Optimization of Asymmetric Timetable Considering Train Energy Consumption and Passenger Satisfaction for Urban Rail

Jin Meng, Changfeng Zhu, Yunqi Fu, Jie Wang, Linna Cheng, Rongjie Kuang

***Abstract*—An asymmetric train schedule optimization method is proposed to solve the problem of subway tidal passenger flow in view of the contradiction between service quality and operating energy consumption in urban rail transit systems. Firstly, the passenger loading process is considered, and the coupling relationship between the train operation status and the dynamic evolution of passengers is established. Based on this, a passenger satisfaction piecewise function is constructed, and the waiting time of passengers on the platform is used to quantify their dissatisfaction. The total train energy consumption and passenger dissatisfaction are taken as the dual objectives of the model, while train operation constraints are considered to establish an asymmetric timetable optimization model. To solve this complex timetable optimization problem, an improved non-dominated sorting genetic algorithm (SNSGA-II) based on simulation is designed. The optimization results show that by comparing timetable optimization schemes under three different passenger flow disturbance scenarios, when the per capita dissatisfaction is identical, the optimized timetable reduces train energy consumption by 5.7%, 9.8%, and 17.6% respectively compared with its benchmark timetable under different passenger flow environments. Sensitivity analysis of the model parameters demonstrates that adjusting the weighting of passenger travel can adapt to operational requirements. Performance comparison between the proposed asymmetric and symmetric timetables under tidal passenger flow reveals that the asymmetric timetable achieves up to 7.12% energy consumption optimization, indicating its effectiveness in adapting to directional and temporal passenger flow variations with more flexible and efficient optimization potential.**

***Index Terms*—Urban rail transit, Asymmetric timetable, Passenger satisfaction, Train energy consumption.**

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I. Introduction

With the continuous expansion of urban rail transit, the total operating energy consumption is increasing year by year, leading to an increase in carbon emissions from transportation companies. According to operational data statistics, train traction energy consumption accounts for more than 50% of urban rail transit electricity consumption. In addition, a relationship of mutual influence and restriction exists between traction energy consumption and service quality. For the same line, the higher the service level, the greater the required traction energy consumption. In the context of energy conservation and carbon reduction, reducing traction energy consumption while ensuring the service level of rail transit has become an urgent problem to be solved. For operating companies, configuring a better train timetable is related not only to the service quality of urban rail transit, but also can help them improve transportation efficiency and reduce train energy consumption. Therefore, developing a train timetable that is guided by passenger time needs and takes train energy consumption into consideration is of great significance to the operation organization of urban rail transit.

In existing studies, many scholars directly convert passenger time demand into passenger waiting time for optimization. Yuan et al. [1] developed a passenger flow control model based on the network level system to reduce the total waiting time of passengers outside the station and on the platform and the number of stranded passengers, taking into account the coordination between variable passenger demand and station capacity and train capacity. Zhang et al. [2] took passenger waiting time and enterprise profit loss caused by train passenger capacity as the objective function to optimize the train operation plan, reducing waiting time, profit loss, and train quantity demand. Ran et al. [3] conducted a comprehensive study on multi-unit operation mode and train undercarriage turnover to optimize the train timetable, reducing the total waiting time of passengers and train operation costs. Sun et al. [4] considered the optimal idling time point of the train during section operation, the appropriate stop time, and headway, and designed a new two-layer solution method based on deep reinforcement learning (DRL) and non-dominated sorting genetic algorithm II (NSGA-II) for model calculation to achieve energy saving of subway trains and reduce passenger waiting time.

On this basis, some scholars have considered the tidal characteristics of urban rail transit passenger flow. Gong et al. [5] considered the unbalanced temporal and spatial distribution of passenger demand on two-way subway lines, proposed an integrated optimization method for train timetables and rolling stock circulation plans with flexible short turns and energy-saving strategies, optimized and reconstructed a quadratic constrained quadratic programming (QCQP) model, aiming to minimize the weighted sum of passenger waiting time and energy cost. Zhou et al. [6] considered the joint optimization of train timetables and vehicle circulation plans on a tidally oversaturated subway line, deployed different types of rolling stock with different loading capacities to match the unbalanced passenger flow, solving with passenger waiting time and operating cost as the optimization objectives.

Although the objective and actual waiting time of passengers can represent the service level of urban rail transit in a macro sense, passenger satisfaction under different waiting times is inherently subjective and cannot fully reflect actual passenger perceptions. Zhang et al. [7] divided passenger waiting time into waiting time outside the station and waiting time inside the station based on time-varying passenger flow, introduced a penalty coefficient to correct perception errors between station areas, used a simulation-based two-stage genetic algorithm to solve the problem, and obtained a relatively optimal train schedule. Chen et al. [8] introduced an exponential function as a platform waiting perception coefficient to correct deviations between passengers' objective waiting time and their psychological perception thereof.

In existing research on reducing train energy consumption, the academic community has proposed various methods to improve energy efficiency through train timetable optimization. Some scholars consider optimizing train operation strategies in sections to ensure each train adopts optimal operation curves. Huang et al. [9] established a mixed integer nonlinear programming model for energy-saving train timetables considering passenger demand and rolling stock circulation plans, reducing energy consumption by optimizing traction strategies for each train in sections. Zhou et al. [10] divided lines into track sections by substations, developed train flow strategies per timetable, and designed an efficient particle swarm algorithm to save traction energy in sections while enhancing regenerative braking energy utilization. Yin et al. [11] simultaneously optimized timetables and train operation curves, constructed two linear-form optimization models, and decomposed the original problem into sub-problems via a Lagrangian relaxation-based heuristic algorithm to achieve higher computational efficiency.

In addition, some scholars have considered optimizing train energy consumption by combining other operating modes and environments. Deng et al. [12] proposed a train operation curve optimization method based on control parameters such as control force and speed under express/local modes, and obtained energy-saving operation curves for sections under both modes. Yao et al. [13] used ambient temperature, train departure interval, and passenger load as input variables to analyze train energy consumption and service levels. Tian et al. [14] employed virtual coupled train set (VCTS) control technology as a train control strategy, introduced four control modes, and investigated energy consumption, safety, and comfort during operation.

Finally, some scholars have conducted noteworthy research, including efficient algorithms. Zhang et al. [15] established a two-level optimization model to optimize timetable stability and train energy consumption, designing an integrated optimization method with particle swarm algorithm. Xu et al. [16] adjusted travel time and station stop time through timetable optimization to improve customer experience and energy efficiency. Yin et al. [17] established an approximate dynamic programming method to avoid dynamic programming's curse of dimensionality, achieving faster computation than genetic and differential evolution algorithms. In separate work, Yin et al. [18] established a real-time scheduling algorithm for nonlinear Markov transition processes, utilizing expert knowledge and reinforcement learning to improve energy consumption, passenger comfort, and train delays. Haahr et al. [19] developed a model considering line constraints, designing a dynamic programming solution to obtain the optimal traction energy consumption, with the solution strategy based on particle swarm algorithm.

Through the above literature analysis, although using perception coefficients can correct deviations between total waiting time and passengers' total psychological perception time, the individual differences in passenger waiting time will lead to inaccurate correction results. Secondly, while optimizing traction strategy selection for trains in sections achieves energy consumption optimization, the energy consumption reduction is relatively limited compared to increasing train frequency.

