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A Koopman-Theory-Based Data-Driven Modelling and Control Method of High-Speed Maglev Trains

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Abstract

The suspension system is one of the key systems of high-speed maglev trains, and its strong nonlinear characteristics and system parameter perturbations under persistent service conditions lead to errors between ordinary linearization control models and actual systems. This paper proposes an online data-driven modelling and model predictive control method based on Koopman operator theory. First, based on the Extended Dynamic Mode Decomposition method, this paper designs offline and online data-driven modelling methods for suspension systems, which achieve global high-dimensional linearization of nonlinear systems without relying on internal mechanisms, and can dynamically capture the time-varying characteristics of system parameters. Second, the online data-driven model was combined with model predictive control to design an online adaptive suspension predictive control strategy with multiple constraint handling capabilities. Finally, under simulated parameter perturbation conditions, the proposed method is validated. The results show that the online Koopman MPC method is more adaptable to changes in system parameters, effectively suppresses system state fluctuations, and significantly reduces the steady-state error in the suspension gap. The proposed method provides a practical and feasible technical solution for the contactless smooth operation and suspension shakedown test of high-speed maglev trains.

Keywords: maglev train, suspension control, data-driven, Koopman operator, dynamic mode decomposition, model predictive control

1 Introduction

High-speed maglev trains have become a key research and development direction for the next generation of transportation vehicles due to the advantages of faster speed, lower noise, smooth and comfortable operation, and low maintenance costs. The suspension system is one of the key systems of high-speed maglev trains, and its control performance directly affects whether the train can operate safely and smoothly. The suspension system is strongly nonlinear and has a coupling relationship with the vehicle body, track, and external disturbances. Especially in scenarios of continuous operation and service, components such as tracks and vehicles experience parameter perturbations and performance degradation. Ordinary parameter modelling methods are unable to capture the dynamic changes in the system, resulting in deviations between the control model and the actual system.

In recent years, some scholars have proposed data-driven methods to construct suspension system models for modelling, analysis, and control of maglev trains, in order to improve the adaptability and matching of the models. For example, some scholars [1,2] have proposed data-driven methods for parameter identification of suspension systems, such as least-squares method and model reference adaptive method, to identify the model parameters of suspension systems. However, the relevant methods are based on known system mechanisms, and for more complex systems, the above parameter identification methods have shortcomings. Regarding the design of suspension control methods, current academic research mainly focuses on control algorithms from the perspectives of linear control (such as PID based state feedback [3,4], LQR control [5], linear MPC [6,7], etc.), nonlinear control (sliding mode control [8,9], neural networks [10], fuzzy control [11], etc.). However, the above control methods rely heavily on traditional parameter models and are still insufficient for controlling suspension systems with parameter perturbations and strong nonlinearity.

For complex nonlinear systems such as maglev train suspension systems, how to establish a control model that reflects the system mechanism and simplify the model while preserving the original system characteristics as much as possible has been a research difficulty in the field of control. Koopman operator theory provides a data-driven analysis method for complex systems. Compared to traditional local linearization modelling methods, Koopman operators can preserve the nonlinear evolution characteristics of the original system and achieve global linearization modelling of the system. With the development of calculation technology, scholars represented by Schmid [12] and Budišić [13] have combined Koopman operator with data-driven methods such as dynamic mode decomposition to achieve data-driven modelling based on Koopman operator. Afterwards, Williams [14] improved the observation function of dynamic mode decomposition and proposed an extended dynamic decomposition method, which improved the fitting accuracy of data-driven models; Proctor [15] and Zhang [16] respectively extended the above method to systems with inputs and time-varying systems. At present, Koopman operator is widely used in fields such as system identification and prediction, nonlinear system control, etc. In terms of control algorithm design, Strässer et al. [17] designed a feedback control algorithm based on the Koopman operator; Some scholars have also applied the Koopman operator to model predictive control [18].

