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Study on Optimization of Urban Rail Train Operation Control Curve Based on Improved Multi-Objective Genetic Algorithm

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Abstract: A multi-objective improved genetic algorithm is constructed to solve the train operation simulation model of urban rail train and find the optimal operation curve. In the train control system, the conversion point of operating mode is the basic of gene encoding and the chromosome composed of multiple genes represents a control scheme, and the initial population can be formed by the way. The fitness function can be designed by the design requirements of the train control stop error, time error and energy consumption. the effectiveness of new individual can be ensured by checking the validity of the original individual when its in the process of selection, crossover and mutation, and the optimal algorithm will be joined all the operators to make the new group not eliminate on the best individual of the last generation. The simulation result shows that the proposed genetic algorithm comparing with the optimized multi-particle simulation model can reduce more than 10% energy consumption, it can provide a large amount of sub-optimal solution and has obvious optimization effect.

Keywords: Multi-objective improved genetic algorithm; urban rail train; train operation simulation; multi particle optimization model

1 Introduction

The train operation process is a complex multi-input and multi-output (MIMO) system with nonlinear, multi-objective and large lag. The complexity of train operation process makes it impossible to describe it by accurate mathematical model. Therefore, it is very difficult to find the optimal train control curve by using the traditional optimization method to solve the train operation simulation model. During the train running, the coasting running process is composed of an infinite number of the coasting points and traction points.

Zhang et al. [1] solved the problem of train handover in wireless LAN of CBTC systems for urban rail transit. Xu et al. [2] presented the last train network delay management model. To solve large-scale practical problems rapidly, an efficient genetic algorithm is designed based on this model. Zhou et al. [3] developed a train trajectory optimization model to minimize the net energy consumption by improving the efficiency of recovery energy utilization. A genetic algorithm (GA) is used to find the optimal train trajectory. Wang et al. [4] presented a multiple-phase train trajectory optimization method under real-time rail traffic management. The proposed method first finds timetable constraint sets for trains under delayed situations. William et al. [5] proposed a novel multi-train trajectory optimization for single-track lines. The multi-train trajectory optimization is formulated as a multiple-phase optimal control problem and solved by a pseudospectral method.

The rest of this paper is organized as follows. Section 2 discusses the optimization idea of urban rail train model based on genetic algorithm, followed by a multi-objective improved genetic algorithm with fixed length chromosome designed in Section 3. The example analysis is discussed in Section 4. Section 5 summarizes the paper.

2 Optimization Idea of Urban Rail Train Model Based on Genetic Algorithm

The genetic algorithm (GA) is widely used in the field of control, and it has the advantages of complex system, no precise mathematical model, powerful global search and local search ability, so it is possible to optimize the train control curve with GA [6–8]. The traditional method cannot use to search the optimal transformation point of the working condition because of the system complexity and the difficulty of establishing accurate mathematical model. Therefore, the GA is used to find the key points in the train operation process, once the better working condition conversion point is found, the train operation control curve will be determined.

Fig. 1 shows the velocity-distance (V–S) curve of a typical single interval train running in the urban rail transit system. The A–B section is the start and traction condition, the B–C and D–E segments are the coasting conditions, the C–D section is the traction condition, and the E–F section is the braking condition.

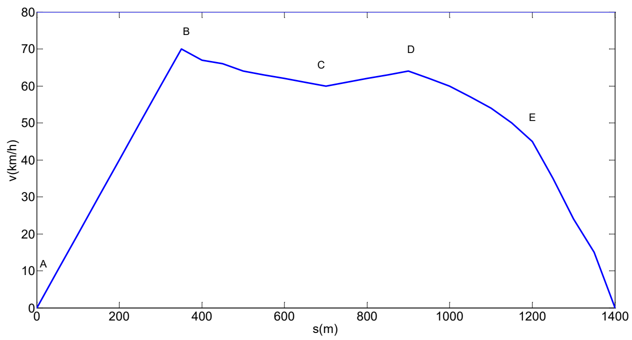

Figure 1: The velocity-distance (V–S) curve and transition points

When the train operation control rules of the single traction-coasting-braking condition are set up, the train operating curve will be determined if the 4 control positions of B, C, D and E are found. According to the general station space in urban rail train system and simulation operation experience, the train control sequence is very common in Fig. 1. So we take the 4 control points for an example to test the effect of train control curve optimization based on genetic algorithm [9–11].

