Scientific Research Publishing

Journal of Transportation Technologies, 2024, 14, 53-63
https://www.scirp.org/journal/jtts
ISSN Online: 2160-0481
ISSN Print: 2160-0473

Robust Parameter Identification Method of Adhesion Model for Heavy Haul Trains

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How to cite this paper: Qian, S., Kong, L.S. and He, J. (2024) Robust Parameter Identification Method of Adhesion Model for Heavy Haul Trains. *Journal of Transportation Technologies*, **14**, 53-63.
https://doi.org/10.4236/jtts.2024.141004

Received: December 14, 2023
Accepted: January 20, 2024
Published: January 23, 2024

Abstract

A robust parameter identification method based on Kiencke model was proposed to solve the problem of the parameter identification accuracy being affected by the rail environment change and noise interference for heavy-duty trains. Firstly, a Kiencke stick-creep identification model was constructed, and the parameter identification task was transformed into a quadratic programming problem. Secondly, an iterative algorithm was constructed to solve the problem, into which a time-varying forgetting factor was added to track the change of the rail environment, and to solve the uncertainty problem of the wheel-rail environment. The Granger causality test was adopted to detect the interference, and then the weights of the current data were redistributed to solve the problem of noise interference in parameter identification. Finally, simulations were carried out and the results showed that the proposed method could track the change of the track environment in time, reduce the noise interference in the identification process, and effectively identify the adhesion performance parameters.

Keywords

Heavy-Duty Train, Kiencke Model, Quadratic Programming, Time-Varying Forgetting Factor, Granger Causality Test

1. Introduction

The implementation of the locomotive traction force is limited by the adhesion force [1]. While for the adhesion performance between locomotive wheels and rails, the medium on the wheel-rail contact interface has the greatest impact. When the third medium is water or oil, the wheel-rail surface roughness decreases, thus making the wheel-rail adhesion performance worse [2]. Therefore, the identification of rail surface state is of great importance, as there is noise interference for the parameters of the identification, it is necessary to construct a robust identification method for rail surface state.

Currently, parameter estimation methods such as least square method, generalized moment estimation method, Bayesian estimation method and maximum likelihood estimation method are used parameter estimation. Reference [3] used search and recursive least square method to obtain the adhesion parameters of wheel-rail surface, so as to adapt to the dynamic change of model parameters. Reference [4] preset typical performance parameters to identify the rail surface performance parameters online, and the identification speed and accuracy were improved. Reference [5] applied the generalized moment estimation method to estimate with various short-term interest rate models, and found that the moment estimation method had a poor estimation performance. Reference [6] studied the Bayesian estimation with term structure model of interest rate, and obtained good results. And the performance of posterior mean estimation was without significant difference. For the parameter identification of locomotive adhesion model in time-varying environment, Reference [7] constructed a maximum likelihood method to the estimate adhesion performance. By introducing in a time-varying forgetting factor, the accuracy of the algorithm and its sensitivity to environmental changes were improved. However, the above mentioned parameter estimation methods did not consider the interference of noise during the identification process. However, according to Reference [8], noise will reduce the accuracy of parameter identification. Therefore, a new method is proposed in this paper, with the following main contributions.

1) The time-varying forgetting factor in the model parameter identification algorithm is improved, with optimized upper and lower limits, for a quicker converge and adaptation to the change of rail surface environment.

2) The Granger causality test is introduced to detect the noise, and the weights of the current data are redistributed after the noise is detected. This reduces the interference of noise to model parameter identification and makes the identification result more accurate. The experimental results show that the improved algorithm can adapt to the change of rail surface environment more quickly, identify model parameters fast, as well as reduce the noise interference.

2. Problem Description

The relationship curve between adhesion force and creep rate is called the adhesion characteristic curve. The actual adhesion characteristic curve is a curve with a certain width [7]. The wheel-rail adhesion model is not only affected by the deterministic factors such as wheelset state and rail surface state, but also by the uncertain factors such as ambient temperature and humidity and rail surface cleanliness. Thus, it is difficult to obtain a very accurate adhesion model. The adhesion-creep mechanism models can be divided into linear models and nonlinear models.