This paper designs a data-driven modelling method based on Koopman operator theory for the high-speed maglev trains to address the parameter perturbations and external disturbances of the suspension system under continuous service conditions. Considering the long-term service conditions of maglev trains, a predictive control method based on online Koopman data-driven is studied to achieve dynamic modelling and control of the maglev train suspension system. The research aims to simplify the suspension control debugging process of high-speed maglev trains, improve the analysis accuracy of the suspension system, enhance the anti-interference and robustness of the control system, and ensure the contactless and smooth operation of the train under continuous high-speed operation conditions.

2 Fundamental Modelling and Analysis of the Suspension System for High-Speed Maglev Trains

Figure 1 is the structure of an EMS high-speed maglev train. The train achieves suspension through the electromagnetic attraction between the suspension electromagnet installed on the suspension frame and the track stator. Each carriage contains 4 sets of suspension chassis, which are connected to the vehicle body through a secondary suspension structure (including air springs, chassis arms, and other structures). The suspension electromagnet is overlapped between two adjacent suspension frame support arms, and the suspension electromagnet and chassis arm are fixed by laminated springs.

In the process of analysing and designing control strategies for suspension sys-

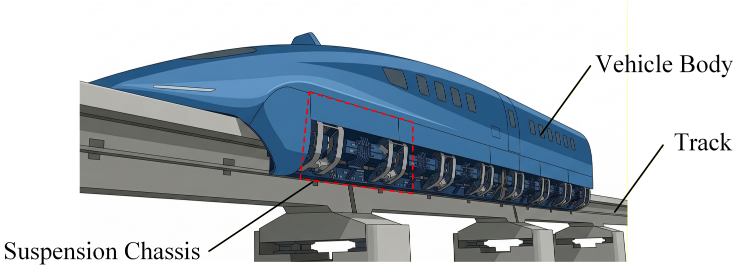

Figure 1: Structure of the EMS high-speed maglev train.

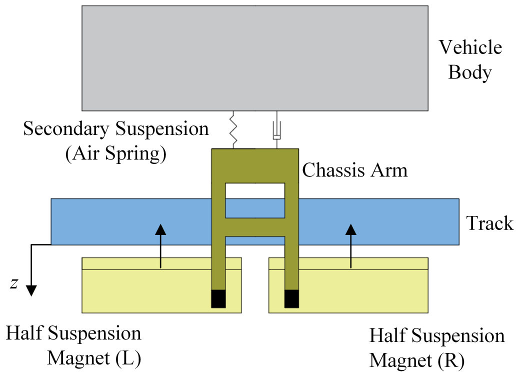

Figure 2: Suspension chassis arm structure.

tems, the single-sided chassis arm of the suspension frame is usually taken as the research object. There are two half sets of suspension electromagnets on each side of the suspension chassis arm, which are independently controlled by a set of suspension controllers.

According to the principles of electromagnetism, taking a single control circuit (semi-electromagnet) as the research object, the expression between the suspension force, suspension current, and suspension gap is

$$F = \frac{\mu_0 N^2 A_M i^2}{4{\delta_c}^2} \tag{1}$$

In (1), μ_0 is the vacuum magnetic permeability, N is the number of coil turns, i represents the excitation current, δ_c represents the actual distance (suspension gap) between the electromagnet and the track, and A_M is the sum of the equivalent pole areas of the six wire packages of the half electromagnet.

In engineering practice, in order to facilitate the design of closed-loop controllers, the above suspension system model is usually abstracted as a single-degree-of-freedom linearized system. Using the suspension electromagnet as the controlled object, the force between the vehicle body and the secondary suspension is approximated as a constant load mass m_v. The deviation value between the suspension gap and the equilibrium point $\Delta\delta_c$ (measured by the gap sensor) and the deviation value between the suspension speed and the equilibrium point $\Delta\dot{\delta}_c$ (obtained by integrating acceleration measurement values) are used as system state variables. The closed-loop feedback controller is designed as follows:

$$i = i_0 - K_p\Delta\delta_c - K_d\Delta\dot{\delta}_c \tag{2}$$

In equation (2), i_0 is the current at the equilibrium point, K_p and K_d are the control coefficients for the suspension gap and suspension speed, respectively. To achieve optimal performance, feedback control parameters can be calculated using methods such as LQR based on parameter models.

