Multi-objective Optimization Improved GA Algorithm and Fuzzy PID Control of ATO System for Train Operation

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Abstract. In order to solve the problem that automatic train operation control system considering the single factor and control is not easy to be accurate, a multi-objective optimization (MO) based on improved genetic algorithm (GA) and fuzzy PID control method is proposed in this paper. Firstly, based on train operation characteristics, a multi-objective model of train operation process is established. Secondly, in order to improve the performance of the algorithm, the train operation process is optimized by using linear weight method and multi-objective genetic algorithm. Third, in order to suppress the local convergence of GA, a dual population genetic mechanism is adopted in the iterative process. Finally, a fuzzy PID controller is embedded into the control designer after target curve and control train operation in real time according to the real time running state. The results show that the proposed algorithm can get a reasonable MO result and accurate real-time control.

Keywords: ATO · Multi-objective optimization (MO) · Genetic algorithm (GA) · Fuzzy PID

1 Introduction

Automatic train operation (ATO) control system is the core of speed and energy consumption control. However, the indicators considered by the researches of ATO control strategy are incomplete, and these indicators cannot reflect the multi-objective features of train operation process [1].

Various control schemes have been proposed in recent works on the ATO control strategy [2–8]. In [2], under actuator saturation caused by constraints from serving motors, an on-line approximation based robust adaptive control problem for the ATO system is proposed. An actuator saturation nonlinearity with unknown system parameters and nonlinear dynamics during the whole operational process is considered explicitly. The robustness of the system can be improved. In order to obtain compromises between journey duration and energy saving, an approach for speed tuning in railway management is proposed in [3]. The proposed method can deal with a bi-criteria optimization problem, which consists in designing speed profiles integrating both criteria in order to provide patterns of speed control. Besides, this method integrates the energy consumption as a criterion to optimize. In [4], in order to minimize

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the net energy at substations, an optimal ATO speed profiles of metro trains taking into account the energy recovered from regenerative brake is designed. Meanwhile, a model of a train with an on-board energy storage device as well as a network model for estimating the energy recovered by the train is presented. In [5], the adaptive optimal control (AOC) method is developed to improve the dual heuristic programming (DHP) design with respect to modeling errors as well as optimality, and an automatic train regulation (ATR) designed was developed and evaluated by using AOC method. The result shows that the AOC method is able to find a near-optimal solution more rapidly and accurately than the DHP method. In [6], a novel online learning control strategy is proposed to solve the train automatic stop control (TASC) problem. Meanwhile, an extensive comparison study on a real-world data set collected in the Beijing subway line is performed. The proposed online learning algorithm can dynamically reduce stopping errors by using the precise location data. In [7], an optimization approach for the speed trajectory of high-speed train in a single section is studied. Besides, a MO model for the speed trajectory is developed by considering the constraints such as safety requirement, track profiles, passenger comfort, and the dynamic performance. It should be noted that numerical examples are given to illustrate the effectiveness of the train operation process optimization. However, there is a little related literature published about the MO based on improved GA and fuzzy PID control method in order to solve ATO control system. The main advantages of the proposed algorithms are summarized as follows:

(i) For the optimization algorithm of the train operation process applied to the ATO system, it is necessary to establish an optimization model of the train running process. In this paper, a more in-depth analysis of the train running process is carried out to derive a formula for calculating the fitness function with acceleration, distance and velocity as real-time measurements to simplify the calculation.

(ii) It is difficult to find a satisfactory solution in the latter part of the iteration by using genetic algorithm. Therefore, this paper uses a dual population genetic mechanism. It uses two populations to evolve at the same time and exchange the outstanding individuals in genetic information with each other, for obtaining a higher equilibrium state by destroying the former equilibrium state within the population, which breaks down the "dominant" position established in the long process of a single population, thus jumping out of local optimum.

(iii) General researches on optimization of train operation are limited to finding a relatively optimized train trajectory, instead of considering its rationality in practice. It is obviously not enough for ATO control system applied to the actual train operation control system. In this paper, a speed controller based on fuzzy PID control strategy is used to track the target curve after finding an optimized trajectory.

2 Multi-objective Model of Train Operation Process

ATO system of the train is a complex nonlinear system. It includes a plurality of input and output variables, and regards energy consumption, precise parking, punctuality, comfort and other performance index as control targets.

2.1 Constraint Model

Energy consumption of the train is represented by the energy consumed when the train overcomes resistance and operates in the whole running process. The train energy function can be obtained:

$$E = \frac{\int Fvdt}{\xi_M} + At + \xi_B \int Bvdt \tag{2}$$

In (2), F is the train running traction: B is the train running braking force; v is the train running speed; A is the train auxiliary power; t is the train inter-station running time; ξ_M is the product factor of that traction electric energy converting to mechanical energy; ξ_B is the product factor of that braking mechanical energy converting to electric energy.

