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REVIEW ARTICLE

METHOD OF GENERATING PLANNED SPEED PROFILE FOR AUTOMATIC TRAIN DRIVING

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ABSTRACT

The core of the automatic driving system of urban rail train is to generate the planned speed profile. Based on this, this paper studies the generation algorithm of planned speed profile in order to achieve multi-objective optimization of operating indicators such as safety, punctuality, accurate stopping, energy saving and comfort of automatic driving of urban rail trains. In this paper, offline planning is studied and an offline planning algorithm based on genetic algorithm is proposed. At the same time, online planning is also studied to deal with the unexpected situation of train operation. This paper puts forward an online adjustment method based on genetic algorithm and global optimization algorithm. The simulation results show that both the offline planning algorithm and the online adjustment method can satisfy the basic constraint conditions of safe, punctual and accurate stopping of the train operation. These two methods also reduce the operation energy consumption and improve the operation comfort. Therefore, the methods pro-posed in this paper can achieve multi-objective optimization of the operation index and effectively deal with the unexpected situation of train operation.

KEYWORDS

Urban Rail, Autonomous Driving, Offline Planning, Online Adjustment, Genetic Algorithm

1. INTRODUCTION

Nowadays, more and more intelligent algorithms have been applied to generate the speed planning profile of automatic train driving (Ning et al. 2019). Many results have been achieved in both offline and online planning (Rodríguez et al. 2015).

Aiming at offline planning, Zhang et al. (2021) optimized the train planning speed profile based on immune annealing genetic algorithm, and achieved good optimization results. For online planning, Huang et al. (2022) calculated a policy-based reinforcement learning algorithm using neural network as a train driving controller. However, there are many unsolvable problems in the stability and structure selection of the neural network algorithm.

Based on existing research, this paper proposes an offline planning algorithm for urban rail train autonomous driving systems, which is based on a genetic algorithm and can generate planning speed profiles offline. Additionally, it suggests an online adjustment method which allows for real-time adjustment of the planning speed profile when unexpected changes in speed limits occur ahead of the train's operation. This approach aims to achieve multi-objective optimization of train operation safety, punctuality, precise stopping, energy consumption, and comfort metrics.

2. TRAIN MULTI-OBJECTIVE OPTIMIZATION MODEL

2.1 Building Train Motion Equations

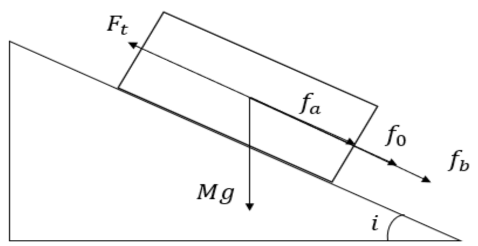

Figure 1: Forces acting on the train

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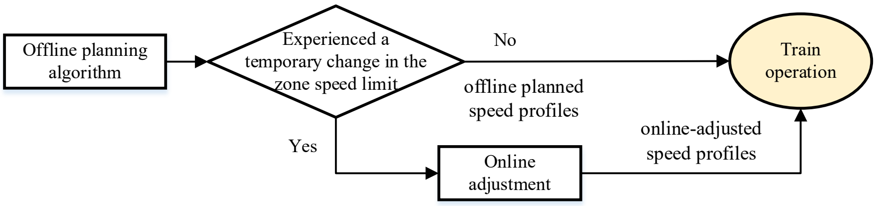

Figure 2: Train operation process

The forces directly affecting the operation of a train include traction force F_t, running resistance f (comprising basic resistance f_0 and additional resistance f_a), braking force f_b, and gravity Mg. The basic force situation of a train on a slope with a gradient of i is shown in Figure 1.

The dynamic equation for the train can be derived as follows (Tang et al. 2021; Xiao et al. 2021):

$$M\frac{dv}{dt} = F_t - f - f_b \tag{1}$$

Where M is the mass of the train, v is the velocity of the train, and running resistance ($f = f_0 + f_a$). The traction forceF_t is determined based on the traction characteristics of the train, while the braking force f_b is determined based on the braking characteristics of the train. In this study, data for a type B urban rail train are used. Under the condition of no load (AW0), the relationship between the maximum traction force F_t, the maximum braking force f_b, and the velocity v of the train is obtained through fitting:

$$F_{\max} = \begin{cases} 203(0 \le v \le 51.5 \text{ km/h}) \\ -0.002032v^3 + 0.4928v^2 - 42.12v + 1343 \\ \qquad (51.5 \le v \le 80 \text{ km/h}) \end{cases} \tag{2}$$

$$f_b = \begin{cases} 166(0 \le v \le 77 \text{ km/h}) \\ 0.134v^2 - 25.07v + 1300(77 \le v \le 80 \text{ km/h}) \end{cases} \tag{3}$$

2.2 Optimization Criteria

This paper evaluates the rationality of the generated speed profile based on the optimization of urban rail train automatic driving safety, punctuality, precise stopping, energy efficiency, and comfort indicators:

1. Safety Criteriat: Safety Constraint: The train's operating speed v on the track must not exceed the track's speed limit vm.