3 Offline Modelling Method for Suspension System Based on Koopman Operator Data-Driven Approach

3.1 Introduction of Koopman Operator and EDMD Method

Due to the nonlinear characteristics of the maglev train suspension system, the parameter model established using traditional local linearization methods has significant modelling errors. After long-term operation of the suspension system, the relevant parameters change, resulting in differences between the control model established based on the original parameters and the actual system. Koopman operator theory provides a data-driven method for transforming strongly nonlinear systems such as suspension systems into high-dimensional linear systems in the modelling and analysis process. Without relying on system model information, only the input and output data of the system need to be processed to establish a data-driven model of the system, while preserving the nonlinear characteristics of the original system.

Extended dynamic mode decomposition (EDMD) is currently the most commonly used data-driven method for approximating infinite-dimensional Koopman operators [15] for control system modelling. The EDMD method performs matrix transformation on the system state dataset and the system input dataset to obtain the following Koopman high-dimensional linearization model:

$$\begin{cases} \mathbf{z}(k+1) = \mathbf{A}\mathbf{z}(k) + \mathbf{B}\mathbf{u}(k) \\ \mathbf{x}(k+1) = \mathbf{C}\mathbf{z}(k+1) \end{cases} \tag{3}$$

as $\mathbf{x}(k)$ is the state variable of the original system at time k, $\mathbf{x}(k)$ is the output variable of the original system at time k (also the state of the system at time), $\mathbf{u}(k)$ is the system input at time k, and $\mathbf{z}(k)$ is the state variable of the system after dimension enhancement.

The Koopman data-driven modelling method based on EDMD method is as follows:

1.Data Collection

Continuously collect $p + 1$ sets of system states as $\mathbf{x}$, forming the system's state sequence $\mathbf{X}_{now}$ and output sequence $\mathbf{X}_{next}$:

$$\mathbf{X}_{now} = [\mathbf{x}(1), \mathbf{x}(2), \dots, \mathbf{x}(p)] \tag{4}$$

$$\mathbf{X}_{next} = [\mathbf{x}(2), \mathbf{x}(3), \dots, \mathbf{x}(p+1)] \tag{5}$$

where $\mathbf{x}(k)$ represents the system states at time k ($k = 1, 2, \dots, p$).

Corresponding to the system status data, continuously collect p sets of system inputs $\mathbf{u}$ to form the input sequence of the system $\mathbf{U}_{now}$:

$$\mathbf{U}_{now} = [\mathbf{u}(1), \mathbf{u}(2), \dots, \mathbf{u}(p)] \tag{6}$$

2. Dimension Enhancement

Select r basis functions $\phi(\mathbf{x})$ (Koopman characteristic functions) to form an upgraded feature function sequence, define the basis vector of the matrix transformation as $\mathbf{\Phi}(\mathbf{x}) = [\phi_1(\mathbf{x}), \phi_2(\mathbf{x}), \dots, \phi_r(\mathbf{x})]^T$ (usually polynomial functions), and perform an upgraded transformation on the system state sequence and output sequence to obtain the upgraded state sequence $\mathbf{Z}_{now}$ and output sequence $\mathbf{Z}_{next}$:

$$\mathbf{Z}_{now} = [\mathbf{z}(1), \mathbf{z}(2), \dots, \mathbf{z}(p)] = [\mathbf{\Phi}(\mathbf{x}(1)), \mathbf{\Phi}(\mathbf{x}(2)), \dots, \mathbf{\Phi}(\mathbf{x}(p))] \tag{7}$$

$$\mathbf{Z}_{next} = [\mathbf{z}(2), \mathbf{z}(3), \dots, \mathbf{z}(p+1)] = [\mathbf{\Phi}(\mathbf{x}(2)), \mathbf{\Phi}(\mathbf{x}(3)), \dots, \mathbf{\Phi}(\mathbf{x}(p+1))] \tag{8}$$