Based on the above analysis, we characterize satisfaction using passenger waiting time and optimize per-capita passenger satisfaction as the objective function, better reflecting actual travel experiences. Additionally, we propose a train energy consumption calculation method based on train motion equations to achieve precise scheduling control. This paper establishes state equations for trains and passengers, introduces a time-satisfaction function to quantify satisfaction based on actual waiting time, adopts per-capita satisfaction and total train energy consumption as dual objectives, and constructs an asymmetric train schedule optimization model incorporating operational constraints. Finally, an improved simulation-based nondominated sorting genetic algorithm (SNSGA-II) solves the model, with a tidal-flow bidirectional line case study validating the model's rationality and algorithm efficiency.

II. Problem Statement

This paper considers a bidirectional urban rail transit line with tidal phenomena. The number of stations on the line is K, station 1 and station K represent the starting station and the terminal station of the line respectively. Depot are set at both ends of the station, the train marshaling method is fixed. Since urban rail transit lines usually include two directions, up and down, let $f=1$ represent the up direction, and $f=2$ represent the down direction. Since the two directions are opposite, the passenger flow demands between uplink and downlink can be considered independent of each other. In order to intuitively describe the operation of the two directions, K stations are abstracted into $2K$ platforms. When the train arrives at the terminal, there are two options: turn back in front of the Depot, or drive into the Depot and

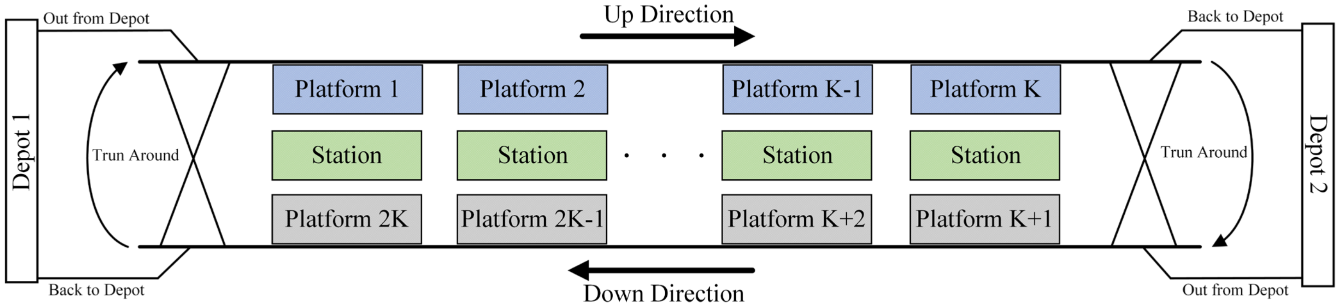

Fig. 1. The layout of the considered urban rail line.

wait for departure instructions. The train is sent from Depot 1 or after turning back, passes through platforms $1,2,\cdots,K-1$ in sequence, and then arrives at the terminal platform of the direction. After passing Depot 2 or the train turns back, the train continues to run in the down direction, passes through platforms $K+1,K+2,\cdots,2K-1$ in sequence, and finally arrives at the terminal platform $2K$ of the down direction. Set station collection to $K=\{1,2,\cdots,k,\cdots k_{\max}\}$, and the train collection to $I=\{1,2,\cdots,i,\cdots i_f\}$. The operation diagram of a certain urban rail transit line is shown in Fig. 1.

III. Optimization Model

A. Assumptions

To facilitate mathematical modeling, this paper adopts these assumptions:

(1) Passengers queue in arrival order at each platform, with uniform distribution across platform screen doors.

(2) Passenger waiting time includes train dwell time at stations.

(3) Line conditions are ideal; only train basic resistance is considered.

(4) Trains stop at all stations without overtaking.

(5) Trains adopt acceleration, coasting, and braking modes in sections.

B. Passenger Behavior

The passenger arrival time period is discretized into several unit time intervals Δt, and the passenger flow intensity in each time interval is counted. Assuming $G(t_{i,k}^{a})$ is the passenger flow intensity arriving at station k at the $t_{i,k}^{a}$ time interval, The cumulative passenger flow between adjacent trains is as follows

$$q_{i,k}^{cum}=\sum_{t_{i-1,k}^{s}}^{t_{i,k}^{s}}G(t_{i,k}^{a}) \tag{1}$$

Where, $t_{i,k}^{s}$ is the departure time of train i at station k; $t_{i,k}^{a}$ is the time when the passenger flow arrives at platform k; $G(t_{i,k}^{a})$ is the intensity of the passenger flow arriving over time; and $q_{i,k}^{cum}$ is the cumulative passenger flow from time period $t_{i-1,k}^{s}$ to $t_{i,k}^{s}$.

Passenger boarding numbers are constrained by both the arriving train's residual capacity and alighting passenger volume. Alighting passenger calculations follow the method in [20]. Since onboard passenger numbers correlate proportionally with alighting volumes, proportionality coefficients determine alighting quantities. $q_{i,k-1}^{dep}$ is the number of passengers on the train when train i is about to arrive at station k, and $n_{i.k}$ is the proportionality coefficient of passengers getting off when train i arrives at station k. Then $q_{i,k}^{off}$ is the number of passengers getting off train i at station k.

$$q_{i,k}^{off}=n_{i.k}q_{i,k-1}^{dep} \tag{2}$$

Assume that the passengers arriving at time $t_{i,k}^{e}\in[t_{i-1,k}^{s},t_{i,k}^{s}]$ just cannot take the train i at station k. When the train capacity is insufficient, passengers will board the train in order according to the principle of queuing, and the passengers who arrive later will inevitably wait for the next train. When the train capacity is sufficient, all the accumulated passengers in time period $[t_{i-1,k}^{s},t_{i,k}^{s}]$ can take this train. Then $t_{i,k}^{e}$ can be determined by the following formula.

$$\sum_{t_{i-1,k}^{s}}^{t_{i,k}^{e}}G\left(t_{i,k}^{a}\right)=\min\left\{Q-q_{i,k-1}^{dep}+q_{i,k}^{off}-q_{i-1,k}^{strand},q_{i,k}^{cum}\right\} \tag{3}$$

Where, Q is the capacity of the train; $q_{i-1,k}^{strand}$ is the number of stranded passengers who were unable to board train i at station k.

Since this article assumes that if a passenger fails to take the first train he encounters, he must take the second train. Therefore, when the cumulative passenger flow plus the number of stranded people exceeds the remaining capacity of the train, a new number of stranded people will appear.

$$q_{i,k}^{strand}=\sum_{t_{i,k}^{e}}^{t_{i,k}^{s}}G\left(t_{i,k}^{a}\right) \tag{4}$$

Based on the above analysis, the number of passengers on board when train i departs from station k can be determined by the number of stranded passengers in the previous stage and the number of passengers boarding in the current stage.

$$q_{i,k}^{dep}=q_{i,k-1}^{dep}(1-n_{i,k})+\sum_{t_{i-1,k}^{s}}^{t_{i,k}^{e}}G\left(t_{i,k}^{a}\right)+q_{i-1,k}^{strand} \tag{5}$$

When the initial state of the operating time, the number of passengers at the station and the number of passengers stranded at the station is determined, the number of stranded passengers at each stage and the number of passengers when the train departs can be solved through the given timetable. Furthermore, the satisfaction of passengers about time at each station can be solved through the number of stranded passengers at each stage and the waiting time $t_{i,k}^{\mathrm{w}}$ of passengers.

$$t_{i,k}^{\mathrm{w}} = t_{i,k}^{\mathrm{s}} - t_{i,k}^{\mathrm{a}} \tag{6}$$

C. Train Operation

Since this paper sets the train's stop time as a fixed value, the departure time of train i at station k is equal to the departure time of train i at station $k+1$ minus the train's stop time and the train's running time from station i to $k+1$.

$$t_{i,k}^{\mathrm{s}} = t_{i,k+1}^{\mathrm{s}} - t_{i,k}^{\mathrm{r}} - t_{i,k+1}^{\mathrm{p}} \tag{7}$$

Where, $t_{i,k}^{\mathrm{r}}$ is the running time of train i between stations k and $k+1$; $t_{i,k}^{\mathrm{p}}$ is the stop time of train i at station k, which is a fixed value given in advance.

