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Research on Multi-objective Optimized Target Speed Curve of Subway Operation Based on ATO System

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Abstract

To optimize the target speed curve of urban rail trains, first analyze the train operation control strategy and optimization principles, and combine the performance index evaluation system of the train automatic operation curve to establish a model of the evaluation index from subway energy saving, train running on time, and From the perspective of passenger comfort, fully utilizing the control structure of the ATO system, based on the PSO-CS multi-objective optimization algorithm, researching the generation of the target speed curve of the subway train operation, and performing simulation experiment analysis. Simulation results show that the PSO-CS algorithm can provide the optimal control target speed curve for urban rail train operation.

Keywords

Performance index, multi-objective optimization algorithm, target speed curve.

1. Introduction

As the speed of urban rail trains increases and the tracking intervals are encrypted, manual driving of trains cannot guarantee driving safety. Therefore, it is necessary to equip train operation control system (referred to as train control system) to realize automatic control of train interval and speed[1]. Urban rail trains equipped with the ATO subsystem can better realize the functions of punctuality, energy saving, and comfort. The automatic speed regulation function is one of the important functions of the ATO subsystem. The realization of this function is composed of the running level mode curve and the automatic speed regulation module. This article, from the perspective of multi-objective optimization, makes full use of the ATO train operation control structure, based on the PSO-CS multi-objective optimization algorithm, to achieve efficient, safe and fast subway operation.Organization of the Text

2. Modeling of train operation process and performance indicators

2.1 Train kinematics model

At present, in the field of train traction calculation and operation simulation, train models mainly include single-mass train models and multi-mass models[2]. Since the study of train energy consumption does not require an overly detailed multi-mass train model, this article establishes a single-mass point as shown in formula (1) for the train's operation process in accordance with the formula parameters and calculation methods in the "Train Traction Calculation Rules" Models [1 ~ 3].

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$$\begin{cases} vdv/dx = F_p(p,v) - f_b(b,v) - f_o(v) - f_{add}(x) \\ dt/dx = 1/v \end{cases} \tag{1}$$

In the formula, F_p indicates the traction force per unit mass, f_b the braking required per unit mass, $f_o(v)$ the basic resistance per unit mass, and $f_{add}(x)$ the additional line resistance experienced by the train. v Indicates speed, b indicates braking, and p is power. The equation takes (the position of the train particle in the section) as the independent variable and the time elapsed is p .

2.2 Multi-objective optimization model

Based on the existing research, based on the characteristics of Pareto optimization, the components of multi-objective optimization are improved, and the multi-objective optimization model shown in formula (2) is obtained[3]:

$$\min Y = F(x) = f(K_e, K_t, K_c)^T \tag{2}$$

$$s.t.\begin{cases} K_e = E_t + E_r + E_b + E_0 \\ K_t = f(T\text{-}T_a;\sigma;t_a) = e^{|T\text{-}T_a|-t_a/2\sigma^2} \\ K_c = e^{|da/dt|-ak/2\sigma^2} \end{cases}$$

Among them: K_e is the energy consumption of the train, K_t is the operating time of the train, K_c is the comfort of the passengers, E_t represents the energy consumed during the traction of the train, E_r represents the energy consumed during the cruising of the train, E_b represents the energy consumed during the braking of the train, and E_0 represents the energy consumed during the idling energy. Since the train does not need traction when it is idle, the energy consumption is 0. It is written here to facilitate subsequent force analysis. T_a specify the running time for the timetable, T the actual running time, t_a the value of represents the acceptable time error, a_k is the target comfort value, σ the width of the model can be adjusted, and a the acceleration of the train. The objective function $F(x)$ under the three constraints of train energy consumption, running time and passenger comfort. After the multi-objective optimization model is established, the respective fitness functions can be solved.

3. Solving the Target Speed Curve of Metro Trains Based on PSO-CS Algorithm

3.1 Algorithm flow design

In the PSO algorithm, there is a symbiotic and cooperative relationship between the behaviors of particles, and the search behavior of each particle will affect each other. At the same time, the best positions of the particles are remembered, and they have the ability to simply learn from past experiences[4]. PSO is a parallel heuristic random search method. Compared with other intelligent algorithms, PSO has the characteristics of no crossover, mutation operator, simple calculation and strong global search ability. During the operation of the algorithm, the particle saves the optimal position pBest it has passed and the global optimal position gBest that all particles have experienced, and guides the particles to move to the global optimal position through information exchange between individuals and groups. The formulas for updating the speed and position of particles are:

