A New Estimation Method of the PID Controller In Automatic Train Operation Systems

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Abstract—PID controller plays an important role in Automatic Train Operation systems. Many researches have been done on the PID parameters estimation. However, the traditional models simplified the characteristics of the trains in different speeds and operation modes. It was difficult to overcome the problems with different kinds of algorithms based on the traditional models, especially the accuracy requirement of the stopping distance. In this paper, a new model of the PID controller was proposed based on the practical train operation stages. And the different response time delay was considered besides of the transmission time delay. With this new model, an Improved Fruit Fly Optimization Algorithm was applied. The tracking performance were greatly improved both on running distance and real time. The simulation results showed a better performance than the traditional methods.

1. INTRODUCTION

In recent years, urban rail transit has developed rapidly in many cities of the world. Automatic Train Operation (ATO) system is an important part of Automatic Train Control (ATC) system, which has been widely used in metro trains. With the ATO system, train runs by tracking the target speed curve in real time. Among all the tracking algorithms, Proportion Integration Differentiation (PID) is the most popular one used in railways. There are only three parameters in a classical PID controller, and which could be adjusted independently due to the tracking performance. The earliest PID parameters estimation method was developed by John Ziegler and Nathaniel Nichols[1]. After that, many researchers and engineers in train control area showed great interesting on it. In 1984, Yasunobu and Miyamoto proposed the automatic train operation system with PID based on fuzzy control algorithm[2]. In 1995, a second-order control system was designed by Sekine and Nishimura which combines fuzzy control and neural network[3]. In 2016, Shi Wei developed a model-free adaptive algorithm to track the target speed curve[4]. And in 2018, Wang Hua et al. improved the PID controller with the genetic algorithm by setting the train working condition switching point, the PID learning rate and the proportional coefficients[5]. However, in most of the models, only the transmission delay was considered and the tracking process of the train was simply divided into three modes: tracking, coasting, and braking. As we know that the trains’ characteristics vary at different speeds, even in the same mode. And the time delay also changes due to the different response schemes, besides of the transmission delay. PID estimation algorithms with the simple traditional models could not track the target curve accurately, especially on the stopping distance.
In this paper, the tracking process was divided more accurately based on the practical train operation stages, including coasting stage, traction start-up stage, retraction stage, traction removal stage and braking stage. Transmission time delay and response time delay were estimated separately in different modes. And an Improved Fruit Fly Optimization Algorithm (IFOA) was applied to achieve the real-time estimation results. Simulation results showed that the new models and algorithm had better performance than the traditional ones.

This paper was organized as follows: firstly, we introduced the models of each different operation stages; secondly, the IFOA was described in detail; thirdly, simulation results were given with a case study in Beijing Subway; finally, we gave the conclusion.

2. MODELS BUILDING

2.1. Force Analysis of Train

As shown in Figure 1, trains run on the railway due to the action of traction force $F_{\text{tra}}$, resistance $F_{\text{br}}$, braking force $F_{\text{bra}}$ and the gravity $G$.

Resistance is consisted by the basic resistance and additional resistance. The calculation formula of resistance is shown in equation (1):

$$f_b(v) = a v^2 + b v + c \quad \text{Basic resistance}$$

$$f_s(v) = M g \theta \quad \text{Ramp resistance}$$

Where, $f_b$ represents the basic resistance of the train, $v$ is the current running speed of the train, $a$, $b$ and $c$ are the Davis coefficient[6], $M$ represents the mass of the train, $g$ is the constant of gravitational acceleration which is 9.81 m/s$^2$ here, and $\theta$ is the slope angle of the track.

The traction force and braking force are calculated according to the characteristic curve.

$$a_{\text{tra max}} = f_{\text{tra}}(v) \quad (2)$$

$$a_{\text{bra max}} = f_{\text{bra}}(v) \quad (3)$$

In the above equations, $a_{\text{tra max}}$ is the maximum traction acceleration (m/s$^2$) that can be output under the current speed of the train, and $f_{\text{tra}}(v)$ is the functional relationship between the maximum traction acceleration and the current running speed of the train. $a_{\text{bra max}}$ is the maximum braking acceleration available at the current speed; $f_{\text{bra}}(v)$ is the function relationship between train running speed and maximum braking acceleration.

