

RESEARCH ON SPEED CONTROL OF HIGH-SPEED TRAIN BASED ON MULTI-POINT MODEL

Tao HOU¹, Yang-yang GUO², Hong-xia NIU³

^{1,2} Lanzhou Jiaotong University, School of Automation and Electrical Engineering, Lanzhou, P.R. China

³ Lanzhou Jiaotong University, Automatic Control Research Institute, Lanzhou, P.R. China

Abstract:

The traditional train speed control research regards the train as a particle, ignoring the length of the train and the interaction force between carriages. Although this method is simple, the control error is large for high-speed trains with the characteristics of power dispersion. Moreover, in the control process, if the length of the train is not considered, when the train passes the slope point or the curvature point, the speed will jump due to the change of the line, causing a large control error and reducing comfort. In order to improve the accuracy of high-speed train speed control and solve the problem of speed jump when the train runs through variable slope and curvature, the paper takes CRH3 EMU data as an example to establish the corresponding multi-point train dynamics model. In the control method, the speed control of high-speed train needs to meet the fast requirement. Comparing the merits and demerits of classical PID control, fuzzy control and fuzzy adaptive PID control in tracking the ideal running curve of high-speed train, this paper chooses the fuzzy adaptive PID control with fast response. Considering that predictive control can predict future output, a predictive fuzzy adaptive PID controller is designed, which is suitable for high-speed train model based on multi-point. The simulation results show that the multi-point model of the high-speed train can solve the speed jump problem of the train when passing through the special lines, and the predictive fuzzy adaptive PID controller can control the speed of the train with multi-point model, so that the train can run at the desired speed, meeting the requirements of fast response and high control accuracy.

Keywords: high-speed train, multi-point model, predictive fuzzy adaptive PID control, speed control

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Contact:

1) [<https://orcid.org/0000-0002-7511-3013>], 2) guo_yangyang07@163.com – corresponding author [<https://orcid.org/0000-0002-8085-8562>], 3) [<https://orcid.org/0000-0002-7732-5183>]

1. Introduction

The technology involved in high-speed trains is a concentrated expression of the top science and technology in rail transit, and it carries the country's major development strategy (Wu et al., 2017; Wieczorek et al., 2018). High speed railway is popular because it can run efficiently by greatly increasing the speed of trains. All countries in the world are vigorously developing high-speed railways to meet the growing demand for travel (Mikulski&Gorzalak, 2017). The key problem involved in the improvement of train speed is that the train should adjust the traction force or braking force in real time according to the actual situation to achieve safe, reliable and efficient operation. However, continuous speed increment also requires faster control and higher precision in the operation of high-speed trains. Therefore, by studying the dynamic characteristics of high-speed trains to establish accurate train models and applying advanced control theory knowledge to design high-performance train controllers, it can improve the comfort of high-speed trains, reduce energy consumption, and achieve high-precision speed control.

The dynamic model of high-speed trains is the basis for studying the speed control algorithm. The accuracy of the model is directly related to the control effect of the algorithm. There are two types of high-speed train models: single-point model and multi-point model. The single-point model regards the train as a particle and concentrates the force of the whole train on this point for analysis. This model is simple and easy to realize. However, the single-point model ignores the length of the train and the interaction between the carriages, which is further different from the actual situation. It can not really reflect the change of longitudinal force inside the train. Moreover, when the train passes through variable slope and curvature, the force analysis of the model is quite different from the actual situation, which results in a large calculation error. The multi-point model regards each carriage as a point and the whole train as a "point chain" for analysis. Since the length information of trains is added to the multi-point model, the additional resistance on ramps and curves is evenly distributed according to the length of the train. Therefore, when the train passes through the point of changing slope or curvature, the influence of line factors on it is a gradual process, which solves the problem of speed jump when the train

passes through the point. Yang & Sun (2001) analyzed the coupling mode between adjacent carriages and established the multi-point train model. Ansari et al.(2009) analyzed the influence of elastic coefficient, damping coefficient, train speed and acceleration between vehicles on the dynamic characteristics of the train model. Lin et al.(2010) analyzed that the coupling force between carriages is a nonlinear force, and proposes an improved sliding mode controller, which improves the robustness of cruise controller. Song et al.(2011) regarded the coupling force between carriages as the internal force of the train and proposes the model of 'multi point-unit shift'. Zhang&Zhuan (2013), Zhang&Zhuan (2014) and Zhang&Zhuan (2015) linearized and discretized the multi-point model of the train, and designed the operation control algorithm of the heavy-load train based on the model predictive control theory to improve the control performance. Astolfi & Menini (2002) studied the decoupling control problem of multi-point model of high-speed train and designed a state feedback controller. Chou & Xia (2007) constructed the performance index functions of penalty speed tracking accuracy, coupling force between carriages and energy consumption of train operation, designed the train cruise controller based on LQR method, and introduced AFC (adaptive fencing controller) to merge the trailer carriages connected in the same state, which reduced the complexity of the controller. High-speed train is a kind of power-dispersed train. The dynamics of each carriage is different in the process of train operation. Therefore, it is necessary to analyze the distribution of traction and braking force of each carriage in detail when the train is running. Based on the above research, this paper selects the multi-point train model.

The research on train speed control algorithm at home and abroad has gone through the process of 'classical control-parameter adaptive control-intelligent control-integrated intelligent control' (Liu et al., 2000; Tang & Huang, 2003; Luo & Xu, 2013). At present, China's high-speed train control system mainly adopts classic PID control. Although the algorithm is relatively simple and easy to implement, PID control is mainly used to process linear systems, while high-speed train is a complex nonlinear system. Moreover, the effect of PID control is directly related to the selection of parameters, and the PID parameters are difficult to set up. Therefore, tradi-

tional PID can not meet the requirements of fast response and high precision for high-speed train control. Fuzzy adaptive PID can make up for the disadvantage that the parameters of traditional PID controller can not be modified online. It has good control effect on complex nonlinear systems. Therefore, this paper selects fuzzy control to adjust parameters of PID controller, K_p , K_i and K_d online to form a fuzzy adaptive PID controller(Liu et al., 2017; Ren et al., 2017). Predictive control is suitable for complex control processes which is difficult to establish accurate mathematical models. It can adjust the current control amount by predicting future output, thereby reducing the current control error and improving the control accuracy(Yang et al., 2011; Ma et al., 2013; Chen et al., 2014; Wang,2016). Therefore, combined with the advantages of predictive control, the output of predictive control after correction is fed back to the fuzzy adaptive PID controller to form a predictive fuzzy adaptive PID controller.