2. Punctuality Criteria: The punctuality of urban rail trains departing and arriving determines the efficiency of transportation. Generally, the deviation between the actual running time of the train and the planned running time is required to be within a 5% range.

3. Precise Stopping Criteria: Since urban rail transit systems are equipped with platform screen doors, the stopping error of urban rail trains is usually required to be within 30cm.

4. Energy Consumption Criteria: The energy consumption of urban rail trains during operation generally includes energy consumption generated during engine traction and energy consumption generated by other equipment (such as air conditioning, lighting equipment). This paper only considers the energy consumption during traction and braking of the train. Therefore, the energy consumption evaluation criterion generally uses the work done by traction force to represent it. The energy consumption index E of train operation can be expressed as:

$$E = \int F_t \mathrm{d}s \tag{4}$$

Where F_t is the traction force of the train, and s is the distance traveled by the train.

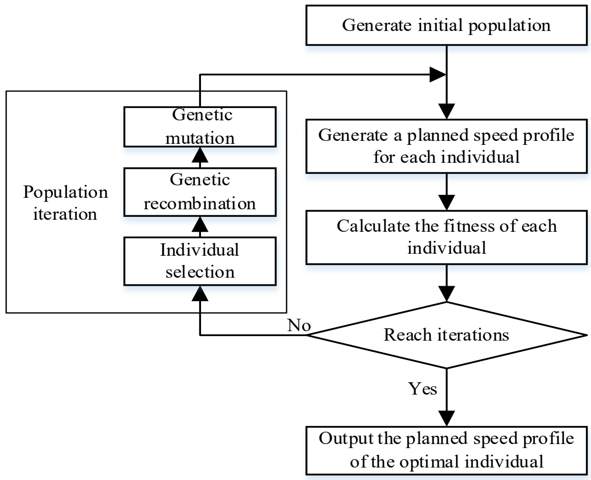

Figure 3: Flow chart of genetic algorithm

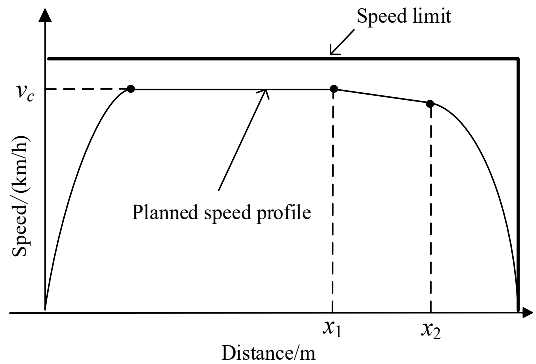

Figure 4: Planned speed profile

1. Comfort Criteria: The international standard ISO 2631 provides evaluation criteria for comfort. The comfort evaluation index of urban rail trains is generally represented by the rate of change of acceleration. The smaller this index, the more comfortable the train operation is. Therefore, the comfort index C of train operation can be expressed as:

$$C = \int \left| \frac{\mathrm{d}a}{\mathrm{d}t} \right| \mathrm{d}t \tag{5}$$

Where a is the acceleration of train operation, and t is the time taken for train operation.

3. PLANNING SPEED PROFILE GENERATION

This article presents an offline planning algorithm based on genetic algorithms for generating speed profiles and introduces an online adjustment method that combines genetic algorithms and global optimization algorithms. This method allows for the real-time generation of adjusted speed profiles when trains encounter unexpected situations during operation, as depicted in Figure 2.

3.1 Offline Planning Algorithm

The train speed profile generation process based on genetic algorithms is depicted in Figure 3.

3.1.1 Initial Population Generation

The train operation process consists of four main operating conditions: traction, cruising, coasting, and braking. The planned speed profile for a single speed-limited section is shown in Figure 4.

