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Online Estimation Method of Train Wheel-Rail Adhesion Coefficient Based on Parameter Estimation

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ABSTRACT: Aiming to address the challenge of directly measuring the real-time adhesion coefficient between wheels and rails, this paper proposes an online estimation algorithm for the adhesion coefficient based on parameter estimation. Firstly, a force analysis of the single-wheel pair model of the train is conducted to derive the calculation relationship for the wheel-rail adhesion coefficient in train dynamics. Then, an estimator based on parameter estimation is designed, and its stability is verified. This estimator is combined with the wheelset force analysis to estimate the wheel-rail adhesion coefficient. Finally, the approach is validated through joint simulations on the MATLAB/Simulink and AMESim platforms, as well as a hardware-in-the-loop semi-physical simulation experimental platform that accounts for system delay and noise conditions. The results indicate that the proposed algorithm effectively tracks changes in the adhesion coefficient during train braking, including the decrease in adhesion when the train brakes and slides, and the overall increase as the train speed decreases. The effectiveness of the algorithm was verified by setting different test conditions. The results show that the estimation algorithm can accurately estimate the adhesion coefficient, and through error analysis, it is found that the error between the estimated value of the adhesion coefficient and the theoretical value of the adhesion coefficient is within 5%. The adhesion coefficient obtained through the online estimation method based on the parameter estimation proposed in this paper demonstrates strong followability in both simulation and practical applications.

KEYWORDS: Hardware-in-the-loop simulation; online parameter estimation; rail vehicle; wheel-rail adhesion

1 Introduction

The traction and braking of trains are achieved through the transmission of tangential forces at the wheel-rail contact patch. The wheel-rail adhesion coefficient is a critical parameter influencing train traction, braking, and control stability. When the adhesion coefficient lies within an appropriate range, trains can efficiently transmit tractive and braking forces, ensuring stable operation [1]. However, due to the complexity of the wheel-rail contact interface and the variability of operating conditions, the adhesion coefficient is difficult to measure directly. This limitation restricts the precision of train operational safety monitoring and control systems. Insufficient adhesion during train operation significantly reduces traction and braking performance, leading to wheel slip at the wheel-rail interface, extended braking distances, and potentially causing rear-end collisions and derailments in severe cases, thereby jeopardizing operational safety [2]. Therefore, accurately estimating the wheel-rail adhesion coefficient has become a key technical challenge for ensuring safe train operation and improving operational efficiency.



In countries with advanced railway technology, research into the adhesion coefficient commenced relatively early, leading to the establishment of a well-developed theoretical framework and a range of application technologies. Notably, significant achievements have been made in adhesion estimation, control, and optimization. Existing research methods for adhesion estimation can be broadly classified into two main categories: conventional methods and novel methods.

Traditional methods primarily rely on theoretical modeling, experimental measurement, and numerical simulation to investigate the adhesion coefficient. In terms of theoretical model development, scholars have proposed various adhesion coefficient calculation models based on tribology theory and wheel-rail contact mechanics, such as adhesion models derived from tribological theories and computational methods based on wheel-rail contact mechanics. These models have, to a certain extent, revealed the variation patterns of the adhesion coefficient [3,4]. For instance, Abdulkadir and Altan [5] proposed an algorithm that combines a Proportional-Integral controller with a swarm intelligence-based tractive force estimator to determine the optimal adhesion coefficient on the adhesion-slip curve; however, the real-time performance of this method faces challenges. Krishnan et al. [6] introduced a torque modulation method that estimates the adhesion coefficient by using the phase difference between the angular velocity of the wheelset and the modulated torque. In the realm of experimental measurement and analysis, researchers have conducted extensive laboratory and field trials to measure and analyze the adhesion coefficient, acquiring data under various operating conditions. This provides a critical basis for adhesion coefficient modeling and estimation [7]. For example, Yuan et al. [8] compared and analyzed the performance of four common adhesion models in calculating the wheel-rail adhesion coefficient, offering new insights for model selection and development. Regarding numerical simulation, with the advancement of computer technology, numerical methods such as multi-body dynamics simulation [9] and state estimation observers [10] have been widely applied to simulate the wheel-rail contact process, enabling more accurate prediction of adhesion coefficient variations [11]. For instance, Zhao et al. [12] designed an intelligent adhesion coefficient sensor based on a sliding mode observer, which transforms the perception of the adhesion coefficient into the observation of the traction motor's load torque to subsequently calculate the coefficient. However, the performance of this method in noisy environments requires further improvement. Chen et al. [13] proposed a wheel-rail adhesion identification method based on an improved recursive Levenberg-Marquardt algorithm, employing the Polach model to fit the nonlinear tangential force. In recent years, progress has also been made in refined wheel-rail contact simulations using the Finite Element Method and studies that combine vehicle-track coupled dynamics [14], further enhancing the accuracy of numerical simulations.

With the rapid development of artificial intelligence and data-driven technologies, adhesion coefficient estimation techniques based on new methods such as neural networks, Kalman filtering, and machine learning have become a research hotspot. These methods are typically applied innovatively within the framework of or in conjunction with traditional approaches, aiming to address the challenges of adhesion estimation under complex operating conditions and demonstrate promising application prospects [15]. In the field of deep learning, Abdurahman et al. [16] proposed an adhesion coefficient estimation algorithm based on a multi-channel deep convolutional neural network combined with the Short-Time Fourier Transform. Verified through experiments under various rail surface conditions and speeds, the method can accurately estimate the adhesion coefficient under normal operating conditions, but it suffers from high computational complexity. To reduce this complexity, Zhang [17] explored the application of the Backpropagation Neural Network (BPNN) structure for adhesion estimation, achieving preliminary success. In the realm of state estimation and filtering, Zhao et al. [18] developed an adhesion controller that incorporated an indirect method for measuring the adhesion coefficient using a Kalman filter. While the Kalman filter exhibits good estimation performance in noisy environments, its accuracy is highly dependent on the fidelity of the model.

To address this issue, Chen et al. [19] applied an improved Square-root Cubature Kalman Filter (SCKF) to adhesion estimation, which enhanced the robustness against variations in model parameters. Regarding machine learning, Zirek and Uysal [20] introduced a voting regression model based on machine learning to effectively estimate the wheel-rail adhesion coefficient by averaging the predictions of multiple individual models with weights. However, this method shows limited adaptability to dynamic changes in speed. To improve dynamic adaptability, Zhu et al. [21] investigated a hybrid approach that combines traditional time-domain dynamic loads with machine learning for adhesion estimation.

Driven by the widespread application of adhesion estimation algorithms, adhesion control methods in engineering have shown a trend of multifaceted development in recent years. For instance, Zhao et al. [22] proposed a cooperative adhesion control method applicable to multi-electric locomotives. This method achieves optimal adhesion utilization for each axle and consequently the optimal torque distribution among multiple motors by optimizing the output torque of each motor. Sun et al. [23] established a co-simulation dynamics model that incorporates adhesion control to study stick-slip vibration behavior, with parameters such as rail surface conditions and track curve radius. Ni et al. [24] introduced a neural network controller based on the Levenberg-Marquardt (LM) algorithm, and its capability for optimizing wheel-rail adhesion was experimentally validated under various operating conditions. Furthermore, Liu et al. [25] achieved precise train operation at the optimal adhesion point by combining a machine learning algorithm with a torque controller.