The Kiencke model is a nonlinear mechanism model that can relatively accurately describe the adhesion-creep behavior between wheel and rail. It is as follows [9]:

$$\mu(\lambda)=\frac{a_0\lambda}{1+p_1\lambda+p_2\lambda^2} \tag{1}$$

where, $\mu(\lambda)$ is the adhesion coefficient with creep rate λ as the variable. a_0 is the initial slope of the adhesion characteristic curve, which is a constant. p_1, p_2 are model parameters and they are variables. For dry, normal and wet rail surfaces, the curves of Kiencke model are shown in **Figure 1**, respectively.

In view of the single-peak feature of the adhesion characteristic curve in **Figure 1**, the creep rate is controlled in the range of $\mathrm{d}\mu/\mathrm{d}v_s \approx 0$, thereby achieving optimal utilization of the adhesion coefficient [7]. However, this method is extremely sensitive to interference due to the existence of differential operations, and has limitations in practical application.

If a real-time adhesion model can be established according to the rail surface condition, the optimal creep rate and adhesion coefficient can be obtained to adapt to the real-time rail surface condition, so that the sensitivity of differential operation to interference can be weakened. The premise of finding the optimal adhesion point is to obtain the real-time adhesion parameters of the locomotive.

It can be known from Reference [7] that the optimal creep rate λ_m and its corresponding maximum adhesion coefficient $\mu_m(\lambda_m)$ are:

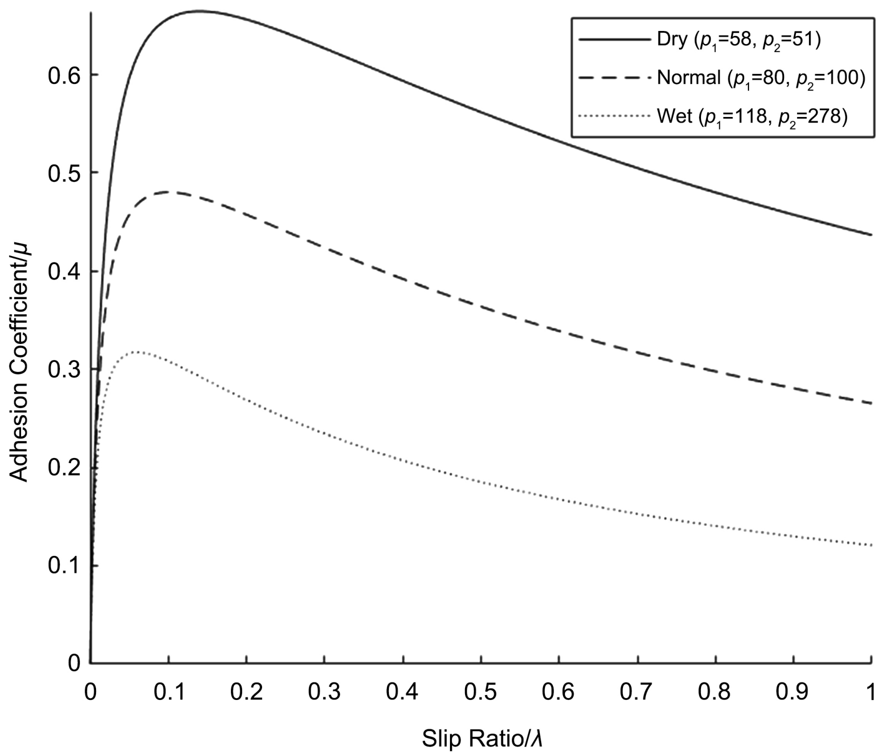

Figure 1. Kiencke model diagram under different orbit environment.

$$\lambda_m = \frac{1}{\sqrt{p_2}},\ \mu_m(\lambda_m) = \frac{a_0}{p_1 + 2\sqrt{p_2}} \tag{2}$$

As shown in Equation (2), the optimal creep rate λ_m depends on p_2, and the maximum adhesion coefficient $\mu_m(\lambda_m)$ depends on p_1 and p_2.

3. Identification of Rail Surface Performance Parameters

The identification structure of the model parameters is as shown in Figure 2.