2. Train mathematical model

In the early passenger trains, traction was only provided by locomotives. With the development of high-speed trains, a large number of power-dispersed EMU appear. For the power dispersed EMU, the dynamics of the car is different, so the calculation of the traction force of each power car is worth studying. The high-speed train is composed of several carriages, and the adjacent carriages are connected together by couplers. The CRH3 EMU consists of four power cars and four trailers. Its structure is shown in Fig. 1. The black circle in the figure indicates that the car is a power car and the white circle indicates that the car is a trailer. Each carriage of the train is equipped with brake module .

The train is subjected to traction or braking force, basic resistance, additional resistance on special lines(including additional resistance of slope, curve and tunnel), and coupling force from adjacent vehicles due to different speeds.

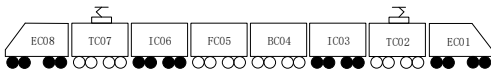


Fig. 1. Basic composition of CRH3 EMU

2.1. Train traction characteristic calculation

Train traction characteristics refer to the relationship between traction force and running speed(Hou,

2015). When the train starts, the maximum traction force is required to overcome the starting resistance. when the train speed is high, traction decreases as speed increases. For CRH3 EMU, when its speed is lower than 119 km/h, the train output quasi-constant moment. When its speed reaches 119 km/h, $P = 8800$ kW reaches the maximum power point, and then the train power is constant. The relationship between traction and power is shown in Formula 1.

$$F = \frac{P \cdot 3.6}{v} \quad (1)$$

Where F is the train traction , P is the train traction power, and v is the train running speed.

Therefore, the traction formula of CRH3 EMU can be obtained as shown in Formula 2.

$$F = \begin{cases} 300 - 0.2857v & 0 \leq v \leq 119(\text{km/h}) \\ \frac{8800 \times 3.6}{v} & 119 < v \leq 300(\text{km/h}) \end{cases} \quad (2)$$

2.2. Train braking characteristics calculation

High-speed trains generally use air brake and electric brake. When the speed is high, the train uses electric braking, and when the speed is lower than a certain value, the train switches to air braking. When both brakes are present, electric braking is used first. For CRH3 EMU, this paper only considers the braking characteristics of electric brake.

The braking characteristics of CRH3 EMU can be obtained as shown in formula 3.

$$B = \begin{cases} 59.8v & v \leq 5(\text{km/h}) \\ 300 - 0.2851v & 5 < v \leq 106.7(\text{km/h}) \\ \frac{8800 \times 3.6}{v} & 106.7 < v \leq 300(\text{km/h}) \end{cases} \quad (3)$$

Where B is the train braking force.

2.3. Train resistance

Resistance refers to an external force that hinders the operation of the train and cannot be manipulated by humans, and its direction is opposite to that of the train. Train resistance can generally be divided into basic resistance and additional resistance. The basic resistance of train refers to a kind of resistance, such as air resistance, which will exist when the train runs on any line such as ramp, bridge, curve or straight line. Additional resistance is the resistance of trains

running in some special lines, such as ramps, curves and tunnels.

2.3.1. Basic resistance

The basic resistance is one of the important parameters in the train traction calculation. There are many factors that cause the basic resistance, such as the sliding frictional resistance between the wheel and the rail, the rolling resistance of the wheel on the rail and the air resistance. Since the factors affecting the basic resistance are complicated and difficult to calculate by mathematical formulas, empirical formulas obtained by a large number of experiments are generally used in practical applications, as shown in formula 4.

$$w_0 = a + b\dot{x} + c\dot{x}^2 \quad (4)$$

Where w_0 is the basic resistance of a unit mass train. a , b and c are basic running resistance coefficients. \dot{x} is the speed of the train.

2.3.2. Additional resistance

The additional resistance of the train refers to resistance other than the basic resistance when the train is running on some special lines (such as curves and ramps). It is not affected by the running state of the train, mainly including ramp resistance, curve resistance and tunnel additional resistance.

(1) Additional resistance on the ramp

The force acting on the ramp of a high-speed train based on the multi-particle model is shown in Fig. 2. If the total length of the train is L , the additional resistance w_a of the ramp for a unit mass train running on a gradient line is shown in formula 5.

$$w_a = i = \frac{L_1 \cdot i_1 + L_2 \cdot i_2}{L} \quad (5)$$

Where w_a is the additional resistance to the unit mass of the train on the ramp, i_1 is the gradient of the train on the first slope, i_2 is the gradient of the train on the second slope, L_1 is the length of the train running on the first slope, L_2 is the length of the train running on the second slope.

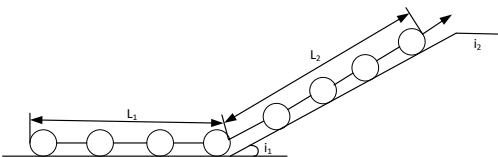


Fig. 2. Schematic diagram of additional resistance on the ramp of multi-point model train

(2) Additional resistance on the curve

Similar to the force analysis of the train on the ramp, the additional resistance that the unit mass train receives on the curve is shown in formula 6.

$$w_s = \frac{A}{R_1} \cdot \frac{L_1}{L} + \frac{A}{R_2} \cdot \frac{L_2}{L} \quad (6)$$

Where w_s is the additional resistance to the unit mass of the train on the curve, R_1 is the radius of the train on the first curve, R_2 is the radius of the train on the second curve, L_1 is the length of the train running on the first curve, L_2 is the length of the train running on the second curve, A is the constant determined by the test and is generally taken as 600.