Currently, despite the existence of various methods for estimating train wheel-rail adhesion, some existing approaches exhibit low sensitivity to parameter variations in dynamic environments and a strong reliance on historical data, making them difficult to adapt to the rapid changes in wheel-rail contact conditions during train operation. Another group of methods, based on complex dynamic models, although offering high accuracy, suffer from significant computational complexity, failing to meet real-time requirements. Additionally, certain methods struggle with robustness issues. To address these limitations of current adhesion estimation techniques, this paper proposes an online estimation method for wheel-rail adhesion coefficient based on parameter estimation. A key innovation of this method is the adoption of a time-varying parameter adaptive identification technique, which enhances its adaptability to dynamic conditions. It is verified through the MATLAB/Simulink and AMESim co-simulation platform and the hardware-in-the-loop semi-physical simulation experimental platform, which can estimate the wheel-rail adhesion coefficient in real-time and accurately in complex environments. The aim is to offer a novel approach for the real-time monitoring of train wheel-rail adhesion coefficient and provide technical support for improving the effective utilization of adhesion between the wheel and rail.

2 Wheel-Rail Adhesion and Wheel-Pair Force Analysis

During the operation of the rail vehicle, traction is transmitted through the adhesive-creep between the wheel and the rail contact spot. Tests have shown that the tangential force between the wheel and the rail is proportional to the normal force exerted by the wheel on the rail, and the proportional coefficient is called the adhesion coefficient, that is:

$$F_{\mu} = Q \cdot \mu = m \cdot g \cdot \mu \quad (1)$$

where F_{μ} is the tangential force between the wheel and the rail; Q is the normal force exerted by the wheel pair on the rail; m represents the mass of the vehicle; g is the gravitational acceleration; μ is the coefficient of adhesion.

Fig. 1 shows the one-eighth model of the vehicle body. Under the action of the normal force Q , the contact parts of the wheels and rails are tightly pressed together. K is the normal force exerted by the brake shoe on the tread of the wheel, which generates the corresponding braking force F_b .

The braking force F_b can be calculated by Eq. (2):

$$F_b = K \varphi_K = \frac{\pi}{4} D^2 P_{BC} \xi \eta \varphi_K \quad (2)$$

where D is the diameter of the brake cylinder; P_{BC} is the real-time brake cylinder pressure; ξ for brake multiplier; η is the mechanical efficiency of the brake caliper; φ_K is the coefficient of friction between the friction pairs.

Based on the force analysis in Fig. 1, the differential equation for the rotation of the pair of wheels can be obtained as:

$$I_w \frac{d\omega}{dt} = R_w (F_\mu - F_b) \quad (3)$$

where I_w is the moment of inertia of the wheel set; ω is the angular velocity of rotation of the wheel set during braking; R_w is the wheel set radius.

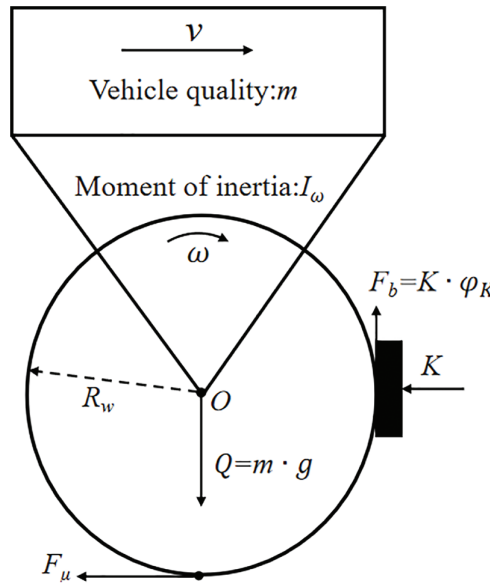


Figure 1: Force analysis of wheel sets in braking state

The braking force F_b is obtained by real-time measurement of the brake cylinder pressure and calculation using Eq. (2). In Eq. (3), the angular velocity of the train wheel set can be measured in real time, the moment of inertia I_w and the wheelset radius R_w can be regarded as constant, and the braking force F_b can be calculated. Since the angular velocity measured in real time has noise interference, parameter estimation is needed for the estimation of the wheel-rail tangential force F_μ .

3 Online Estimation Algorithm and Implementation Method for the Coefficient of Adhesion

3.1 Online Parameter Estimator

Before calculating the wheel-rail tangential force F_μ , it is necessary to obtain a linear parametric model of the wheel-pair motion to design the parameter estimator. A linear parametric model is a combination of known data and unknown parameters, represented as a linear function of the uncertain parameters, that is:

$$y(t) = W(t) \times a + b \quad (4)$$

where the n -dimensional vector y is the system output of measurable variables, the $n \times m$ -order matrix W is the signal matrix of deterministic parameters or deterministic parameters as independent variables, the m -dimensional vector a is the unknown parameters to be estimated, b is the n -dimensional vector composed of scalar functions of deterministic parameters.

Firstly, the design method of the online estimator is based on error prediction. Assuming that at time t , the estimated value of a is $\hat{a}$, the predicted value $\hat{y}(t)$ of $y(t)$ at time t is estimated based on parameter estimation and the model:

$$\hat{y}(t) = W(t) \hat{a}(t) + b \quad (5)$$

The difference between the predicted output $\hat{y}(t)$ and the measured output $y(t)$ is the prediction error, denoted as Δy , that is:

$$\Delta y = \hat{y}(t) - y(t) = W(t) \hat{a} - W(t) a \quad (6)$$

Calculate the error using the least squares method with the forgetting index. Based on the prediction error Δy , the least squares method with the forgetting index defines the total error J , as follows:

$$J = \int_0^t e^{-\int_r^t \varsigma(\tau) d\tau} (\Delta y(r))^2 dr = \int_0^t e^{-\int_r^t \varsigma(\tau) d\tau} [W(r) \hat{a} - W(r) a]^2 dr \quad (7)$$

In Eq. (7), ς is the time-varying forgetting factor, the forgetting index $e^{-\int_r^t \varsigma(\tau) d\tau}$ represents the weight of the prediction error at each moment in the calculation parameter to estimate the total error J . This term makes the Δy that is closer to the current moment t have a greater weight. Conversely, the weight of the Δy that is farther away from the current moment is smaller and gradually “forgotten”. This reduces the reliability of the old data and increases the reliability of the new data, making the algorithm more adaptable.