As shown in figure 3, the train starts from the beginning and initially operates in the traction condition, accelerating until it reaches the cruising speed v_c. Then, it switches to the cruising condition to maintain a constant speed. After reaching point x_1, it transitions to the coasting condition, where the train is primarily influenced by resistance. Finally, at point x_2, it switches to the braking condition until it comes to a stop. Through analysis, it's possible to determine the cruising speed, traction level, braking level, and the position of the transition from cruising to coasting for each speed-limited section. This information allows for the generation of a specific speed profile. For a route with multiple speed-limited sections, the i-th individual u_i in the algorithm's population is represented as (v_{ci}, l_{ti}, l_{bi}, p_{ci}). In the equation, v_{ci} is the cruising speed within the speed-limited section, l_{ti} is the traction level, l_{bi} is the braking level, p_{ci} is the position at which the transition from cruising to coasting condition.

3.1.2 Planned Speed Profile for Each Individual Generation

For each individual in the population, the corresponding planning speed profile is calculated separately. Taking the i-th individual u_i as an example, the calculation process mainly includes two steps: point-by-point calculation to get the braking profile and point-by-point calculation to get the shortest time planning profile.

(1) Point-by-point calculation to get the braking profile

The total length L of the line in the operating interval is discretely divided into N points in equal distance, and in units of Δn for each calculation step. Starting from the end point of the interval, the whole line is traversed and calculated point by point through brake level l_{bi} in reverse until the speed reaches the cruising speed v_{ci} of the interval. The speed limit profile of the interval is obtained by connecting with the cruising speed profile. It can be expressed as ($V_{li,1}$, $V_{li,2}$, $V_{li,3}$ $\cdots V_{li,N}$), wherein, each point on the profile contains three kinds of parameters: position $s_{limi,n}$, speed $v_{limi,n}$, brake level $l_{limi,n}$, which can be expressed as $V_{li,n}$ =($s_{limi,n}$, $v_{limi,n}$, $l_{limi,n}$). The speed limit profile is shown in Figure 5.

(2) Point-by-point calculation to get the shortest time planning profile

After the speed limiting profile is generated, it traverses the whole line from the beginning of the interval with each calculated step Δn as the unit. Through the traction stage condition lti, the train accelerates to the interval cruising speed vci. Then it keeps the cruising speed unchanged

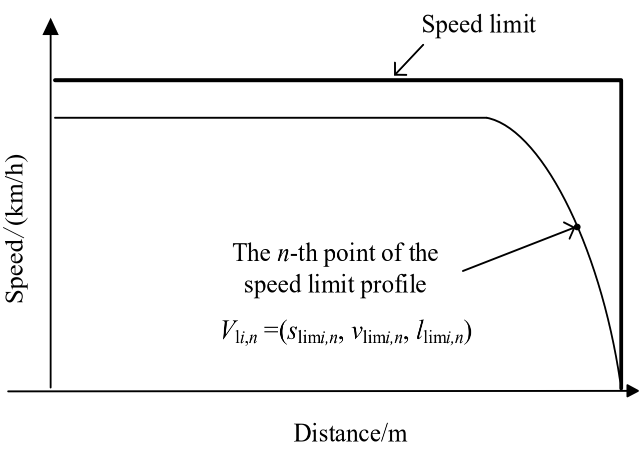

Figure 5: Speed limit profile

to the position where the cruising changes to coasting condition pci, and then keeps coasting condition. Finally, the train changes to the braking condition until the speed reaches the speed limiting profile. The braking stage is obtained from the speed limit profile.

After calculating to the end point, the total time Tc,i is obtained. At the same time, and the shortest time planning speed profile is generated, which can be expressed as (Vi,1, V i,2⋯V i,N). At the n-th point Vi,n on the profile, it contains position sni, velocity vni, acceleration ani, and total running time tni from the starting point to the n-th point. It can be expressed as (sni, vni, ani, tni).

3.1.3 Calculating Individual Fitness

The quality of each individual's speed profile planning is mainly reflected through its corresponding fitness. The magnitude of fitness is determined by the fitness function. This paper primarily considers optimizing the safety, punctuality, precise stopping, energy consumption, and comfort indicators of train operation. Additionally, a penalty function f_{penalty} is introduced to improve algorithm iteration efficiency. Hence, the fitness function for the ith individual in the population is shown as Equation (6):

$$K_i = \lambda_1 k_{t,i} + \lambda_2 k_{p,i} + \lambda_3 k_{e,i} + \lambda_4 k_{c,i} - f_{penalty} \tag{6}$$