From Reference [7], it is known that a nonlinear Kiencke model can be converted into a linear model, with input as U, output as Z, then there is $U^{\mathrm{T}}(k) = [\lambda\mu(\lambda) \quad \lambda^2\mu(\lambda)]$ and $Z(k) = a_0\lambda - \mu(\lambda)$. By identifying parameters, the interference of Gaussian noise $v(k) \sim N(0,\sigma)$ occurred, therefore the quadratic programming is used to solve the extreme value function, where:

$$H(k) = \sum_{k=1}^{L} \begin{bmatrix} U_1(k)\cdot U_1(k) & U_1(k)\cdot U_2(k) \\ U_1(k)\cdot U_2(k) & U_2(k)\cdot U_2(k) \end{bmatrix} \tag{3}$$

$$f(k) = -2\sum_{k=1}^{L} [Z(k)\cdot U_1(k) \quad Z(k)\cdot U_2(k)] \tag{4}$$

$$x(k) = (p_1(k) \quad p_2(k))^{\mathrm{T}} \tag{5}$$

In Equation (3), (4) and (5), $H(k)$ is a symmetric matrix, $f(k)$ is a vector matrix, $x(k)$ is the input matrix, while $p_1(k)$ and $p_2(k)$ are inputs at the k moment. The objective function $J(k)$ is obtained to be:

$$J(k) = \frac{1}{2}x^{\mathrm{T}}(k)\cdot 2H(k)\cdot x(k) + f(k)\cdot x(k) \tag{6}$$

It can be seen from the above that the $x(k)$ enabling Equation (6) of the minimum value is the parameter estimate we are looking for. The quadratic programming iteration methods such as quasi-Newton's method can be used to solve this extremum.

3.1. Time-Varying Forgetting Factor

In order to track the change of rail adhesion state, a time-varying forgetting factor is introduced as follows [7]:

$$H(k) = \eta H(k-1) + \frac{(2-\eta)}{2} I(k) \tag{7}$$

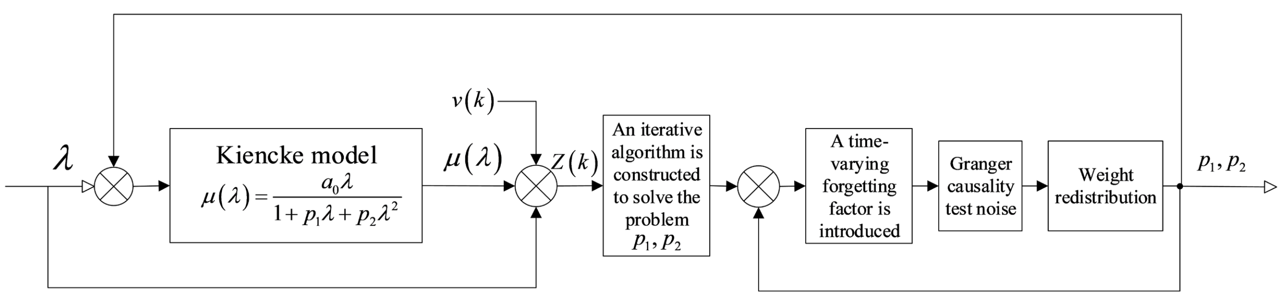

Figure 2. Structure of model parameter identification.

$$f(k)=\eta f(k-1)+\frac{(2-\eta)}{2}\cdot(-2)\left[Z(k)\cdot U_1(k) \quad Z(k)\cdot U_2(k)\right] \tag{8}$$

In Equation (7), η is the forgetting factor, and $I(k)=\begin{bmatrix} 2U_1(k)\cdot U_1(k) & 2U_1(k)\cdot U_2(k) \\ 2U_1(k)\cdot U_2(k) & 2U_2(k)\cdot U_2(k) \end{bmatrix}$ refers to the current data. The influence of forgetting factor on the estimation algorithm is mainly on the sensitivity of the algorithm. When the forgetting factor is small, the influence of historical data on the algorithm estimate is small, and the influence of current data on the algorithm estimate is large, that is, the algorithm is more sensitive to parameter sharp change caused by environment change and the accuracy of the estimate is affected. When the forgetting factor is large, the influence of historical data on the algorithm estimate is large, while the influence of current data on the algorithm estimate is small, therefore the accuracy of the algorithm is high.