The purpose of the online parameter estimator is to find the estimated value $\hat{a}$ in the new calculation cycle so that the total error of parameter estimation J is minimized, and at each current moment t there is:

$$\frac{\partial J}{\partial \hat{a}} = 0 \quad (8)$$

Thus there is:

$$\left[\int_0^t e^{-\int_r^t \varsigma(\tau) d\tau} W^T W dr \right] \cdot \hat{a}(t) = \int_0^t e^{-\int_r^t \varsigma(\tau) d\tau} W^T W a dr \quad (9)$$

After differentiating t on both sides of Eq. (9) and simplifying it, the differential equation used for real-time online update of the estimated value $\hat{a}$ can be obtained, that is:

$$W^T W \hat{a} + \left[\int_0^t e^{-\int_r^t \varsigma(\tau) d\tau} W^T W dr \right] \cdot \dot{\hat{a}} = W^T W a \quad (10)$$

make

$$P = \left[\int_0^t e^{-\int_r^t \varsigma(\tau) d\tau} W^T W dr \right]^{-1} \quad (11)$$

If P is called the estimator gain matrix, then the differential equation of the estimator variable $\hat{a}$ used for online parameter update can be obtained.

$$\dot{\hat{a}} = -PW^T \Delta y = -PW^T (W\hat{a} + b - y) \quad (12)$$

3.2 Stability Analysis of Parameter Estimator

Denoted $\tilde{a} = \hat{a} - a$ as the parameter estimation error, the parameter estimator should be such that the parameter estimation error is asymptotically convergent or bounded convergent, as can be obtained from Eqs. (11) and (12):

$$\frac{d(P^{-1}\tilde{a})}{dt} = -\gamma(P^{-1}\tilde{a}) - P^{-1}\dot{\tilde{a}} \quad (13)$$

Eq. (13) can be regarded as a first-order filter with input of $-P^{-1}\dot{\tilde{a}}$, output of $P^{-1}\tilde{a}$, and “bandwidth” of γ . The parameter estimation error is bounded when there exists a positive constant γ_0 such that $\gamma \geq \gamma_0$, and the matrix P^{-1} has a lower bound, the steady-state parameter estimation error $\tilde{a}$ is:

$$\tilde{a}(\infty) = -\frac{\dot{\tilde{a}}}{\gamma} \quad (14)$$

If the parameter a does not change over time (i.e., $\dot{a} = 0$), it is known from Eq. (13) that $P^{-1}\tilde{a}$ converges to 0 with the exponent γ , and there is:

$$P^{-1}\tilde{a} \leq P^{-1}(0)\tilde{a}(0)e^{-\gamma_0 t} \quad (15)$$

Therefore, the parameter estimation error $\tilde{a}$ will gradually converge to 0, that is, the estimated parameter $\hat{a}$ gradually converges to its true value a . At the same time, from Eqs. (6) and (12), it can be obtained that:

$$\dot{\tilde{a}} = -PW^T W\tilde{a} \quad (16)$$

Select Lyapunov function:

$$V = \tilde{a}P^{-1}\tilde{a} \quad (17)$$

Taking the derivative of Eq. (17), it is known that its derivative satisfies:

$$\dot{V} = -\tilde{a}^T W^T W\tilde{a} - \gamma\tilde{a}^T P^{-1}\tilde{a} \leq 0 \quad (18)$$

From this, it is known that the online parameter estimator is stable.

3.3 Online Estimation Implementation Based on Parameter Estimation

Currently, on rail vehicles such as high-speed trains or urban rail transit trains, the rotational speed of the wheel sets is measured by the axle speed pulse sensor installed at the axle end. For the angular acceleration of the wheels, there is no direct means for measurement. Considering the influence of measurement noise

and various interferes, in order to eliminate the differential of the diagonal velocity of the wheels in Eq. (3) and convert it into the form of linearized parameters, The two sides of Eq. (3) are filtered with a first-order filter $1/(q + \lambda)$ (where q is the Laplacian operator and λ is the transition frequency of the first-order filter). The unit impulse response function of the first-order filter is $e^{-\lambda t}$, and the filtered Eq. (3) is expressed as:

$$\int_0^t e^{-\lambda(t-\tau)} \frac{d\omega}{d\tau} d\tau - \int_0^t e^{-\lambda(t-\tau)} \frac{R_w}{I_w} F_\mu d\tau + \int_0^t e^{-\lambda(t-\tau)} \frac{R_w}{I_w} F_b d\tau = 0 \quad (19)$$

During the braking anti-skid process, although F_μ and F_b also change over time, they are much slower relative to the time constant $1/\lambda$ of the filter and can be regarded as constants in the integral operation, so Eq. (19) can be transformed into the form of linearized parameters:

$$\omega(t) = \frac{1 - e^{-\lambda t}}{\lambda} \frac{R_w}{I_w} F_\mu - \frac{1 - e^{-\lambda t}}{\lambda} \frac{R_w}{I_w} F_b + \lambda \int_0^t e^{-\lambda(t-\tau)} \omega d\tau + \omega(0) e^{-\lambda t} \quad (20)$$

Denoted $\hat{F}_\mu$ as the estimated value of the uncertain parameter F_μ , substituting $\hat{F}_\mu$ into Eq. (20) yields the estimated value $\hat{\omega}$ of the angular velocity $\omega(t)$ of the wheel as:

$$\hat{\omega} = \frac{1 - e^{-\lambda t}}{\lambda} \frac{R_w}{I_w} \hat{F}_\mu - \frac{1 - e^{-\lambda t}}{\lambda} \frac{R_w}{I_w} F_b + \lambda \int_0^t e^{-\lambda(t-\tau)} \omega d\tau + \omega(0) e^{-\lambda t} \quad (21)$$

make

$$W = \frac{1 - e^{-\lambda t}}{\lambda} \frac{R_w}{I_w} \quad (22)$$

Then the estimation error $\Delta\omega$ of the diagonal velocity of the wheel can be defined as:

$$\Delta\omega = \hat{\omega} - \omega(t) = W\hat{F}_\mu - WF_\mu \quad (23)$$

Based on the estimation error $\Delta\omega$ of the wheel diagonal velocity, the parameter estimation total error J is defined by the least square method with the forgetting exponent, as follows:

$$J = \int_0^t e^{-\int_r^t \varsigma(t-\tau) d\tau} \Delta\omega^2 dr = \int_0^t e^{-\int_r^t \varsigma(t-\tau) d\tau} (W\hat{F}_\mu - WF_\mu)^2 dr \quad (24)$$

The differential equation for the online real-time update of the estimation parameter $\hat{F}_\mu$ is available:

$$\dot{\hat{F}}_\mu = -PW \Delta\omega = -PW (W\hat{F}_\mu - WF_\mu) \quad (25)$$

The tangential force F_μ can be estimated in real time, and then the adhesive coefficient μ can be obtained.

4 Simulation Analysis and Semi-Physical Platform Validation

To verify the effectiveness of the adhesive coefficient estimation method, this paper divides the system into three parts based on the working principle of the rail vehicle braking system: the longitudinal dynamic model of train braking, the braking control model, and the air braking unit model. The estimation method is verified through joint simulation under braking anti-skid conditions and a semi-physical test bench.

4.1 Construction of the Joint Simulation Platform

First, the longitudinal braking dynamics model of a single four-axle train was established using MATLAB/Simulink. The vehicle model incorporates sub-models for the car body, bogie, wheelset, and suspension system. The wheelset sub-model further includes dynamics, wheel-rail adhesion, and basic braking device components. The friction coefficient of the basic braking device varies with the train's initial and instantaneous speeds. According to the Polach nonlinear contact theory model, the adhesion curve represents the changing adhesion state as the wheelset slips. A braking control model was developed based on a finite state machine. This control module calculates and allocates the target braking force and brake cylinder pressure according to the specified target deceleration and the train's mass. The anti-slip control module primarily determines the wheels' state based on external input signals. When the slip condition reaches a threshold, it actuates the anti-slip valve to reduce brake cylinder pressure, thereby restoring the wheels to an adhesive state.