The traction force, braking force, and traction energy required for train operation in sections are determined by the train's dynamic equations.

$$\frac{\mathrm{d}v}{\mathrm{d}t} = \frac{F_{\mathrm{f}}(v(t)) - F_{\mathrm{b}}(v(t)) - F_{\mathrm{r}}(v(t))}{(1+\Phi)(m_0 + q_{i,k}^{\mathrm{dep}} m_1 / 1000)} \tag{8}$$

Where, Φ is the traction rotation mass coefficient; m_0 and m_1 are the train's own weight and unit passenger weight respectively; F_{f} and F_{b} are the maximum traction and braking force that the train can output at speed v.

F_{r} denotes the train's basic resistance, comprising air resistance and mechanical friction resistance, exhibiting positive correlation with instantaneous speed.

$$F_{\mathrm{r}} = A + B \cdot v(t) + C \cdot v^2(t) \tag{9}$$

Where, A, B and C is the empirical coefficient, and its calculation method is based on [21]

The train operation strategy in sections consists exclusively of acceleration, coasting, and braking. Therefore, the train's running time in an interval equals the sum of its acceleration, coasting, and braking times; similarly, the interval running distance equals the sum of acceleration, coasting, and braking distances.

$$t_{i,k}^{\mathrm{r}} = t_{i,k}^{\mathrm{f}} + t_{i,k}^{\mathrm{d}} + t_{i,k}^{\mathrm{b}} \tag{10}$$

$$L_k = l_{i,k}^{\mathrm{f}} + l_{i,k}^{\mathrm{d}} + l_{i,k}^{\mathrm{b}} \tag{11}$$

Where, L_k is the interval running distance between stations k and $k+1$.

D. Objective Function

(1) Average passenger dissatisfaction

Passenger dissatisfaction exhibits positive correlation with station waiting time: longer waits yield higher dissatisfaction. Within $t_{i,k}^{\mathrm{a}} \in [t_{i-1,k}^{\mathrm{s}}, t_{i,k}^{\mathrm{s}}]$, Passengers arriving at the platform within one hour before train departure board sequentially according to queuing principles. Since this paper considers passenger flow demand across the entire operating period, passenger satisfaction during off-peak periods is characterized solely by platform waiting time. During peak hours, some passengers cannot board the first arriving train due to capacity constraints, resulting in significantly reduced satisfaction. After arriving at the platform, passengers form an expected train arrival time under waiting psychology perception, constituting a waiting time window $[0, t_{\min}]$. However, passenger waiting time cannot always be guaranteed within $[0, t_{\min}]$ due to inevitable deviations in vehicle arrival times.

When the passenger arrives at $[t_{i-1,k}^{\mathrm{s}}, t_{i,k}^{\mathrm{s}}]$ and plans to take the train i at station k, the following situations will occur: ① When the passenger's arrival time is $t_{i,k} \in [t_{i-1,k}^{\mathrm{s}}, t_{i,k}^{\mathrm{e}}]$ and $t_{i,k}^{\mathrm{w}} \in [0, t_{\min}]$, the train arrival time meets the passenger's psychological expectations, the dissatisfaction is 0. ② When the passenger's arrival time is $t_{i,k}^{\mathrm{a}} \in [t_{i-1,k}^{\mathrm{s}}, t_{i,k}^{\mathrm{e}}]$ and $t_{i,k}^{\mathrm{w}} \in [t_{\min}, t_{\max}]$, since the train arrival time does not meet the passengers' psychological expectations, the passengers will perceive the waiting time as long, which will increase their dissatisfaction. after the waiting time exceeds the psychological expectation, the waiting time and dissatisfaction are not linearly related. The greater the deviation between $t_{i,k}^{\mathrm{w}}$ and $t_{\min}$, the greater the dissatisfaction. Due to variability in train departure intervals, this paper models passenger satisfaction change with waiting time under maximum departure intervals. When passengers board the first train after waiting only the maximum interval, their dissatisfaction equals -1. ③ When $t_{i,k}^{\mathrm{a}} \in [t_{i,k}^{\mathrm{e}}, t_{i,k}^{\mathrm{s}}]$, the passenger arrives at station k and cannot take the train i but takes the train $i+1$, the passenger does not take the first train. At this time, the passenger's dissatisfaction is -1.

Based on situation ① and ②, a satisfaction piecewise function is constructed using passenger waiting time to evaluate passenger travel quality. Introducing the time satisfaction piecewise function $F\left(t_{i,k}^{\mathrm{w}}\right)$.

$$F\left(t_{i,k}^{\mathrm{w}}\right) = \begin{cases} 0 & t_{i,k}^{\mathrm{w}} \in [0, t_{\min}] \\ -\dfrac{2 \cdot \exp\left[-\varphi\left(t_{i,k}^{\mathrm{w}} - t_{\min}\right)\right]}{1 + \exp\left[-\varphi\left(t_{i,k}^{\mathrm{w}} - t_{\min}\right)\right]} & t_{i,k}^{\mathrm{w}} \in [t_{\min}, t_{\max}] \end{cases} \tag{12}$$

Where, $t_{\min}$ is the minimum departure time interval; $t_{\max}$ is the maximum departure time interval; φ is the time sensitivity coefficient, $\varphi > 0$, The function sensitivity increases as φ increases. The function example is shown in Fig. 2.

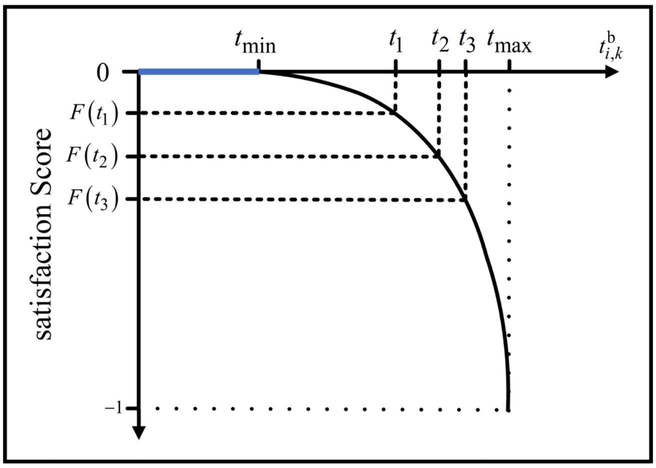

Fig. 2. Passenger dissatisfaction function.

As shown in Fig. 2, when the passenger dissatisfaction is the lowest, $F(t_{i,k}^{\mathrm{w}})=0$, and when the passenger dissatisfaction is the highest, $F(t_{i,k}^{\mathrm{w}})=1$. The second segment of the piecewise function is a satisfaction function constructed using a decreasing exponential Sigmoid function, where this function is generated by transforming the Tangent Sigmoid function.

