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OPTIMIZATION ALGORITHM FOR URBAN RAIL TRANSIT OPERATION SCHEDULING BASED ON LINEAR PROGRAMMING

Shuang Wu[*] AND Jinlong Wu[†] AND Yifeng Sun[‡] AND Tong Yao[§]

Abstract. At present, the traditional urban public transportation system cannot meet people's daily travel needs. Urban Rail Transit (URT) has been rapidly promoted in major cities due to its advantages such as low energy consumption, high frequency, and large traffic volume. To achieve a more excellent and energy-saving operation scheduling strategy, the research first combines the train dynamics model and the energy consumption model. Since the optimization problem of URT is a linear problem, the attraction model of the Firefly algorithm can determine the calculation time consumed by the algorithm, which is very suitable for the complex optimization problem of URT. Therefore, the FA based optimization algorithm for urban rail transit operation scheduling (FURTOSO) based on the Firefly algorithm is studied and designed. Therefore, based on the study of the four working conditions of traction, cruise, coasting, and braking, a Firefly Algorithm for Urban Rail Transit Operation Scheduling (FURTOSO) was designed. Finally, the study optimizes the operation scheduling of Chengdu Metro Line 8 from two aspects: driving strategy and train schedule. The research demonstrates that the FURTOSO algorithm only needs 76 iterations to reach a stable state, with a fitness value of 0.6827. In practical applications, the utilization rate of train RBE is 30.1%, the total energy consumption (TEC) is $2.661 * 1011J$, and the energy saving rate is 13.03%. In summary, the FURTOSO algorithm proposed in the study has excellent performance and has better energy-saving effects in Chengdu Metro Line 8.

Key words: Urban Rail Transit; Scheduling Optimization; Regenerative Braking; Firefly Algorithm; Energy Conservation

1. Introduction. As the boost of China's urbanization, it is difficult for conventional public transportation systems to meet the rapidly growing passenger demand of cities [1]. At this time, urban rail transit (URT) emerged as the times require. It has advantages such as fast speed, large traffic volume, and environmental protection, which greatly alleviates urban congestion [2]. Currently, 40 cities in China have opened URTs, with a total of 212 lines constructed and a total operating mileage of 6730.27 kilometers. However, it has generated huge electricity consumption, with an estimated annual electricity consumption of 40 billion kilowatt hours, accounting for over 5% of the total national electricity consumption in the future. Therefore, studying the optimization of URT operation scheduling is of great significance. The power consumption of URT system mainly includes traction, ventilation, air conditioning, and lighting; Traction and ventilation and air conditioning account for 3/4 of the TEC, but there are still difficulties in studying energy conservation and emission reduction in some areas, such as ventilation and air conditioning systems [3]. It relies on developing efficient equipment and reducing working hours [4]. The energy consumption of traction power supply is closely related to the operating time under traction conditions. Therefore, the energy loss during train operation (TO) can be reduced through reasonable arrangement of driving strategies and schedules for TO. However, at present, there are few studies on the optimization of URT operation scheduling. The optimization of URT is a linear problem, and the Firefly algorithm (FA) can be used to solve the trust optimization problem with discrete variables after optimization by many scholars due to its simplicity and efficiency. In addition, as a new type of fully intelligent algorithm, the FA algorithm is mostly studied to solve simple optimization problems, and the use of this algorithm can make it adaptable to more fields. To solve the energy consumption problem of URT, the study starts with the utilization of regenerative braking energy and applies its FA algorithm to the scheduling optimization of multi train operation. Based on this, a FA based optimization algorithm for urban rail transit operation scheduling (FURTOSO) is constructed.

[*]Department of Transportation Engineering, Yangzhou Polytechnic Institute, Yangzhou 225000, China
[†]Department of Transportation Engineering, Yangzhou Polytechnic Institute, Yangzhou 225000, China
[‡]Suzhou Sip Ourlead Indudtrial Equipment Co., Ltd, Suzhou 215000, China
[§]School of economics and management, Sichuan Tourism University, Chengdu 610100, China (Corresponding author, Yaotong2011tony@163.com)

The research aims to reduce the power consumption during URT operation and alleviate urban congestion. In addition, the new era requires high-quality and sustainable development, and URT must focus on energy conservation and emission reduction. The innovation points of the research mainly include the following two points: firstly, efficient utilization of regenerative braking energy to optimize the scheduling and energy-saving of multiple trains; secondly, the use of FA algorithm, an emerging swarm intelligence algorithm, to design efficient attraction models. The research structure is mainly divided into four parts. The first part is a review of relevant research results; The second part is to introduce regenerative braking energy into the optimization of multi train operation scheduling and establish the FURTOSO algorithm; The third part is the validation of the effectiveness and practicality of the proposed research methods; The final part is a summary of the research. This study aims to reduce the energy consumption required for URT traction power supply and achieve the goal of energy-saving optimization for the entire URT line, which is of great significance for the long-term development and environmental protection of URT in the future.