The train's pneumatic braking system comprises components like braking commands, transmission units, microcomputer braking control systems, pneumatic control units, anti-slip valves, and basic braking devices. Upon receiving a braking command, the microcomputer braking control unit adjusts the target braking pressure in real-time, considering factors such as air spring pressure. The pneumatic control unit then receives signals from this control unit and generates compressed air at the required pressure. This air flows through the anti-slip valve into the brake cylinders of the basic braking devices. There, it actuates the pistons, causing brake blocks or shoes to press against the wheel treads or discs, resulting in vehicle deceleration. Following the principles of the rail train braking system and its operation, the pneumatic braking unit model—including elements such as Electro-Pneumatic (EP) valves, relay valves, and anti-slip valves—was constructed using AMESim's pneumatic component library. A co-simulation platform integrating MATLAB/Simulink and AMESim was established via their simulation interfaces (refer to Fig. 2). The modeling approaches for these individual components are detailed in related literature [26,27] and are not elaborated upon here. Simulations were performed according to the described modeling principles. The estimated adhesion was derived using the online wheel-rail adhesion coefficient estimation method based on parameter estimation.

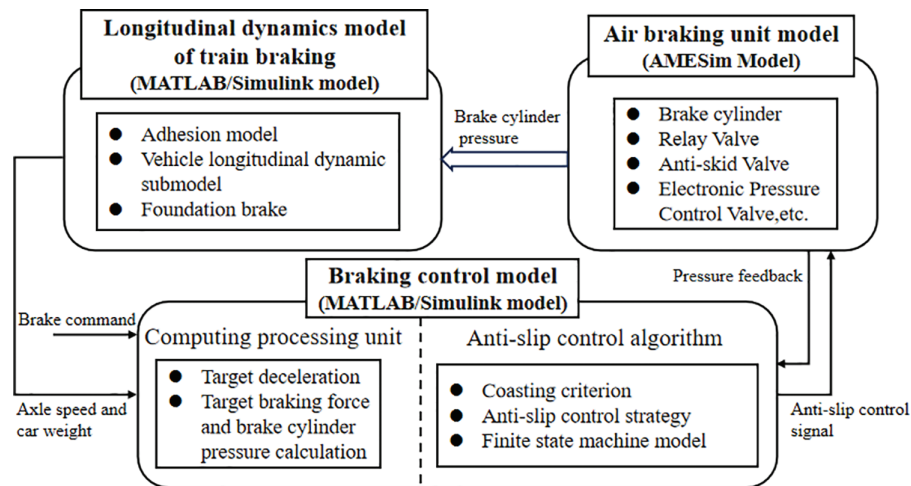


Figure 2: Train braking system model and the relationship between the systems

In the simulation, Polach nonlinear contact theory model is used to simulate the wheel-rail tangential force [28], and its calculation formula is:

$$F_{\mu} = \frac{2Q\mu}{\pi} \left(\frac{k_A \varepsilon}{1 + (k_A \varepsilon)^2} + \arctan(k_s \varepsilon) \right) \quad (26)$$

$$\varepsilon = \frac{1}{4} \frac{G \pi i j C}{Q \mu} S \quad (27)$$

$$C = \sqrt{\left(\frac{S_x}{S} c_{11} \right)^2 + \left(\frac{S_y}{S} c_{22} \right)^2} \quad (28)$$

$$\mu = \mu_0 [(1 + A) e^{-BV} + A] \quad (29)$$

where k_A and k_s are the attenuation coefficients, ε is the tangential stress gradient, i and j are the half-axis length of the elliptical contact spot, calculated using the Hertz contact algorithm; c_{11} and c_{22} are the transverse and longitudinal Kalker constants, which can be obtained by looking up a table based on the ratio of the long and short semi-axes of the contact spot; G is the rigidity modulus, which is set to 80 GPa in this manuscript; $S = \sqrt{S_x^2 + S_y^2}$ is the total slip rate; S_x and S_y are the transverse and longitudinal slip rates; μ_0 is the maximum coefficient of adhesion; A is the ratio of the adhesion coefficient corresponding to infinite slip to the maximum adhesion coefficient; B is the exponential attenuation coefficient of the tangential force, and V is the wheel-rail relative sliding velocity.

The Polach model is adjusted by tuning five parameters— k_A , k_s , μ_0 , A and B —to adapt to different wheel-rail contact conditions. Among these, k_A and k_s primarily influence the slope of the adhesion curve and the slip rate at the adhesion saturation point. In contrast, μ_0 , A , and B mainly determine the value of the adhesion coefficient. The specific parameter values for the Polach model, corresponding to low-adhesion and high-adhesion conditions, are listed in Table 1 and will be applied in the subsequent simulation experiments.

Table 1: Parameters of the polach adhesion model

Parameters of the adhesion model	k_A	k_s	μ_0	A	B
Low-adhesion model	0.1	0.085	0.11	0.17	0.47
High-adhesion model	0.6	0.5	0.25	0.3	0.6

4.2 Analysis of Simulation Results

The coasting condition caused by emergency braking with an initial speed v_0 of 250 km/h is simulated. Fig. 3 shows the estimator's estimation of the adhesion coefficient, where the theoretical value of the adhesion coefficient is obtained from the Polach model and the estimated value of the adhesion coefficient is obtained from the adhesion estimation algorithm.

As can be seen from Fig. 3, during the braking process of the train, the adhesive coefficient shows an overall upward trend as the speed decreases. Due to the complex state of the rail surface, when traveling on a low-adhesion road, if the maximum tangential force that can be provided between the wheels of a certain pair is less than the braking force, sliding occurs. The train's anti-skid control system has to judge the state of the wheels based on the external input signal. When it is determined that wheel slip occurs, the anti-slip valve

is actuated to reduce the brake cylinder pressure, restoring the wheel to a re-adhesion state. It can be seen that within a slip cycle, the process of the estimated adhesion decreasing due to slip and then increasing after the train's anti-slip action can maintain tracking with the theoretical adhesion coefficient value. Throughout the entire anti-slip process, as the train speed decreases, during the overall rise in the theoretical adhesion coefficient value, the estimated adhesion coefficient value also maintains tracking. This indicates that the adhesion coefficient prediction value is relatively accurate, and the use of the estimated adhesion coefficient value exhibits good tracking performance relative to the theoretical value.

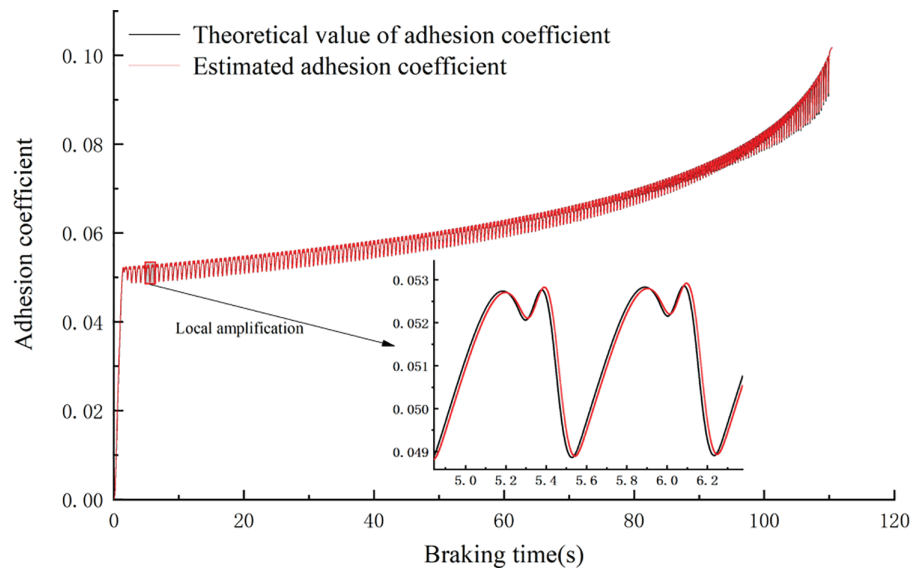


Figure 3: Comparison of the theoretical and estimated values of the adhesion coefficient

However, during the actual operation of the train, there will be system delay, noise interference and measurement noise from signal acquisition. To further verify the train adhesion coefficient estimation algorithm based on the parameter estimation proposed in this paper, the proposed adhesion estimation algorithm will be tested in a hardware-in-the-loop simulation with delay and noise environment.