In the equation, $\mathbf{z}(k) = \mathbf{\Phi}(\mathbf{x}(k))$ represents the dimensionality upgrade state at time k. Compared to the original state of the system, $\mathbf{z}(k)$ has a higher dimensionality to achieve a high-dimensional linearization approximation of the nonlinear characteristics of the system.

3. System Matrix Calculation

The EDMD method is based on the least squares method to solve the residual minimization problem, obtain a data-driven model matrix, and achieve an approximate estimation of the Koopman operator:

$$\min_{\mathbf{A},\mathbf{B}} \|\mathbf{Z}_{next} - \mathbf{A}\mathbf{Z}_{now} - \mathbf{B}\mathbf{U}_{now}\|_2^2 \tag{9}$$

$$\min_{\mathbf{C}} \|\mathbf{X}_{now} - \mathbf{C}\mathbf{Z}_{now}\|_2^2 \tag{10}$$

Equations (9) and (10) represent the sum of squared residuals between the augmented data and the Koopman model, respectively. The least squares solution is the Koopman system matrix $\mathbf{A}$, $\mathbf{B}$, and $\mathbf{C}$, which can be calculated as follows:

$$[\mathbf{A} \quad \mathbf{B}] = \mathbf{Z}_{next} \begin{bmatrix} \mathbf{Z}_{now} \\ \mathbf{U}_{now} \end{bmatrix}^{+} \tag{11}$$

$$\mathbf{C} = \mathbf{X}_{now}\mathbf{Z}_{now}^{+} \tag{12}$$

In equations (11) and (12), $\mathbf{Z}^{+}$ represents the Penrose-Moore inverse of matrix $\mathbf{Z}$. Due to the large dimensionality of data sequences, the SVD decomposition method is used for solution:

$$\begin{cases} \mathbf{Z} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^{T} \\ \mathbf{Z}^{+} = \mathbf{V}\mathbf{\Sigma}^{-1}\mathbf{U}^{T} \end{cases} \tag{13}$$

The system matrices $\mathbf{A}$, $\mathbf{B}$, and $\mathbf{C}$ constructed by the above process reflect the evolution mechanism of the system state and input. Compared to ordinary parameter modelling methods, Koopman's data-driven modelling approach comprehensively considers the nonlinear factors of the system and the coupling disturbances of unknown parameter mechanisms, transforming the nonlinear state of the system into a high-dimensional linearized state and achieving numerical modelling of complex nonlinear systems. Compared with the numerical expressions established by classical fitting methods, the model established by Koopman data-driven method has clear spectral characteristics, which enables the Koopman data-driven model to clearly reflect the inherent and evolutionary characteristics of the system.

3.2 Design of Data-Driven Modelling Method for Suspension System Based on Koopman-EDMD

Consider the suspension system as a nonlinear system with one input (control current i) and two outputs (suspension gap δ_c, suspension velocity $\dot{\delta}_c$). The state space expression of the Koopman data-driven model for the suspension system is:

$$\begin{cases} \mathbf{z}_s(k+1) = \mathbf{A}_s\mathbf{z}_s(k) + \mathbf{B}_s\mathbf{u}_s(k) \\ \mathbf{x}_s(k+1) = \mathbf{C}_s\mathbf{z}_s(k+1) \end{cases} \tag{14}$$

where $\mathbf{x}_s = [\delta_c, \dot{\delta}_c]^T$, $\mathbf{u}_s = [i]$, $\mathbf{z}_s$ is the enhanced-dimensional system state. Based on the aforementioned EDMD method, data-driven modelling of the suspension system is carried out, as shown in Figure 3.