2. Related Work. Most of the energy consumed by URT operation is used for traction conditions. Therefore, the research on scheduling optimization of traction energy consumption has extremely important practical significance. The factors affecting traction energy consumption mainly include infrastructure and TO. Currently, most cities have completed the basic construction of URT. However, it is very difficult and costly to reconstruct the infrastructure of the completed lines. Therefore, many related researchers have conducted discussions about the scheduling URT TO. Zhao S et al., in order to adapt to the asymmetric tidal time-varying characteristics of URT line passenger demand and reduce the cost of train operation, studied the introduction of cycle balance into the top-level optimization, and built a low cost oriented integer linear programming model. The results of a case study based on even a certain URT route show that this method not only meets the service level of travel needs, but also improves the efficiency of circulation and utilization [5]. Li X et al. studied and analyzed the overall travel characteristics of passengers after the URT operation in order to study the passengers' choice of URT and public transportation after the URT operation, and then used the random forest algorithm to establish the passenger travel mode selection model after the URT is put into use. The experimental results indicate that travel cost is the most critical factor affecting passengers' travel decisions, and whether to travel during peak hours has a relatively small impact on passengers' choices, which provides support for transportation decisions [6]. Li W et al. proposed a multi-objective optimization model for urban railways to optimize and improve the utilization rate of regenerative braking energy and reduce energy consumption, while ensuring the service quality of the URT system while meeting passenger service needs without increasing the deviation of train running time for one lap. The model was solved using a non dominated sorting genetic algorithm - II. The research results show that the optimal energy-saving schedule reduces total energy consumption by 8.72%, but the deviation of one week train operation time increases by 728 seconds; The total energy consumption decreased by 6.09%, but the deviation of train operation time for one week did not increase [7]. Tang J et al. proposed a data-driven URT schedule optimization method to reduce the operating costs and improve service quality of URT company. They constructed a dual objective optimization model with the goal of minimizing the total waiting time of passengers and the company's departure time. The study conducted an experiment on a certain line in Beijing, and the results verified the effectiveness of this method. This method can provide high-quality and reasonable timetable solutions for URT system managers [8]. URT trains will continuously generate energy conversion during operation. Currently, the energy processing method generated under braking conditions is energy feedback. Then, the RBE is fed back to the AC power grid through a grid connected inverter. If other vehicles are in the traction phase, RBE can be preferentially used. Besides, the attraction model of FA algorithm determines the running time of the algorithm, which can be well used for complex problems such as high-dimensional multi-objective user dynamic optimization. Shen X et al. proposed a new method about URT RBE to enhance the utilization rate of train RBE. The simulation illustrates that the method could enhance the utilization of RBE [9]. Yang Z et al. designed an energy management strategy (EMS) according to deep reinforcement learning to optimize the EMS of URT supercapacitor energy storage systems. This research demonstrates that this method can dynamically adjust the voltage threshold, and significantly improve the energy saving and voltage stabilizing effects [10]. Zhang C et al. proposed a joint optimization model for dual track railway networks to optimize train scheduling in the railway network. Then, this study uses the heuristic algorithm of Lagrange relaxation method to solve the above model. The calculation verifies the effectiveness and efficiency of the model budget method [11]. Christy J J et al. studied the use of adaptive discrete firefly algorithms to solve broadcast scheduling problems in order to achieve optimal broadcast scheduling algorithms for intelligent transportation systems. This experiment verifies the effectiveness of this method [12]. Based on the above research, it can be concluded that the research on scheduling optimization of train passengers or time is relatively mature. However, there is very little research on multi train coordination and how to coordinate the utilization of RBE and passenger comfort. For enhancing the operational efficiency of URT trains while ensuring passenger satisfaction, the study starts from the perspective of driving strategies and timetables. Then, this study establishes the FURTOSO algorithm based on the FA algorithm to optimize the coordinated operation scheduling of multiple trains.

3. Optimization of UTR Train Operation Scheduling Based on FA Algorithm.

3.1. Construction of Train Dynamics Model and Energy Consumption Model.. Currently, most cities have completed the construction of URTs, but there are problems with the difficulty and high cost of basic design transformation for the completed station routes. Therefore, this study optimizes scheduling and energy conservation from the TO. The operation of URT trains is divided into four working conditions according to the force conditions: traction, cruise, coasting, and braking. When a train is running, it will switch under four states according to line conditions such as speed limits [13, 14]. The initial state of TO must be traction condition. When the train operates under this working condition, it generally adopts the maximum traction force to accelerate, and the braking force is 0. At this time, the train accelerates at the maximum acceleration. The cruise condition is that the time from the start of the train to the braking stop is always affected by the basic resistance; And the train maintains a state of uniform motion. The distance between stations in urban rail transit is relatively short, so cruise mode is usually not used during TO. During TO, the four-stage operation mode is only used in sections with long distance between stations [15, 16]. To reduce the energy consumption required for TO, the coasting condition will be used for transition before entering braking, at which time the train is only influenced by resistance. When a train arrives at a station and needs to stop, braking is generally used, and the train speed continues to decrease. For tracking TO, it is necessary to consider the safety of the front and rear trains during operation. The study only considers increasing the speed limit for tracking trains based on the line speed limit. The calculation is shown in Equation 3.1.

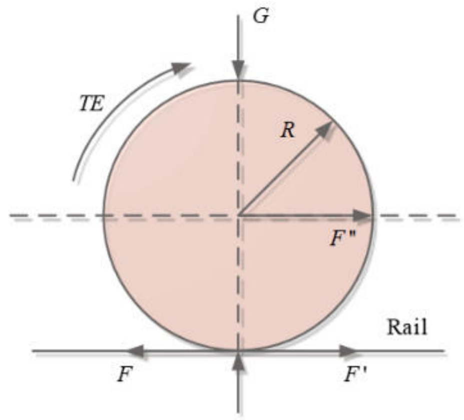
$$V_L = \min\left\{V_{TSL}, \sqrt{2LA_E}\right\} \tag{3.1}$$

V_{TSL} in Equation 3.1, denotes the speed limit of the tracking train line, km/h; is the distance between the tracking train and the vehicle in front, m; A_E denotes the maximum braking speed of the tracking train, m/s^2. The train dynamics model during URT TO mainly focuses on longitudinal dynamic effects. This study establishes a train dynamics model in view of the above basic principles. The train dynamics model established in the study is considered as a single particle model, and only the train length is considered when calculating the slope. Urban rail trains are usually divided into motor cars and trailers. The motor train is responsible for converting electrical energy into mechanical energy to provide running power for the train; The trailer itself does not have a power unit, so the traction body required for the train is provided by the traction motor of the motor car. The formation mechanism of locomotive traction force and the characteristic curve of train traction are shown in Figure 3.1. In Figure 3.1(a), the vehicle exerts gravity on the rail, and the wheel receives a reaction force from the rail through the contact point. When the traction motor operates, it outputs a torque to the wheels. Which causes the wheel to rotate at the center of the circle, generating a force and a reaction force ; Where is the radius of the circle. At this point, will prevent the sliding action between the wheel and the rail, and will be converted into a force to push the wheel to roll. Figure 3.1 (b) showcases the actual output traction force of a train with different maximum traction forces at different speeds. It is shown in Equation 3.2.