4.3 Hardware-in-the-Loop Simulation Validation

4.3.1 Hardware-in-Loop Simulation Test Platform

Fig. 4 shows the physical structure of the hardware-in-loop simulation platform. The test platform is mainly composed of test bench simulation software and physical hardware. The simulation software runs in the industrial control computer on the test bench, including the human-machine interaction interface and the train braking model. The simulation software comprises the longitudinal dynamics model of train braking and the braking control model in the Matlab/Simulink model in Section 4.1, as shown in Fig. 4a. The hardware physical object is the air braking unit, as shown in Fig. 4b. Its braking performance meets the requirements of the international standards for rail vehicle anti-slip control, UIC541-05 and EN15595-2018. The information exchange between the virtual train and the hardware of the hardware-in-the-loop test platform is achieved through the Multiple Vehicle Bus (MVB) bus and data acquisition and conversion circuits. Among them, the signals transmitted via the MVB bus include the brake commands generated by the driver's controller, the virtual train's load, and the requests and feedback of electric braking force. The signals hardwired through the data acquisition and conversion circuits include the virtual train's axle speed and the brake cylinder pressure of the braking mechanism.

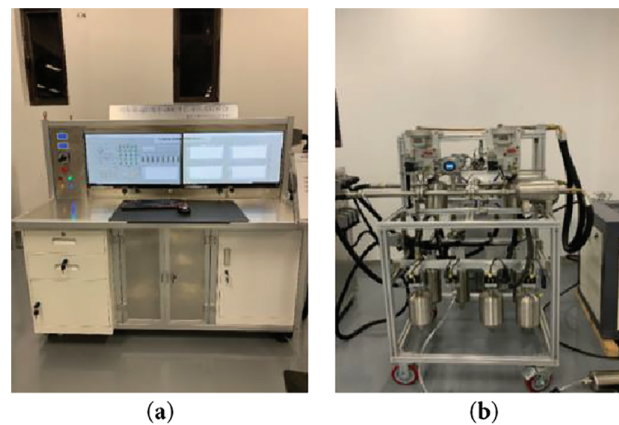


Figure 4: Train brake anti-skid control hardware-in-the-loop simulation test bench. (a) The longitudinal dynamics model of train braking and the braking control model. (b) The air braking unit

4.3.2 Test Results and Analysis

This section verifies the adhesion estimation algorithm through hardware-in-the-loop semi-physical simulation experiments. System delay and noise interference from harsh environments during train operation are important factors affecting train performance and safety. During the test on the test bench, there were system delays and interference noises in the acquisition and transmission of brake signals and valve signals in the hardware physical part, which made the input signals of train-related parameters received by the model more in line with the actual train operation environment.

As shown in Fig. 5, due to noise interference during the process of collecting input signals from the hardware physical part, the theoretical value of the adhesion coefficient will have some noise during the test process. The estimated value of the adhesion coefficient lags slightly and fluctuates compared to the theoretical value. This lag and fluctuation are caused by delays in the physical system, signal acquisition time, and other reasons. Within a slip cycle, the process where train slip causes the adhesion coefficient to decrease and the adhesion coefficient to rise after the train's anti-slip, and as the train speed decreases and the overall adhesion coefficient rises, the estimated adhesion can maintain good tracking with the theoretical value of the adhesion coefficient. This indicates that this method also has good inhibitory effects on noise.

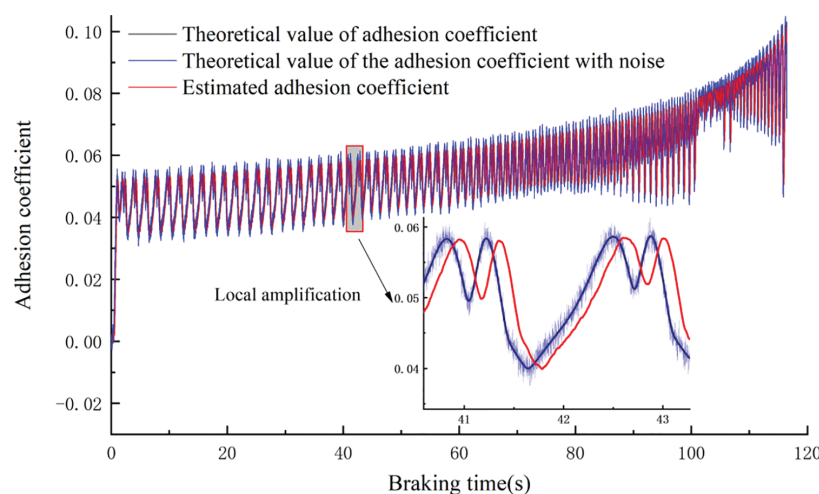


Figure 5: Comparison of the adhesion coefficient based on the semi-physical simulation test bench

To further verify the effectiveness of the adhesion estimation method, this paper conducted multiple test conditions on the hardware-in-the-loop simulation testbed, analyzing conditions such as different rail surface adhesion conditions, different braking levels, and different train loads. Tests were conducted under both low adhesion conditions and high adhesion conditions, i.e., tests where wheel slip occurs during braking and tests where it does not. As shown in Figs. 6 and 7, these are Condition 1: low adhesion, emergency braking, full load test and Condition 2: high adhesion, emergency braking, full load test. Error analysis was performed for these two conditions. Because there is a delay effect between the theoretical value of the adhesion coefficient and the estimated value of the adhesion coefficient, the delay effect should be eliminated before error analysis. By comparing the adhesion coefficient estimation value from pure simulation tests with that from the hardware-in-the-loop platform tests, it was found that the system delay is approximately 100 ms. After eliminating the delay, the theoretical value of the adhesion coefficient is subtracted by the estimated value of the adhesion coefficient to obtain the difference, and then the difference is divided by the theoretical value of the adhesion coefficient to obtain the percentage error. The percentage errors for the two test conditions are shown in Figs. 8 and 9, respectively:

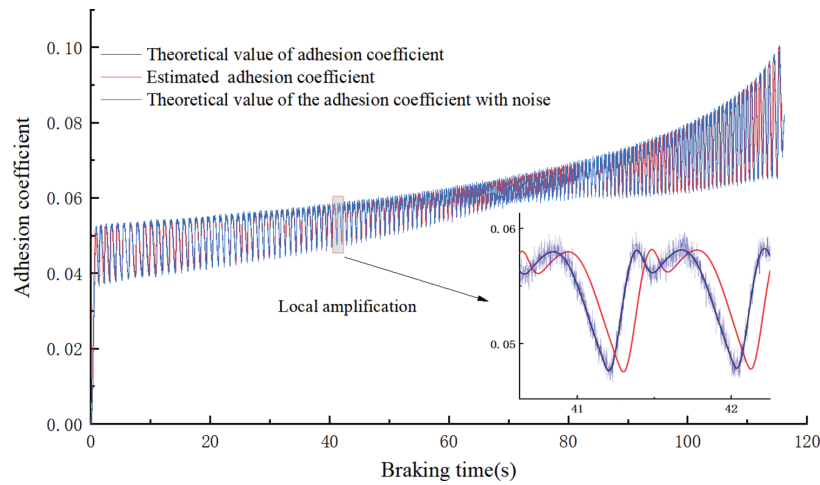


Figure 6: Comparison chart of adhesion coefficients under low adhesion conditions

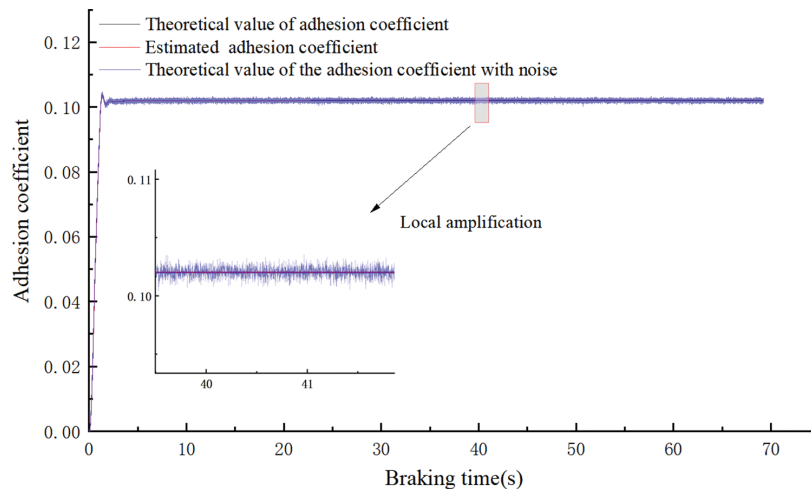


Figure 7: Comparison chart of adhesion coefficients under high adhesion conditions

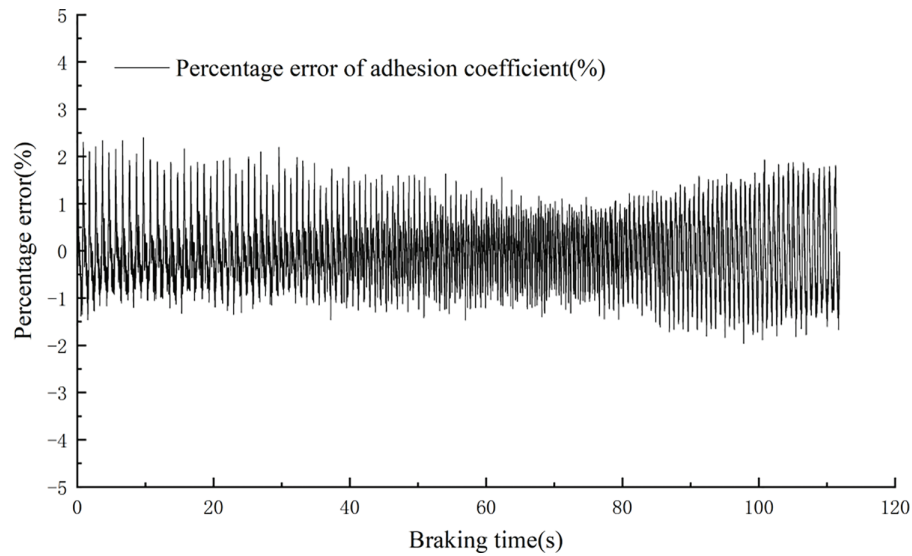


Figure 8: Percentage error of the adhesion coefficient under low adhesion conditions

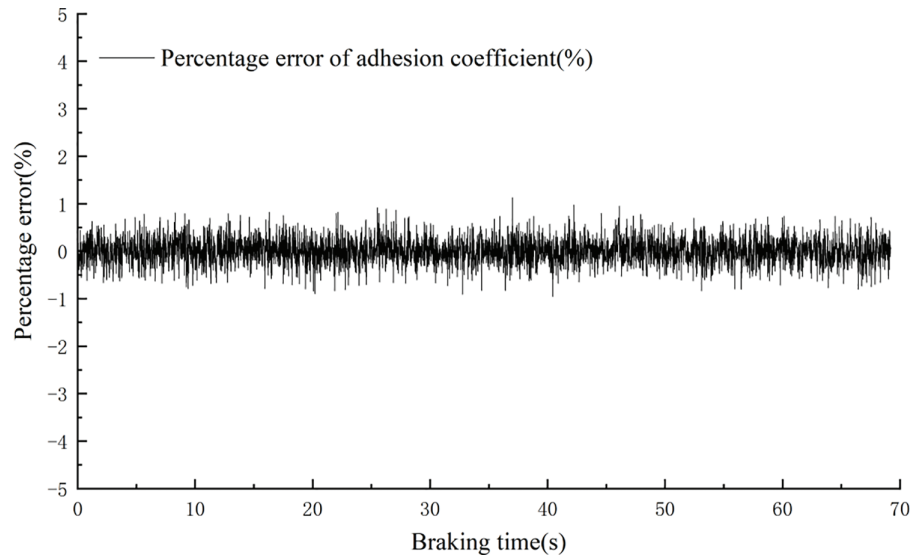


Figure 9: Percentage error of the adhesion coefficient under high adhesion conditions

Fig. 6 is the adhesion coefficient comparison diagram under low adhesion conditions. The estimated adhesion coefficient can still maintain tracking during train slip. Fig. 7 is the adhesion coefficient comparison diagram under high adhesion conditions. Because the train does not experience slip under high adhesion, the axle speed is basically equal to the train speed, so the adhesion coefficient does not change due to variations in slip ratio. Compared to Fig. 6, the adhesion coefficient in Fig. 7 remains basically constant during braking. Additionally, the estimated adhesion coefficients in both test conditions can maintain tracking with the theoretical adhesion coefficient values. An error analysis was conducted for the two test conditions. The error for Condition 1 is shown in Fig. 8, and its error is basically maintained within 5%. The error for Condition 2 is shown in Fig. 9, where the theoretical adhesion coefficient remains basically constant during braking,

resulting in smaller error fluctuations, which are basically maintained around 1%. This result is acceptable for engineering applications.