Based on situation ③, the dissatisfaction of passengers who failed to take the first train they encountered is -1. We only need to calculate the number of stranded people $q_{i,k}^{\mathrm{strand}}$ who took train i at station k to get this part of the dissatisfaction.

Average passenger satisfaction represents passenger experience. Total satisfaction comprises: the satisfaction from boarding the first train within passengers' expected time, the satisfaction from boarding the first train beyond expected time, which varies nonlinearly with waiting time, and the stranded passenger satisfaction.

$$S_{\mathrm{tot}}=\sum_{t_{i,k}^{\mathrm{s}}-t_{\min}}^{t_{i,k}^{\mathrm{e}}} G(t_{i,k}^{\mathrm{a}})+\sum_{t_{i-1,k}^{\mathrm{s}}}^{t_{i,k}^{\mathrm{s}}-t_{\min}} G(t_{i,k}^{\mathrm{a}})F\left(t_{i,k}^{\mathrm{w}}\right)-q_{i,k}^{\mathrm{strand}} \tag{13}$$

The average satisfaction per person is determined by total passenger satisfaction divided by total boarding count. Since minimization is required, the objective function S_{avg} is obtained by multiplying the original function by -1.

$$S_{\mathrm{avg}}=-\frac{\sum_{i\in I,k\in K}\left(S_{\mathrm{tot}}\right)}{\sum_{i\in I,k\in K} G\left(t_{i,k}^{\mathrm{a}}\right)} \tag{14}$$

(2) Train energy consumption

This paper employs total train energy consumption to represent enterprise transportation benefits. During operation, trains utilize maximum traction and braking forces during acceleration/deceleration phases, determining required traction force, braking force, speed, and traction energy for each train in sections.

The traction energy consumption of train i in section $\left[k,k+1\right]$.

$$E^{\mathrm{T}}\left(t_{i,k}^{\mathrm{r}}\right)=\int_0^{t_{i,k}^{\mathrm{f}}} F_{\mathrm{f}}\left(t\right)\cdot v\left(t\right)\mathrm{d}t+\int_0^{t_{i,k}^{\mathrm{y}}} F_{\mathrm{f}}\left(t\right)\cdot v\left(t\right)\mathrm{d}t \tag{15}$$

The regenerative braking energy of train i in section $\left[k,k+1\right]$.

$$E^{\mathrm{B}}\left(t_{i,k}^{\mathrm{r}}\right)=\int_0^{t_{i,k}^{\mathrm{b}}} \eta\cdot F_{\mathrm{b}}(t)\cdot v(t)\mathrm{d}t \tag{16}$$

Where, η is the regeneration coefficient that determines the efficiency of the regenerative braking system, $\eta\in\left[0,1\right]$.

Regenerative braking energy can be stored and reused. Thus, sectional net energy consumption equals traction energy consumption minus regenerative braking energy.

$$E\left(t_{i,k}^{\mathrm{r}}\right)=E^{\mathrm{T}}\left(t_{i,k}^{\mathrm{r}}\right)-E^{\mathrm{B}}\left(t_{i,k}^{\mathrm{r}}\right) \tag{17}$$

Since traction force varies with passenger load in sections, energy consumption differs among trains running identical sections. The total energy consumption E_{tot} equals the sum of energy consumed by all trains across all sections.

$$E_{\mathrm{tot}}=\sum_{i\in I,k\in K} E(t_{i,k}^{\mathrm{r}}) \tag{18}$$

Where, L_i is the distance from station k to station $k+1$.

E. Model Constraints

(1) Train operation related constraints

Train departure intervals must exceed the minimum interval to ensure operational safety, while remaining below the maximum interval to prevent excessive passenger waiting.

$$t_{\min}\le t_{i+1,k}^{\mathrm{s}}-t_{i,k}^{\mathrm{s}}\le t_{\max} \tag{19}$$

To ensure passengers entering stations during operational hours can board, the last train's departure time must be no earlier than the subway service end time.

$$t_{i_{\max},k}^{\mathrm{s}}\ge t^{\mathrm{end}} \tag{20}$$

Train speed remains equal when entering and exiting sections, while continuously satisfying maximum speed constraints.

$$\begin{cases} v\left(0\right)=v\left(t_{i,k}^{\mathrm{s}}\right)=v\left(t_{i,k}^{\mathrm{s}}+t_{i,k}^{\mathrm{r}}\right) \\ 0\le v\left(t\right)\le V_{\max} \end{cases} \tag{21}$$

(2) Restrictions on passenger behavior

The number of passengers at each station and train at the start of the operating hours is 0.

$$\begin{cases} q_{0,k}^{\mathrm{plat}}=0 \\ q_{i,0}^{\mathrm{dep}}=0 \end{cases} \tag{22}$$

This paper stipulates that passengers stranded due to insufficient train capacity must board the subsequent train, requiring the second train's capacity to exceed the stranded passenger count.

$$q_{i,k}^{\mathrm{strand}}\le Q-q_{i+1,k-1}^{\mathrm{dep}}+q_{i+1,k}^{\mathrm{off}} \tag{23}$$

IV. ALGORITHM DESIGN

Considering that the optimization objectives in the model include satisfaction based on passenger waiting time and train energy consumption level, and the timetable optimization problem has a complex structure, involving both micro and macro levels. Each train timetable solution is determined by the departure time of each train at the departure station. Solution evaluation requires simulating inter-station operations to derive intermediate variables, necessitating calculation of boarding/alighting volumes per train per station, onboard passengers at departure, and waiting passengers per station per time interval for energy and dissatisfaction metrics. To simulate passenger loading and compute these variables, an improved Simulation-based Nondominated Sorting Genetic Algorithm (SNSGA-II) is designed. SNSGA-II retains non-dominated sorting and crowding distance calculation while incorporating simulation models and adaptive genetic operations, achieving superior balance between computational efficiency and solution quality.

According to the above analysis, the algorithm is divided into two parts. Algorithm 1 (the above behavior is used as an example) can derive relevant intermediate variables and target variables based on the train schedule obtained by the NSGA-II algorithm. The NSGA-II algorithm evaluates the quality of the current solution based on the objective function value obtained by Algorithm 1. Algorithm 1 is shown in Table. I.

TABLE I
SIMULATION ALGORITHM OF THE PASSENGER LOADING PROCESS

Algorithm 1

Input: The generated solution X_r^l, passenger demands $G(t_{i,k}^{a})$.

Related intermediate variable(s): $q_{i,k}^{cum}$, $q_{i,k}^{dep}$, $q_{i,k}^{off}$, $t_{i,k}^{e}$, $t_{i,k}^{w}$ and $q_{i,k}^{strand}$.

Output: S_{avg} and E_{tot}.

```
for i = 1 : I do
    for k = 1 : K do
        calculate q_{i,k}^cum, q_{i,k}^strand and q_{i,k}^dep constraints (1), (4) and (5)
        according to X_r^l, G(t_{i,k}^a);
        if k > 1 then
            calculate q_{i,k}^off by constraints (2) according to q_{i,k}^dep;
        end if
        calculate t_{i,k}^e by constraints (3) according to q_{i,k}^off, q_{i,k}^dep,
        q_{i,k}^strand, q_{i,k}^cum;
        calculate t_{i,k}^w by constraints (6) according to X_r^l, G(t_{i,k}^a);
        calculate S_avg according to constraints (13), (14);
        calculate E_tot according to constraints (18);
    end for
end for
Retrun S_avg and E_tot
```

According to Algorithm 1, the SNSGA-II framework is designed as shown in Algorithm 2. Set the maximum number of iterations l_{max} and the population size M, define l and r as the number of iterations and the encoding index of the individual, X_r^l is the individual r in the generation l, p is the parent of the lth generation, and $P_l = \left\{X_1^l, \cdots, X_r^l, \cdots X_M^l\right\}$. Each individual represents a train schedule plan, and the decision variable is the set of train departure times at the departure station: $t = \left\{t_{i,1}^{s}\right\}, \forall i \in I$. Encode the decision variables and randomly generate M feasible solutions as the initial population X_r^0. SNSGA-II algorithm is shown in Table. II.