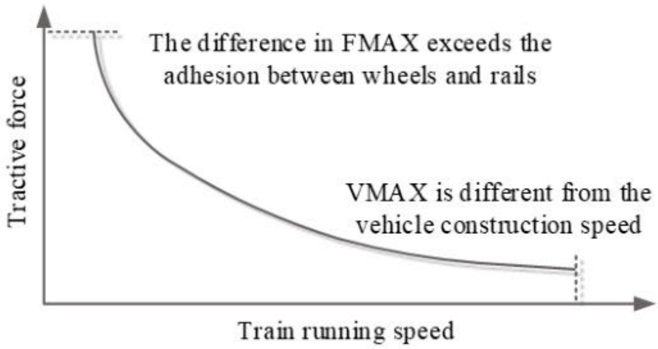
$$F = \zeta F_{\max} \tag{3.2}$$

In Equation 3.2, ζ denotes the percentage of the actual output traction acceleration and maximum acceleration; denotes the maximum traction force. The maximum braking force of a train also changes with the speed, and its actual output braking force is calculated as shown in Equation 3.3.

$$A = \Psi A_{\max} \tag{3.3}$$



(a) Formation process of locomotive traction force



(b) Characteristic curve of train traction

Fig. 3.1: Formation Mechanism of Locomotive Traction Force and Train Traction Characteristic Curve

Ψ in Equation (3) denotes the percentage of the actual output braking acceleration to the maximum acceleration; denotes the maximum braking force. The resistance during TO is not controlled artificially and includes basic resistance and additional resistance based on their causes. The basic resistance is the resistance that a train will encounter during any operation process. Affected by many factors, it is difficult to analyze each factor in a specific way. Therefore, the empirical formula obtained from multiple experiments is utilized for calculating the basic resistance B_0 , as shown in Equation 3.4.

$$B_0 = a + bv + dv^2 \tag{3.4}$$

In Equation 3.4, v is the running speed; $a, bandd$ are empirical coefficients. Additional resistance is the resistance generated when passing a special route, which is only related to the environment. The additional resistance is divided into slope additional resistance and curve additional resistance. The calculation of unit slope additional resistance is shown in Equation 3.5.

$$w_i = \frac{W_i}{Mg} \cdot 1000 = 1000 \tan\theta \tag{3.5}$$

In Equation (5), W_i is the additional resistance of the ramp;M is the weight;g is the gravity's acceleration; θ is the included angle of the ramp; $\tan\theta$ will be given during line design. The calculation of the additional resistance w_c per unit curve is shown in Equation3.6.

$$w_c = \frac{600}{R} \tag{3.6}$$

After completing the above train dynamics model, it is also necessary to model the train energy consumption. This study aims to achieve scheduling optimization and energy conservation by planning the driving strategy and timing of trains. Therefore, the main consideration is the traction energy consumption during TO, ignoring the equipment energy consumption. The relevant schematic diagram is showcased in Figure 3.2. Figure 2 indicates that the energy required for TO is generated by the substation, and the generated DC power is input into the traction substation. Then, the DC power is transmitted to the conversion device through the train pantograph, converting the DC power into AC power for the generator to operate. Currently, there are two methods for solving the traction energy consumption of a single train: traction work and active current. Calculating the energy consumed by the train through traction work is shown in Equation 3.7.

$$E_1 = \frac{\sum_{i=1}^{n} Fv \cdot \Delta l_i}{3600} \tag{3.7}$$

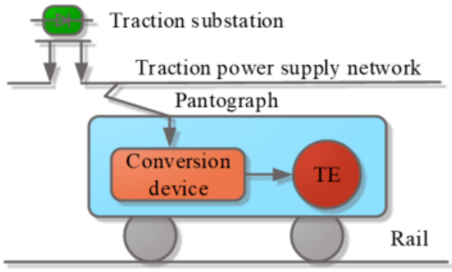


Fig. 3.2: Schematic Diagram of Energy Flow of Traction System

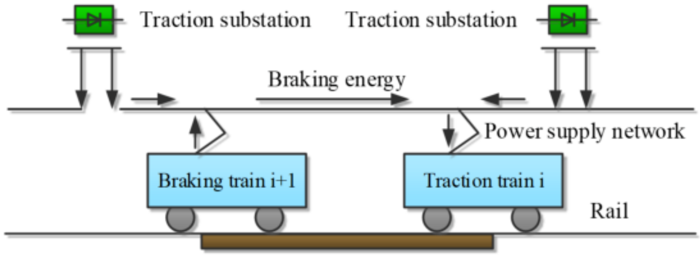


Fig. 3.3: Schematic Diagram of Renewable Energy Utilization

In Equation 3.7, F_v is the corresponding traction force when the train speed is v,kN; is the distance the train runs in a section, m. The energy consumption calculated by active current is shown in Equation 3.8.

$$E_2 = \frac{U_p \left\{\sum_{i=1}^{n}\right\} [(\overline{I})_t]\Delta t_i}{60 \cdot 100} + \frac{U_p I_{SUE} \sum_{j=1}^{m} \Delta T_j}{60 \cdot 100} \tag{3.8}$$

U_p in Equation 3.8 is the network voltage of the pantograph, V; $\overline{I}$ serves as the average active current, A; Δt_i and Δt_j are respectively the running time under traction and other working conditions, min; $I_{SUE}$is the active power of self-use electricity, A. The active current method is suitable for situations where the energy consumption curve for TO is known. Suitable calculation methods can be used according to different environments in practical applications.

3.2. Design of Optimal Algorithm for Urban Rail Transit Operation Scheduling Based on FA. Compared with railways, URT trains have the characteristics of strong departure periodicity, more stops, and frequent traction and braking switching. Therefore, the energy generated during train braking is extremely high [17]. Traditional air braking methods can cause huge energy losses. Therefore, with the continuous updating of braking technology, URT currently mainly uses electric braking. Electric braking includes regenerative braking (RB) and resistance braking. The RB method can reuse the energy lost by traditional methods and provide it to other trains in the same power supply section for use; If the braking force is insufficient, resistance braking can be used. Due to the high cost of energy storage equipment and its difficulty in promotion, research is mainly aimed at optimizing TO schedules to increase the overlap time between braking and traction of front and rear vehicles. The study then maximizes the RBE from trains and feeds it back to the power supply network for use by other trains, thereby reducing energy losses. Figure 3.3 demonstrates the renewable energy utilization specifically.