As the environment change is unpredictable, a feedback control with upper and lower limits is used to adjust the forgetting factor in real time, so as to track the environment change [10]. The time-varying forgetting factor of feedback control is designed as follows:

$$\eta_k=\begin{cases}\eta_{\max}-K_p\cdot\xi_k & \eta_k>\eta_{\min}\\ \eta_{\min} & \eta_k\le\eta_{\min}\end{cases} \tag{9}$$

where, η_k refers to the forgetting factor at the k moment, *i.e.* the time-varying forgetting factor. $\xi_k=\left|\hat{\mu}(k)-\mu(k)\right|$ is the error at the k moment, *i.e.* the difference between the observed value $\mu(k)$ and estimated value $\hat{\mu}(k)$. K_p is the control parameter, while $\eta_{\max}$ and $\eta_{\min}$ are the upper and lower limits of η_k. When the error becomes larger and the forgetting factor decreases, it indicates that the environment has changed or that the model parameters have not been accurately identified. The weight of historical data is small, and the weight of current data is large. Therefore, the algorithm is more sensitive to changes in the environment, so as to identify the model parameters faster. When the error is reduced to be in a certain range and the forgetting factor is increased to a certain extent, it indicates that the algorithm has been able to accurately identify the model parameters at this moment. The weight of the historical data is as large as that of the current measurement data, and the amount of information is increased. The accuracy of the algorithm is improved.

3.2. Weight Redistribution

In order to reduce the interference of noise to parameter identification and improve the parameter identification speed, the Granger causality test method is applied [11].

This method detects by defining the signal-to-noise ratio. When $k>5$, two consecutive sample subsets X_1 and X_2 are constructed as follows:

$$X_1=\left\{I(k),H(k-1),H(k-2)\right\} \tag{10}$$

$$X_2=\left\{H(k-3),H(k-4),H(k-5)\right\} \tag{11}$$

where, $I(k)$ refers to the current data, $H(k-1)$, $H(k-2)$, $H(k-3)$, $H(k-4)$, $H(k-5)$ refer to data at the moment $(k-1)$, $(k-2)$, $(k-3)$, $(k-4)$, $(k-5)$, respectively. Thus, the average values $\overline{X_1}$ and $\overline{X_2}$ of sample subsets X_1 and X_2 are as follows:

$$\overline{X_1} = \frac{I(k) + H(k-1) + H(k-2)}{3} \tag{12}$$

$$\overline{X_2} = \frac{H(k-3) + H(k-4) + H(k-5)}{3} \tag{13}$$

And the variances S_1, S_2 of sample subsets X_1 and X_2 are:

$$S_1 = \frac{\left(\overline{X_1} - I(k)\right)^2}{3} + \frac{\left(\overline{X_1} - H(k-1)\right)^2}{3} + \frac{\left(\overline{X_1} - H(k-2)\right)^2}{3} \tag{14}$$

$$S_2 = \frac{\left(\overline{X_2} - H(k-3)\right)^2}{3} + \frac{\left(\overline{X_2} - H(k-4)\right)^2}{3} + \frac{\left(\overline{X_2} - H(k-5)\right)^2}{3} \tag{15}$$

As the sample subsets X_1, X_2 and variances S_1, S_2 are all matrices, the signal-to-noise ratio is expanded into a signal-to-noise ratio matrix, with the following definition equation S [11]:

$$S = \frac{\overline{X_1} - \overline{X_2}}{S_1 + S_2} \tag{16}$$

In general, the larger the signal-to-noise ratio matrix, the better. However, the critical signal-to-noise ratio matrix can be changed according to different objects. The critical matrix interval designed in this paper is as follows:

$$\begin{bmatrix} a_1 & a_2 \\ a_3 & a_4 \end{bmatrix} < S < \begin{bmatrix} b_1 & b_2 \\ b_3 & b_4 \end{bmatrix} \tag{17}$$

where, a_1, a_2, a_3, a_4, b_1, b_2, b_3, b_4 are all constants to be designed. When the signal-to-noise ratio matrix is within this interval, the time-varying forgetting factor η_k in Equation (9) is to be reassigned a new value, *i.e.* $\eta_k = \eta_{\max}$. The weight of historical data is increased to enhance the influence of historical data on algorithm estimates. By such weight redistribution, the interference is reduced, the convergence speed is higher, and so is the identification accuracy.