Using Condition 1: low adhesion, emergency braking, full load test as the control group, Fig. 10 is the test diagram for Condition 3: low adhesion, normal braking, full load test; Fig. 11 is the test for Condition 4: low adhesion, emergency braking, empty load test. The percentage errors for the two test scenarios are shown in Figs. 12 and 13, respectively:

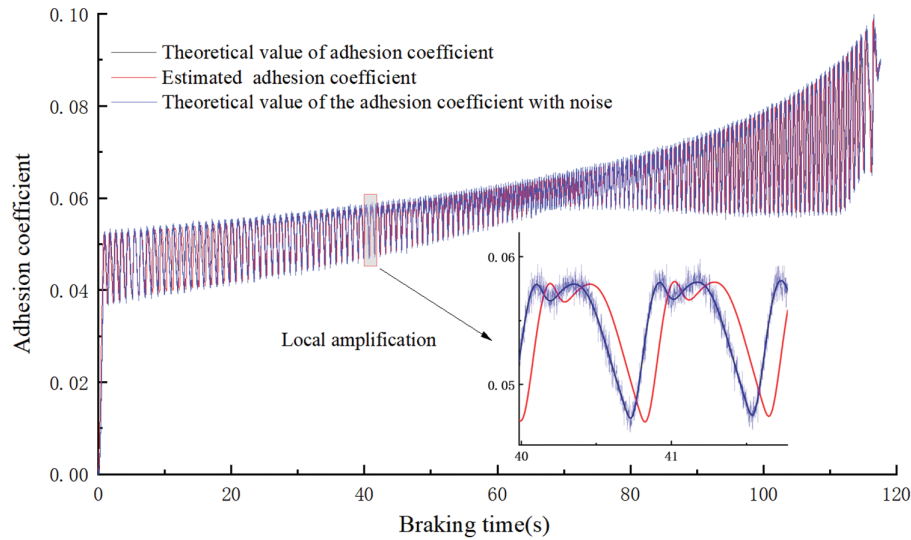


Figure 10: Comparison chart of commonly used braking adhesion coefficients

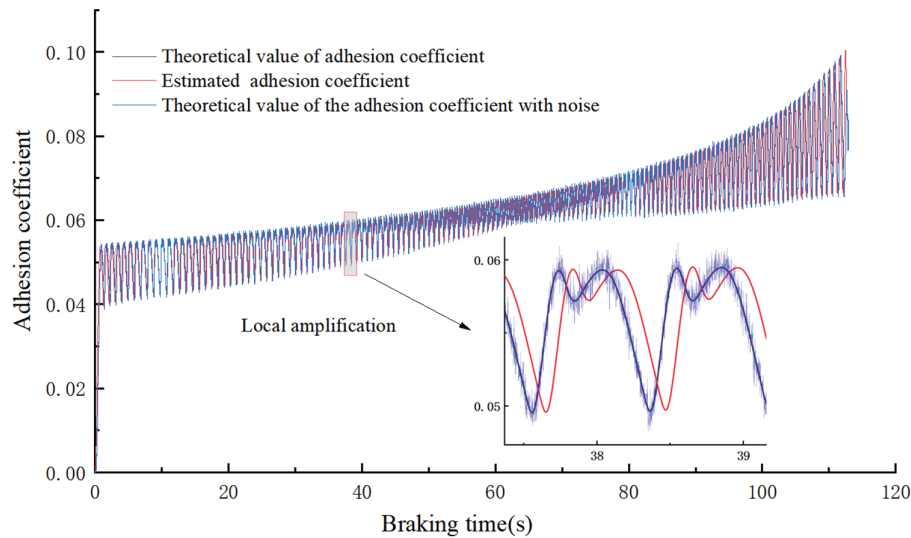


Figure 11: Comparison chart of no-load adhesion coefficients

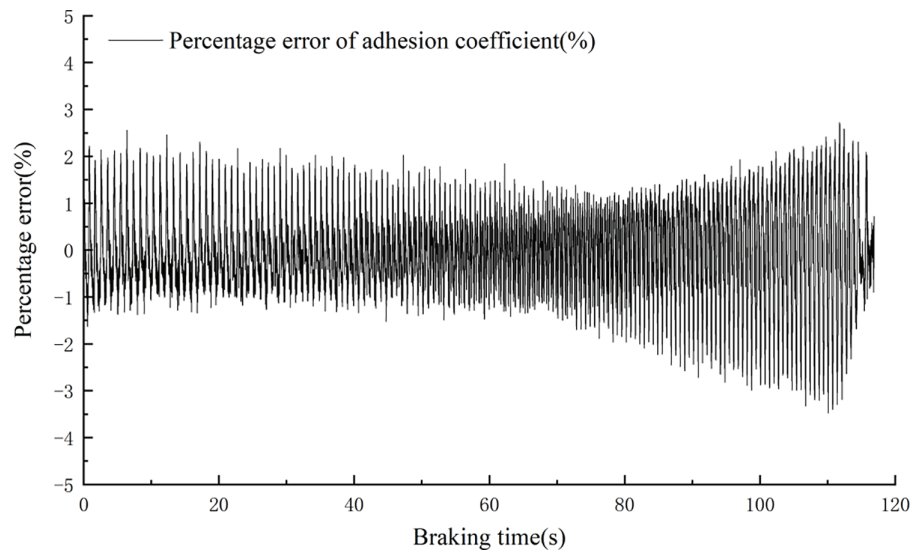


Figure 12: Percentage error of commonly used braking adhesion coefficients

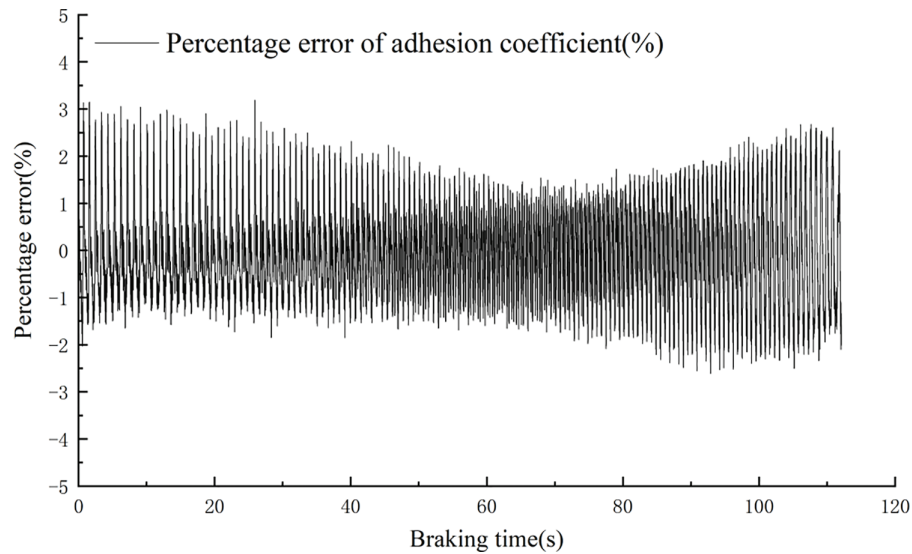


Figure 13: Percentage error of no-load adhesion coefficient

As shown in Figs. 10 and 11, under normal braking conditions and different load test conditions, the estimated adhesion coefficient and the theoretical adhesion coefficient can also basically maintain tracking. An error analysis is performed on the theoretical and estimated adhesion coefficients. The errors for the two conditions are shown in Figs. 12 and 13, respectively. The percentage error between the theoretical adhesion coefficient and the estimated adhesion coefficient is basically maintained within 5%, proving the effectiveness of the adhesion coefficient estimation method proposed in this paper.