$$v_i^{t+1} = wv_i^t + c_1r_1\left(pBest - x_i^t\right) + c_2r_2\left(gBest - x_i^t\right) \tag{3}$$

$$x_i^{t+1} = x_i^t + v_i^{t+1} \tag{4}$$

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The CS algorithm uses lévy flight to update the position. This flight is an equation of random walk. The update formula (5) is as follows:

$$x_i^{t+1} = x_i^t + \alpha \oplus L(\lambda) \tag{5}$$

In the PSO algorithm, particles can exchange information with their own historical optimal position and group optimal position, so that the particles can quickly converge and gather near the optimal solution position of the population[5]. The algorithm has good global and local optimization capabilities. On the one hand, the CS algorithm can ensure that the optimal solution can be retained to the next generation, and at the same time, the optimal solution does not have the danger of being expelled from the population. At the same time, the found bird nest can be discarded, and a new bird nest can be established to explore new solutions, so that the solutions generated in the search space have sufficient diversity. Therefore, we can learn from each other's strengths and combine the two to give full play to their respective advantages. That is, after each iteration uses PSO to update the particle position, the CS algorithm is used to further optimize the particles with a certain probability to improve the algorithm performance. This hybrid algorithm is called PSO-CS, and its process is as follows:

Step 1: Initialize the relevant parameters, randomly generate N individuals as the initial population, and initialize the position and velocity of the particles separately;

Step 2: Calculate the fitness value of each particle objective function, and store the individual historical optimal position and the population global historical optimal position;

Step 3: Determine whether the end condition of the algorithm is met. If yes, go to step 8. Otherwise, go to step 4.

Step 4: Use the above formulas (3) and (4) to update the velocity and position of the particles, respectively.

Step 5: Use the CS algorithm to continue to optimize the population with a probability of 0.5, that is, generate a random number rand0 with uniformly distributed features between [0 1]. If rand0> 0.5, go to step 2, otherwise go to step 6.

Step 6: The position of the bird's nest in the CS algorithm is the particle position. Use formula (5) to perform an update operation on the position of the bird's nest, and test the updated bird's nest. Compared with the previous generation of the bird's nest, the bird's nest with a better test result enters the next step.

Step 7: Generate a random number rand1 uniformly distributed between [0 1] and compare it with the set value pa = 0.25 of the probability that the bird's nest will be found. When rand1 is greater than pa, the position of the bird's nest changes arbitrarily, otherwise it does not change. After the test, the position of the bird's nest is compared with the position of the bird's nest in the previous step.

3.2 Fitness function design

The multi-objective optimization problem of urban rail train operation uses a weighted summation method, which can be converted into a solution to the single-objective problem problem, as shown below:

$$f = w_1 K_e + w_2 K_t + w_3 K_c \tag{6}$$

$$s.t. \begin{cases} v(0) = v(S) = 0 \\ v(s) < v_{\lim}(s), \quad s \in [0, S] \end{cases} \tag{7}$$

Among them, $w_1 \sim w_3$ are the weights of each fitness index: $v(0)$ and $v(S)$ are the initial and final speeds of the train, respectively; $v(s)$ and $v_{\lim}(s)$ are the actual and limit speeds of the train at the location. Therefore, after satisfying the constraint conditions of the above formula, the multi-objective

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can be finally converted into $\min\{f\}$. For the control effect, the smaller the f value is, the better it is. In the intelligent algorithm, the reciprocal value should be used as the evaluation function of fitness:

$$F = 1/f \tag{8}$$

4. Analysis of experimental simulation results

PSO algorithm parameter settings: the number of train input control sequences is 7, the number of iterations is 500, and the number of populations is 20; the inertia weight is w = 1, the learning factor is c1 = c2 = 2, the step factor is 0.54; the weights of each fitness index in multi-objective optimization The parameters are: w1 = 0.35, w2 = 0.3, and w3 = 0.35. Operating parameters: The target time of the train running interval is 295s, and the running time error within 4s is considered to be on-time arrival; the parking error is within 0.3m.