(3) Additional resistance in the tunnel

When the train runs in the tunnel, the air resistance is greater than that in the open area, and the increased air resistance is the additional resistance in the tunnel. The factors affecting the additional resistance in the tunnel are complicated, so the empirical formula is generally used in practical applications. Additional tunnel resistance to a unit mass train running is shown in formula 7.

$$w_t = 0.00013L_s \quad (7)$$

Where w_t is the additional resistance of the unit mass train in the tunnel, L_s is the length of the tunnel.

In summary, the calculation formula of the total resistance of the unit mass train during operation is as shown in formula 8.

$$w = w_0 + w_a + w_t + w_s \quad (8)$$

2.4. Coupling force

Compared with the traditional single-point train model, the multi-point train model needs to consider the interaction between carriages. The EMU is a multi-body system that is physically coupled by multiple cars. The coupling relationship between the cars can be expressed as an "elastic-damped" component, as shown in Fig. 3. The kinetic equation is expressed as shown in formula 9.

$$f_{i(i+1)} = k(x_i - x_{i+1}) + d(\dot{x}_i - \dot{x}_{i+1}) \quad (9)$$

Where $f_{i(i+1)}$ is the coupling force between carriage i and carriage $i+1$. x_i and x_{i+1} are respectively the positions of carriage i and carriage $i+1$. \dot{x} and \dot{x}_{i+1} are respectively the speeds of carriage i and carriage $i+1$. k is the elastic coupling coefficient of coupler system. d is the damping coupling coefficient of the coupler system.

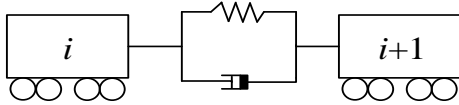


Fig. 3. Schematic diagram of the coupling force between adjacent cars

The multi-point dynamics model of train transforms a single input single output nonlinear system into a strongly coupled multi-input multi-output nonlinear system. It can be expressed by formula 10. Where n is the number of carriages included in the train. $\lambda_j u_j$ is the traction force on the carriage j (u_j represents the actual traction or braking force. λ_j represents the marking position for distinguishing the power carriage from the non-power carriage. if λ_j is 1, it means that the carriage is a power carriage. if λ_j is 0, it means that the carriage is a non-power carriage). m_j is the quality of the carriage j . B_j is the braking force of the carriage j .

Assuming that the air resistance of the train is all concentrated on the locomotive, the multi-particle dynamic equation of the high-speed train is shown in formula 11.

$$\begin{cases} m_1 \ddot{x}_1 = \lambda_1 u_1 - k(x_1 - x_2) - d(\dot{x}_1 - \dot{x}_2) - m_1(a + b\dot{x}_1) - m_1 c \dot{x}_1^2 - w_1 - B_1 \\ \vdots \\ m_j \ddot{x}_j = \lambda_j u_j - k(x_j - x_{j-1}) - d(\dot{x}_j - \dot{x}_{j-1}) - k(x_j - x_{j+1}) - d(\dot{x}_j - \dot{x}_{j+1}) - m_j(a + b\dot{x}_j) - m_j c \dot{x}_j^2 - w_j - B_j \quad (j = 2, \dots, n-1) \\ \vdots \\ m_n \ddot{x}_n = \lambda_n u_n - k(x_n - x_{n-1}) - d(\dot{x}_n - \dot{x}_{n-1}) - m_n(a + b\dot{x}_n) - m_n c \dot{x}_n^2 - w_n - B_n \end{cases} \quad (10)$$

$$\begin{cases} m_1 \ddot{x}_1 = \lambda_1 u_1 - k(x_1 - x_2) - d(\dot{x}_1 - \dot{x}_2) - m_1(a + b\dot{x}_1) - c \dot{x}_1^2 (\sum_{j=1}^n m_j) - w_1 - B_1 \\ \vdots \\ m_j \ddot{x}_j = \lambda_j u_j - k(x_j - x_{j-1}) - d(\dot{x}_j - \dot{x}_{j-1}) - k(x_j - x_{j+1}) - d(\dot{x}_j - \dot{x}_{j+1}) - m_j(a + b\dot{x}_j) - w_j - B_j \quad (j = 2, \dots, n-1) \\ \vdots \\ m_n \ddot{x}_n = \lambda_n u_n - k(x_n - x_{n-1}) - d(\dot{x}_n - \dot{x}_{n-1}) - m_n(a + b\dot{x}_n) - w_n - B_n \end{cases} \quad (11)$$

3. Design of predictive fuzzy adaptive PID controller

Predictive fuzzy adaptive PID control system is mainly composed of prediction module and control module. The prediction module adopts Dynamic Matrix Control (DMC). Its main function is to predict the speed of the train at the next moment, and adjust the control amount of the train at the current time according to the predicted speed, thereby reducing the tracking error. The control module is a fuzzy adaptive PID controller, which is used to control the traction and braking of the train to make the train run at the desired speed. The structure of the predictive fuzzy adaptive PID system is shown in Fig. 4.

As shown in Figure 4, y_r is the target speed. u is the output of the fuzzy adaptive PID controller, which is used to control the traction and braking of the train. y is the speed of the train. y_m is the speed prediction value before error correction. y_p is the speed prediction value after error correction.

In order to make the speed $y(k)$ of the train at time k better follow the target speed y_r , the output u of the fuzzy adaptive PID controller at time k is taken as the input of the prediction model to obtain the forecast output y_m . The predicted value and train speed $y(k+1)$ at time $k+1$ are sent to the feedback correction link to obtain the corrected predicted output y_p . By calculating the error e between the predicted value and the expected speed, and taking the error as the input of the fuzzy adaptive PID controller, a new train speed control value can be obtained. Repetition of the above process can make the high-speed train run at the desired speed.

