

## Adaptive and ADRC information fusion method for high speed train braking system

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### Abstract

Aiming at the problem of poor adaptability and lag of traditional braking control methods of high-speed train, a high-speed train braking information fusion method based on adaptive linear auto disturbance rejection is proposed to arrange the transition process for accurate braking and stable operation of the train, and an extended state observer is designed to estimate and compensate the internal disturbance and external disturbance, so as to enhance the anti-interference ability of the system. By introducing adaptive control into linear ADRC, the real-time adaptive self-tuning of parameters is realized, the efficiency of parameter tuning is improved, and the problem that too many parameters have a direct impact on the control effect in ADRC is solved. The simulation results show that the control method can estimate and compensate the disturbance well, shows good robustness, and can track the ideal parking curve quickly and accurately.

**Keywords:** high-speed train braking, information fusion, linear active disturbance rejection control, adaptive control.

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### 1. Introduction

As high-speed trains have the characteristics of strong transportation, less time-consuming and low energy consumption, they have become one of the most effective means of modern transportation on a global scale and have attracted great attention [1]. During the automatic driving of high-speed trains, the operation control of train traction and braking is realized through the on-board information, which replaces the driver to complete the starting acceleration, constant speed operation, deceleration braking, and other driving functions of the train, to improve the comfort of passengers and energy efficiency during train operation save, make the balance performance of train power structure reach the best operation state [2]. Accurate parking is one of the important performance indicators of the ATO system to ensure the gentle change of speed and realize that high-speed trains can stop at the actually required position [3]. However, the operation process of high-speed trains is non-linear, multi-objective, multi-constrained, and time-varying, coupled with a complex environment, making it difficult for

traditional speed control strategies to meet the requirements of the safe and punctual operation. Therefore, exploring a control strategy that can achieve precise speed tracking and parking has important application value.

Aiming at the modeling and speed tracking control methods involved in the braking system of high-speed trains, Hecquet et al.[4] the multi-dimensional modeling of the train in the braking system of high-speed EMU is carried out based on finite element analysis, and described the braking force and the EMU in detail. The speed is non-linear, but the effect of braking force and speed tracking is not good in the numerical simulation. According to the characteristics of a multi-power combination of high-speed trains, Li Zhongqi [5] and others established a distributed autoregressive model to achieve high-precision tracking control of a given speed during the braking process of each power unit. It is worth noting that time-varying dynamic factors have many influencing factors on the operation performance of high-speed trains in open air environment, such as aerodynamic friction and vibration. These influencing factors are too complicated and difficult to describe correctly. In terms of speed tracking control, most of the PID control algorithms are simple and easy to

implement, but the algorithm switches frequently when controlling the speed, which is not conducive to the smooth running of the train, the comfort is poor, and the parking accuracy is not high. In recent years, many advanced control strategies have been tried in the ATO braking system to overcome the above-mentioned problems. Wu [6] et al. used the steady-state error of PID control to control the ATO braking system but did not consider the interference of speed limit and road slope. When the line is disturbed, the speed of the tracking error range of the train running state is somewhat insufficient. Chen Xiaoqiang [7] et al. aimed at the disadvantages of inflexible control and low parking accuracy caused by the fixed parameters of the traditional PID algorithm. Fuzzy control was introduced into the traditional PID control to realize the online adjustment of the parameters of the PID controller. To a certain extent, the parking accuracy of the train is improved. Zhang Shengping [8] et al. aimed at the problem of poor robustness of traditional PID and fuzzy PID algorithms, and improved fuzzy PID control through neural network algorithms to obtain the optimal combination of proportional coefficients, integral coefficients, and differential coefficients, thereby realizing the self-control of PID parameters. Adapt to adjustment to improve the accuracy of automatic train control. However, this method relies too much on system parameters, and it is difficult to obtain accurate train mass and drag coefficient parameters in practice. Luo Hengyu [9] and others adopted an adaptive control method. When the train operating conditions are constantly changing, there is no need to re-encode the controller, which ensures accurate tracking effects and solves the problem of relying on system parameters, but also does not solve the training quality. Once the train runs on complex lines, such as curves, ramps, and tunnels, parameters such as resistance coefficients and drag coefficients will cause frequent adjustments of control inputs and affect the comfort of passengers. Yang [10] and others used the Ellman neural network to establish a dynamic model of the high-speed train using a large amount of offline data, but did not consider the time-varying model and external disturbance during train operation. Yang [11] et al. established the motion dynamics model of high-speed trains for adaptive speed tracking control. Also, to accurately describe the dynamics characteristics of high-speed trains, considering external interference and parameter uncertainty, the traction and control The characteristics of power and various resistances are analyzed. Yuan Haijun [12] et al. proposed an optimal PID control method based on feature models, which reduces the complexity of the model by simplifying the original dynamic model, and uses gradient correction identification algorithms to identify and optimize the model time-varying parameters, which improves the control to a certain extent. effectiveness.