3.3. Algorithm Flow

The algorithm flow chart is shown in **Figure 3**.

4. Simulation Results and Analysis

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, MKS, CGS, sc, dc, and rms do not have to be defined. Do not use abbreviations in the title or heads unless they are unavoidable. In order to verify the influence of improved time-varying forgetting factor, its range and weight redistribution

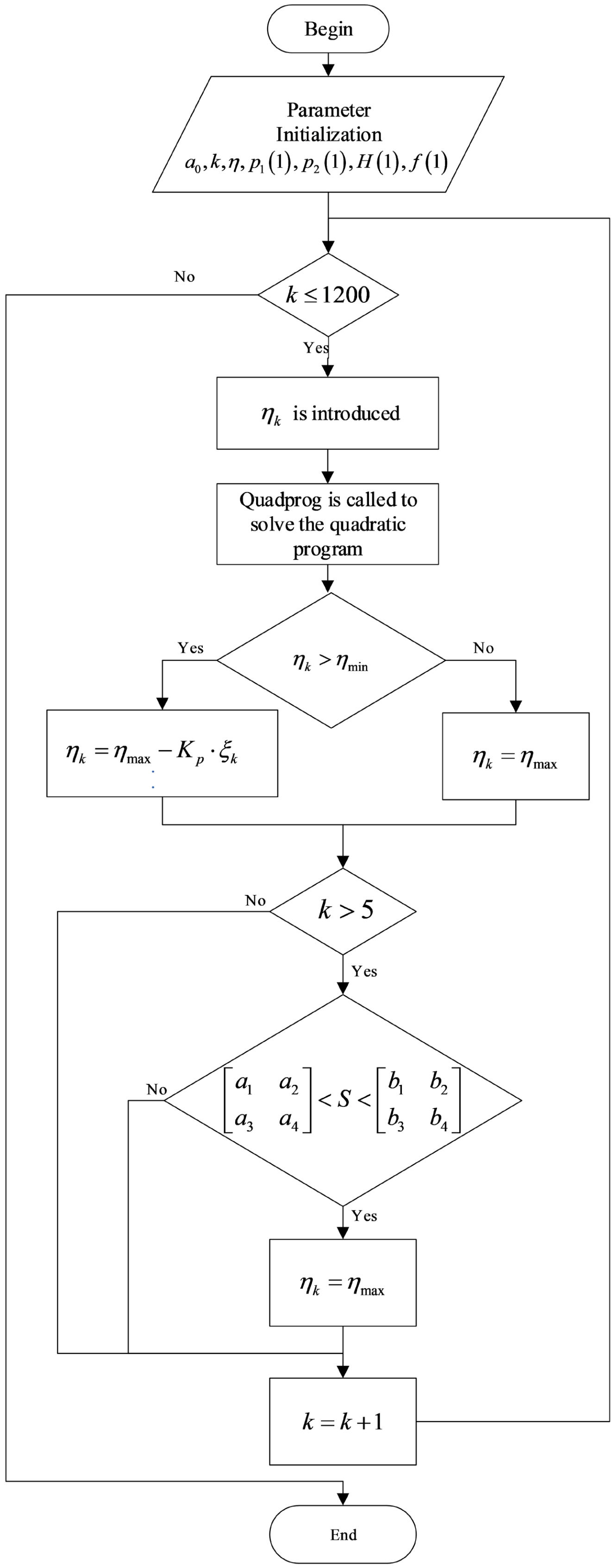

Figure 3. Algorithm flow chart.

on the parameters of the identification model, a comparative simulation experiment was carried out by using Matlab program. The experiment is as follows:

A time-varying forgetting factor was introduced into Algorithm 1, as shown in Equation (7). The weight of the current data $I(k)$ was $(2-\eta)/2$. The value range of the time-varying forgetting factor was $0.251\sim1$, and the weight redistribution step was added. For Algorithm 2, the weight of the current data $I(k)$ was 1, the value range of the time-varying forgetting factor was $0.971\sim1$, and the weight redistribution step was not added. The simulation results are shown in **Figures 4-6**.