In Figure 3.3, this study assumes that train $i+1$ is in the inbound braking condition, and the generated RBE is transmitted to the power supply network in the form of electrical energy. Meanwhile, train leaves the station under traction condition. This can use the RBE E_r generated during the overlapping time of two train working conditions. In practical situations, it is not possible to ensure the complete overlap of the working conditions of two trains. Therefore, the utilization rate of RBE generated by train $i+1$ can be calculated based on the train i's overlapping time. The utilized RBE $E_b u$ is Equation 3.9.

$$E_{bu} = \frac{Rr \cdot t_0}{t_a} \tag{3.9}$$

t_0 in Equation 3.9 is the overlapping time of two train working conditions; t_a serves as the braking time of train $i+1$. After the above preparation, it can be concluded that the URT TO scheduling optimization problem is a strategic problem that extends from two stations to multiple stations. The operation process between a single train and two stations is a known distance between two stations. There are different line conditions such as different ramps and curves on the section line, and the process of trains stopping from the starting station to the terminal station. From this, it can be concluded that the URT train scheduling optimization problem is essentially a linear problem. Its description is based on line speed limits, operation time, and station spacing as constraints, with the goal of minimizing TO energy consumption. Then it optimizes the running schedule based on the FA algorithm and designs the FURTOSO algorithm. There are four working conditions during TO, and understanding the dynamic relationship of trains in different conditions can be the basis for constructing the FURTOSO algorithm. Therefore, in view of Newton's second law, the dynamic equations under four operating conditions can be obtained. Then, the study uses the FA algorithm to randomly set several different firefly locations within the solution interval. Subsequently, it iteratively updates these solutions and ultimately finds the theoretically optimal solution. Compared with other intelligent optimization algorithms, FA algorithm has the advantages of fewer parameters, good stability, and easy operation. The core idea is that fireflies with lower absolute brightness congregate with fireflies with higher absolute brightness. The objective function is defined by the absolute brightness of the firefly. In this study, the objective function values corresponding to the absolute brightness I_p's positions and $\vec{z_p}$ of the firefly p at the $\vec{z}_p = (\vec{z}_{p1}, \vec{z}_{p2}, \cdots, \vec{z}_{px})$ position are equal. The relative brightness of firefly p versus q firefly is defined as Equation 3.10.

$$I_{pq}\left(l_{pq}\right) = I_p e^{-\vartheta l_{pq}^2} \tag{3.10}$$

I_{pq} in Equation 3.10 is the distance between fireflies; ϑ is the light absorption coefficient. The greater the relative measure, the greater the attraction. The calculation of attraction is shown in Equation 3.11.

$$AF_{pq}\left(d_{pq}\right) = AF_0 e^{-\vartheta d_{pq}^2} \tag{3.11}$$

In Equation 3.11 is the Cartesian distance between fireflies; is the greatest attraction. Then, the position update of the firefly after moving to can be obtained, as shown in Equation 3.12.

$$\vec{z}_q\left(t+1\right) = \vec{z}_q\left(t\right) + AF_{pq}\left(l_{pq}\right)\left(\vec{z}_p\left(t\right) - \vec{z}_q\left(t\right)\right) + \tau\vec{\mu}_q \tag{3.12}$$

$\vec{z}_p\left(t\right)$ and $\vec{z}_q\left(t\right)$ in Equation 3.12 are the spatial locations of fireflies p and q, respectively; t is the number of iterations; τ is the step length factor; $\vec{\mu}_q$ denotes a random number vector. To sum up, the process of FA algorithm can be obtained. Figure 3.4demonstrates the details.

In Figure 3.2, the process first initializes the algorithm, and then moves the firefly. It then updates the absolute metric and iterates through the loop. Optimization of single TO scheduling mainly involves allocating the time for each operating condition. Optimization of multi TO scheduling is achieved by adjusting the train schedule. In short, multi station optimization of a single train is an extreme point problem; Multi train multi station optimization is a balancing problem. The FURTOSO algorithm is based on the operation optimization control of a single train to further optimize the train schedule. Constraints for multi TO include vehicle parameters, line conditions, and train schedules. The train timetable ensures that the train can work securely, specifying the parameters required for operation. Therefore, designing a reasonable timetable can improve the overlapping time of braking and traction for different trains on the same line to decrease energy consumption. The details are shown in Figure 3.4.

Figure 3.5 illustrates the v-t curve of trains 1 and 2 running on the same line. The TO's overlapping time can be changed by changing the departure interval, operation time between stations, and dwell time. Therefore,

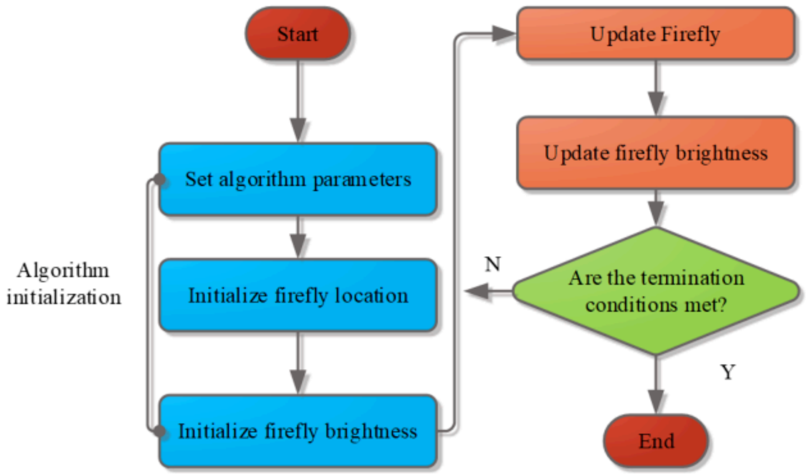


Fig. 3.4: Flow of FA Algorithm

reasonable scheduling has practical significance for URT TO scheduling optimization. For multi TO scheduling optimization problems, it is necessary to find the interval $H = \{h_1, h_2, ..., h_{n-1}\}$ with the lowest TEC for all trains with a number of n. The study assumes that the time when the i^{th} train departs from the j^{th} platform is Y_i^j, the time when it arrives at the $j+1^{th}$ platform is D_i^j, and the departure interval between the i^{th} and $i+1^{th}$ trains at the starting platform is $h_i = D_{i+1}^1 - D_i^1$. The main purpose is to minimize the energy consumption of all platforms through which the train passes and generate the most regenerative energy during operation. Therefore, based on the constraints of acceleration, traction, and braking force, an optimization model for multi train and multi platform operation scheduling is established. Model 1 represented by Equation 3.13.

