K+1}+\sum_{j'=1}^{k_2}\eta_{j',N}+\sum_{j'=1}^{k_2}\gamma_{j',1}+\sum_{j=1}^{n_1}\beta_{j,2N}).\end{aligned} \tag{5}$$

$$T^{d}_{1}=0. \tag{6}$$

$$T^{d}_{n_\rho}=T. \tag{7}$$

$$\left|J_{\rho}\right|=n_{\rho}. \tag{8}$$

$$T^{d}_{j+1}=T^{d}_{j}+\frac{T}{n_1}\quad \forall j\in J_1. \tag{9}$$

$$T^{d}_{j+1}-T^{d}_{j}\geq I_{\min}\quad \forall j\in J. \tag{10}$$

$$T^{d}_{j+1}-T^{d}_{j}\leq I_{\max}\quad \forall j\in J. \tag{11}$$

The departure and arrival times of a train are determined by the pure running time, stopping time, and additional starting and stopping time of the interval [8]. The departure and arrival times are:

$$t^{d}_{j,s}=t^{a}_{j,s}+y^{s}_{j}\tau^{p}_{s}\quad \forall j\in J, s\in S. \tag{12}$$

$$t^{a}_{j,s}=t^{d}_{j,s-1}+\tau^{r}_{s-1,s}+(y^{s}_{j}+y^{s-1}_{j})\tau^{A}\quad \forall j\in J, s\in S. \tag{13}$$

Adjacent trains should meet the time constraints of departure, arrival, and arrival intervals, as follows:

$$t^{a}_{j,s}-t^{d}_{j-1,s}\geq y^{s}_{j-1}y^{s}_{j}I_{da}+y^{s}_{j-1}(1-y^{s}_{j})I_{dt}+(1-y^{s}_{j-1})y^{s}_{j}I_{ta}\quad \forall j\in J_2, s\in S_2. \tag{14}$$

3.4 Constraint Condition

The constraints of the model include three aspects: departure frequency, passenger flow and complete turnover.

(1) Departure frequency constraint

The maximum capacity of the urban rail system in the long term should meet the requirement that the density of trains should not be less than $30 pairs/h$, and the maximum operating interval should not be greater than 10 minutes when a single train is running.

$$\sum_{j=1}^{2} Y_j \geq 30 \text{ , Y} \leq 10. \tag{15}$$

$$Y \leq \frac{3600}{\min(t_{j,s}^a + t_{j,s}^d)}. \tag{16}$$

(2) Passenger flow constraints

In order to ensure that the capacity to transport passengers meets the passenger flow requirements [9], the number of passengers of various types can be calculated based on the train operation schedule, and the number of arriving passengers within the departure interval of adjacent trains is:

$$Q_{j,sn}^a = \lambda_{sn}(t_{j,s}^d - t_{j-1,s}^d) \quad \forall j \in J \quad s,n \in S. \tag{17}$$

According to the assumption, passengers only take direct trains without transferring, so the number of arriving passengers is expressed as:

$$Q_{j,sn}^W = Q_{j,sn}^a y_j^n \quad \forall j \in J \quad s,n \in S. \tag{18}$$

The number of passengers on board is determined by the remaining capacity of the train and the number of people waiting on the platform. The number of waiting passengers includes the remaining passengers in front of the train and the newly arrived passengers in the gap. According to the relationship between the remaining capacity of the train and the number of waiting passengers, is:

$$\varphi = \begin{cases} 0 & K_{j,s-1}^r \leq \sum_n (Q_{j-1,sn}^r + Q_{j,sn}^W) \\ 1 & K_{j,s-1}^r > \sum_n (Q_{j-1,sn}^r + Q_{j,sn}^W) \end{cases}. \tag{19}$$