2.2. The Train Dynamics Model

2.2.1. Coasting Stage

When the ATO system issues coasting instructions, the train will not coast immediately due to the transmission time delay $T_r$. The traction state will remain for a period of time, continuing the traction
instructions of previous cycles, and the traction instructions will disappear after $T_1$. At the same time, when the train receives the instruction transmitted by the ATO system, the traction acceleration of the train also decreases slowly due to the response time delay $T_2$. Therefore, the control model of coasting stage can be illustrated in Figure 2 as

$$a_t = \begin{cases} 
  a_{bf} & t \leq T_1 \\
  a_{bf} \cdot \exp(-\frac{t-T_1}{T_2}) & t > T_1
\end{cases}$$ (4)

$$F_{res} = (av^2 + hv + c + \theta) \cdot Mg / 1000$$ (5)

$$a_{res} = F_{res} / M$$ (6)

$$a = a_t - a_{res}$$ (7)

$$V_{out} = V_{in} + a T_s$$ (8)

Where $a_t$ is the actual traction acceleration of the train after the delay, $a_{bf}$ represents the traction or braking acceleration sustained in the previous stage, $T_1$ and $T_2$ are transmission delay and response delay, $F_{res}$ is the running resistance, $a_{res}$ is the resistance acceleration of the current train, $T_s$ is the control time slot, $V_{in}$ is the input speed of the train at the current moment, and $V_{out}$ is the output speed of the train at the next moment.

2.2.2. Traction Stage

In this paper, the traction stage is divided into traction start-up stage, retraction stage and traction removal stage based on the practical situation. Different stages have different parameters in different models. However, the models have the similar modes. To save the space, the traction starting stage is mainly introduced here. It needs to be emphasized that estimation algorithm should be applied to different stages due to different parameters.

The control block diagram of traction start-up stage is shown in the Figure 3.

$$a_t = \begin{cases} 
  0 & t \leq T_3 \\
  a_{bf} \cdot [1 - \exp(-\frac{t-T_3}{T_3})] & t > T_3
\end{cases}$$ (9)
\[ F_{res} = (av^2 + bv + c + \theta) \cdot Mg / 1000 \]  
(10)

\[ a_{res} = F_{res} / M \]  
(11)

\[ a_{res} = f_{res}(v) \]  
(12)

\[ a = a_{t} \cdot P_{bra} - a_{res} \]  
(13)

\[ V_{out} = V_{in} + aT_S \]  
(14)

Where \( T_s \) and \( T_r \) are respectively the transmission delay and response delay in the traction start stage, and \( P_{t} \) is the traction motor efficiency of the train.

2.2.3. Braking Stage

The control block diagram of the braking stage is shown in the following Figure 4:

![Control model of braking stage](image)

Figure 4. The control model of braking stage

According to the control block diagram, the model is obtained as follows:

\[
a_t = \begin{cases} 
a_{bf} & t \leq T_g \\
a_{bra} \cdot \left(1 - \exp\left(-\frac{t - T_g}{T_{10}}\right)\right) & t > T_g 
\end{cases} \]  
(15)

\[ F_{res} = (av^2 + bv + c + \theta) \cdot Mg / 1000 \]  
(16)

\[ a_{res} = F_{res} / M \]  
(17)

\[ a_{bra} = f_{bra}(v) \]  
(18)

\[ a = a_{t} \cdot P_{bra} - a_{res} \]  
(19)

\[ V_{out} = V_{in} + aT_S \]  
(20)

Where \( T_s \) and \( T_r \) are respectively the transmission delay and response delay in the braking stage, and \( P_{bra} \) represents the train braking coefficient at this time.

3. IMPROVED FRUIT FLY OPTIMIZATION ALGORITHM

Fruit Fly Optimization Algorithm is to simulate the foraging process of fruit fly and optimize the target parameters within the search radius through sensitive smell and keen vision[7].

The traditional FOA has some limitations due to the following reasons:

- The maximum search step size is fixed. The individual position updating method greatly reduces the diversity of FOA.

- Easy to fall into local optimal. Since each iteration is based on the individual position of the maximum flavor concentration value, it is difficult for the whole algorithm to jump out of the current optimal value and easily fall into the local optimal value.