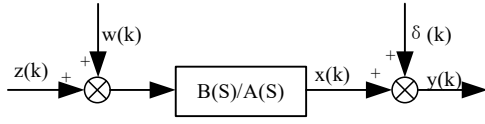
Active Disturbance Rejection Controller (ADRC) is a nonlinear control strategy, which is similar to PID control. When the control target is in the non ideal operation state, the control strategy to eliminate the error is formulated in combination with the actual operation state of the target. But the difference is that it can estimate and compensate for external disturbances and internal disturbances, overcome

the shortcomings that PID requires an accurate model to set the control parameters, and eliminate the side effects produced by integral feedback. It has the characteristics of high accuracy, fast response, and strong anti-interference ability, and has been widely used in military systems [13], power systems [14] [15], precision machining [16], etc. It has been found in a large number of practical applications that active disturbance rejection control can actively resist disturbances, improve system stability and control quality, and reduce control energy loss. This method does not rely on an accurate model. It is characterized by nonlinearity, parameter instability, multi-variable coupling, time-varying, so it is difficult to establish an accurate mathematical model for the train speed tracking control. It only needs to understand the order and input of the controlled object. The number of output channels and connection methods, signal delay time, and control channel gain can solve this problem. It has strong stability and robustness, but the selection of parameter values will directly affect the control effect. Zhang Wenquan [17] and others proposed a linear ADRC algorithm to simplify the structure of the algorithm, use the linear extended state observer (LESO) to estimate the total disturbance of the system, and introduce the particle swarm algorithm in the parameter tuning process to reduce the difficulty of parameter tuning. However, the PSO algorithm is easy to fall into the local optimum, and manual adjustment is required. At present, it is difficult for high-speed train braking systems to achieve the best of both worlds in terms of accuracy and anti-disturbance capabilities. Therefore, an adaptive linear active disturbance rejection control (ALADRC) is proposed to solve the problem of online real-time adaptive self-tuning of multiple parameters in the feedback link and the simplified expanded state observer link. , Thereby improving the braking control performance of high-speed trains.

## 2. High-speed train braking mathematical model

The braking control process of a high-speed train is complex. Factors such as train speed, mechanical properties, track lines, and control methods will affect the actual braking effect of high-speed trains, which in turn affects parking accuracy, ride comfort, and punctuality. The high-speed train is now regarded as a mass point, and the brake analysis is performed on the mass point to replace the train braking. Because the multi-particle model analysis requires a relatively high calculation speed and performance of the computer, which is not conducive to the feedback of real-time control, this paper selects the single-particle model to model the high-speed train braking system.

The block diagram of the mathematical model is:



**Figure 1.** Block diagram of the mathematical model of the train

During the braking process, the train will receive many external forces that are opposite to the direction of movement, which generally refers to the resistance generated by the friction between the train and the air, and the train and the rail. However, in the actual operation process, the resistance of the train cannot be directly obtained, but these two resistances are closely related to the running speed of the train. Based on a large number of experiments, an empirical formula is obtained.

$$w = a_0 + a_1v + a_2v^2 \quad (1)$$

In the formula,  $w$  is the resistance of the train;  $v$  is the running speed of the train;  $a_0$  is the sum of the rolling mechanical resistance coefficient and the additional resistance parameters generated by the ramp curve;  $a_1$  is the other mechanical resistance coefficient;  $a_2$  is the air resistance coefficient. The resultant force received when the train is braking is composed of the braking force  $z$  and the resistance  $w$ , the motion equation of train braking can be described as