Suppose that the 4 points of B, C, D and E can form a feasible control sequence in Fig. 1, and then the 4 transition points should be satisfied:

$$\begin{cases} S_B < S_C < S_D < S_E \\ \lambda_B \le S_B \le \mu_B \\ \lambda_E \le S_E \le \mu_E \\ S_B > S_a, S_E < S_b \end{cases} \quad (1)$$

In which, S_B, S_C, S_D and S_E are respectively the 4 control points positions of B, C, D and E; λ_B and μ_B are respectively constants related to the position B; λ_E and μ_E are respectively constants related to the position E; S_a and S_b are the starting point and terminal position for some intervals, respectively. The control sequence which is not composed of 4 points, the constraint condition of the similar formula (1) should also be satisfied. The working sequence is the basis of chromosome coding. Each individual represents a working condition sequence, and a working condition sequence implies an operation control scheme. N sequences are selected to form n individuals, thus forming a population of genetic algorithms. The fixed length chromosome multi-objective improved genetic algorithm (MIGA) will be put forward and the definition is that the multi-objective improved genetic algorithm with several fixed genes constitute individual and the chromosome length maintain unchanged during the calculation [12–15].

3 Design of A Multi-Objective Improved Genetic Algorithm with Fixed Length Chromosome

3.1 Coding Design

In the working sequence, the position of the transition point is an unknown variable, and the position of the transition point can be represented by one gene. A working conditions sequence is represented by a chromosome with several genes. Because the station space of urban rail system is generally around 2000 m; on the other hand, the transformation point position of working condition is accurate to m which can meet the requirements. Therefore, the binary encoding of the genes, if $2^l - 1$ is more than 4000, while the length of gene $l = 11.65$, that is, l can take the 12 that it can meet the requirements. If we need to improve the computational accuracy, or the calculating interval distance is more than 2000 m, we can achieve by increasing the gene length [16–20].

3.2 Generation of the Initial Populationt

The mainly selection factor of the initial population should consider the population size and population quality. Population size is generally set before calculating and it can be adjusted according to calculation efficiency. Because the particularity and complexity of the problem, it is necessary to constrain the individuals in the initial population to ensure the population quality and the computational effect when designing the genetic algorithm. Because gene coding is randomly generated, it may lead to many genes have no sequence or do not meet the constraints of Formula (1). In addition, even if the individual can meet the Formula (1) constraint condition, still it may not meet the operation simulation algorithm. That is, the control sequence itself is unable to achieve, at this time it may cause that the fitness function is 0. So, when producing each gene, it should be sorted and checked. The check condition of the individual is:

$$f_i \geq \beta \geq 0 \tag{2}$$

In which: f_i is the fitness value of individual i; β is the selection constant of the fitness value which is determined by the experience.

3.3 Selection Operator Design

The roulette wheel selection method is often used in operator selection, and the optimization algorithm is added. The roulette wheel selection method is actually based on the selection of individual fitness value according to the proportion of the population, so it can also be called the proportion selection.

The basic idea of the roulette wheel selection method is:

(1) Calculating the fitness $f(x_i)$ of each individual in the group ($i = 1,2,...M$), M is a group size.

(2) The probability of each individual being inherited to the next generation group is calculated.

$$P(x_i) = \frac{f(x_i)}{\sum_{j=1}^{N} f(x_j)} \tag{3}$$

(3) Calculating the cumulative probability of each individual.

$$q_i = \sum_{j=1}^{i} P(x_j) \tag{4}$$

(4) A pseudo random number r is produced in the interval [0, 1] which is uniformly distributed.

(5) If $r < q[1]$, the individual is 1; otherwise, the individual can select k, and $q[k-1] < r \leq q[k]$ is established.

(6) Repeat M times of the (4) and (5) steps.

Since roulette selection operator is the most common selection algorithm, it is no longer detailed here.