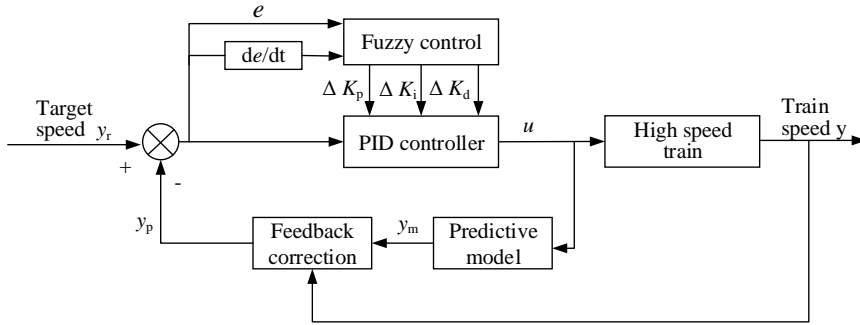


Fig. 4. Structure of predictive fuzzy adaptive PID control system

3.1. Fuzzy adaptive PID control

Once the controlled object is selected, the parameters of the traditional PID controller K_p , K_i , K_d cannot be modified online, so the traditional PID control is more suitable for the control system that can establish an accurate mathematical model, but its control effect on complex nonlinear systems is poor. Fuzzy adaptive PID can make up for the shortcomings of traditional PID. It has a good control effect on the nonlinear system. The key to design a fuzzy adaptive PID controller is to find the fuzzy relationship between the three parameters of the PID and the error e and the error rate ec . For the design of the train operation controller, the error e of the ideal speed and the actual speed and its change rate ec are generally selected as the input of the fuzzy controller, and then the three parameters K_p , K_i , and K_d are modified online according to the fuzzy rule. In this paper, the fuzzy adaptive PID controller is a two-dimensional controller with two inputs and three outputs. The error e between the expected speed y_r and the corrected predicted value y_p and its change rate ec are input. The output is the correction amount ΔK_p , ΔK_i , ΔK_d for the three parameters of the PID. According to the control accuracy requirements, the input and output variations are selected in 7 levels {NB, NM, NS, ZO, PS, PM, PB}. The table of fuzzy control rules with three parameters of ΔK_p , ΔK_i and ΔK_d is shown in Tables 1 to 3.

3.2. Predictive control

DMC is a predictive control algorithm based on step response of object. At each moment k of the train operation, it is necessary to determine the M control increments from that moment so that the controlled

object's output predicted value at the next P moments is as close as possible to the expected value under the action of the increment(Li et al.,2018; Lu et al.,2016).

Table 1. Fuzzy control rules for ΔK_p

e	ec						
	NB	NM	NS	NO	PS	PM	PB
NB	PB	PB	PM	PM	PS	ZO	ZO
NM	PB	PB	PM	PS	PS	ZO	NS
NS	PM	PM	PM	PS	ZO	NS	NS
NO	PM	PM	PS	ZO	NS	NM	NM
PS	PS	PS	ZO	NS	NS	NM	NM
PM	PS	ZO	NS	NM	NM	NM	NB
PB	ZO	ZO	NM	NM	NM	NB	NB

Table 2. Fuzzy control rules for ΔK_i

e	ec						
	NB	NM	NS	NO	PS	PM	PB
NB	NB	NB	NM	NM	NS	ZO	ZO
NM	NB	NB	NM	NS	NS	ZO	ZO
NS	NB	NM	NM	NS	ZO	PS	PS
NO	NM	NM	NS	ZO	PS	PM	PM
PS	NM	NS	ZO	PS	PS	PM	PM
PM	ZO	ZO	PS	PS	PM	PM	PB
PB	ZO	ZO	PS	PM	PM	PB	PB

Table 3. Fuzzy control rules for ΔK_d

e	ec						
	NB	NM	NS	NO	PS	PM	PB
NB	PS	PS	NB	NB	NB	NM	PS
NM	PS	NS	NB	NM	NM	NS	ZO
NS	ZO	NS	NM	NM	NS	NS	ZO
NO	ZO	NS	NS	NS	NS	NS	ZO
PS	ZO	ZO	ZO	ZO	ZO	ZO	ZO
PM	PB	NS	PS	PS	PS	PS	PB
PB	PB	PM	PM	PM	PS	PS	PB

3.2.1. Predictive model

A control increment $\Delta u(k)$ is applied to the system at time k , and the predicted P output values of the future under the control are obtained as shown in formula 12.

$$y_{PM}(k) = y_{p0}(k) + \alpha \Delta u_M(k) \quad (12)$$

Where $\Delta u_M(k)$ is M continuous control increments ($\Delta u_M(k) = [\Delta u_M(k, k), \dots, \Delta u_M(k + M - 1, k)]$).

$y_{PM}(k)$ is the predicted output value of the controller in the future P time under the action of M control increments $\Delta u_M(k)$, P is the system optimization time domain, and M is the system control time domain ($y_{PM}(k) = [y_{PM}(k + 1, k), \dots, y_{PM}(k + P, k)]^T$). $(k+1, k)$ represents the prediction of the value of time $k+1$ at time k ; α is the predicted model vector of the controlled object for the step response ($\alpha = [\alpha_1, \alpha_2, \dots, \alpha_N]^T$, N is the modeling time domain). $y_{p0}(k)$ is the initial predicted value of the system ($y_{p0}(k) = [y_{p0}(k + 1, k), \dots, y_{p0}(k + P, k)]^T$).

It can be seen from the above formula that at any time k , as long as the initial value $y_{p0}(k)$ of the object is known, the predictive output of the future time can be calculated by the predictive model based on the future control increment.