$$\begin{cases} \min E_1 = \sum_{i=1}^{n} \sum_{j=1}^{k-1} \int_{D_i^j}^{Y_i^{j+1}} F\left[v(t)dt\right] \\ s.t \begin{cases} K_{min} \leq D_i^j - Y_i^j \leq K_{max}, i = 1, 2, 3, ..., n; j = 2, 3, ..., k-1 \\ \sum_{i=1}^{k-1} D_{i+1}^1 = T_0 \\ H_{min} \leq D_{i+1}^1 - D_i^1 \leq H_{max} \\ \sum_{j=1}^{k-1} (Y_i^{j+1} - Y_i^j) \\ v(t) \leq min(V_{max}, \sqrt{2LA_g}) \\ \left|Y_{(t)}\right| \leq Y_{max} \\ F[v(t)] = \zeta F_{max}, \zeta \epsilon [0, 1] \\ A[v(t)] \leq A_{max} \\ v(0) = v(D_i^j) = v(Y_i^j) = 0, i = 1, 2, ..., n \end{cases} \\ \max E_2 = \sum_{i=1}^{n-1} \sum_{j=2}^{k-1} \int_{Y_{j+1}^{(j)}}^{Y_{i+1}^j} A[v(t)]v * 95\% * t_{io1}^j / t_{i+1bk}^j dt \end{cases} \tag{3.13}$$

The E_1 and E_2 of Equation 3.13 are the TEC and the total energy utilized for regenerative energy of the train during operation time; T_o is the departure time interval between the first train and the last train; $t_{i\ \mathrm{ol}}^j i$ is the overlapping time period between the braking time of the $i+1$-th train and the acceleration time of the i-th train at the j-th station; $t_{i+1\ \mathrm{bk}}^j$ is the braking time period of the Ith vehicle at the J station; k_{min} and k_{max} are the minimum and maximum dwell times; H_{min} and H_{max} are the minimum and maximum intervals, respectively. To find the interval with the lowest TEC during the operation of all trains, a model with h_i as an indirect variable is studied and equivalently converted to a model with h_i as a decision variable, as shown in

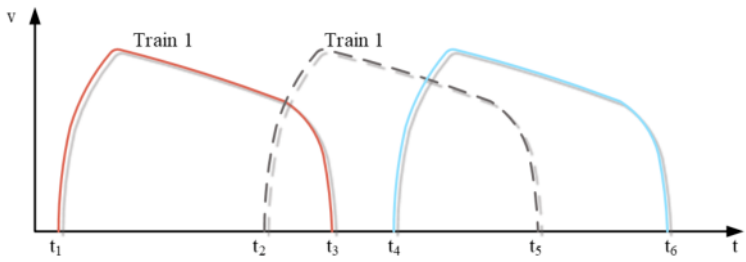


Fig. 3.5: Operation Curve of Multiple Trains at the Same Time

Equation 3.14.

$$\begin{cases} \min E_1 = \sum_{i=1}^{n} \sum_{j=1}^{k-1} \int_0^{T_i^j} F\left[v(t)\right] v(t) dt \\ s.t \begin{cases} K_{min} \leq D_i^j \leq K_{max}, i = 1, 2, 3, ..., n; j = 2, 3, ..., k-1 \\ \sum_{i=1}^{k-1} h_i = T_0 \\ H_{min} \leq h_i leq H_{max}, i = 1, 2, ...n-1 \\ \sum_{j=1}^{k-1} (D_i^j - T_i^j) = T \\ v(t) \leq min(V_{max}, \sqrt{2LA_g}) \\ \left|Y_{(t)}\right| \leq Y_{max} \\ F[v(t)] = \zeta F_{max}, \zeta \epsilon [0,1] \\ A[v(t)] \leq A_{max} \\ v(0) = v(T_i^j) = v(T_i^j + v_i^j = 0, i = 1, 2, ..., n; j = 1, 2, ..., k-1 \end{cases} \\ \max E_2 = \sum_{i=1}^{n-1} \sum_{j=2}^{k-1} \int_0^{T_{i+1}^j} A[v(t)] v * 95\% * t_{i \circ 1}^j / t_{i+1bk}^j dt \end{cases} \tag{3.14}$$

T_i^j in Equation 3.14 denotes the total operation time of the i vehicle from Station j to Station $j+1$; h_i is the interval between the i^{th} vehicle and the $i+1^{th}$ vehicle. To sum up, a multi TO in view of the FURTOSO algorithm can be obtained, as shown in Figure 3.6.

4. Result Analysis of the FURTOSO Algorithm.

4.1. Performance Analysis of the FURTOSO Algorithm. For proving the FURTOSO algorithm's function proposed in the study, Matlab software was used for simulation. To more scientifically test the superiority of the FURTOSO algorithm in handling the URT train optimal scheduling problem, comparative experiments were conducted using currently commonly used bacterial foraging optimization (BFO), particle swarm optimization (PSO), and genetic algorithm (GA) [18, 19, 20]. The study ran the four algorithms independently 50 times. Then it also takes the optimal operation result of the objective function value as the final optimization result.