TABLE II
FRAMEWORK OF "NSGA-II + ALGORITHM 1" ALGORITHM.

Algorithm 2

Input: Timetable generation constraints, passenger demands $G(t_{i,k}^{a})$.

Output: The best found solution $X_r^{l_{max}}$.

```
P_0 <- by initialize population( M ) according to Timetable
    generation constraints;
for l = 0 : l_max do
    Tournament selection; SBX crossover; Polynomial mutation;
    calculate S_avg and E_tot according to Algorithm 1;
    evaluate( P_l );
    if l != 0 then
        R <- P_l ∪ P_l';
        Assign-rank-and-crowding( R );
        Elitist strategy;
    else
        Assign-rank-and-crowding( P_0 );
    end if
end for
Retrun X_r^{l_max}.
```

V. STUDY ANALYSIS

A. Overview of Routes and Passenger Flow

In order to verify the effectiveness of the SNSGA-II algorithm, this paper takes a subway line as an example for calculation. The total length of the line is 26.055 km, with 12 stations throughout the line. The tidal passenger flow phenomenon is obvious on this line. The Up direction passenger flow demand is shown in Fig. 3, and the Down direction passenger flow demand is shown in Fig. 4. The proportion of passengers getting off at each station is shown in Fig. 5. The historical reference data of the original interval distance and running time are shown in Fig. 6.

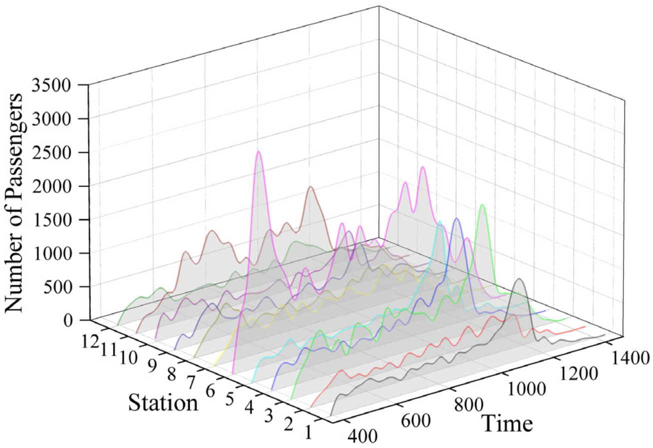

Fig. 3. Up direction passenger flow demand.

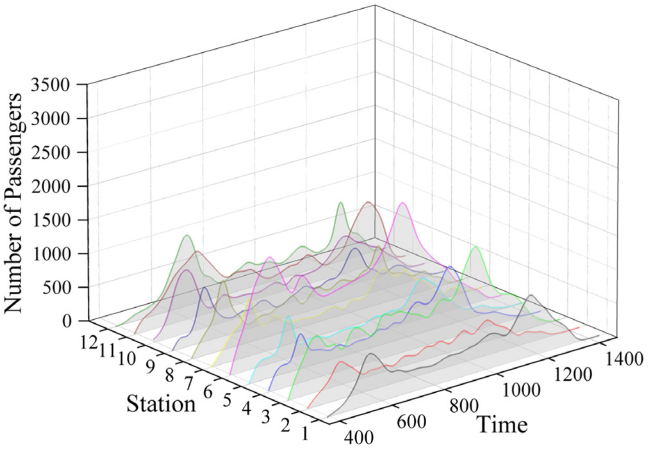

Fig. 4. Down direction passenger flow demand.

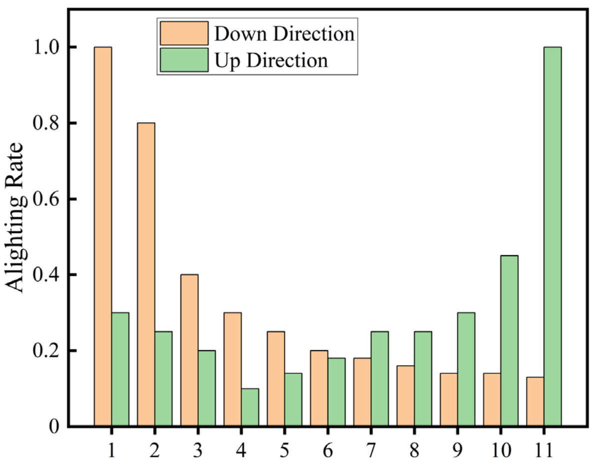

Fig. 5. Section passenger flow alighting rate.

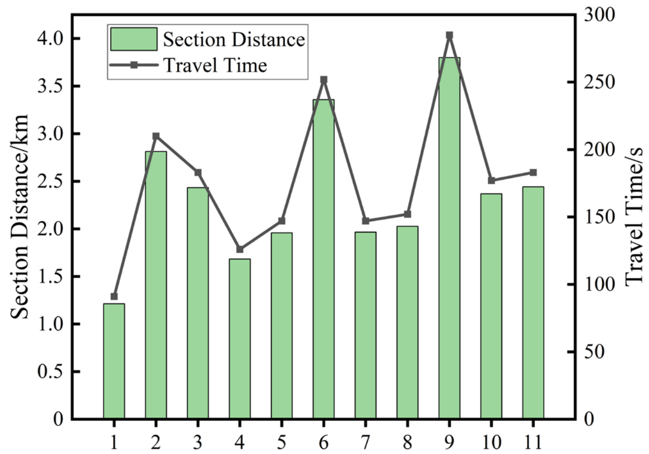

Fig. 6. Section running distance and time.

The relevant parameters are shown in Table. III.

TABLE III
MODEL RELATED PARAMETERS

Symbol	Meaning	Numeric
Φ	Traction rotation coefficient	0.06
m_0 / t	Train weight	192
m_1 / kg	Average passenger quality	60
Q	Train capacity	1468
A	Resistance empirical coefficient	5.023
B	Resistance empirical coefficient	0.045
C	Resistance empirical coefficient	0.0009
φ	Time Sensitivity Factor	0.05
η	Regenerative braking coefficient	0.5
$t_{\min}$ / s	Minimum departure time interval	240
$t_{\max}$ / s	Maximum departure time	600
$t_{i,k}^{p}$ / s	Train stop time	30
Δt / s	Unit time granularity	1

B. Optimization Results Analysis

In the optimization calculation, the passenger flow condition is the given historical passenger flow demand. The population size is set to 50. After generating the initial solution, 100 iterations are performed. At the same time, the fitness value of the objective function of each generation is recorded to better reflect the convergence of the SNSGA-II algorithm. The change of the fitness value of the objective function of each generation is shown in Fig. 7. The relationship between the total energy consumption of the train and the per capita satisfaction during the iteration of the SNSGA-II algorithm is shown in Fig. 8.