3.2.2. Rolling optimization

In the process of control, excessive change of control increment should be avoided. In order to solve this problem, soft constraints can be added to the optimization performance index. The optimization performance index at time k is shown in formula 13.

$$\min J(k) = \|y_r(k) - y_{PM}(k)\|_Q^2 + \|\Delta u_M(k)\|_R^2 \quad (13)$$

Where Q is error weighted matrix ($Q = \text{diag}(q_1, \dots, q_p)$), (q_1, \dots, q_p) are weighted coefficients, which represent suppression of tracking error). R is the control weighting matrix ($R = \text{diag}(r_1, \dots, r_M)$), r_1, \dots, r_M are weighted coefficients, which represent suppression of changes in control). $y_r(k)$ is the desired speed ($y_r(k) = [y_r(k + 1), \dots, y_r(k + P)]^T$).

$$\Delta U_M(k) = (A^T Q A + R)^{-1} A^T Q [y_r(k) - y_{p0}(k)] \quad (14)$$

Where A is the $P \times M$ matrix composed of the step response coefficient a_i .

$$A = \begin{bmatrix} a_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ a_M & \ddots & a_1 \\ \vdots & \ddots & \vdots \\ a_P & \cdots & a_{P-M+1} \end{bmatrix}$$

From the above formula, the optimal value of $\Delta u(k), \dots, \Delta u(k + M - 1)$ can be obtained, and the control increment $\Delta u(k)$ at time k is taken as the object. At the next moment, repeat the above process to get a new control increment.

3.2.3. Feedback correction

In order to eliminate the deviation caused by unknown factors such as model mismatch and environmental interference in practice, the predicted value obtained by formula 12 is corrected online by feedback correction method. By comparing the predicted value with the actual system output $y(k+1)$ at time $k+1$, the output error is obtained as shown in formula 15.

$$e(k + 1) = y(k + 1) - y_m(k + 1, k) \quad (15)$$

This error reflects the influence of some uncertain factors not included in the model on the system output, which can be used to supplement model-based prediction by predicting future output errors. The $e(k+1)$ weighting method can be used to correct the future output prediction value of the system, as shown in formula 16.

$$y_p(k + 1) = y_m(k + 1) + h e(k + 1) \quad (16)$$

Where $h = [h_1, h_2, \dots, h_N]^T$ is the correction vector. $y_p(k + 1)$ is the corrected predicted value, which is multiplied by the shift matrix and then used as the initial predicted value of the next moment.

4. System simulation and result analysis

4.1. System Simulation

4.1.1. Train model design

The train of the multi-point model is designed using the parameters of the CRH3 EMU (Xie et al., 2017). Taking the first power carriage as an example, the simulation model is shown in Fig. 5. The other seven carriages have similar structures except for the basic parameters and the force. The model includes a traction module and a braking module. If the train speed is greater than the desired speed, the train reduces the speed by braking. If the train speed is less than the desired speed, the train increases the speed by pulling. In this model, f_1 is the coupling force from the adjacent carriage, f_2 is the basic resistance of the train, and the force of the train is consistent with the actual situation. Therefore, it is reasonable to use the train model to simulate the high-speed train.

4.1.2. Ideal curve design

When the train is running, the actual line will not always be straight. It usually has special lines such as ramps, curves and tunnels. According to the speed-time curve designed in this paper, the train accelerates at the beginning and runs at a constant speed after reaching a certain speed. When the train reaches the parking position, the train starts to decelerate and brake. The simulated $v-t$ curve is shown in Fig. 6, in which the maximum speed of train operation is 80m/s.

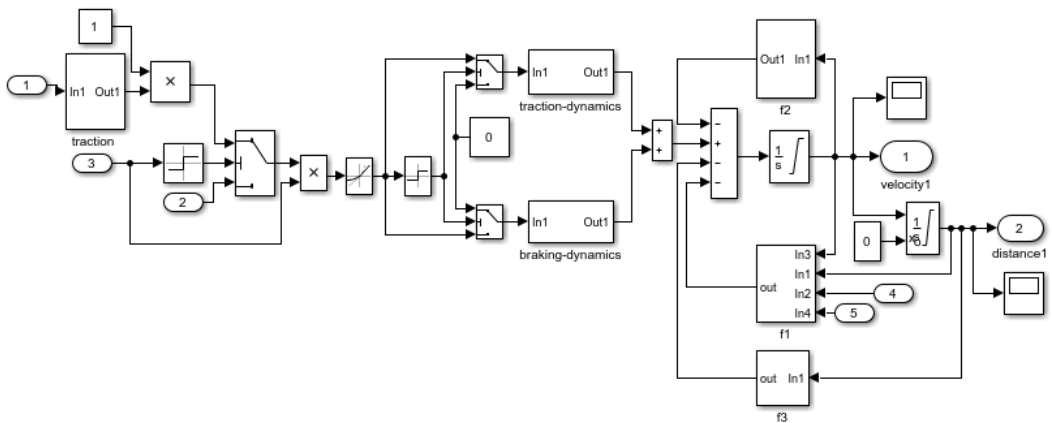


Fig. 5. The simulation model of the first carriage of CRH3 EMU

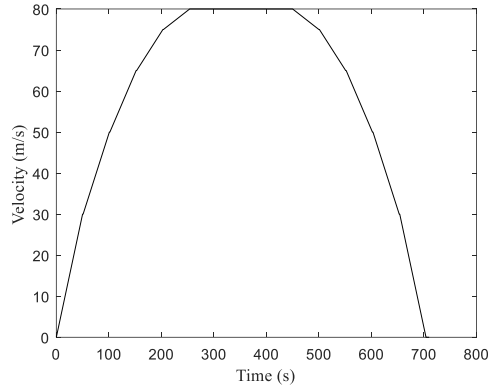


Fig. 6. Ideal speed-time curve

4.1.3. Simulation model design

According to the principle and process of predictive fuzzy adaptive PID control, a simulation model is established in Simulink, as shown in Fig. 7. In DMC model, the sampling time $T_s = 1s$, the model length $N = 60$, the control time domain $M = 1$, and the optimization time domain $P = 15$.