(3) Train bottom turnover constraint

If the departure time and arrival time of the train at the starting point and terminal of the upstream and downstream directions meet the maximum connection time, then the bottom of the train to return, otherwise need to distance from the nearest train yard line bottom [10]. Therefore, the reentry time constraints of the bottom of the main passenger flow direction at the starting station (K+1 station) and the terminal station (2K station) are respectively:

$$a_{j,K+1} = \begin{cases} 0 & \tau_1^{R,\min} \leq t_{j,N+1}^d - t_{j,K}^a \leq \tau_1^{R,\max} \\ 1 & other \end{cases} \quad \forall j \in J_1. \tag{20}$$

$$\beta_{j,2N} \begin{cases} 0 & \tau_2^{R,\min} \leq t_{j,1}^d - t_{j,2N}^a \leq \tau_2^{R,\max} \\ 1 & other, t_{j,2k}^a \leq T \end{cases} \quad \forall j \in J_2. \tag{21}$$

From the perspective of operation, it is necessary to ensure that the number of on-line car bottom is not greater than the number of available car bottom of each car yard. The two car yards are respectively restricted, is:

$$m_1 - \sum_{j=1}^{k_1} a_{j,N+1} + \sum_{j=1}^{k_2} \eta_{j,N} \geq 0. \tag{22}$$

$$m_2 - \sum_{j=1}^{k_2} \gamma_{j,1} + \sum_{j=1}^{k_1} \beta_{j,2N} \geq 0. \tag{23}$$

4 Urban Rail Train Group Operation Adjustment Reinforcement Learning Strategy

This article combines train operation environment and Q-learning [11], and obtains a real-time scheduling strategy for dynamically adjusting the epidemic through algorithm simulation and offline training. The algorithm diagram is shown in Fig. 2:

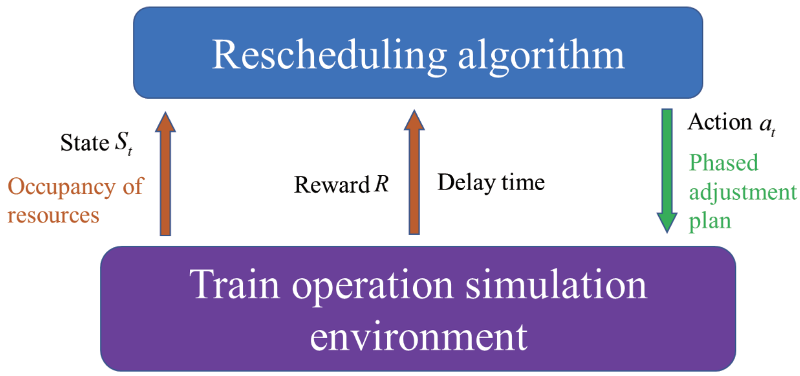


Fig. 2. Reinforcement learning system framework for dynamic adjustment of train operation

4.1 Reward Function

The minimum passenger travel cost and the minimum operating cost of the urban rail company are key performance indicators, and their mathematical model is used as the objective function, as shown in equation (1), as the main reward function ϕ_T . During the Q-learning process, an instant reward function was designed for each state transition:

$$\phi_T = \begin{cases} -1 & if \left| d_{j,s} - t \right| > X \\ 0 & other \end{cases}. \tag{24}$$

In the formula, X is a user-defined constant. When the scheduled vehicle does not arrive after the specified time, the timely function is -1, otherwise it is 0.

4.2 Design of Reinforcement Learning Algorithm

The core of reinforcement learning algorithm is value function iterative learning, which measures the quality of selecting an action at a certain time t corresponding to state Z_t When the agent selects an action in state Z_t , it selects the action based on the Q value of the state action pair, maximizing the cumulative reward value obtained by the agent Therefore, the formula for updating the value function is:

$$Q(Z_t, action) = (1-\omega)Q(Z_t, action) + \omega(\sigma + \phi \max Q(Z_{t+1}, action^{'})). \quad \textbf{(25)}$$

$Q(Z_t, action)$ represents the utility function of the action taken by state Z_t at the current moment t, where ω is the step size factor with a value range of $\omega \in (0,1]$, which needs to be selected based on the actual problem characteristics The larger ω, the greater the impact of the current reward value on $Q(Z_t, action)$, and the slower the convergence speed $\sigma[0,1]$ represents the discount factor, $\sigma \to 0$ indicates that the agent maximizes the current reward value, and $\sigma \to 1$ indicates that the agent is more focused on future reward values ϕ is the reward value obtained by taking action in the current state Z_t. The algorithm is represented as follows:

$$\pi(action|z) = \begin{cases} 1-\varepsilon+\varepsilon/|A(z)| & if, a = \arg\max(Q(z, action)) \\ \varepsilon/|A(z)| & f, a \neq \arg\max(Q(z, action)) \end{cases}. \quad \textbf{(26)}$$