Where λ_1, λ_2, λ_3, λ_4 are the weights of each performance indicator, satisfying $\lambda_1+\lambda_2+\lambda_3+\lambda_4=1$. $k_{t,i}$, $k_{p,i}$, $k_{e,i}$, $k_{c,i}$ correspond to the punctuality, precise stopping, energy consumption, and comfort indicators, respectively. To facilitate the comparison of indicators with different magnitudes, normalization is performed on each indicator as follows:

$$k_{t,i} = | T_{c,i} - T_0 | \tag{7}$$

$$k_{p,i} = \left| S_i - S_0 \right| \tag{8}$$

$$k_{e,i} = \frac{E_{\max} - E_i}{E_{\max} - E_{\min}} \tag{9}$$

$$k_{c,i} = \frac{C_i - C_{\min}}{C_{\max} - C_{\min}} \tag{10}$$

Where $T_{c,i}$ is the actual running time for the ith individual, T_0 is the planned running time from the timetable, S_i is the actual stopping position for the ith individual, S_0 is the target stopping position, E_i is the energy consumption indicator for the ith individual, $E_{\max}$、$E_{\min}$ are the highest and lowest energy consumption indicators in the population, C_i is the comfort indicator for the ith individual, and $C_{\max}$、$C_{\min}$ are the highest and lowest comfort indicators in the population.

Regarding the penalty function f_{penalty}, for individuals whose speed exceeds the track speed limit, f_{penalty} is set to +∞ to eliminate such individuals. For individuals with a deviation between actual running time and planned running time greater than 5%, or stopping errors greater than 30cm, the penalty function can be expressed as:

$$f_{\text{penalty}} = \lambda \times (Error_c + Error_p) \tag{11}$$

Where λ are penalty coefficients, Errorc is the percentage deviation between actual running time and planned running time, and Errorp is the actual stopping error value. When the number of iterations of the population has reached the target number of iterations, the planned speed profile of the individual with the highest fitness is output, which can be expressed as (G1, G2 ⋯GN). The n-th point Gn can be expressed as (sn, vn, an, tn).

3.1.4 Population Iteration

1. Individual selection

After obtaining the fitness of each individual, the core idea of selecting surviving individuals based on the roulette wheel selection method is to choose individuals proportionally according to their fitness. Individuals with higher fitness have a greater probability of being selected, while those with lower fitness still have some chance of being chosen, thus maintaining the diversity of the population.

2. Genetic recombination

To perform crossover on the surviving individuals, firstly, two surviving individuals need to be randomly selected as parents, denoted as *parent*1 and *parent*2. Then, the genes at corresponding positions of the individuals are subject to recombination. Recombination aims for the offspring to inherit characteristics from the parents while not being identical. The crossover formula is as follows:

$$son = parent1 + \eta(parent2 - parent1) \tag{12}$$

Where son represents the newly generated individual through recombination, η is the crossover ratio factor. The surviving individuals along with the newly generated individuals constitute the population of the new generation.

3. Genetic mutation

To prevent premature convergence, it's necessary to introduce mutation to the individuals within the population of the new generation. The mutation principle involves determining the position of the gene within its upper and lower bounds, then converting it into a probability within the range [0,1]. Let p denote this probability. The mutation calculation method is given as:

$$q' = \begin{cases} q + U\alpha(1-p), & r \geq p_{\mathrm{m}} \\ q + U\alpha p, & r < p_{\mathrm{m}} \end{cases} \tag{13}$$

Where r is a randomly generated number between 0 and 1, pm is the gene mutation probability. q' represents the original gene value, U denotes the mutation range, which is the difference between the upper and lower bounds of the gene. α is a non-zero random number generated between -1 and 1. When $\alpha \geq 0$, the gene is increased based on its original value. When $\alpha < 0$, the gene is decreased based on its original value. This mutation method ensures that the mutated gene stays within its defined bounds while introducing variability into the population.

3.2 Online Adjustment Method

When a train encounters unexpected situations during its operation, this article proposes an online adjustment method for planning speed profiles. This method combines genetic algorithms with a real-time computational global optimization algorithm. The method's principles are illustrated in Figure 6.

As illustrated, the computation time for a genetic algorithm to plan a route and converge to a result is defined as an emergency time window. The moment t_0 is the time when the speed limit changes temporarily due to an emergency situation, t_1 is the time after the emergency time window, and t_2 is the time when the train reaches the end of the section. Firstly, a planned speed profile is generated in real-time at moment t_0 using a global optimization algorithm, controlling the train to follow this planned speed profile during the emergency time window (t_0- t_1). Simultaneously, a planned speed profile is generated within the emergency time window (t_0- t_1) using genetic algorithm. Finally, the train is controlled to follow this planned speed profile from the end of the emergency time window to the end of the section (t_1- t_2).