Compared with the traditional FOA, we improve the algorithm in these two aspects:
Figure 5. Flow chart of improved fruit fly algorithm

3.1. Subgroup Division
The population is divided into two parts, a larger part with population $A_1$ and a less part with population $A_2$. At the early stage of iteration, the maximum search radius of population $A_1$ and $A_2$ are fixed value $R_{MAX}$. At the later stage of iteration, the radius of population $A_1$ decreases exponentially in order to avoid the local optimal search and improve the search accuracy. Its evolution mechanism is as follows:

$$A_1 = \lambda N$$  \hspace{1cm} (21)

$$A_2 = (1 - \lambda)N$$  \hspace{1cm} (22)

$$R_{MAX} = \begin{cases} R_{MAX} & G < \text{max gen} \cdot \alpha \\ R_{MAX} \cdot \left(1 - \frac{k}{\text{max gen}}\right) & G \geq \text{max gen} \cdot \alpha \end{cases}$$  \hspace{1cm} (23)

$$R_{2_{-MAX}} = R_{1_{-MAX}}$$  \hspace{1cm} (24)

Where $\lambda$ is the coefficient of a colony with range [0.5,1]; $R_{1_{-MAX}}$ and $R_{2_{-MAX}}$ represent the maximum search radius of population $A_1$ and $A_2$ respectively. The search radius of population $A_1$ decreases with the increase of iteration times $G$. $\alpha$ is the coefficient of radius reduction with range [0,1]. When $\alpha = 1$, the search radius of population $A_1$ is the same as that of population $A_2$, and the maximum
search radius of population $A_i$ is always $R_{MAX}$. The search strategy of the twin group ensures both the global search in the early stage and the local search precision in the later stage.

### 3.2. Fusion Mechanism

In order to prevent the algorithm from falling into local optimal, the fusion mechanism between subpopulations is proposed. If the optimal flavor intensity value does not change after k iterations, it may fall into the local optimal. The specific manifestations are as follows equations:

$$A_i' = A_i - \beta A_i \quad \text{ (25)}$$
$$A_i' = A_i + \beta A_i \quad \text{ (26)}$$

Where $\beta$ is the population transfer coefficient whose range is $[0,1]$, and $A_i'$ and $A_j'$ are the numbers of population after the fusion. The flow chart of the Improved Fruit Fly Algorithm is shown in Figure 5.

### 3.3. Performance Comparation of IFOA

To compare the performance of different algorithms with IFOA, simulations are carried with a population size 15 and maximum 300 iterations. The parameters of the metro train PID controller $K_p$, $K_i$ and $K_d$ are estimated and optimized. The results are shown in TABLE 1.

| Algorithm name | $K_p$ | $K_i$ | $K_d$ | $Rss(\text{m}^2/\text{s}^2)$ | $T(\text{s})$ |
|----------------|-------|-------|-------|---------------------------|--------------|
| Genetic Algorithm | 0.991 | 0 | 0.000058 | 0.0614 | 42.86 |
| PSO Algorithm | 0.498 | 0 | 0.1437 | 0.0508 | 35.649 |
| FOA | 0.579 | 0 | 0.2157 | 0.0476 | 33.08 |
| IFOA | 0.656 | 0 | 0.2345 | 0.0191 | 33.8849 |

It can be seen from the simulation results that the computing time of genetic algorithm is significantly higher than that of other algorithms, and the convergence precision is also lower than others. The simulation results of particle swarm optimization algorithm are only superior to genetic algorithm. Compared with the fruit fly optimization algorithm, although the running time of the improved fruit fly optimization algorithm is slightly increased, the convergence accuracy is greatly improved. It shows that the improvement of the algorithm has a good effect. Therefore, the improved fruit fly optimization algorithm is suitable for the problem in this paper.

### 4. THE SIMULATION RESULTS

In order to verify the performance of the IFOA, a case study is done with Yizhuang Line in Beijing Subway. The operation data between Yizhuang Bridge and Yizhuang Cultural Park station is selected for simulation on MATLAB software. The simulation results are shown in Figure 6.
According to the simulation results, the tracking speed curve obtained by IFOA has a very good tracking effect on the target speed curve.

5. CONCLUSION
Aiming at the practical engineering problems of urban rail transit, this paper proposed a new estimation method of train PID controller with five operating stages: coasting stage, traction start-up stage, retraction stage, traction removal stage and braking stage, with corresponding parameters. After comparing the performance of genetic algorithm, particle swarm optimization algorithm and fruit fly optimization algorithm, the improved fruit fly optimization algorithm had better performance both in accuracy and real time. The improved fruit fly optimization algorithm was used to verify the new models and estimate PID controller parameters. Good simulation results were obtained, which provided significance for PID controller parameters estimation both in theoretical research and practical engineering.

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