1. Collect suspension gap (from gap sensor), suspension velocity (from accelerometer integration), and control current (from current sensor) data from n consecutive suspension system, filter the state data, and construct a system data sequence.

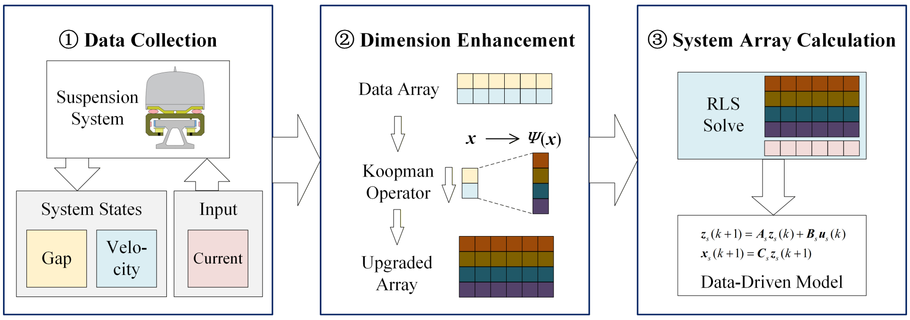

Figure 3: Data-driven modelling process for suspension system.

2. Based on Koopman characteristic function, perform dimensionality enhancement on the system data sequence.

3. Based on the data sequence after dimensionality enhancement, solve the system matrix and obtain the data-driven model of the suspension system.

3.3 Data-Driven Modelling Experiment of Suspension System

Based on the experimental platform, conduct Koopman data-driven modelling experiments, establish a data-driven model for the experimental platform, and compare it with the response of the actual system. Set the target suspension gap of the experimental platform to 8~12 mm. As the actual suspension system experiences random noise disturbances during operation, which approximately follow a Gaussian distribution, the control current can be considered linearly independent of the system state.

Collect 30 sets of suspension gap, suspension velocity, and control current data under different target gaps and operating conditions, with a sampling interval of 0.01 s and 10 s for each set of data. Perform low-pass filtering and deduplication on the data to form the system state dataset of the experimental platform. Based on the aforementioned Koopman data-driven modelling method, construct a Koopman data-driven model for the experimental platform. The form of the system matrix is $\mathbf{A}_s \in \mathbb{R}^{6\times 6}$, $\mathbf{B}_s \in \mathbb{R}^{6\times 1}$, $\mathbf{C}_s \in \mathbb{R}^{2\times 6}$.

Collect an additional set of test platform status and input data as the test set. Figure 4 shows the comparison between the Koopman data-driven model response and the actual response of the experimental platform under the same input current conditions.

This paper uses relative root mean squared errors (RRMSE) to evaluate the modelling accuracy of data-driven models. The definition of RRMSE is:

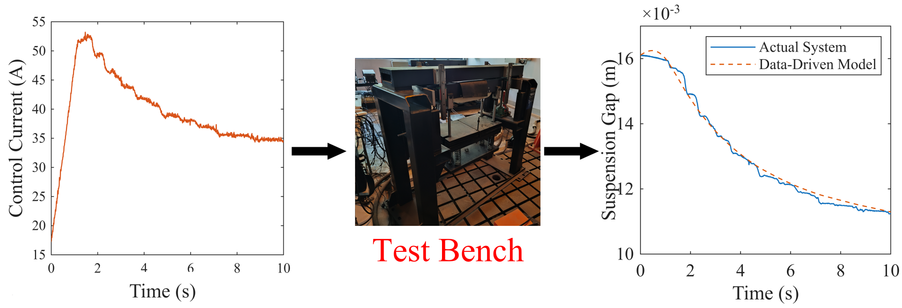

Figure 4: Comparison between the data-driven model and actual system response.

$$\text{RRMSE} = \sqrt{\sum_{k=1}^{N_T} \|\mathbf{x}_{Pk} - \mathbf{x}_{Tk}\|_2^2} \Bigg/ \sqrt{\sum_{k=1}^{N_T} \|\mathbf{x}_{Tk}\|_2^2} \tag{15}$$

In the formula, $\mathbf{x}_{Pk}$ and $\mathbf{x}_{Tk}$ represent the k-th set of data for the model prediction value sequence and the state data sequence, respectively.