Simulation experiments were performed in the Matlab environment. Two algorithms, PSO and PSO-CS, were used to optimize the train operation process. The optimization process and results are shown in the following table:

Table 1 Comparison table of simulation results of PSO algorithm and PSO-CS algorithm

Number of iterations	algorithm	Energy consumption (KJ)	On-point error (s)	Comfort index	adaptability
10	PSO	86863.58	67.2312	3.7625	0.4650
	PSO-ABC	106779.09	25.4369	2.5787	0.9624
50	PSO	132959.47	23.0324	3.3513	1.2002
	PSO-ABC	123309.95	22.5471	2.5303	1.2443
100	PSO	134125.16	22.1121	3.3616	1.2512
	PSO-ABC	153944.15	0.0695	3.1135	6.8892
300	PSO	125347.63	6.8672	3.5274	2.6416
	PSO-ABC	153943.62	0.0674	3.1161	7.0388
500	PSO	154877.19	1.3947	4.3276	4.7745
	PSO-ABC	153943.62	0.06121	3.1132	7.0381

An analysis of the above table is as follows:

1) Under the premise of not speeding, the PSO algorithm and the PSO-CS algorithm can find a feasible solution that satisfies the conditions at the 100th iteration, that is, the parking error is less than 0.3m and the on-time error is less than 4 seconds. This shows that the proposed algorithm has good convergence and can search for relevant solutions of the problem in a short time.

2) When the program continues to iteratively optimize, after the 500th iteration, the total fitness value of the PSO-CS algorithm is the largest, indicating that the multi-objective overall optimization performance of the algorithm is the best and the overall control effect is the best.

3) After the 500th iteration, the punctuality, energy consumption and comfort index of the PSO-CS algorithm are compared with the PSO algorithm, and the optimization results are the best, indicating that the proposed algorithm has the best performance.

Figures 1 and 2 are the speed-distance curves of the train before optimization with the PSO algorithm and after optimization with the PSO-CS algorithm. It can be seen from Figures 1 and 2 that the speed during the train operation is first accelerated and then decelerated. process. Because the selected line

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has both an uphill and a downhill slope, the slope will generate additional resistance to affect the train's operation.

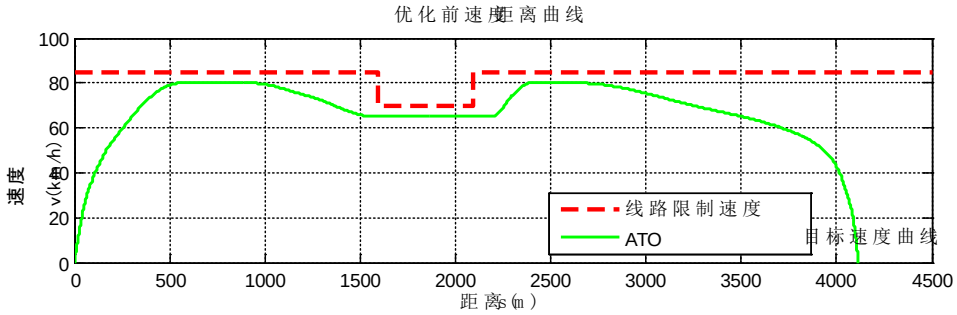

Figure 1. Target speed curve before optimization

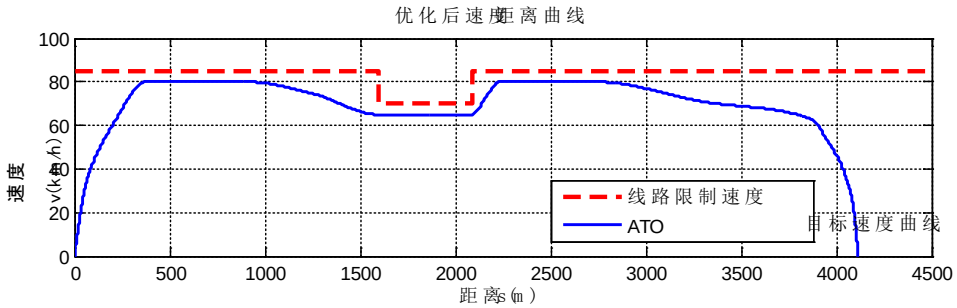

Figure 2. Optimized target speed curve

5. Conclusion

On the premise of ensuring the safe running of the train, a multi-objective optimization mathematical model for automatic driving of urban rail trains was established with the optimization goals of punctuality, precise parking, comfort and energy saving. The PSO algorithm and the CS algorithm are combined, and the improved hybrid algorithm improves the search ability of the global optimal value and accelerates the convergence. Using this PSO-CS algorithm can provide the optimal control target curve for the train automatic speed regulation module. Because the data used in the experiment on the lines and trains are more or less different from the actual situation, after the ATO operation mode curve obtained by the above-mentioned bionic intelligent calculation is completed, it needs to be compared with the field test results, and corresponding adjustments must be made to make it offline. The calculated results can achieve better operating results in practical applications and meet the needs of system design.

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