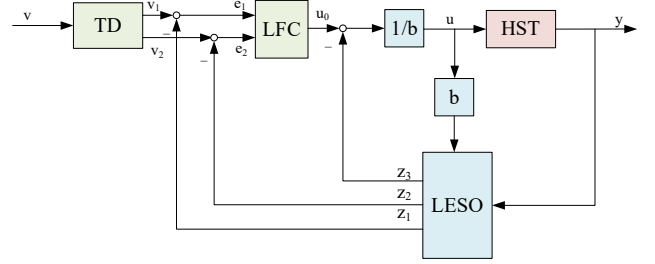
$$\begin{cases} F = z - w \\ w = a_0 + a_1v + a_2v^2 \\ \frac{dv}{dt} = cF \end{cases} \quad (2)$$

Where,  $F$  is the resultant force received by the train;  $z$  is the braking force of the train;  $w$  is the resistance received by the train;  $c$  is the acceleration coefficient; among them,  $a_0$ ,  $a_1$ ,  $a_2$ ,  $c$  are not constant coefficients, and  $c$  is the mass of the train. Related,  $a_0$ ,  $a_1$ ,  $a_2$  are affected by external environmental factors such as weather conditions.

### 3. Controller design

#### 3.1 Linear active disturbance rejection controller

Linear active disturbance rejection control (LADRC) consists of tracking differentiator (TD), linear extended state observer (LESO), and linear feedback control (LFC). Composition [18]. Figure 2 is a schematic diagram of the linear active disturbance rejection controller structure.



**Figure 2.** Schematic diagram of the linear active disturbance rejection controller structure

Among them, TD is used to arrange the transition process, according to the set value  $v$  to arrange the transition process  $v_1$  and extract its derivative signal  $v_2$ , ESO obtains the estimated value of the system state variable  $z_1 \sim z_n$  and the total disturbance of the system  $z_{n+1}$ , LFC calculates the control law  $u_0$  according to the state error  $e_1 \sim e_n$  of the system [19], and uses the disturbance estimation value  $z_3$  to compensate for the error feedback control quantity  $u_0$  to determine the final control quantity.

##### 3.1.1 Tracking Differentiator

As shown in Figure 2, the transition process is arranged with the set value  $v$  as input

$$\begin{cases} e = v_1 - v \\ v_1(k+1) = v_1(k) + T^*v_2(k) \\ v_2(k+1) = T^*f_{st}(v_1(k), v_2(k), u(k), r, h) \end{cases} \quad (3)$$

Among them,  $v_1(t)$  tracks  $v(t)$ ,  $v_2(t)$  is the differential signal of  $v_1(t)$ ;  $T$  is the sampling period;  $u(k)$  is the control quantity at the  $k$ th sampling time;  $r$  is the fast factor;  $h$  is the filter factor, which determines the parameters of the filter effect.

Let  $h = T$ ,  $f_{st}(r, h)$  is the fastest comprehensive function, namely

$$\begin{cases} d_0 = rh^2 \\ y(k) = v_1(k) + hv_2(k) \\ a = \begin{cases} v_2 + y/h & , |y| \leq d_0 \\ v_2 + 0.5(\sqrt{r^2h^2 + 8r|y(k)| - rh}) & , |y| \geq d_0 \end{cases} \\ f_{st} = \begin{cases} -a/h, & |a| \leq d \\ -r\text{sign}(a), & |a| > d \end{cases} \end{cases} \quad (4)$$

##### 3.1.2 Extended state observer

As shown in Figure 2, the system output  $y$  and input  $u$  are used to track the estimated state and total disturbance. Among them,  $z_1(t)$ ,  $z_2(t)$  give an estimate of the state variable of the object;  $z_3(t)$  gives an estimate of the total disturbance of the object;  $\beta_1$ ,  $\beta_2$ ,  $\beta_3$  are the gains of the observation.

$$\begin{cases} e = z_1(k) - y(k) \\ z_1(k+1) = z_1(k) + T^*(z_2(k) - \beta_1 e) \\ z_2(k+1) = z_2(k) + T^*(z_3(k) - \beta_2 * \text{fal}(e, a_1, \delta_1) + bu(k)) \\ z_3(k+1) = z_3(k) - T\beta_3 \text{fal}(e, a_2, \delta_1) \end{cases} \quad (5)$$

### 3.1.3 Linear feedback control

State error feedback rate:

$$\begin{cases} e_1 = v_1(k) - z_1(k) \\ e_2 = v_2(k) - z_2(k) \\ u_0 = \beta_{01} \text{fal}(e_1, \alpha_1, \delta) + \beta_{02} \text{fal}(e_2, \alpha_2, \delta) \\ u(k) = u_0 - \frac{z_3}{b} \end{cases} \quad (6)$$

Among them,  $e_1$ 、 $e_2$  are the differential error terms of displacement and displacement respectively;  $\alpha_1$ 、 $\alpha_2$ 、 $\delta$  are fixed parameters;  $\beta_{01}$ 、 $\beta_{02}$  are gain coefficients;  $-z_3/b$  is compensation term.