3.4 Crossover Operator Design

The crossover operator is a crossover operation based on cross probability P_c, which uses single crossover method and adds an optimization algorithm. Suppose that the genetic composition of the 2 individuals and the transition point of the work condition are represented the Fig. 2. After the 27 point crossover of the chromosomes, the progeny chromosomes begin to exchange after 27 bits (italics in the figure) to form new individuals.

419	795	1165	1412
000110100011	001100011011	010010001111	010110000100
315	752	864	1539
000100111011	001011110000	001101100000	011000000011

(a) Before crossing (father generation)

419	795	1888	1539
000110100011	001100011011	011101100000	011000000011
315	752	143	1412
000100111011	001011110000	000010001111	010110000100

(b) After crossing (child generation)

Figure 2: Change of the transition point sequence in the working condition before and after crossing

Seen from the condition transformation sequence of the 2 new individual in the Fig. 2, the first individuals $S_D = 1888 > S_b = 1600$, the second individual $S_D = 143 < S_C = 752$, the both do not satisfy the constraints Formula (1). So, before beginning the next step, the crossed new individual should be gene sequencing, and check the new individual effectiveness. If the intersections do not satisfy the constraint conditions, it needs to be repeated until the constraints are satisfied [21].

The computation step of the crossover operation for the four optimization genes is as follows:

(1) Supposing the loop variable is $i = 1$, then select the best individual I_m ($1 \le m \le N$) from the population and make $f_m = \max(f_1, f_2, ... f_N)$.

(2) Selecting the individual I_i and I_{i+1} ($1 \le i \le N-1$)from the population in the order of the past.

(3) Randomly generating r random numbers in the range [0–1], and compared with a given probability P_c, if $r \le P_c$,the procedure will turn to the fourth step and otherwise go to the eighth step.

(4) Randomly generating the random integer k in the range [2~48] (the first is ineffectiveness crossover, the 48th is the chromosome length), the individual I_i and I_{i+1} begins crossing and interchanging from $k \sim 48$ bit of the chromosome.

(5) Reordering the crossed genes according to the order from small to large.

(6) Checking the individual $I_i^{'}$ and $I_{i+1}^{'}$ after the intersection whether its meet the constraints; If satisfied, the procedure will turn to the seventh step, otherwise, it will turn to the fourth step.

(7) Calculating the fitness value the individual $f_i^{'}$ and $f_{i+1}^{'}$ of the individual $I_i^{'}$ and $I_{i+1}^{'}$, if $f_i^{'} \ge \beta$ and $f_{i+1}^{'} \ge \beta$, the procedure will turn to the eighth step, otherwise, it will turn to the fourth step.

(8) Making $I_i^{'}$ and $I_{i+1}^{'}$ ($r \le P_c$) or I_i and I_{i+1} ($r \ge P_c$) join in the new population.

(9) Supposing $i = N-1$, the crossover operation will be over, the procedure turns tenth step; otherwise, make $i = i+2$ and turn second step.

(10) Picking out a new population of the best individual of $I_l^{'}$, $1 \le l \le N$ ($f_l^{'} = \max(f_1^{'}, f_2^{'}, ... f_N^{'})$); if the fitness value $f_l^{'} < f_m$ of $I_l^{'}$,the worst individual of the new group will be replaced by I_m,otherwise the best individual is $I_m = I_l^{'}$ and the calculation is finished.

3.5 Mutation Operator Design

For the binary gene coding, the mutation operation takes the mutation probability P_m to flip the gene bits of each binary in the chromosome, that is, the bit will be from 1 to 0 or from 0 to 1. Similarly, the mutation operator should also join the optimization operation. When the chromosome changes, the position of the working condition should be changed. At the same time, the gene sorting and the validity check are also similar to the crossover [22]. The computational process of the individual gene conservation and variation is as follows:

(1) Supposing the loop variable is $i = 1$, then select the best individual I_o from the population and make $f_o = \max(f_1, f_2, ... f_N)$.

(2) Selecting the individual I_i ($1 \le i \le N$) from the population in the order and the loop variable $t = 1$.