Because train operation process is the major thing to consider, so the train auxiliary power A can be ignored. Simultaneously, setting the value of product factor ξ_M, ξ_B to 1 and simplifying formula 3 according to integral linearity, and the traction force F and the braking force B are expressed with $m \cdot a - R$, and vdt are expressed with ds, which can be expressed as:

$$E = \int (F + B)vdt = \int (ma - R)ds \tag{3}$$

Therefore, the Eq. (3) above is discretized, then train running energy consumption model can be expressed:

$$K_E = \sum_{i=1}^{n} (ma_{i-1} - R_{i-1})(s_i - s_{i-1}) \tag{4}$$

In (4), s_i is position of running point; R_i is resistance of running point; a_i is accelerated speed of running point; K_E is the energy consumption measurement index.

Comfort reflects the riding quality of passengers, and it is usually expressed by the accumulation of the acceleration difference in the unit time. Therefore, train running comfort model can be expressed:

$$K_C = \sum_{i=1}^{n} |a_i - a_{i-1}| \tag{5}$$

In (5), K_C is the comfort measurement index.

The indicator model of exact parking is the distance difference between running distance of train in the whole running process and the distance of train from running starting point to docking stations. The parking error of the docking station will keep within the range of ±20 cm, the exact parking model can be expressed as:

$$K_P = |S_z - S'| \tag{6}$$

In (6), K_P is parking accuracy error measurement index; S_Z is the actual driving distance of the train; *S'* is the distance between two stations.

The punctuality model can be expressed by the difference between the train running time and the given time, and then train punctuality model can be obtained:

$$K_T = \left| \sum_{i=1}^{n} T_i - T \right| \tag{7}$$

s_i and a_i refer to the position and accelerated speed of i-th operation condition.

After gaining s_i and a_i, v_i and t_i can be gained by the following formula:

$$v_i = \sqrt{2a_i(s_i - s_{i-1}) + v_{i-1}^2} \tag{8}$$

$$t_i = \frac{v_i - v_{i-1}}{a_i} \tag{9}$$

For the punctuality index, *T* is the specified running time of the train in the running interval. The error of actual running time of the train and specific time is not more than 5%.

2.2 Multi-objective Optimization Model

In summary, the multi-objective optimization model is shown as

$$\min\{K_E, K_C, K_P, K_T\} \tag{10}$$

In (8), min represents getting the minimum value of the function, namely, each sub-goal function takes the minimum value as much as possible. This paper presents by linear weight method to gather it as single objective optimization problems. Before the polymerization, each index should be nondimensionalized, and the solution should be obtained by the genetic algorithm.

$$f = w_1K_E + w_2K_C + w_3K_P + w_4K_T \tag{11}$$

In (11), w_1, w_2, w_3 and w_4 are weight coefficients, the formula is expressed as follows

$$\begin{cases} w_i = w'_{1i} \times w_{2i} \\ w_{2i} = 1/|\Delta f_i(X)| \\ a_i \le f_i(X) \le b_i \\ \Delta f_i(X) = \frac{b_i - a_i}{2} \end{cases} \tag{12}$$

where w'_{1i} represents the principal factor, and satisfy $w_{11} + w_{12} + w_{13} + w_{14} = 1$, which reflects the relative importance of the i-th indicator; w_{2i} represents the correction factor, which is used to adjust the effect of each target on differences in dimension and magnitude; $f_i(X)$ represents the objective function value of the i-th indicator; a_i and b_i represent the upper and lower bounds of the objective function values of the i-th index; $f_i(X)$ is the tolerance of the objective function value of the i-th indicator. The train operation optimization is equivalent to find a train trajectory to take into account the various operational indicators. In (12), X is the trajectory, and $f_i(X)$ is the objective function value of the i-th index.

In the formula (13), $w_i(i = 1, 2, 3, 4)$ expresses weight of each fitness index. The formula (4), (5), (6), (7), (8) and (9) are substituted into formula (11), we can get fitness function:

$$F = 1/f = \begin{pmatrix} w_1 \sum_{i=1}^{n} (ma_{i-1} - R_{i-1})(s_i - s_{i-1}) + w_2 \sum_{i=1}^{n} |\mathrm{a}_i - \mathrm{a}_{i-1}| + w_3 |S_Z - S'| \\ + w_4 \left(\sum_{i=1}^{n} \left[\left(\sqrt{2a_i(s_i - s_{i-1}) + v_{i-1}^2} - v_{i-1} \right) / a_i \right] - T \right) \end{pmatrix}^{-1} \tag{13}$$

In (13), F is fitness function. From the formula (13), it is can be seen that this paper designs a fitness calculating function with acceleration, distance and velocity as real-time measurements. This fitness calculating function greatly simplifies the calculation in the iterative process, which can guarantee the accuracy and optimization of the results.