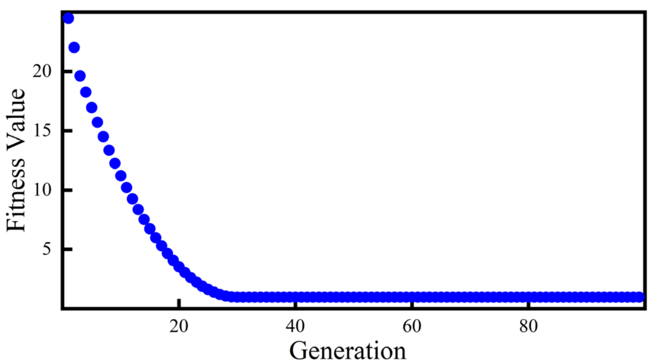

Fig. 7. Convergence diagram of SNSGA-II algorithm.

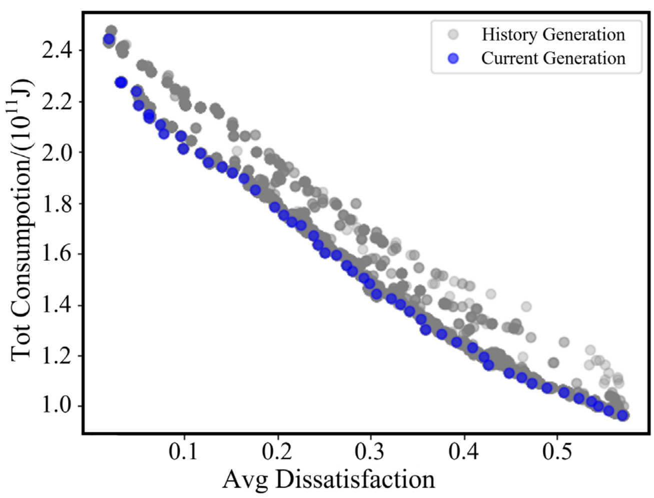

Fig. 8. Pareto frontier solution of SNSGA-II algorithm.

As shown in Fig. 7, the fitness value of the SNSGA-II algorithm has remained unchanged at the 31st generation, indicating that the algorithm has converged at the 31st generation. The fitness value changes relatively smoothly, indicating that the SNSGA-II algorithm has a high adaptability to this case.As shown in Fig. 8, overall, the SNSGA-II algorithm took 579 s to iterate 100 generations, and from the 30th generation, as the number of iterations increases, the overall trend of the population has stopped changing, indicating that the population has converged. In terms of the distribution range of the solution, when the per capita passenger dissatisfaction changes from 0.018 to 0.569, the train energy consumption level changes from 2.446×10^{11} to 9.64×10^{10} J. From the change of the target value, the higher the per capita satisfaction, the more energy consumption is required. This is because in order to reduce the waiting time of passengers, the train will choose to maintain a smaller departure time interval. Overall, except for the random generation of the initial solution, the distribution of the solution is relatively uniform. Finally, the train energy consumption level is positively correlated with the per capita dissatisfaction, that is, the higher the passenger dissatisfaction value, the greater the energy consumption.

C. Comparison of Timetable Options under Different Passenger Flow Scenarios

This paper considers three passenger flow disturbance scenarios, namely “weak tidal passenger flow”, “tidal passenger flow” and “strong tidal passenger flow” (“Scenario 1”, “Scenario 2” and “Scenario 3”). The "tidal passenger flow" scenario refers to historical data, and there are obvious passenger flow peaks in the morning and evening. For example, at 08:00, the downward direction is about 4 times that of the upward direction, and at 17:45, the upward direction is about 3 times that of the downward direction. "Weak tidal passenger flow" and "strong tidal passenger flow" are generated based on historical data by keeping the passenger flow OD structure unchanged and adjusting the passenger travel time. For example, for a certain passenger, his boarding location and destination remain unchanged, but the travel time is adjusted from peak period to off-peak period (weak tidal passenger flow), or from off-peak period to peak period (strong tidal passenger flow). Examples of changes in up and down direction passenger flow demand for three disturbance scenarios are shown in Fig. 9 and Fig. 10.

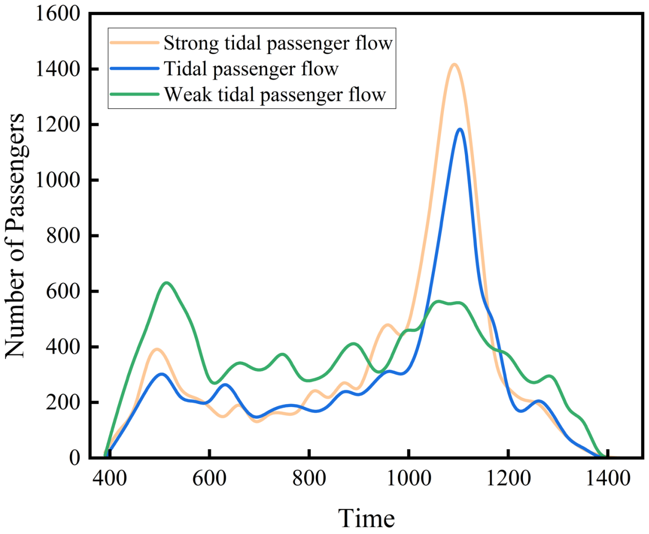

Fig. 9. Up direction passenger flow demand in three scenarios.

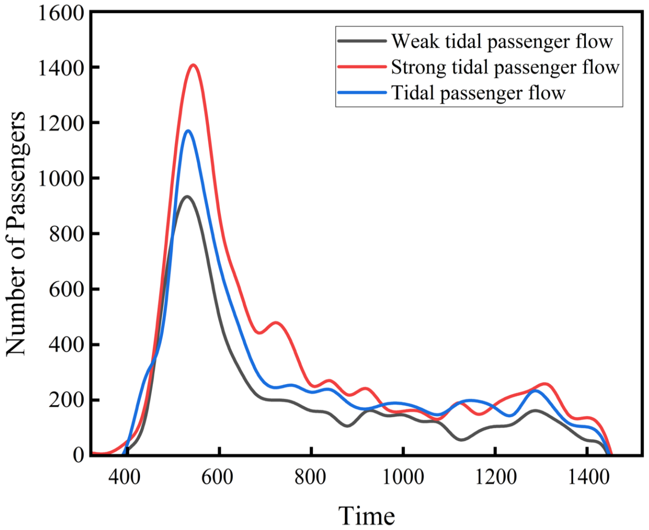

Fig. 10. Down direction passenger flow demand in three scenarios.

This paper optimizes the timetables for the passenger flow scenarios of "weak tidal passenger flow", "tidal passenger flow" and "strong tidal passenger flow". For comparison, designed a time-divided scheduling strategy as a benchmark solution, taking the departure interval of 06:30-08:00 and 16:00-19:00 as 5min30s, and the departure interval of the remaining time periods as 8min. During the optimization process, the population size is set to 50, and 100 iterations are performed. The horizontal and vertical axes of the figure represent the two optimization goals of per capita dissatisfaction and total train energy consumption, respectively. Lines of different colors represent different scenarios, and each point in the figure represents a complete timetable solution.Benchmark and optimized solution performance per scenario appears in Fig. 11.