## 3.2 Design of adaptive linear active disturbance rejection controller

### 3.2.1 Parameter tuning of the extended state observer

For the discrete third-order extended state observer listed in formula (5), the LESO parameter simplification strategy based on the system bandwidth parameterization algorithm can be used for tuning [20]. The three parameters are simplified as follows:

$$\begin{cases} \beta_1 = 3\omega, \\ \beta_2 = 3\omega^2, \\ \beta_3 = 3\omega^3. \end{cases} \quad (7)$$

Based on formula (7), the setting of LESO parameters  $\beta_1$ 、 $\beta_2$ 、 $\beta_3$  is equivalent to the setting of the new parameter  $\omega$ . Therefore, the new formula (8) is introduced to calculate  $\omega(k)$ :

$$\omega(k) = e^{\eta_\omega(k)} \quad (8)$$

Define LESO observation error as:

$$\hat{e}(k) = z_1(k) - r(k-1) \quad (9)$$

Among them,  $r(k-1)$  is the command value accepted by the LADRC controller at the time  $(k-1)$ . Defined based on the formula (9):

$$\hat{e}(k) = \hat{e}(k) + \Delta \hat{e}(k+1) \quad (10)$$

The  $\eta_\omega(k)$  update algorithm proposed by formula (12) can ensure the convergence of the observation error of the LESO module command. Let  $0 < K_\omega(k) < 2$  then:

$$\eta_\omega(k+1) = \eta_\omega(k) + K_\omega(k) \frac{1}{3h\omega(k)} \times \left[ -\frac{1}{1-3h\omega(k)} \frac{\partial r(k)}{\partial y(k)} \right]^{-1} \frac{\hat{e}(k)}{e(k)} \quad (11)$$

equation:

$$V_\omega(k) = \hat{e}^2(k), \quad (12)$$

It is a Lyapunov function that guarantees that the prediction output error  $e(k)$  of the LESO link can converge to 0.

### 3.2.2 Linear Feedback Module Parameter Tuning

From the LADRC controller in Figure 2 and formula (6), the formula for the nonlinear feedback link can be obtained as follows:

$$u(k) = \beta_1 e_1(k) + \beta_2 e_2(k) + \frac{z_3(k)}{b} \quad (13)$$

definition:

$$\beta(k) = [\beta_1(k) \quad \beta_2(k)] \quad (14)$$

definition:

$$e(k) = [e_1(k) \quad e_2(k)] \quad (15)$$

Where  $e_1(k)$  and  $e_2(k)$  are the input signals of the nonlinear feedback link.

definition:

$$\eta(k) = [\eta_{01}(k) \quad \eta_{02}(k)] \quad (16)$$

To ensure that the parameters in  $\eta(k)$  can make the output error of the controlled system converge to zero, the real-time and effective online update of  $\eta(k)$  is defined as:

$$\begin{cases} e_r(k+1) = e_r(k) + \Delta e_r(k), \\ e_r(k) = r(k-1) - y(k) \end{cases} \quad (17)$$

Among them,  $e_r(k)$  is recorded as the system tracking error. On this basis, the  $\eta(k)$  update algorithm proposed by formula (18) can ensure the convergence of the controller tracking error. Let  $0 < K_i(k) < 2$ ,  $i=01 \sim 02$  then:

$$\eta(k+1) = \eta(k) + \alpha(k) K(k) \gamma^{-1}(k) \frac{e(k)^T e_r(k)}{e(k)e(k)^T} \quad (18)$$

In formula (19), define:

$$\begin{cases} \alpha(k) = \frac{\partial u(k)}{\partial y(k)}, \\ \gamma(k) = \frac{\partial \beta(k)}{\partial \eta(k)}, \\ K(k) = \begin{bmatrix} K_{01}(k) \\ K_{02}(k) \end{bmatrix} \end{cases} \quad (19)$$