3 Improved Genetic Algorithm and Fuzzy PID Control

The main disadvantages of genetic algorithm are summarized as follows: (1) the local search ability of the algorithm is weak, and it is easy to fall into local optimal solution; (2) The convergence speed of the algorithm is relatively slow [9].

3.1 A Dual Population Genetic Mechanism

Population will constantly evolve as time goes on, thus, it will have more and more excellent quality. However, due to their growth, evolution, environment and the limitations of the initial population, they will gradually evolve to the characteristics of the relative advantage of the state after a substantial amount of time has lapsed. Thus, the character of the population will not greatly change.

Dual population genetic mechanism is a parallel mechanism, and it uses two populations to evolve simultaneously. It exchanges the genetic information carried by the excellent individuals in the population. In order to break the equilibrium state of the population, to achieve a higher equilibrium state, it will jump out of local optimization. The calculating process of the Improved genetic algorithm is shown in Fig. 1.

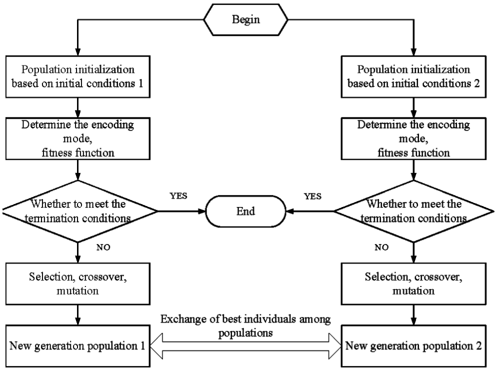

Fig. 1. Flow chart of dual population genetic algorithm mechanism

The schematic diagram of the optimal individual in the exchange population can be shown as follows (Fig. 2):

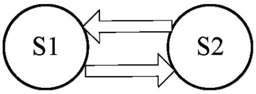

Fig. 2. Exchange of optimal individuals

3.2 Fuzzy PID Method

To verify the tracking effect of controller on target curve, the solved velocity curve shall be tracked by using self-adaptive fuzzy PID speed controller. Self-adaptive fuzzy PID speed controller includes two parts, one is fuzzy controller, and the other is PID controller [10–12]. Its fundamental principle of Self-adaptive fuzzy PID controller is to find out the fuzzy relation between each parameter of PID and deviation *e* and deviation variation rate *ec*. The functional block diagram is shown as Fig. 3:

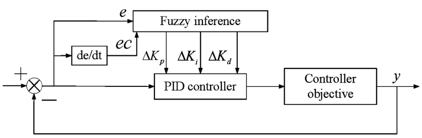

Fig. 3. Principle of self-adaptive fuzzy PID speed controller

In design of fuzzy controller, the PID parameter (K_P, K_I, K_D) should be used in deviation *e* and deviation variation rate *ec* to design the controller as shown in Fig. 4.

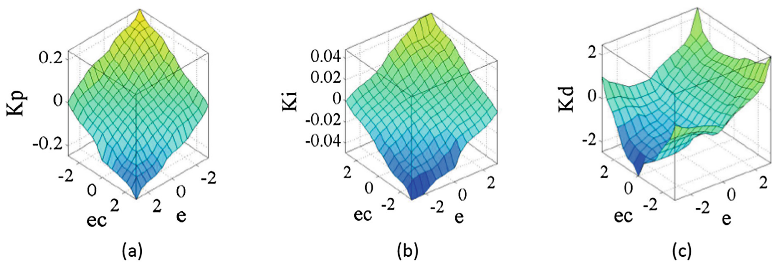

Fig. 4. PID parameter fuzzy control-rule

4 Instance Simulation

4.1 Data Processing in Train Operation Environment

The basic parameters of train are shown in Table 1:

Table 1. Basic parameters of train

Parameter name	Parameter characteristics
Train weight (t)	332
Maximum running speed/(km/h)	80
Formation scheme	4 motor 2 trail
Mean starting acceleration (m/s^2)	(0–35 km/h) $\geq$ 1.0
Mean acceleration (m/s^2)	(0–80 km/h) $\geq$ 0.6
Mean deceleration frequently used for braking (m/s^2)	(80–0 km/h) $\geq$ 1.0

4.2 Operate Curves of Optimization by Genetic Algorithm

To verify the optimal performance of genetic algorithm, Matlab2010a platform is used to simulate in this paper. It is not advisable to obtain extremely small optimization progress when consuming a huge computational cost in the optimization of the train operation. This article sets the following initialization parameters. The population size is 50, maximum population algebra is 200, crossover probability is 0.8, and mutation probability is 0.02. Operate curves of optimization by genetic algorithm,genetic algorithm iterative convergence curve are shown in Figs. 5 and 6.