(3) Choosing a binary gene location b_t ($1 \le t \le 48$, $b_t = 0$ or $b_t = 1$) by according to the gene sequence from the individual I_i.

(4) Randomly generating r random numbers in the range [0–1], and compared with a given probability P_m, if $r \le P_m$, the procedure will flip b_t, otherwise the procedure will unchanged.

(5) If $k = 48$, the procedure will turn to the sixth step, otherwise $t = t+1$ and turn to the third step.

(6) Reordering and validity checking the mutated gene sequence of the individual $I_i^{'}$, then calculate the fitness value of $f_i^{'}$,if $f_i^{'} \ge \beta$, the procedure will turn to the seventh step; if it does not pass the validity check or $f_i^{'} < \beta$, the procedure will turn to the third step.

(7) Supposing $i = N$, the mutation operation will be over, the procedure turns eighth step; otherwise, make $i = i+1$ and turn second step.

(8) Picking out a new population of the best individual of $I_p^{'}$ ($f_p^{'} = \max(f_1^{'}, f_2^{'}, ... f_N^{'})$); if the fitness value $f_p^{'} < f_o$ of $I_l^{'}$, the worst individual of the new group will be replaced by f_o, otherwise refresh the best individual is $I_o = I_p^{'}$ and the calculation is finished.

3.6 Fitness Function Design

The optimization model of train operation control system is a very complex multi-objective optimization problem [23–24]. The basic requirements include energy consumption, running time, parking accuracy and comfort. The optimization model mainly includes 3 aspects of energy consumption c, running time (the time error Δt) and parking accuracy (the parking error Δs) in this paper. Then designing the fitness function:

$$f_i = \frac{A}{c^p (w_1 \Delta t + w_2 \Delta s + \varepsilon)^q}, 1 \le i \le N \tag{4}$$

In which: A and ε are the normal constants, $\varepsilon \leq 1$ is used to prevent the denominator of 0. A can be adjusted according to the fitness value, it will remain unchanged when the system starts to calculate; p and q are the constant which are used to adjust the proportion between the c and the sum of Δt and Δs; w_1 and w_2 respectively are the weight of Δt and Δs, $w_1 + w_2 = 1$.

It is impossible to establish a precise algorithm to calculate the fitness value of train operation process because of the complexity of train operation control. So the feasibility of the given control sequence can only be calculated by train operation simulation. For the control sequence composed of 4 switching points, the train operation process is divided into 5 stages: Starting traction stage, coasting stage, traction acceleration stage, the second coasting stage and stop braking stage. Through the simulation of each operation stage, it can calculate the energy consumption, running time and parking position during the train operation. On the basis of these parameters, the fitness value of individuals can be calculated according to the Formula (4). The simulation algorithm of train operation and the multi particle optimization model are basically the same [25–26].

4 Example Analysis

The proposed algorithm uses MATLAB Simulation with the data of B urban rail train in Zhengzhou. The parameters of the line 1 are: The interval length of flat slope line is 1400 m, 2 stations, including the curve with 300m length and 2500 m radius; simulation calculation parameters: the initial time step is 400 ms, the condition transformation time is 2 s, the calculation error of driving speed is 2 km/h, the velocity curve error is 1 km/h, the speed fluctuation is 15 km/h; The short distance and short running time of the operation of urban rail train make the population size smaller, which is conducive to the formation of global optimum. So GA parameters are: The population size is 40, the gene length is 12, the chromosome contains 4 genes, the crossover probability is 0.60, the variation probability is 0.05. The running time is equal to the calculation time of the multi particle optimization model; the termination condition: The evolution generation is 50 or meeting requirements of the time error (2 s), the parking error (1 m) and interval energy ($c \leq c_0$, c_0 is the interval energy consumption of the multi particle optimization model). In the fitness function, $A = 100$, $p = 1.0$, $q = 1.0$, it does not distinguish the weights. The calculation results of the both algorithms are shown in Tab. 1, and the statistical average values are calculated continuously 30 times.