4.4 Analysis of the Impact of Changes in Constant Parameters on Estimation Results

Although experiments under different conditions were conducted and analyzed in this paper, and the algorithm shows good effectiveness, some parameters in the aforementioned research can be regarded as

constants during short-term operation but will change over long-term operation. For example, parameters such as wheel radius, moment of inertia, and the friction coefficient between the friction pair and the wheel may affect the adhesion coefficient estimation value due to wear. This section takes the wheel radius parameter as an example for experimental analysis. By changing the wheel radius parameter, the condition after wheel wear is simulated. Using Condition 1 as the experimental control group, Condition 5 was tested after changing the wheel radius parameter. The wheel radius parameter in Condition 1 was 0.42 m, and in Condition 5, the wheel radius parameter was set to 0.4 m. The test results are shown in Fig. 14. An error analysis was performed on Condition 5 after eliminating the delay, and the percentage error is shown in Fig. 15:

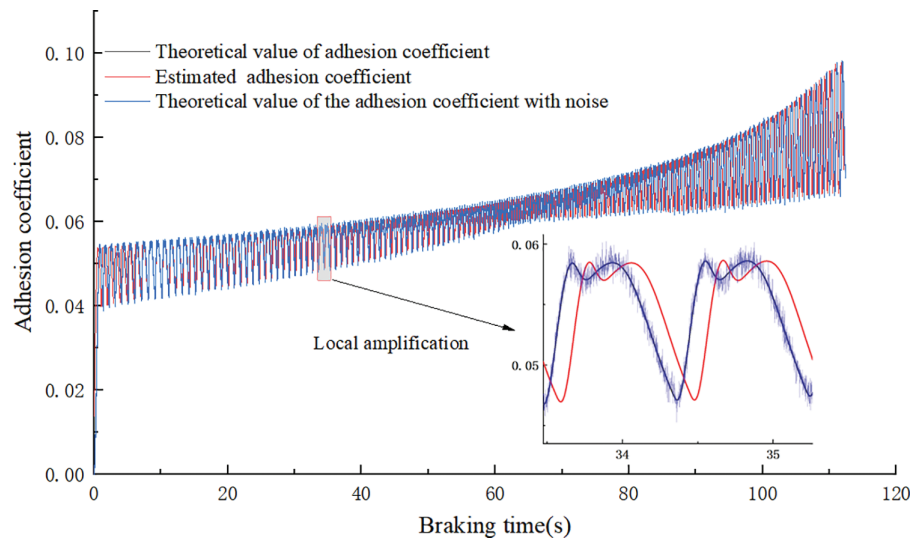


Figure 14: Comparison chart of adhesion coefficients with a radius of 0.4 m

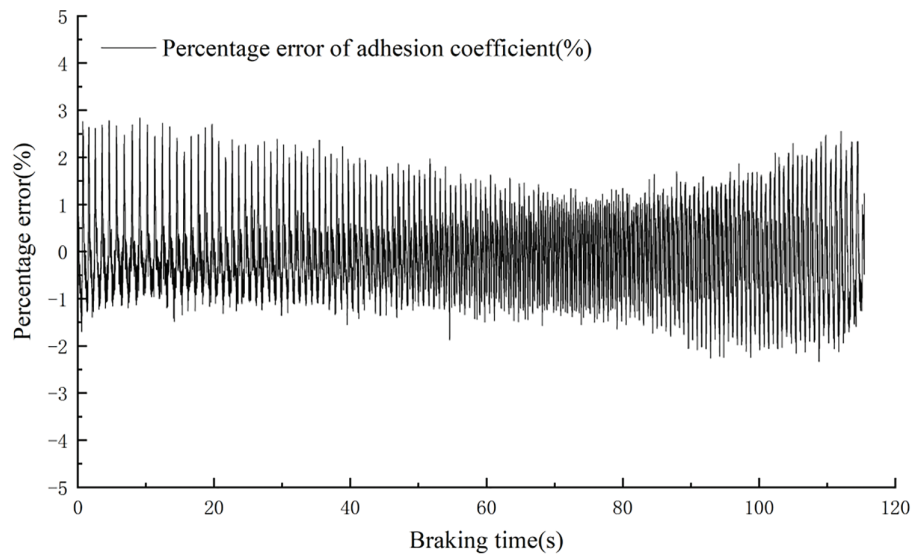


Figure 15: Percentage error of the adhesion coefficient with a radius of 0.4 m

As shown in Fig. 14, after the wheel radius wears down, the estimated adhesion coefficient can still maintain tracking during train slip. An error analysis was performed on it, and the results are shown in Fig. 15. Compared with the error diagram before radius wear Fig. 8, wheelset wear does indeed have a certain impact on the estimated adhesion. However, over time, the error does not gradually increase, and the percentage error can still be maintained within 5%, indicating that the wear variation of the wheel radius has a relatively small impact on the adhesion estimation.

5 Conclusions

In this paper, an adhesive estimation algorithm based on parameter estimation is proposed for the adhesive coefficient that has an important influence during train braking. The designed adhesion estimation algorithm is experimentally verified by using the joint simulation of MATLAB/Simulink and the hardware-in-the-loop semi-physical simulation test platform. It provides a new technical approach for the real-time monitoring of the wheel-rail adhesion coefficient of trains and offers more reliable technical support for the safe operation of trains.

Conduct a force analysis on the wheel set under braking conditions to obtain the motion equation of the wheel set. Subsequently, the research on the online parameter estimator was carried out. The theoretical basis for the implementation of the online parameter estimator method was given, and its stability was verified. The estimation method of the wheel-rail adhesion coefficient is given by combining the online estimator with the force analysis of the wheel pair.

A co-simulation platform based on MATLAB/Simulink and AMESim was established. The effectiveness of the adhesion estimation algorithm was verified through co-simulation. The results show that during train braking, as the speed decreases, the adhesion coefficient shows an overall upward trend. Among these, the estimated adhesion, within a slip cycle, due to the drop in the adhesion coefficient caused by slip and the rise after the train's anti-slip action, can maintain tracking with the theoretical adhesion coefficient value. Throughout the entire anti-slip process, as the train speed decreases and the theoretical adhesion coefficient value shows an overall upward trend, the estimated adhesion can also ensure tracking.

The adhesion estimation algorithm was verified based on the hardware-in-the-loop semi-physical simulation test platform. The semi-physical simulation platform collects the physical part of the hardware input signal with noise interference, so the input of the adhesion coefficient has noise fluctuations. Although the estimated value of the adhesion coefficient has a certain lag and fluctuation compared with the theoretical value, it still has good followability, a good noise suppression effect, and has high engineering application value. The effectiveness of the estimation algorithm was verified through four groups of experiments under different conditions. The results show that in the four groups of experiments, the percentage error between the theoretical adhesion coefficient and the estimated adhesion coefficient is basically within 5%, proving the effectiveness of the algorithm proposed in this paper.

The limitation of this paper is that some parameters that may change over time, such as wheelset radius and friction coefficient of the friction pair, were treated as constant parameters in this study. The goal of future research is to estimate some parameters that may vary over time, such as the friction coefficient of the friction pair, using multi-parameter estimation methods, and to include research on the influence of the suspension system on adhesion estimation.

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Availability of Data and Materials: All the data used and analyzed are available in the manuscript.

Ethics Approval: Not applicable.

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

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