4.2. Simulation results

The CRH3 EMU with multi-point model is controlled by traditional PID controller. The simulation results of the previous four carriages are shown in Fig. 8, the velocity tracking errors are shown in Fig. 9, and their acceleration curves are shown in Fig. 10.

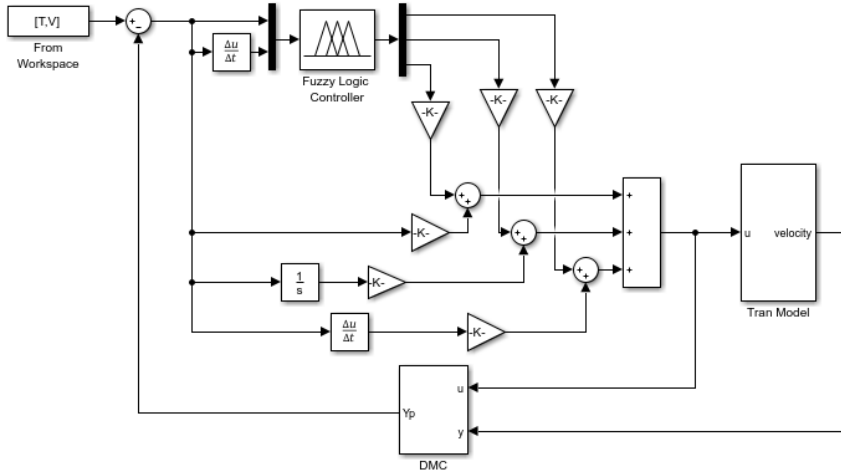


Fig. 7. Predictive fuzzy adaptive PID control simulation model

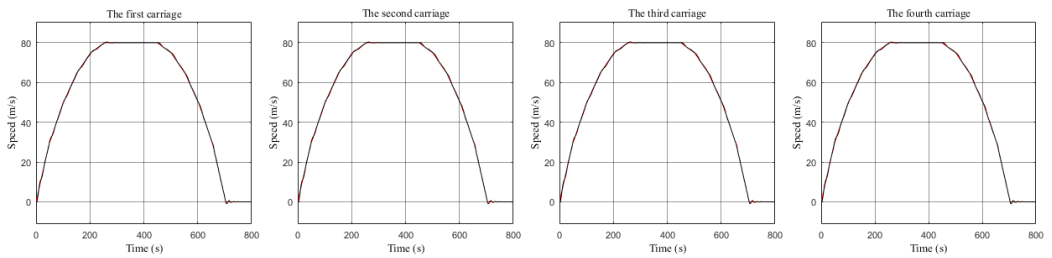


Fig. 8. Multi-point model train PID control speed tracking curve

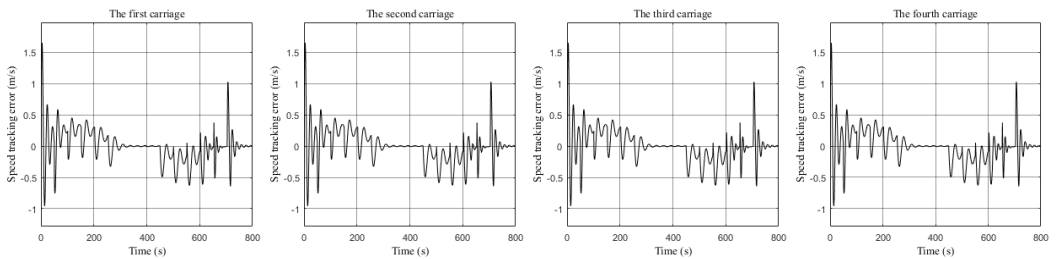


Fig. 9. Multi-point model train PID control speed tracking error

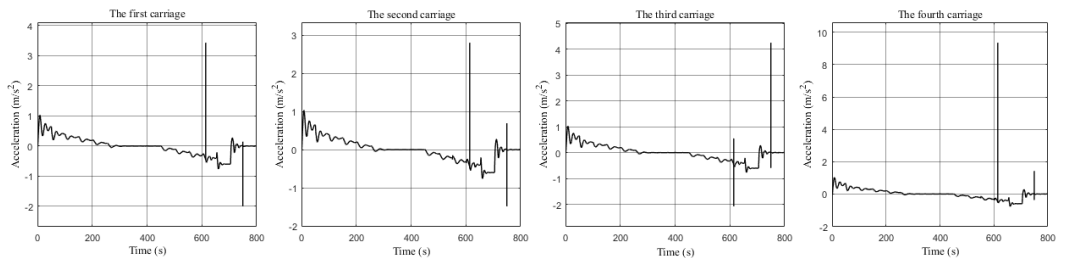


Fig. 10. Multi-point model train PID control acceleration curve

The simulation results show that the maximum speed tracking error of the first carriage is 1.6519 m/s and the average speed tracking error is 0.1725 m/s. The maximum speed tracking error of the second carriage is 1.6514 m/s and the average speed tracking error is 0.1724 m/s. The maximum speed tracking error of the third carriage is 1.6527 m/s and the average speed tracking error is 0.1721 m/s. The maximum speed tracking error of the fourth carriage is 1.6533m/s, and the average speed tracking error is 0.1723m/s. The acceleration fluctuation of the four carriages is large, and the maximum acceleration is 3.4m/s^2 .

In order to further reduce the tracking error, the CRH3 EMU with multi-point model is controlled by a predictive fuzzy adaptive PID controller. For the previous 4 cars, the simulation results are shown in Fig. 11. the velocity tracking errors are shown in Fig. 12, and their acceleration curves are shown in Fig. 13.

From the above simulation results, the speed tracking error of the predictive fuzzy adaptive PID control of the single-point model is -0.0023m/s when there is no slope on the line and the high-speed train runs to 18500m. When there is a slope on the line and the high-speed train runs to 18500m, the speed tracking error is 0.4111m/s . The calculated results show that the variation of speed with slope on the line is 0.4134m/s , which is 0.52% higher than that without slope on the line.