Among them, $\pi(action|z)$ represents the probability of selecting an action in state z. During the learning process, a random number $rand \in (0,1)$ is generated. If the random number is less than ε, the agent randomly selects actions with equal probability in all currently available action sets. Conversely, the agent selects the action value with the highest value function Regarding the high-speed rail scheduling process, ε Set the value to:

$$\varepsilon = \frac{0.8}{1+e^{\frac{10\times(i-0.6\times B)}{B}}}. \quad \textbf{(27)}$$

Among them, i is the current number of iterations, and B is the maximum number of iterations in the learning process. The advantage of this design is that it can balance exploration and utilization of the two processes, and the ε value gradually decreases to 0 as the number of iterations increases.

5 Algorithm Verification and Case Analysis

In order to verify the effectiveness of the proposed method, Shijiazhuang Metro Line 1 was selected for verification analysis,the validity of the proposed intelligent adjustment method is verified by computer simulation and actual scheduling scheme. The configuration of the simulation system is as follows: desktop computer Intel Core i7-4790CPU@3.60 GH, 12 GB memory, reinforcement learning algorithm based on MATLAB2019a.

The route map of Shijiazhuang Metro Line 1 is shown in Fig. 2, starting from Xiwang in the west, with a total of 26 stations and 25 sections. The names of the stations are: Xiwang Station, Shiguang Street Station, Changcheng Bridge Station, Heping Hospital Station, Martyrs Cemetery Station, Xinbai Square Station, Jiefang Square Station, Ping'an Street Station, Beiguo Mall Station, Museum Station, Sports Stadium Station, Beisong Station, Tanggu Station, Fuze Station, Yuanboyuan Station, Business Center Station, Convention and Exhibition Center Station, Dongzhuang Station Xizhuang Station, Xiaohe Avenue Station, Nancun Station, Shijiazhuang East Station, Torch Square Station, Retained Station, Baifo Station, and Chaohuiqiao Station, numbered 1-26 in sequence. The stations with turn back lines include Fuze, Convention and Exhibition Center, Xizhuang, Xiaohe Avenue, Shijiazhuang East Station, Liucun, Tanggu, Beiguo Mall, Xinbai Square, Heping Hospital, and Xiwang. The length from the center of the station to the end of the turn back line is approximately 0.4 km. Assuming that there is currently no turn back line available, if it is necessary to rebuild the turn back line.

The main parameters of subway operation are shown in Table 4.

Table 4. Distance between stations and interval train operation time of Shijiazhuang Metro Line 1

Interval name	Station spacing (km)	Train operation time (s)	Interval name	Station spacing (km)	Train operation time (s)
$e(1,2)$	1.064	91	$e(14,15)$	1.441	107
$e(2,3)$	1.316	101	$e(15,16)$	1.146	95
$e(3,4)$	1.174	100	$e(16,17)$	0.898	80
$e(4,5)$	3.607	221	$e(17,18)$	0.876	84
$e(5,6)$	1.403	108	$e(18,19)$	0.984	85
$e(6,7)$	1.404	105	$e(19,20)$	1.267	105
$e(7,8)$	1.030	89	$e(20,21)$	0.862	80
$e(8,9)$	1.195	95	$e(21,22)$	1.083	91
$e(9,10)$	1.622	122	$e(22,23)$	1.156	94
$e(10,11)$	1.285	102	$e(23,24)$	1.337	103
$e(11,12)$	2.345	165	$e(24,25)$	1.220	95
$e(12,13)$	0.810	77	$e(25,26)$	1.290	102
$e(13,14)$	1.270	102			

5.1 Algorithm Validity Verification

Fig. 3 shows the convergence diagram of the algorithm iteration. The improved genetic algorithm tends to converge after 80 iterations, and the solution time is within 30 minutes.