Figure 4.1 showcases the fitness convergence curve results of different algorithms. Figure 4.1 demonstrates that compared to the other three algorithms, the FURTOSO algorithm possesses higher convergence accuracy and faster convergence speed for solving the objective function. The algorithm only needs 76 iterations to reach a stable state, with a fitness value of 0.6827. The BFO algorithm has the worst convergence effect, requiring 815 iterations to reach the objective function. The PSO algorithm requires 135 iterations, and the GA algorithm requires 203 iterations. The FURTOSO algorithm proposed in the study can quickly converge to the target state due to its strong local search ability, which can quickly and easily find the optimal solution in a region. Due to the lack of dynamic speed adjustment, the PSO algorithm is prone to falling into local optima, resulting in lower convergence accuracy and difficulty in convergence. The BFO algorithm mainly focuses on adjusting parameters during operation, so it is difficult to ensure the progress and convergence speed of the solution when

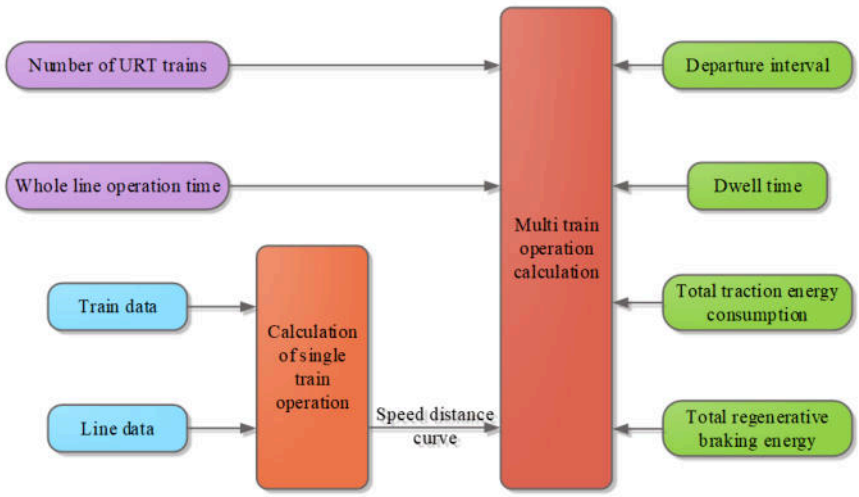


Fig. 3.6: Multi-Train Operation Process Based on FURTOSO Algorithm

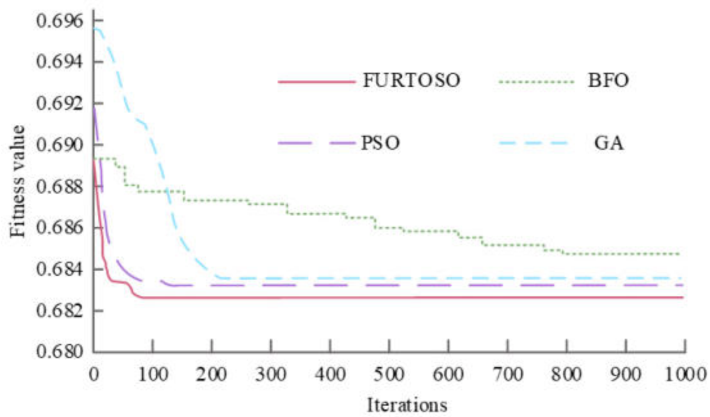


Fig. 4.1: Convergence Change Curve Results of Different Algorithms

optimizing different types of problems. The GA algorithm is prone to issues of non-standard and inaccurate encoding, and its local search ability is poor, resulting in very slow convergence speed.

Table 4.1 indicates the comparison of the four algorithms' optimization. Table 4.1 illustrates that overall, the optimal value (OV) and average OV of the FURTOSO algorithm are the smallest, 6.82669945e-001 and 6.82717688e-001, respectively. The optimal objective function value can be obtained by minimizing the number of iterations. The OV and average OV of BFO algorithm are 6.83921100e-001 and 6.84410765e-001, respectively. The FURTOSO algorithm proposed in the study has simple mathematical principles, fewer parameters, and minimal impact of parameters on the algorithm. Therefore, it can obtain optimization results in a shorter time, and it can simultaneously achieve high operational efficiency and accurately solve URT scheduling optimization problems. The parameters of the BFO algorithm do not have self-adaptability, so its operational efficiency cannot be guaranteed; The PSO algorithm requires selecting appropriate parameters to achieve optimal results for different problems, which can affect the efficiency and optimization results of the algorithm; The ability of GA algorithm to explore new spaces is limited, and it will consume a lot of time when conducting a large amount of calculations. In summary, the FURTOSO algorithm has better performance. It can efficiently and

Table 4.1: Optimization Results of Different Algorithms

Algorithm	FURTOSO	BFO	PSO	GA
Optimal Value	6.8266e-001	6.8392e-001	6.8335e-001	6.8365e-001
Average OV	6.8271e-001	6.8441e-001	6.8355e-001	6.8374e-001
Tending to OIA	76	815	135	203

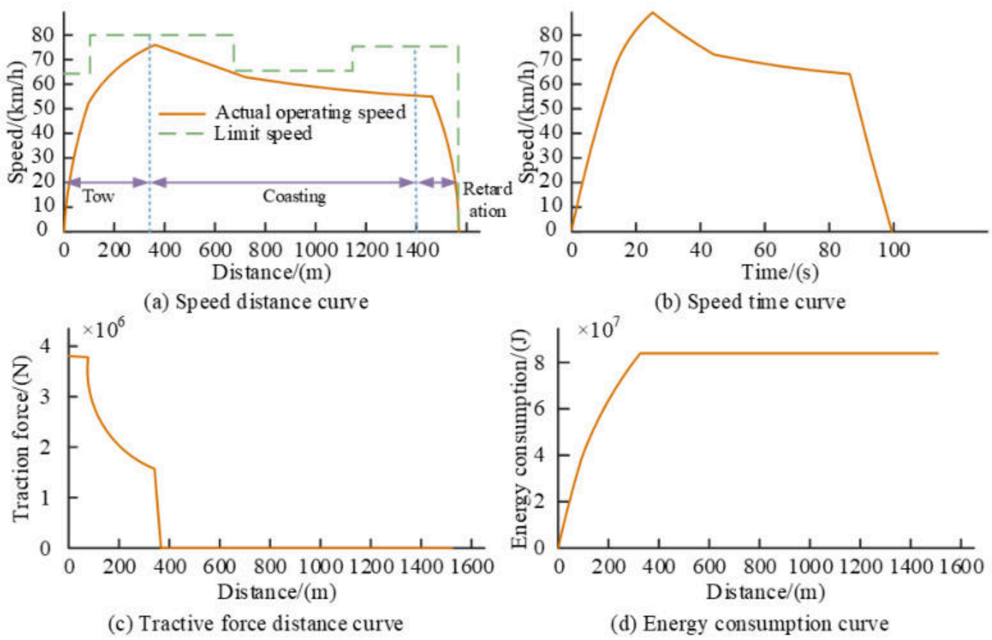


Fig. 4.2: Optimization Results of Single Train and Single Station Based on FURTOSO Algorithm

accurately solve the problem of URT operation scheduling optimization.