It can be seen from **Figures 4-6** that when k = 30, Algorithm 1 had already identified p_1, when k = 250, Algorithm 1 had already identified p_2, and with an identification accuracy up to 1%. When k = 230, the accuracy of Algorithm 1 in estimating the maximum adhesion coefficient was up to 0.1%. Compared with Algorithm 2, Algorithm 1 identifies model parameters faster and with smaller fluctuations, which improves the accuracy of algorithm identification. When the rail surface status changes, Algorithm 1 can track the parameter changes faster.

In summary, the identification of the model parameters can be improved when the weight of the current data $I(k)$ is $(2-\eta)/2$, the value range of the time-varying forgetting factor is $0.251\sim1$, and with the weight redistribution step added. Meanwhile, the speed of identification is faster, the fluctuation is smaller, the noise reduction effect is better, and the algorithm identification accuracy is higher. When the rail surface state changes, such algorithm can track parameter changes faster.

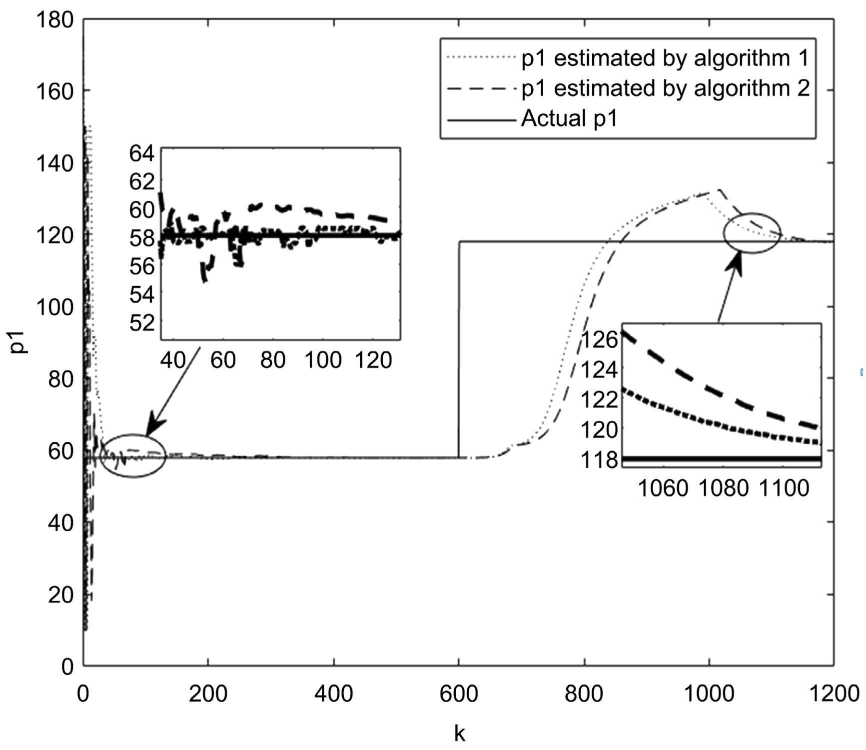

Figure 4. Comparison diagram of identification of model parameter p1.