3.2.1 Global Optimization Algorithm

This paper proposes a real-time global optimization algorithm that optimizes the comfort and energy consumption of train operations while ensuring the punctuality and precise stopping of trains. Firstly, the algorithm initially generates a planned speed profile for the shortest train travel time. Based on this, it adjusts the traction and braking levels. Then, according to the planned travel time in the train's schedule, it uses a linear approximation method to adjust the highest cruising speed within the section. Finally, it generates a planned speed profile that meets the constraint conditions, which can be denoted as (D1, D2 , D3 ···DN)

3.3 Online Adjustment Process

When the train encounters a sudden change in speed limits ahead during its operation, assuming the total length of the segment is L and the planned travel time according to the timetable is T0. Discretizing the remaining length of the operating section (L-s0) into N equidistant points, the planned speed profile based on a global optimization algorithm can be represented as (D1, D2 , D3 ···DN).

Assuming genetic algorithm is used for route planning, and the time it takes to obtain convergence results for the entire route is denoted as the emergency time window T_{window}. Begin iterating from n=1 to traverse each point on the speed profile generated by the global optimization algorithm. Define the first point discovered where the total time exceeds (T_{window}+ t_0) as the endpoint of the emergency time window, denoted as w. The train's status at the endpoint are as follows:

$$D_w = (s_w, v_w, a_w, t_w) \tag{14}$$

To control the train's movement from the starting point s_0 to the endpoint of the emergency time window s_w following the speed profile generated by the global optimization algorithm. Simultaneously, using D_w as the starting point for offline calculations, assuming the remaining length of the operating section (L-s_w) is discretized into Q equidistant points, and employing a genetic algorithm to compute the offline planned speed profile within the time interval (t_w-t_0). It can be represented as (G_1, G_2 , G_3 ···G_Q). Each point on the profile, G_n, contains four types of parameter: position s_n, speed v_n, acceleration a_n, and the total time taken from the starting point to the n-th point t_n: G_n =(s_n, v_n, a_n, t_n). Finally, control the train's movement following the offline planned speed profile after the endpoint of the emergency time window.

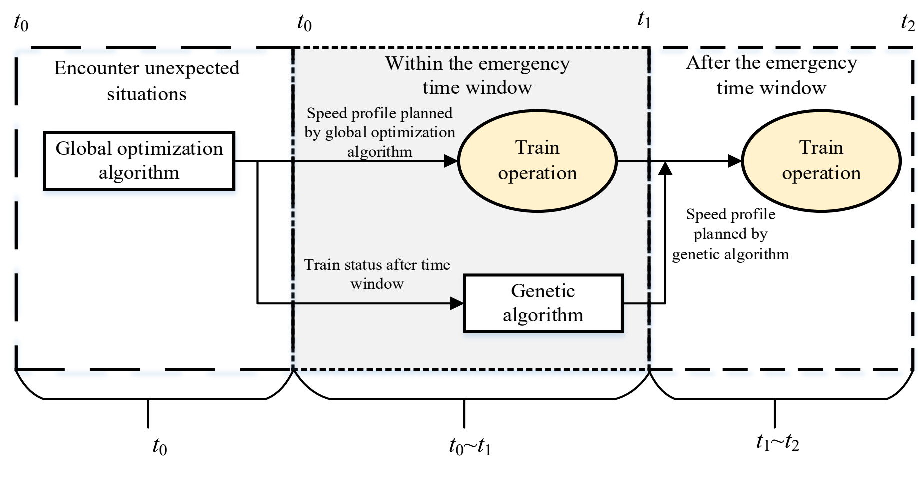

Figure 6: Principle of planning speed profile online adjustment

Table 1: Simulation parameter table

Parameter Category		Parameter Value
Line condition	Distance between stations /m	1287
	Time planned in the schedule /s	111
	Speed limit 0-83m/(km/h)	60
	Speed limit 83-572m /(km/h)	80
	Speed limit 572m-1287 /(km/h)	60
The time algorithm takes to get the speed profile	Genetic algorithm/s	1.5
	Global optimization algorithm/s	0.0002