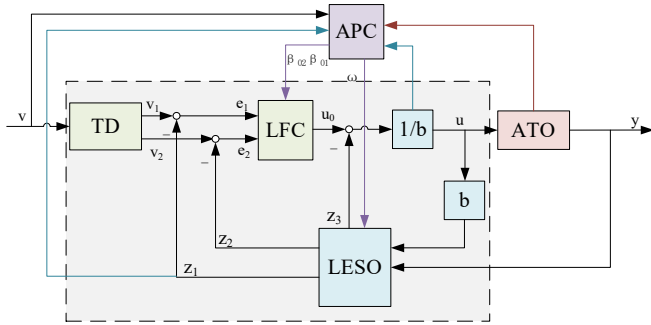
The equation:

$$V(k) = e_r^2(k) \quad (20)$$

It is a Lyapunov function that guarantees that the tracking error  $e_r(k)$  of the controlled system can converge to 0.

### 3.2.3 Structure of adaptive active disturbance rejection controller

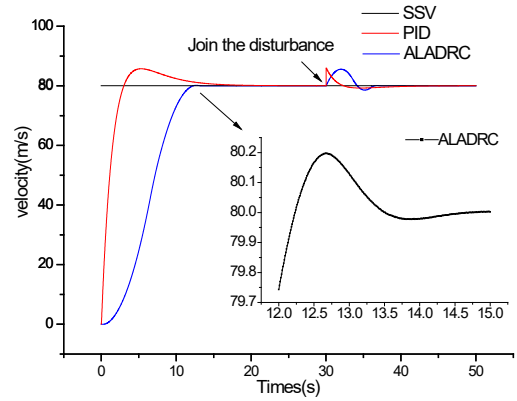
As shown in Figure 3, LADRC is a linear active disturbance rejection controller,  $v$  is the speed command,  $u$  is the output of the adaptive linear active disturbance rejection controller, and  $y$  is the system output. The high-speed train outputs the speed signal and feeds it back to the extended state observer and the parameter tuning algorithm. The parameter tuning algorithm is based on the system input, output, feedback, and various intermediate variables to adaptively calculate and tune the parameters of the linear active disturbance rejection controller.



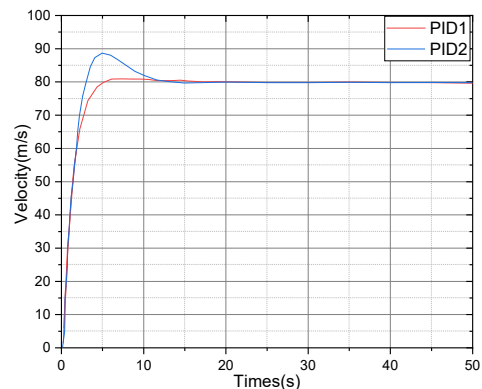
**Figure 3.** Schematic diagram of the structure of adaptive linear active disturbance rejection controller

## 4. Experiment and simulation

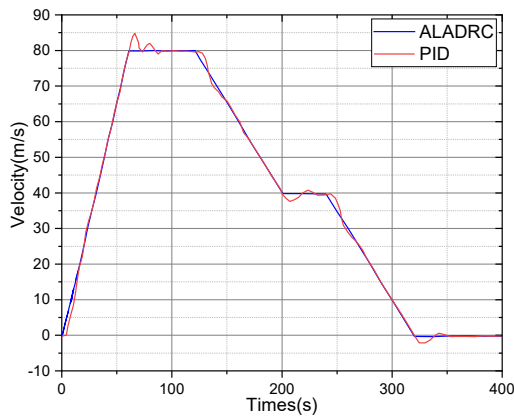
The parameters of the ALADRC controller are selected as follows:  $r=2$ ,  $h=0.01$ ,  $T=0.01$ ,  $b=1$ ,  $\delta=0.05$ , with the step signal as the input of the system, when the damping coefficient  $c=0.5$ , the control variable gain coefficient  $r=3$ . The precision factor  $h=0.2$ , the compensation factor  $b=1$ , the dynamic response is performed, and the control quantity step response value 600 is added at  $t=30s$ , and it reaches a stable state after the auto disturbance rejection control. The comparison of the dynamic response of ALADRC control and PID control is shown in Figure 4. In Figure 4, the PID control parameters  $k_p = 7.8$ ,  $k_i = 1.8$ ,  $k_d = 0$ ; the PID control parameters in Figure 5 are  $k_p = 8.0$ ,  $k_i = 1.0$ ,  $k_d = 0$ ,  $k_p = 7.0$ ,  $k_i = 2.2$ ,  $k_d = 0$ .