For the CRH3 EMU with multi-point model, the previous 4 carriages are used as an example. The speed tracking curve and speed tracking error of the predictive fuzzy adaptive PID control on the line without the slope are shown in Fig. 11 and Fig. 12. The speed tracking curve and speed tracking error of the predictive fuzzy adaptive PID control on the line with the slope are shown in Fig. 18 and Fig. 19.

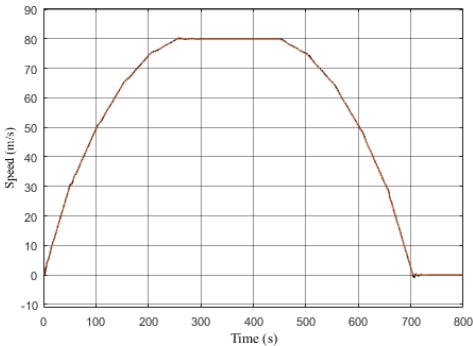


Fig. 14. Speed tracking curve of single point model without slope

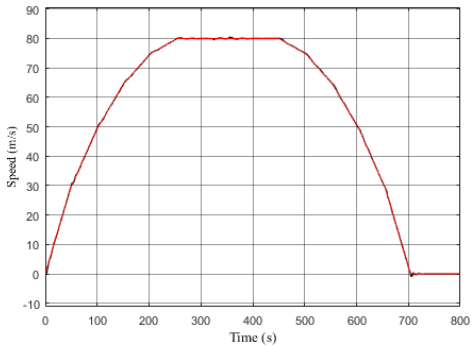


Fig. 16. Speed tracking curve of single-point model with slope

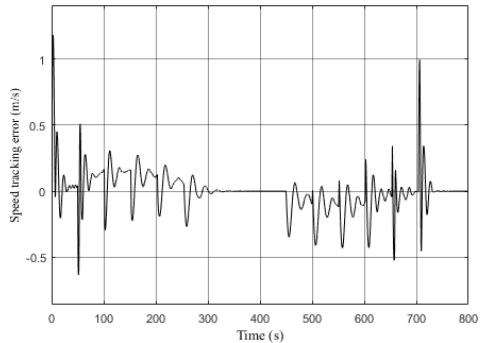


Fig. 15. Speed tracking error of single point model without slope

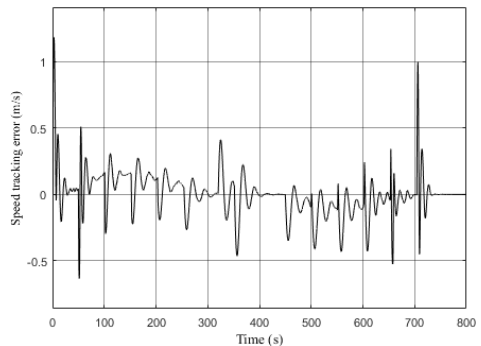


Fig. 17. Speed tracking error of single-point model with slope

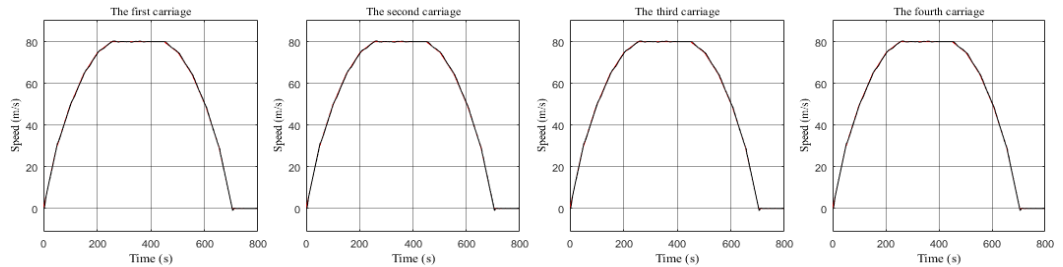


Fig. 18. Predictive fuzzy adaptive PID control speed tracking curve with slope on the line

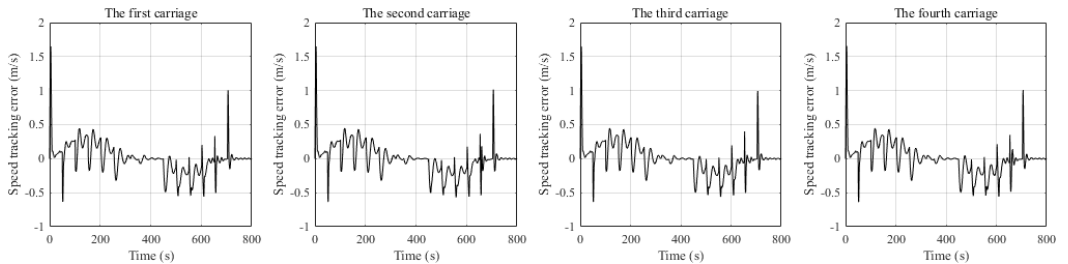


Fig. 19. Predictive fuzzy adaptive PID control speed tracking error with slope on the line

From the above simulation results, taking the first carriage as an example, the speed tracking error of the predictive fuzzy adaptive PID control of the multi-point model is -0.0125m/s when there is no slope on the line and the high-speed train runs to 18500m. When there is a slope on the line and the high-speed train runs to 18500m, the speed tracking error is 0.0484m/s . The calculated results show that the variation of speed with slope on the line is 0.0609 m/s , which is 0.08% higher than that without slope on the line.

From the analysis of the above results, it can be seen that the multi-point model of the high-speed train can effectively solve the problem of speed jump at the changing slope on the line, and the problem of speed jump at the changing curvature of trains is similar to the above.