Table 2: Simulation operation index comparison

Algorithm	Operation time/s	Parking Position /m	Energy Consumption /kWh	Comfort/(m/s^3)
Genetic algorithm	110.54	1286.70	13.65	52.86
Global optimization algorithm	110.86	1286.82	14.65	86.14
Online adjustment	110.78	1286.90	13.86	65.96

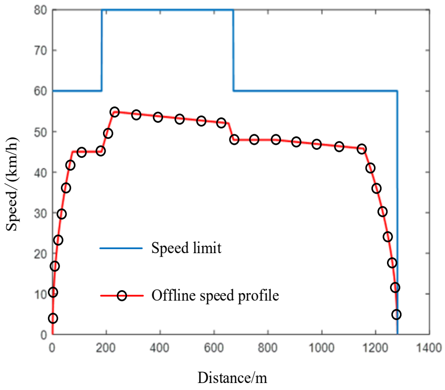

Figure 7: Offline programming speed profile

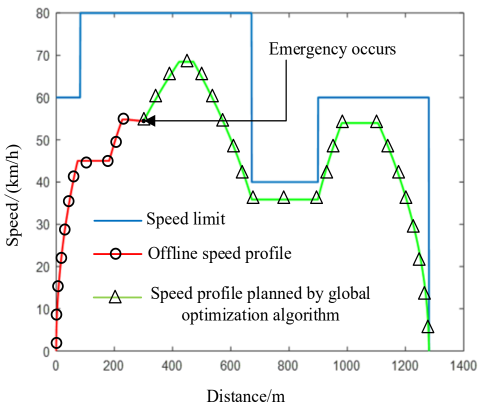

Figure 8: Speed profile planned by global optimization algorithm

4. SIMULATION VERIFICATION

4.1 Simulation Parameters

Select a specific operating section of a real railway route, and the corresponding simulation parameters are as shown in Table 1:

4.2 Simulation Results

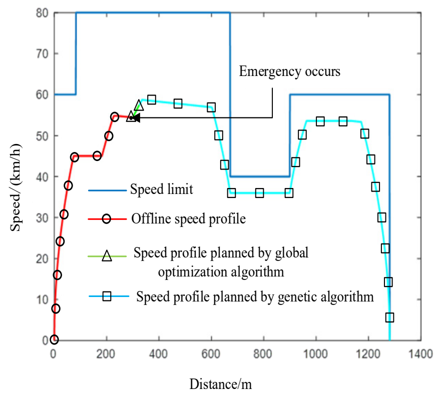

Figure 9: Speed profile planned by online adjustment

The use of sections to divide the text of the paper is optional and left as a decision for the author. Where the author wishes to divide the paper into sections the formatting shown in table 2 should be used. Firstly, the offline planned speed profile based on the offline planning algorithm, as shown in Figure 7.

Assuming that when the train reaches 300 meters, it receives a signal indicating a temporary speed limit change to 40 km/h in the segment between 673 to 900 meters. Firstly, generate a real-time planned speed profile based on the global optimization algorithm. Then, use genetic algorithm to compute the speed profile within the emergency time window. Speed profile planned by global optimization algorithm and online adjustment are respectively shown in Figure 8 and 9.

Train performance indicators are compared as shown in Table 2, energy consumption and comfort are calculated using formulas (2) and (3) respectively. The offline planned speed profiles achieved better multi-objective optimization results, validating the effectiveness of the offline planning algorithm proposed in this paper. In the event of unexpected situations, both the global optimization algorithm-planned speed profiles and the online-adjusted speed profiles meet the constraints for train operation, including safety, punctuality, and precision parking. However, the global optimization algorithm-planned speed profiles exhibit poorer optimization results in terms of energy consumption and comfort. The online-adjusted speed profiles, on the other hand, demonstrate improved optimization results for energy consumption and comfort indicators, confirming the effectiveness of the online adjustment method proposed in this paper.

5. CONCLUSION

This article proposes an offline planning algorithm based on genetic algorithms to generate planned speed profiles offline. Subsequently, it introduces an online adjustment method based on genetic algorithms and global optimization algorithms. This method allows for real-time adjustment of the planned speed profile when the train encounters changes in speed limits ahead due to unforeseen circumstances. It achieves multi-objective optimization for train operation.

However, the method proposed in this article uses a single mass point model to model the train. For longer vehicles such as heavy freight trains that require consideration of multi-mass point models. The challenge of real-time adjustment of planned speed profiles is identified as a future research direction. In addition, how to further improve the iterative efficiency of genetic algorithm and reduce the emergency time window as much as possible is also the next work plan.

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