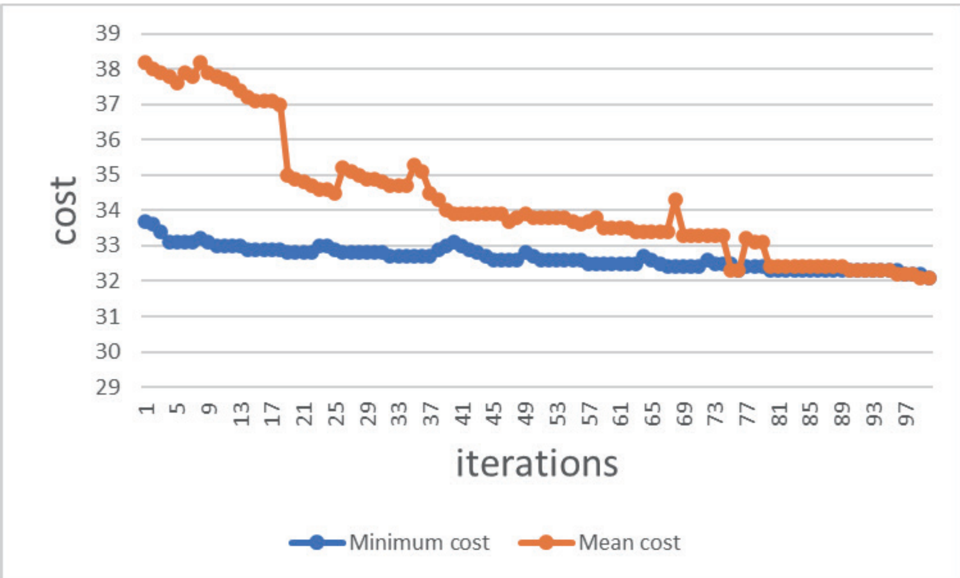


Fig. 3. Algorithm convergence process

5.2 Improvement Plan

Table 5 shows the comparison results of the improved train schemes. The evaluation index comparison between the optimized and the existing operation scheme is shown in Table 6.

Table 5. Comparison of operational plans

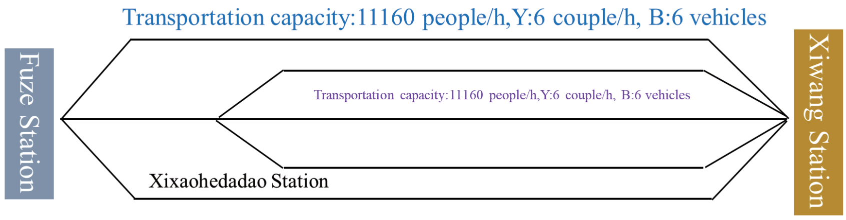
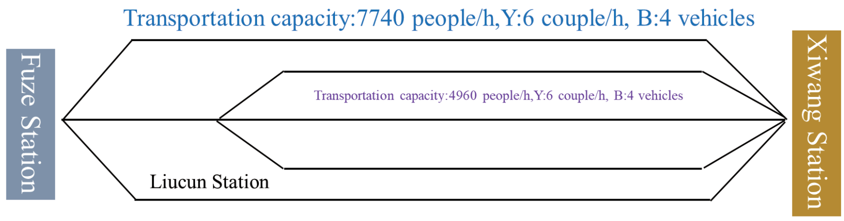
Plan	Schematic diagram of train operation scheme
Existing operation scheme	
Optimize operation scheme	

Table 6. Comparison of evaluation indexes of different routing schemes

Evaluating indicator	Existing operation scheme		Optimize operation scheme		Variation	Rate of change
	Train formation	Departure frequency/ (pair/h)	Train formation	Departure frequency/ (pair/h)		
	6	6+6	4	6+4		
Total waiting time of passengers/min	68 782.5		90 478		21 695.5	31.54%
Vehicle kilometers/km	4 162.824		2 228.32		-1 934.504	-46.47%
Number of on-line train sets/train	23		18		-5	-21.74%

After calculation, the total objective function value of the operation scheme optimized from 8:00 to 9:00 in the morning peak on working days is 314 940, and the total objective function value of the existing operation scheme is 329 054.2, a decrease of 14 114.2, which shows that the train operation scheme optimized in the morning peak is better than the existing train operation scheme. Although the existing train operation scheme has less waiting time for passengers, and the optimized operation scheme is unfavorable for passengers, the overall objective function is smaller. Considering the passenger travel cost and enterprise operation cost, the optimized train operation scheme is more favorable.