The maximum running speed of train follows the speed limit on the line, and the speed of train entering into a station is less than the speed limit in station. It can be seen from Fig. 7 that the fitness function increases with the increase of genetic algebra. When the genetic algebra is greater than 50 generations, the fitness function does not change. At this time, the genetic algorithm has obtained the ideal optimal solution.

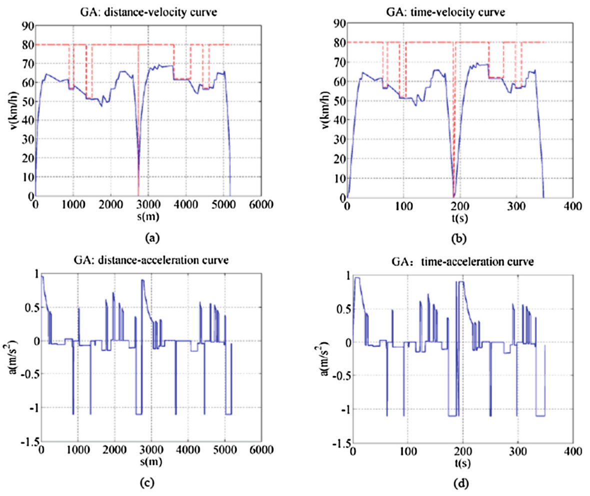

Fig. 5. Operate curves of optimization by genetic algorithm

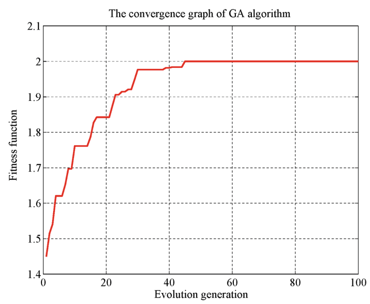

Fig. 6. Genetic algorithm iterative convergence curve

4.3 Tracking Curve of Control by Fuzzy PID

The quality of train tracking target curve directly reflects the feasibility of control algorithm. The tracking simulation results can be gained by velocity controller through tracking and simulating the target curve. Tracking curve of control by fuzzy PID are shown in Fig. 7.

As shown in Fig. 7, there are no large fluctuation in process of train tracking target curve. Meanwhile, the tracking curve and target curve are basically coincident, which shows that the following performance of train for target curve is pretty good. Thus, the proposed algorithm is feasible.

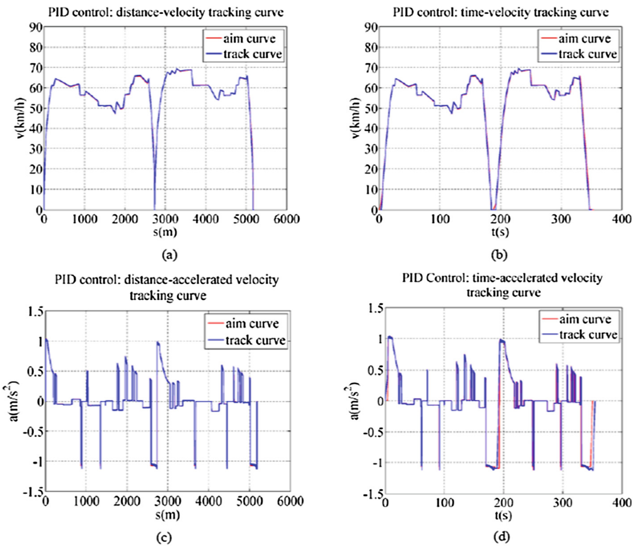

Fig. 7. Tracking curve of control by fuzzy PID

5 Conclusion

In this paper, the multi-objective optimization model of train is presented, and the train operation process is optimized by genetic algorithm. Meanwhile, to obtain a better solution, a dual population genetic mechanism is adopted in the iterative process, so as to improve the performance of genetic algorithm. The optimized result shows that the punctuality, precision parking, comfort, energy saving and other multiple performance requirements of train have been met. Finally, based on generating train running target curve by genetic algorithm, the self-adaptive fuzzy PID control is embedded in the train control system, and the target curve is tracked. The problem of speed controller following target curve can be handled well, the train can operate smoothly and safely, and possess perfect robustness.

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