4.2. Application Analysis of FURTOSO Algorithm. For proving the FURTOSO algorithm's availability in practical applications, the simulation took Chengdu Metro Line 8 as the research object. The weight of a train consists of its own weight and the weight of passengers. It uses six carriages and is organized into four motor cars and two trailers, with 230 people for each trailer and 250 people for each motor car. This study assumes a weight of 60 kg per passenger, resulting in a total train weight of 288.6 t. Other parameters of the train are set as follows, with a length of 120m and a maximum operating speed of 80km/h; The basic resistance parameters a, c, and c are 2.031, 0.0622, and 0.001807, respectively; The maximum acceleration and deceleration are both 1m/s2; The minimum and maximum dwell times are 30s and 45s respectively; The minimum and maximum departure times are 2 min and 11 min respectively; The interval between the first train and the last train is 990 minutes. Chengdu Line 4 has a total length of 28.8km, an operating time of 52 ± 0.5min, and a maximum operating speed of 80km/h. It starts at Lianhua Station and ends at Shilidian Station, with a total of 24 stations.

Figure 4.2 shows the optimization results of single train and single station operation scheduling based on the FURTOSO algorithm. From Figure 4.2 (a) to (d), the optimization results of distance speed, time speed, distance traction, and distance energy consumption for micro TO are summarized. From the overall analysis of Figure 8, with a fixed total operating time, the train traction time and coasting time are longer, and the cruise time and braking time are shorter. The energy consumption is $8.42 * 107J$, which is 20.04% lower than

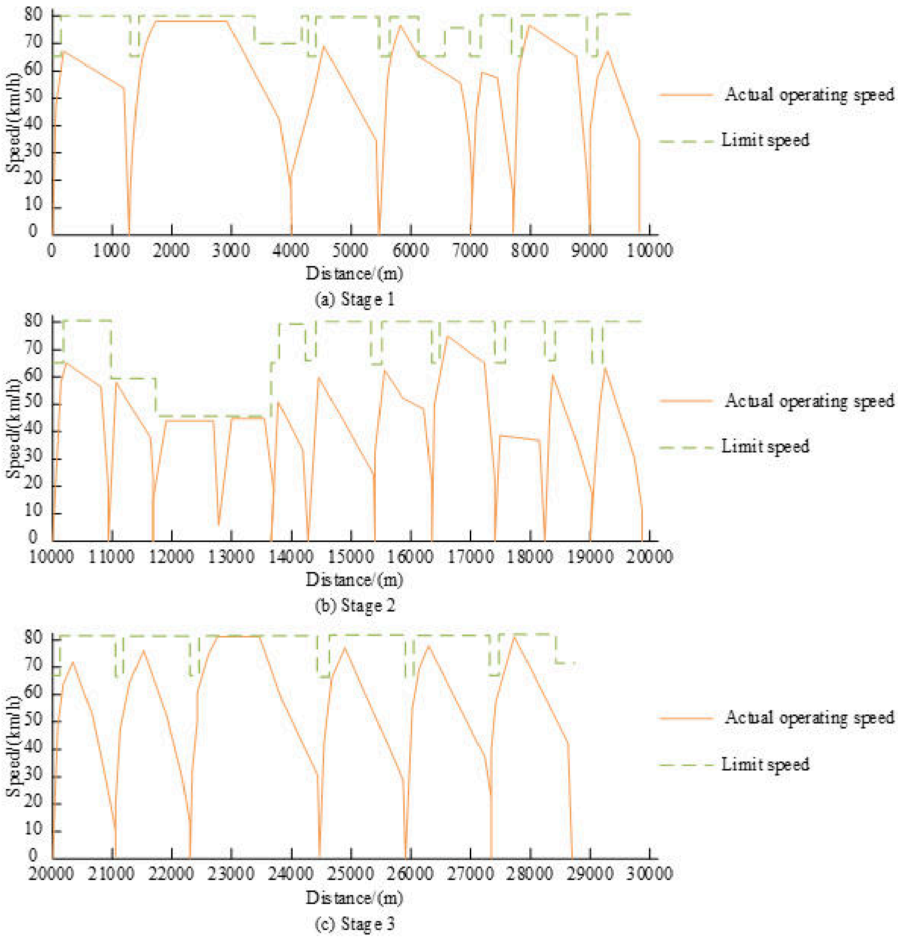


Fig. 4.3: Speed-Distance Curve of a Single Train Passing 24 Stations Based on the FURTOSO Algorithm

the energy consumption of 10.53 * 107J before optimization.

Figure 4.3 (a) to (c) show the speed distance variation curve of a single train passing through 24 stations from Lianhua to Shilidian based on the FURTOSO algorithm, from stage 1 to stage 3. Most trains operate in a three-stage strategy mode of traction, coasting, and braking between stations. In a few stations, it uses a four-stage mode of operation, namely, traction - coasting - cruise - braking. The slope from Jiuxing Avenue to Yongfeng Station is relatively large, reaching 35 ‰. Therefore, a four-stage model is used for optimization.

The research compares the consumption results of this part before and after optimization, and Table 4.2 demonstrates the results. Table 4.2 showcases that after optimizing Chengdu Metro Line 8 using the FURTOSO algorithm, the energy consumed by trains operating in most station sections has decreased. Due to the time evolution of the FURTOSO algorithm for TO between stations, the overall energy consumption of TO has been reduced by 12.78% from the perspective of the overall line effect. This confirms the feasibility of using the FURTOSO algorithm for URT scheduling optimization. The full day operation time of Chengdu Metro Line 8 is 990 minutes, with a total of 157 trains departing; From this, it can be concluded that the average departure interval is 381 seconds, and the overall operation time of a single train is 3120 seconds. If the station conducts uniform departure, a maximum of 9 vehicles can operate simultaneously on the line. Therefore, the study takes 10 trains as a group to optimize the solution. The optimized set of train departure intervals is $(288, 288, 288, 288, 289, 497, 497, 497, 497)$, with an overlap time of 895s. Based on this, there are about 17 sets of trains in total throughout the day, and the optimization results for multiple trains are obtained, as shown