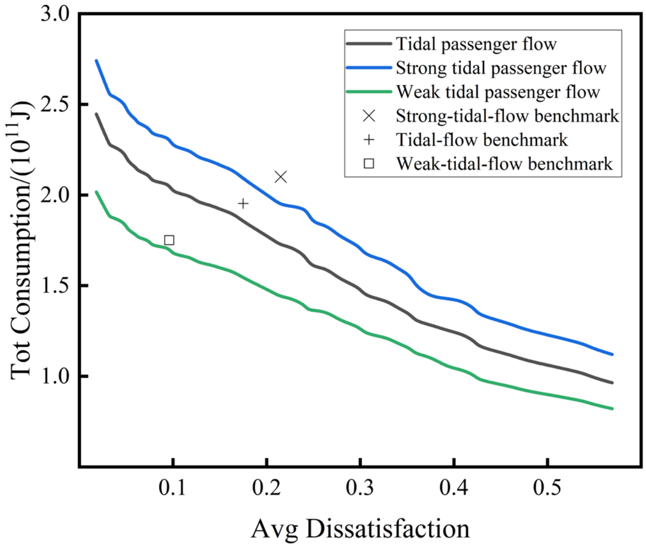

Fig. 11. Comparison of timetable options for each scenario.

As shown in Fig. 11, all timetable optimization schemes are optimized when the passenger flow conditions are the same. Besides, when passenger dissatisfaction is the same, the train energy consumption of the schedule optimization scheme is significantly lower than that of the baseline scheme. The comparison of the three scenarios shows that at the same train energy consumption level, the more significant the tidal characteristics, the higher the per capita passenger dissatisfaction, because insufficient train capacity occurs during peak passenger flow periods, resulting in more stranded passengers, which significantly increases passenger dissatisfaction. The train energy consumption and passenger dissatisfaction of the three passenger flow disturbance scenarios are shown in Table. IV. The benchmark scenarios 1, 2, and 3 in Table IV correspond to passenger flow scenarios 1, 2, and 3, respectively.

As shown in Table. IV, compared with the benchmark solution, under the premise of ensuring that passenger dissatisfaction does not increase, the train energy consumption levels in the "weak tidal passenger flow", "tidal passenger flow" and "strong tidal passenger flow" scenarios are reduced by 5.7%, 9.8% and 17.6% respectively. And under the condition of the same train energy consumption, the per capita dissatisfaction optimization rate of the three scenarios compared with their benchmark solutions reached 16.9%, 18.8% and 24.7%. The optimization rate of the solution is low in the weak tidal passenger flow scenario, because the symmetric scheduling strategy adopted by thebenchmark solution performs better in the "weak tidal passenger flow" scenario, and the benefits of optimizing the thebenchmark solution performs better in the "weak tidal passenger flow" scenario, and the benefits of optimizing the timetable are small. When the tidal characteristics of urban rail transit passenger flow are obvious, significant benefits can be brought by designing an asymmetric timetable.

TABLE IV
COMPARISON OF ENERGY-SAVING OF OPTIMIZATION SCHEMES

Name	Benchmarks 1	Benchmarks 2	Benchmarks 3	Scenario 1	Scenario 2	Scenario 3
Net energy consumption/(10^{11})	1.749	1.953	2.113	0.821-2.017	0.964-2.446	1.121-2.741
Passenger dissatisfaction	0.096	0.175	0.215	0.011-0.522	0.018-0.569	0.025-0.587
Net energy consumption optimization rate/(%)	-	-	-	5.7	9.8	17.6
Dissatisfaction optimization rate/(%)	-	-	-	16.9	18.8	23.7

D. Parameter Analysis of Time Sensitivity Coefficient φ

This section reflects the changing relationship between passenger satisfaction and train energy consumption by conducting a sensitivity analysis on the time-sensitive coefficient φ. The passenger flow condition adopts the historical passenger flow demand, and the train interval running time and distance, and the proportion of getting off refer to historical data. In the optimization calculation, the population size of both scenarios is 50, and 100 iterations are performed. The impact of the parameter changes of the simulation optimization model on the optimization results is shown in Fig. 12 and Fig. 13.

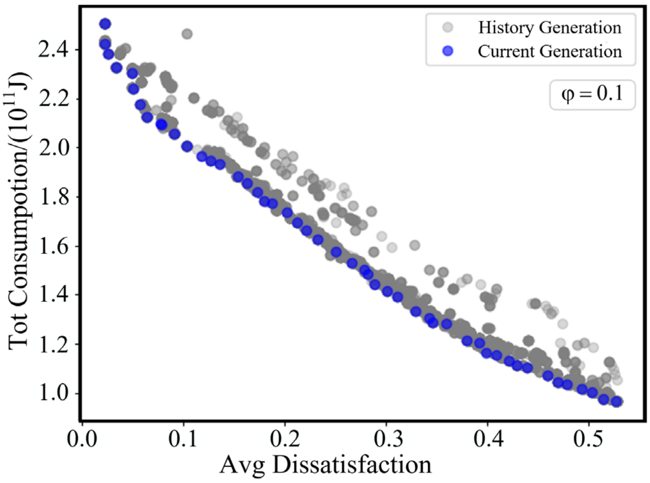

Fig. 12. Pareto frontier solution of SNSGA-II algorithm when $\varphi = 0.1$.

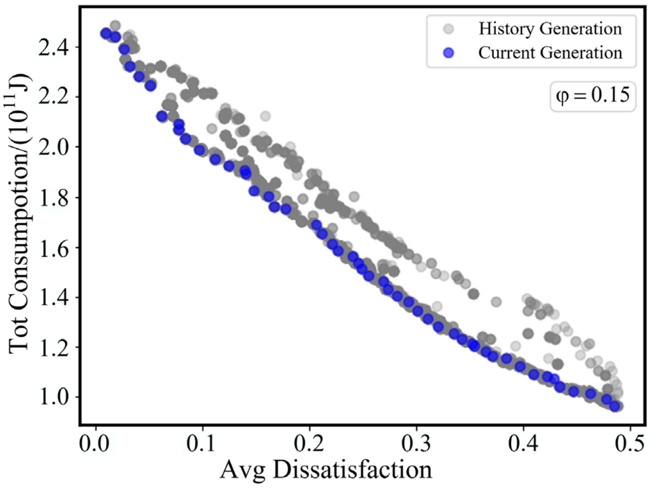

Fig. 13. Pareto frontier solution of SNSGA-II algorithm when $\varphi = 0.15$.

As shown in Fig. 12 and Fig. 13, When $\varphi = 0.1$, the average passenger dissatisfaction changes from 0.018 to 0.524, and the train energy consumption level changes from 2.510×10^{11} to 9.45×10^{10} J. When $\varphi = 0.15$, the average passenger dissatisfaction changes from 0.017 to 0.488, and the train energy consumption level changes from 2.467×10^{11} to 9.36×10^{10} J. The larger the time sensitivity coefficient φ, the smaller the upper limit of the passenger satisfaction interval. And while keeping the passenger satisfaction unchanged, reducing the value of parameter φ will require more train energy consumption. This is because the larger the φ, the higher the sensitivity of the function. Under the same passenger waiting time, when φ increases, the passenger satisfaction will increase. Therefore, in practical applications, the value of parameter φ can be adjusted to control the value weight of passenger travel and train energy consumption.

E. Advantages of Asymmetric Timetable

This section compares the performance of the symmetric and asymmetric timetables. An asymmetric timetable is one in which the departure intervals in the up and down directions are not exactly the same due to differences in the up and down passenger flow characteristics. The passenger flow conditions of both scenarios are based on historical passenger flow demand, and the train interval running time and alighting ratio refer to historical data.. In the optimization calculation, the population size of the two scenarios is 50, and 100 iterations are performed. The optimization results of the symmetric and asymmetric schedules in the same passenger flow scenario are shown in Fig. 14.