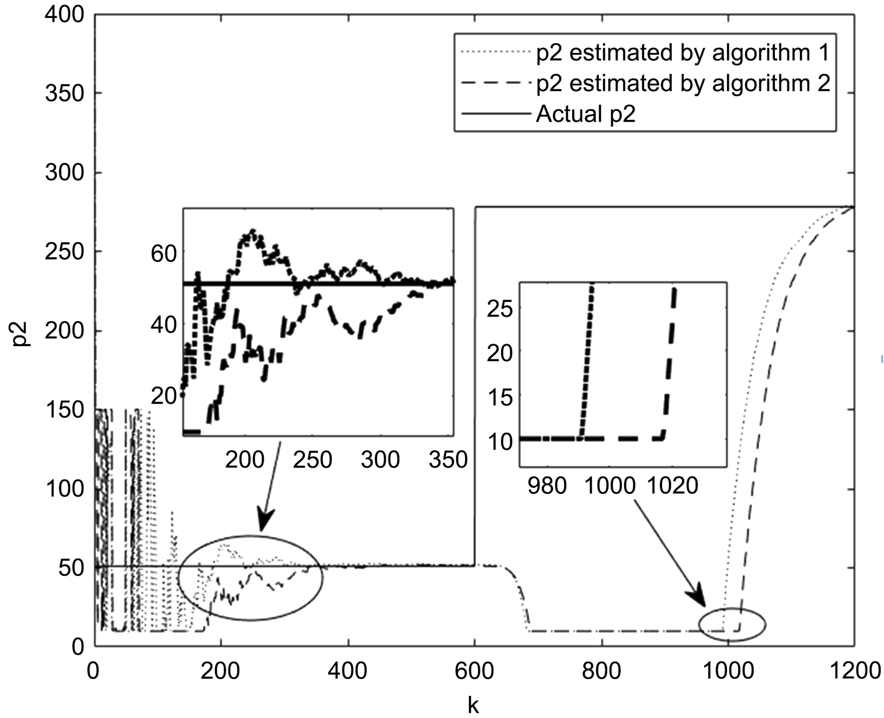

Figure 5. Comparison diagram of identification of model parameter p2.

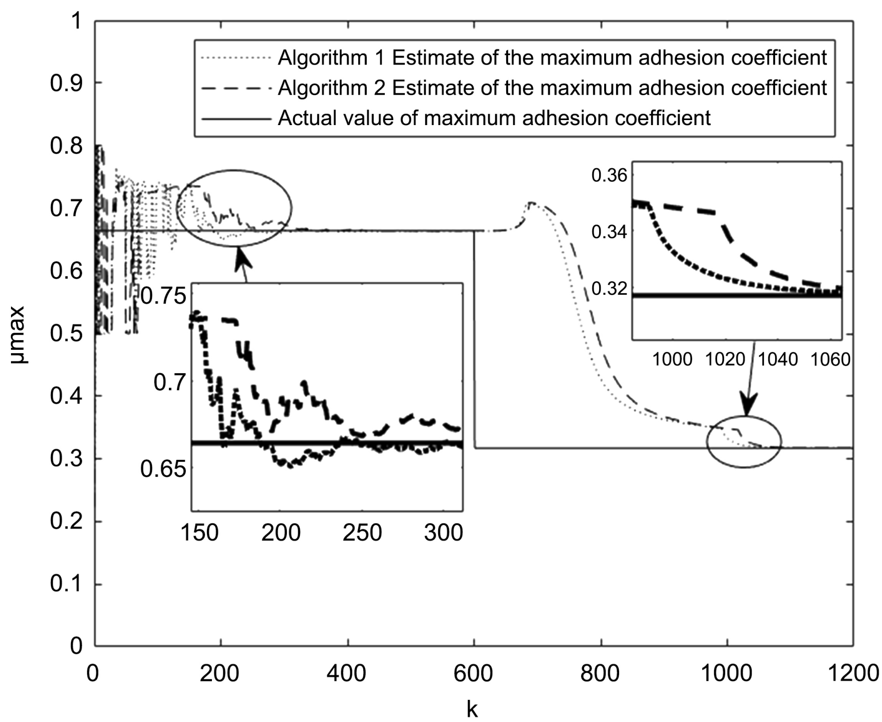

Figure 6. Comparison diagram of maximum adhesion coefficient estimates.

5. Conclusion

An iterative algorithm is constructed by this paper to identify model parameters. A time-varying forgetting factor is introduced into the iterative algorithm to change the weight of historical data and current data. When the value range of the time-varying forgetting factor is chosen to be $0.251 \sim 1$, the algorithm can quickly track changes in the track environment. The Granger causality test method is adopted by the iterative algorithm to detect interference in the identification, so that the weights can be redistributed to make the identification results more accurate. In the next step of research, FIR filter is to be added in to the identification algorithm to further reduce the noise interference and improve the identification accuracy.

Funding Statement

This word was supported by the National Natural Science Foundation of China under Grant 62173137, Project of Hunan Provincial Department of Education grant number 23A0426.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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