Table 4.2: Comparison of Results Before and After Train Optimization at Large Gradient Stage

Sec.	Start/End Station	Oper. Time/s	Actual Energy	Opt. Energy (J)	Energy Saving Rate
1	Lianhua-Wenxing	93	7.42	5.21	29.78
2	Wenxing-Jiang'an Campus	207	20.63	12.89	37.52
3	Jiang'an-Pearl River	97	8.31	6.70	19.37
4	Pearl River-Shunfeng	101	10.54	8.45	19.83
5	Shunfeng-Sanyuan	71	4.95	3.87	21.82
6	Sanyuan-Shiyang	85	8.76	6.69	23.69
7	Shiyang-Qing'an	71	5.83	7.32	-25.56
8	Qing'an-Banjialin	75	6.59	5.01	23.98
9	Banjialin-Gaopeng Ave.	197	13.86	14.28	3.03
10	Gaopeng Ave.-Jiuxing Ave.	69	5.23	4.07	21.61
11	Jiuxing Ave.-Yongfeng	62	4.18	3.12	25.36
12	Yongfeng-Fangcaojie	107	7.72	4.49	41.84
13	Fangcaojie-Nijiaqiao	81	6.68	5.16	23.65
14	Nijiaqiao-Wangjiang Campus	76	7.52	6.68	11.17
15	Wangjiang Campus-East Lake	89	2.93	1.62	45.27
16	Donghu Park-Dongguang	87	5.66	4.28	24.38
17	Dongguang-Jingyuansi	86	5.89	6.01	-2.04
18	Jingyuansi-Dongda Road	106	7.57	8.57	-13.21
19	Dongda Road-Shuangqiao Rd.	118	9.12	10.53	-15.46
20	Shuangqiao Rd.-Wannian Rd.	151	15.62	19.12	-22.86
21	Wannian Rd.-Shanbanqiao Rd.	117	10.36	8.71	15.93
22	Shanbanqiao-Dongjiao Memory	108	10.15	8.63	18.42
23	Dongjiao Memory-Shilidian	100	9.93	9.06	8.76
Total	Lianhua-Shilidian	2354	195.45	170.47	12.78

in Table 3. Table 3 shows that train departure intervals are at the peak end of the overlapping time. The total overlap time of the entire line is 15475s, the utilization rate of RBE is 30.1%, and the TEC is $2.661 * 1011J$. Compared to the actual energy consumption of $3.059*1011J$, the optimized energy saving rate of the FURTOSO algorithm is 13.03%. In summary, the FURTOSO algorithm has excellent applicability in the operation and scheduling optimization of URT trains.

5. Conclusion. URT has the advantages of green safety, speed and punctuality. It plays a significant role in promoting the modernization process, improving the transportation environment, guiding and optimizing the urban spatial layout, and driving the innovative development of the urban economy. However, the large-scale and high-speed development of URT system in China. Therefore, how to promote the application of advanced technology in the URT industry, optimize the operation scheduling of URT, and reduce more energy consumption is crucial for smart cities. In response to the above problems, a FURTOSO algorithm was established to optimize TO scheduling with the minimum energy consumption of TO as the goal. The experiment showcases that the FURTOSO algorithm has higher convergence accuracy and faster convergence speed for solving the objective function. It only requires 76 iterations to reach a stable state, with a fitness value of 0.6827. The BFO algorithm requires 815 iterations, the PSO algorithm 135 iterations, and the GA algorithm 203 iterations to stabilize in the target state. In practical applications, train departure intervals are all at the peak end of the overlapping time, with a utilization rate of 30.1% of RBE and a TEC of $2.661 * 1011J$. Compared to the actual energy consumption of $3.059 * 1011J$, the optimized energy saving rate of the FURTOSO algorithm is 13.03%. In summary, the FURTOSO algorithm has good performance and optimization effects. However, there are still shortcomings in the research. When modeling the operation process of multiple trains, only the overlapping time of traction and braking before and after the maximum is considered, without considering the passenger's

Table 4.3: Optimization Results of Multiple Trains Based on FURTOSO Algorithm

Parameter	Optimization results
Departure interval/s	288, 288, 288, 288, 289, 497, 497, 497, 497, 288, 288, 288, 288, 289, 497, 497, 497, 497, 288, 288, 288, 288, 289, 497, 497, 497, 497, 288, 288, 288, 289, 497, 497, 497, 497, 497, 288, 288, 288, 289, 497, 497, 497, 497, 288, 288, 288, 289, 497, 497, 497, 497, 288, 288, 288, 288, 288, 289, 497, 497, 497, 288, 288, 288, 288, 288, 289, 497, 497, 497, 497, 497, 288, 288, 288, 289, 497, 497, 497, 497, 497, 288, 288, 288, 289, 497, 497, 497, 288, 288, 288, 288, 288, 289, 497, 497, 497, 288, 288, 288, 288, 289, 497, 497, 497, 497, 288, 288, 288, 288, 289, 497, 497, 497, 497, 288, 288, 288, 288, 288, 289, 497, 497, 497, 497, 288, 288, 288, 288, 289, 497, 497, 497, 497, 288, 288, 288, 288, 289, 497, 497, 497, 497, 288, 410, 410
Station dwell time/s	35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 35, 34, 34, 35, 35, 34, 34, 35, 35
Operating time/s	93, 207, 97, 101, 71, 85, 71, 75, 197, 69, 62, 107, 81, 76, 89, 87, 86, 106, 118, 151, 117, 108, 100
Overlap time/s	15475
Total energy consumption/J	1.6879×10^8

riding experience and high and low peak operating conditions. If the passenger's riding experience is poor, on the one hand, they will adopt improper behavior to affect the operation of URT, resulting in multiple train operations being chaotic, and on the other hand, it will reduce the participation of subsequent URT, The operating cost of URT will increase. The differentiated operation mode between high and low peaks can improve train operation efficiency, reduce or slow down URT operation during low peaks, and also reduce URT energy consumption. In future research, factors such as passenger waiting time can be added, and multi-objective optimization technology can be used to improve the multi train operation model.

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