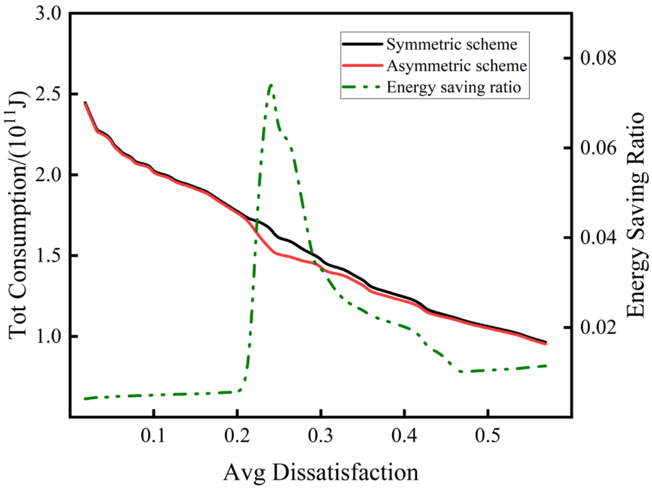

Fig. 14. Comparison of symmetric and asymmetric timetable schemes.

As shown in Fig. 14, the energy efficiency of the asymmetric scheme is better than that of the symmetric scheme, reaching a peak of 7.12% at a per capita dissatisfaction of 0.244. When the per capita dissatisfaction is lower or higher than 0.244, the energy saving ratio shows a gradually decreasing trend; when the per capita dissatisfaction is lower than 0.206 or higher than 0.409, the difference between the two schemes is less than 2%. This is because when the per capita dissatisfaction is low, the shortest departure interval is taken as much as possible in both the uplink and downlink directions; when the per capita dissatisfaction is high, the longest departure interval is taken as much as possible in both the uplink and downlink directions. In these two cases, the asymmetric scheme degenerates into a symmetric scheme, so there is little difference in the optimization objectives. When the average dissatisfaction is around 0.244, the timetable is more flexible and the optimization space is larger, and the asymmetric timetable has a significant optimization effect. Fig. 15 shows the part between 06:00-10:00 of the above asymmetric timetable optimization scheme. This scheme is a scheme with a passenger dissatisfaction of 0.152 and a total train energy consumption of 1.918×10^{11} under the conditions of historical passenger flow.

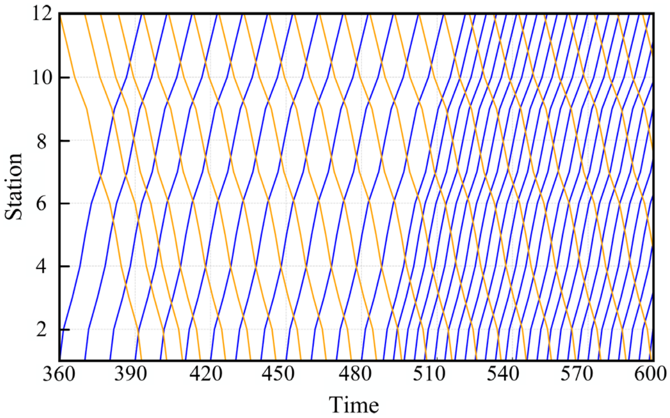

Fig. 15. Optimized timetable.

As shown in Fig. 15, the timetable optimization scheme is asymmetric. When passenger dissatisfaction is low, trains will run at the minimum departure time interval during peak hours. The departure time interval in the upward direction after 08:00 is relatively short, because this is the morning peak period of the up direction passenger flow. The departure time interval in the downward direction is relatively long between 06:00 and 10:00, indicating that the downward passenger flow is relatively small during this period. In addition, by observing the difference in the departure time intervals in the upward and downward directions, we can find that the passenger flow tidal phenomenon of the line is quite obvious.

VI. CONCLUSION

In order to improve the energy efficiency of subway train operation and passenger travel experience while solving the problem of subway tidal passenger flow, this paper establishes an energy-saving asymmetric timetable optimization model based on train operation status and passenger dynamic evolution equations. Taking passenger dissatisfaction and total train energy consumption as the optimization objectives, a simulation-based SNSGA-II solution algorithm is designed to achieve the optimization results of the asymmetric train timetable of urban rail transit based on the Pareto optimal solution. Using a bidirectional line with tidal passenger flow as an example and incorporating historical data, the effectiveness of the model and algorithm is verified. The main conclusions include six points.

(1) The SNSGA-II algorithm, which integrates adaptive genetic operations with train status and passenger flow loading simulations, exhibits rapid convergence. The algorithm converges within 30 iterations and produces a uniformly distributed Pareto solution set. Using the obtained Pareto optimal solutions, energy-saving timetable optimization can be achieved. Results indicate that when per capita dissatisfaction increases from 0.018 to 0.569, total train energy consumption decreases significantly, revealing an inherent trade-off between service quality and operational efficiency in practical operations.

(2) When passenger flow exhibits strong tidal characteristics, symmetric timetables is poorly matched with passenger flow, whereas asymmetric timetable designs yield substantial benefits. In the comparative experiments between the baseline scheme and the optimized scheme under strong tidal scenario, the optimized timetable is the most optimized compared to the baseline scheme, with the total train energy consumption optimized by 17.6%. Under weak tidal scenarios, owing to lower passenger volumes, the asymmetric timetable yields minimal benefits with only 5.7% optimization.

(3) By quantifying the discrepancy between actual waiting time and passengers' psychological perception time, the nonlinear relationship between waiting duration and dissatisfaction is characterized. A piecewise satisfaction function based on passengers' actual waiting time is proposed. The dissatisfaction value of each passenger is considered when constructing the model, and the optimization result is more in line with the actual travel experience of passengers. Case analysis shows that the nonlinear dissatisfaction and detention penalty mechanism based on passenger waiting time can reduce the satisfaction deviation by 23.7% in the strong tidal scenario, verifying the influence of psychological perception factors on the optimization results.

(4) Through the sensitivity analysis of the model input parameter φ, the changing relationship between passenger satisfaction and train energy consumption is explored. The results show that when the parameter φ is larger, the timetable scheme has better performance, but the value weight of passengers in travel is weakened, resulting in a worse experience for passengers in travel, so in practical application, the value of parameter φ should be weighed.

(5) The energy-saving advantage of asymmetric timetables is significant. Under tidal passenger flow scenario, the asymmetric timetable can effectively adapt to the differences in passenger flow direction and time period by flexibly adjusting the departure intervals in the uplink and downlink directions, and has a significant optimization effect. Experiments show that compared with the symmetric timetable, the asymmetric scheme can achieve 7.12% energy consumption optimization when the per capita dissatisfaction is 0.244. In addition, when the per capita dissatisfaction and satisfaction are low or high, the advantages of the asymmetric timetable will be reduced.

(6) This paper considers setting up Depot at both ends of the line. In future research, the initial number of trains in the Depot at the beginning of the operation time can be considered. Based on this expansion, the number of trains can be considered. And scheduling strategies such as express-slow trains, long-short route, etc. can be added. Coordinated optimization of multi-line timetables and integration with bus systems can be incorporated. In addition, the train operation can also consider the energy-optimal interval control strategy. However, since different strategies require different operating times, the model complexity will increase significantly.

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