Table 1: Comparison results of multi particle optimization model and MIGA

Algorithm	Interval distance (m)	Operation time (s)	Average speed (km/h)	Total energy consumption (kwh)
Multi particle optimization model	1400	98.9	55.9	2.14
MIGA	1400	98.1	56.2	1.91

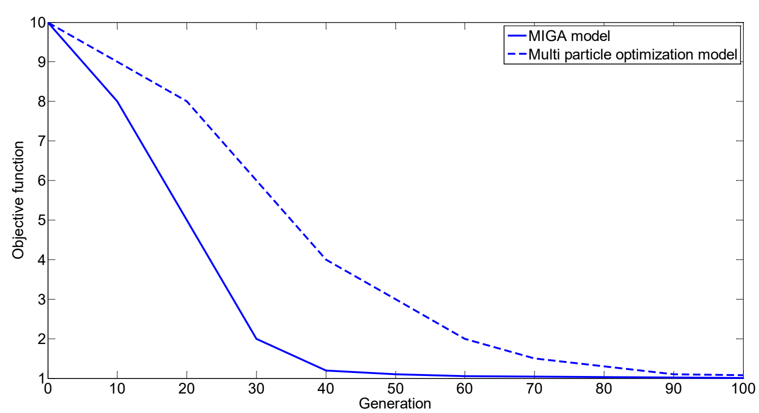

Figure 3: The cure between generation and objective function

According to the above calculation conditions and the equal sequence length, the convergence success rate reaches 77% when using the genetic algorithm in the 50 generations, and the average convergence generation is 14.52; the average stopping error of the best individuals is 0.43 m each generation, the average time error is 1.63 s, the average energy consumption reduces 8%; the stop error of the optimal individual is 0.11 m, the energy consumption reduces 15%. In addition, the computation speed of MIGA is also very fast. When it evolves to the 50 generation, the computation time is about 1 s, which is acceptable for no-online simulation.

Fig. 4 is the calculation results of a multi particle optimization model and MIGA of train operation control curves. It can be seen from Fig. 2 that the MIGA is similar to the train control curve calculated by the multi particle optimization model. The $v-s$ curve is divided into 5 segments, and the whole curve has 4 typical transition points: Traction to coasting, coasting to traction, the second traction to coasting and coasting to braking.

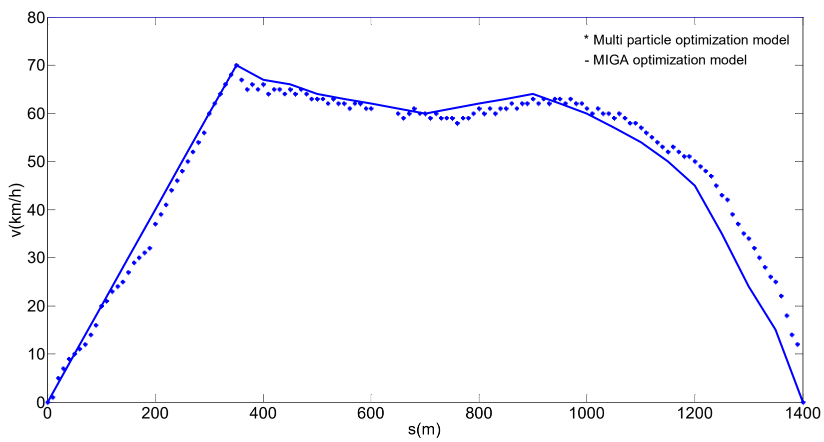

Figure 4: Train operation control curves of multi particle optimization model and MIGA

5 Summary

The fixed length chromosome multi-objective improved genetic algorithm will be less converge generations than other algorithms when the line is moderate length, no steep slope and large limited speed change section. Compared with the multi particle optimization model, MIGA can reduce energy consumption by more than 10%, and has the higher parking accuracy, the smaller time error, the higher convergence success rate and the smaller evolutionary time, and the computation speed can meet the need of off-line calculation. The algorithm takes into account the functions of punctuality, parking precision, energy consumption and comfort. This algorithm has a good reference value for the research of multi-target operation process of urban rail train, and provides a valuable analysis method for further study of automatic train driving system.

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Conflicts of Interest: The authors declare that they have no conflicts of interest to report regarding the present study.

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