6 Conclusion

Through the research process of this paper and the analysis of specific cases, practical deficiencies are also found, such as: the consideration of constraints is not comprehensive enough, and the premise assumptions of the model are idealized. Therefore, the next research plan is to improve the optimization model and establish a function more close to the reality. The improvement ideas are as follows:

(1) The model assumes that the crowd consciously queues up, and the people who arrive first get on the bus first, which will be different from the actual ride. The dynamic number of the crowd is identified by the on-

site camera, and the actual dynamic change of the number of people is automatically estimated according to the morning and evening peak.

(2) The actual research focus of this paper is a single line rather than the whole urban rail transit network. How to realize the linkage of the whole urban rail transit network and dynamically adjust the travel strategy is my future research direction and also the demand of smart city development.

(3) Digital twinning can establish a digital real-time model, and the application of digital twinning model in urban rail transit scheduling will greatly improve the scientific nature and timeliness of traffic scheduling.

References

[1] N. Krisanarach, G. Mitsuo, O. Hayato, A parallel multi-objective genetic algorithm with learning based mutation for railway scheduling, Computers & Industrial Engineering 130(2019) 381-394.

[2] P.-L. Mo, A. D'Ariano, L.-X. Yang, L.P. Veelenturf, Z.-Y. Gao, An exact method for the integrated optimization of subway lines operation strategies with asymmetric passenger demand and operating costs, Transportation Research Part B: Methodological 1149(2021) 283-321.

[3] E. Altazin, S. Dauzère-Pérès, F. Ramond, S. Tréfond, A multi-objective optimization-simulation approach for real time rescheduling in dense railway systems, European Journal of Operational Research 286(2)(2020) 662-672.

[4] R.-S. Wang, Q. Zhang, T. Zhang, P. Lin, S.-X. Ding, Z.-M. Yuan, Real-time rescheduling approach of train operation for high-speed railways using problem-specific knowledge under a station blockage, Scientia Sinica (Informationis) 52(11) (2022) 2121-2140.

[5] X.-Z. Zhou, T. Wang, Y.-M. Ren, Y.-F. Miao, P. Yan, Research on Intercity Train Rescheduling Considering Withdrawal of Train, Railway Transport and Economy 44(3)(2022) 15-22.

[6] X.-L. Meng, X.-Q. Cheng, R.-H. Gao, M.-J. Qian, L.-M. Jia, High-speed train rescheduling under circumstance of infectious epidemic emergency, Journal of Railway Science and Engineering 20(4)(2023) 1211-1222.

[7] Y.-H. Lu, L.-X. Yang, F.-T. Meng, D.-Y. Xia, J.-G. Qi, Collaborative Optimization of Train Timetable and Passenger Flow Control Strategy for Urban Rail Transit, Journal of Transportation Systems Engineering and Information Technology 21(6)(2021) 195-202.

[8] Z.-R. Li, Y. Bai, Y. Chen, X.-J. Ming, G.-W. Cao, Optimization Model of Unpaired Timetable for Metro Trains under Asymmetric Passenger Flow, China Railway Science 43(6)(2022) 207-218.

[9] H.-M. Niu, X.-S. Zhou, R.-H. Gao, Train Scheduling for Minimizing Passenger Waiting Time with Time-Dependent Demand and Skip-Stop Patterns: Nonlinear Integer Programming Models with Linear Constraints, Transportation Research Part B: Methodological 76(2015) 117-135.

[10] S.-J. Li, R.-H. Xu, K. Han, Demand-Oriented Train Services Optimization for a Congested Urban Rail Line: Integrating Short Turning and Heterogeneous Headways, Transportmetrica A: Transport Science 15(2)(2019) 1459-1486.

[11] C.-Y. Li, W. Sun, L.-M. Tang, A Reinforcement Learning of Cloud Resource Scheduling Algorithm Based on Adaptive Weight, Journal of Harbin University of Science and Technology 26(2)(2021) 17-25.