5. Conclusion

In this paper, a multi-point model of CRH3 EMU is established, and the advantages of predictive control and fuzzy control are added to the traditional PID control. A predictive fuzzy adaptive PID controller for high-speed train with multi-point model is designed. The controller is used to control the train, so that the train can run as expected. The simulation results show that the speed control of the high-speed train with multi-point model can effectively solve

the problem of speed jump at the changing slope and the variable curvature on the line. In the control method, compared with the traditional PID control, the speed tracking error and acceleration fluctuation of the fuzzy adaptive PID control are obviously improved. The system has fast response capability, small tracking error and high control precision.

In this paper, the ideal speed-time curve of high-speed train speed control is designed according to the ideal line. In the further research, in order to better meet the actual situation, a real line will be selected to design the ideal speed-time curve of the train.

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Reference

- [1] ANSARI, M., ESMAILZADEH, E., & YOUNESIAN, D., 2009. Longitudinal dynamics of freight trains. *International Journal of Heavy Vehicle Systems*, 16(1), 102-131.
- [2] ASTOLFI, A., & MENINI, L., 2002. Input/output decoupling problems for high speed trains. *American Control Conference. Proceedings*, Danvers, MA, USA, 549-554.

- [3] CHEN, X.Q., MA, Y.J., & HOU, T., 2014. Study on Speed Control of High-Speed Train Based on Predictive Fuzzy PID Control. *Journal of System Simulation*, 26(1), 191-196.
- [4] CHOU, M., & XIA, X., 2007. Optimal cruise control of heavy-haul trains equipped with electronically controlled pneumatic brake systems. *Control Engineering Practice*, 15(5), 511-519.
- [5] HOU, T., 2015. *Speed Control Study of Multi-mode Intelligent Control Based on Multi-information Fusion and Filter on High-speed Train*. Lanzhou: Lanzhou Jiaotong University.
- [6] LI, Z.Q., DING, J.Y., YANG, H., et al, 2018. Generalized Predictive Control Tuning for High-speed Train Based on Controller Matching Method. *Journal of The China Railway Society*, 40(9), 82-87.
- [7] LIN, C.J., TSAI, S.H., CHEN, C.L., et al, 2010. Extended sliding-mode controller for high speed train. *Proceedings of the 2010 International Conference on System Science and Engineering, Piscataway, NJ, USA: IEEE*, 475-480.
- [8] LIU, H., QIAN, C.Y., & SHI, Z.D., 2017. ATO System Control Algorithm Based on Fuzzy Adaptive PID. *Urban Mass Transit*, (3), 40-43.
- [9] LIU, H.W., ZHAO, H.D., & JIA, L.M., 2000. A Study on the Control Algorithm for Automatic Train Operation. *China Railway Science*, 21(4), 38-43.
- [10] LU, X.J., WANG, X.J., DONG, H.Y., et al, 2016. Research on Sliding Mode Predictive Control of Energy-saving Operation of High-speed Train. *Control Engineering of China*, 23(3), 289-293.
- [11] LUO, H.Y., & XU, H.Z., 2013. Study on Model Reference Adaptive Control of ATO Systems. *Journal of the China Railway Society*, 35(7), 68-73.
- [12] MA, Y.J., CHEN, X.Q., & HOU, T., 2013. Study on the Speed Control of High-speed Train Based on Fuzzy Predictive Control. *Computer Measurement & Control*, 21(1), 96-99.
- [13] MIKULSKI, J., & GORZELAK, K., 2017. Conception of modernization of a line section example in the context of a fast railway connection. *Archives of Transport*, 44(4), 47-54.
- [14] REN, L.J., FAN, D.W., & YANG, J.X., 2017. Research on ATO Algorithm Based on Fuzzy PID Control with Optimized GA. *Railway Standard Design*, 61(2), 127-130.
- [15] SONG, Q., SONG, Y.D., TANG, T., et al, 2011. Computationally inexpensive tracking control of high-speed trains with traction/braking saturation. *IEEE Transactions on Intelligent Transportation Systems*, 12(4), 1116-1125.
- [16] TANG, T., & HUANG, L.J., 2003. A survey of control algorithm for automatic train operation. *Journal of the China Railway Society*, 25(5), 98-102.
- [17] WANG, L.S., 2016. *Predictive Control for Automatic Operation of High-Speed Trains Based on Multi-point Model*. Beijing: Beijing Jiaotong University.
- [18] WIECZOREK, S., PALKA, K., & GRABOWSKA-BUGNA, B., 2018. A model of strategic safety management in railway transport based on Jastrzebska Railway Company Ltd. *Scientific Journal of Silesian University of Technology. Series Transport*, 98, 201-210.
- [19] WU, Z.F., YANG, E.Y., & DING, W.C., 2017. Design of large-scale streamlined head cars of high-speed trains and aerodynamic drag calculation. *Archives of Transport*, 44(4), 90-97.
- [20] XIE, G., ZHANG, D., HEI, X.H., et al, 2017. Online identification method of time-varying parameters for longitudinal dynamics model of high-speed train. *Journal of Traffic and Transportation Engineering*, 17(1), 71-81.
- [21] YANG, C.D., & SUN, Y.P., 2001. Mixed H2/H cruise controller design for high speed train. *International Journal of Control*, 74(9), 905-920.
- [22] YANG, H., ZHANG, K.P., WANG, X., et al, 2011. Generalized Multiple-model Predictive Control Method of High-speed Train. *Journal of the China Railway Society*, 33(8), 80-87.
- [23] ZHANG, L., & ZHUAN, X., 2013. Braking-penalized receding horizon control of heavy-haul trains. *IEEE Transactions on Intelligent Transportation Systems*, 14(4), 1620-1628.
- [24] ZHANG, L., & ZHUAN, X., 2015. Development of an optimal operation approach in the MPC framework for heavy-haul trains. *IEEE Transactions on Intelligent Transportation Systems*, 16(3), 1391-1400.
- [25] ZHANG, L., & ZHUAN, X., 2014. Optimal operation of heavy-haul trains equipped with electronically controlled pneumatic brake systems using model predictive control methodology. *IEEE Transactions on Control Systems Technology*, 22(1), 13-22.