In Figure 4, the overshoot after PID control is 7.12%, and the time required to reach a steady-state is 21.75s. In Figure 4, the overshoot and steady-state time after PID control are 1.15%, 37.38s, 11.18%, 15.59s, respectively. According to three groups of different control parameters, it is difficult for PID control to guarantee a small overshoot and a short stabilization time at the same time. If you want to reduce the overshoot, reduce the value and increase the adjustment time; if you want to reduce the steady-state time, reduce Value, the overshoot becomes larger, and the overshoot will seriously affect the stability of train operation and the comfort of passengers. The overshoot after ALADRC control is only 0.24%, and the stabilization time is relatively short. When the step disturbance is added, the PID control system stabilizes after 13.76s, and the steady-state error is about 0.02m/s. The ALADRC control system is stable after being disturbed in 7.61 seconds, and can quickly and accurately reach a stable state. In terms of control accuracy and anti-interference ability, the ALADRC control algorithm is more able to meet the fast and stable operation requirements of high-speed trains.

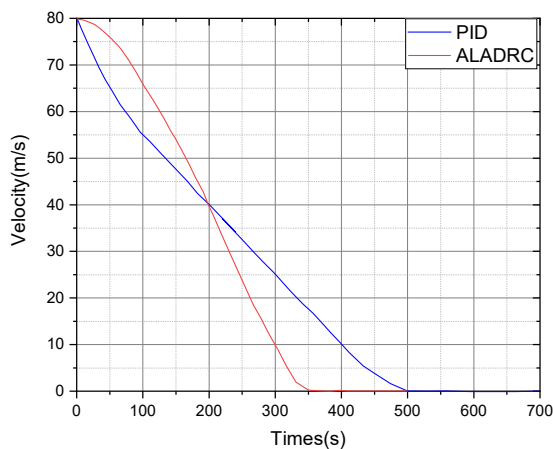






As shown in Figure 6, assuming that the input signal is the best speed reference curve of a high-speed train, under the condition of no external interference, compare the speed tracking curves of the ALADRC control algorithm and the PID control algorithm. It can be seen from the speed tracking curve that when the speed changes slowly, the PID control algorithm will have a small delay, but it can also track the speed well, while the ALADRC control algorithm can quickly track. At  $t=65s, 120s, 200s, 240s, 320s$ , when the speed changes drastically, PID control will have a large overshoot and need time to adjust to the reference speed, while the overshoot of the ALADRC control algorithm is very small. Controlled at about  $0.2m/s$ , compared with PID control, there is a significant improvement in stability. Therefore, ALADRC control is better than PID control in following the train speed reference curve.

The traction model of the Beijing-Shanghai high-speed train is selected, the unit resistance  $w = 0.062 + 0.082v + 0.00014v^2$ , the initial braking speed is set to  $80m/s$ , and the effective braking distance is  $4000m$ .



From the simulation results in Figure7, it can be seen from the speed curve of the braking process that the PID control changes rapidly when the train starts to brake, and the control switching is more frequent, which affects the passenger’s riding experience, while the ALADRC control starts after the train starts to brake. The speed change is relatively gentle, and the acceleration change at adjacent moments is less than  $0.18m/s^2$ . In actual operation, passengers will not feel shaking. After the system is stabilized, the overshoot will approach 0, which can better ensure the stability of the high-speed train during braking. Moreover, the entire braking process of PID control takes 500s, and the entire braking process of ALADRC control takes 350s, which meets the control requirements. Therefore, the train braking system based on ALADRC is more effective than PID control in braking speed.

### 5. Conclusion

This paper takes the high-speed train automatic driving system as the research object, and establishes the mathematical model of high-speed train braking based on the dynamic analysis of the high-speed train. Aiming at the accurate stopping of high-speed trains during automatic driving, an adaptive linear active disturbance rejection controller is proposed, which uses the linear active disturbance rejection controller to enhance the stability and robustness of the system, introduces an adaptive parameter adjustment mechanism, and simulates through MATLAB. Verify the effectiveness of the control algorithm. The control method can ensure the parking accuracy of the train, and can also adapt to variability of model parameters and variability of external conditions without affecting the comfort of the ride. In the future work, more emphasis should be placed on the model establishment, compensation and stable speed control of ultra-high speed train, combined with artificial intelligence, fault diagnosis and appropriate control algorithm to ensure the safety and reliability of high-speed train in the process of running.

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