Due to factors such as noise fluctuations in sensor signals, there are certain differences between the model response and the measured data. The RRMSE of both data is 0.0287, which is still within a reasonable range ($< 5\%$), indicating that the Koopman model has good modelling accuracy and can meet the data-driven modelling requirements of the suspension system.

4 Predictive Control Method for Suspension System Based on Online Data-Driven Modelling

4.1 Online Data-Driven Method Based on Recursive Updates

Due to the time-varying characteristics of the parameters of the suspension system under persistent service conditions, in order to further improve the accuracy of the system model, it is necessary to update the Koopman data-driven model online during operation.This section refers to the recursive least squares (RLS) and adopts a recursive update method to implement Koopman online data-driven modelling.

Firstly, collect the state and input of the system from time 1 to k. Based on the classic EDMD method for data processing, construct the Koopman data-driven model based on historical data:

$$\begin{cases} \mathbf{z}_s(k+1) = \mathbf{A}_k \mathbf{z}_s(k) + \mathbf{B}_k \mathbf{u}_s(k) \\ \mathbf{x}_s(k+1) = \mathbf{C}_k \mathbf{z}_s(k+1) \end{cases} \tag{16}$$

Set the augmented sequence $[\mathbf{Z}_{now}^T, \mathbf{u}_{now}^T]^T$ of the system's upgraded data is denoted as $\mathbf{W}_{now}$, and a recursive update matrix $\mathbf{\Gamma}_k = \mathbf{W}_{now}\mathbf{W}_{now}^T$ is defined, then (11) can be rewritten as:

$$[\mathbf{A}_k \quad \mathbf{B}_k] = \mathbf{Z}_{next}\mathbf{W}_{now}^T\mathbf{\Gamma}_k \tag{17}$$

Next, consider the online modelling during the system operation process. Assuming the system data at time k is $\mathbf{w}(k) = [\mathbf{z}_s(k)^T, \mathbf{u}_s(k)^T]^T$. At time $k+1$, if the system collects a new set of data, the system will update the dimensional data sequence as follows:

$$\mathbf{Z}_{next}^{'} = [\mathbf{Z}_{next}, \mathbf{z}_s(k+1)] \tag{18}$$

$$\mathbf{W}_{now}^{'} = [\mathbf{W}_{now}, \mathbf{w}(k)] \tag{19}$$

$$\mathbf{\Gamma}_{k+1} = (\mathbf{W}_{now}^{'}\mathbf{W}_{now}^{'T})^{-1} = (\mathbf{\Gamma}_k^{-1} + \mathbf{w}(k)\mathbf{w}(k)^T)^{-1} \tag{20}$$

Let

$$\gamma(k+1) = \mathbf{w}(k)^T\mathbf{\Gamma}_{k+1} \tag{21}$$

Then

$$\gamma(k+1) = \frac{\mathbf{w}(k)^T\mathbf{\Gamma}_k}{1 + \mathbf{w}(k)^T\mathbf{\Gamma}_k\mathbf{w}(k)} \tag{22}$$

$$\mathbf{\Gamma}_{k+1} = \mathbf{\Gamma}_k - \mathbf{\Gamma}_k\mathbf{w}(k)\gamma(k+1) \tag{23}$$

The system matrix is updated as follows:

$$\begin{aligned}[\mathbf{A}_{k+1} \quad \mathbf{B}_{k+1}] &= \mathbf{Z}_{next}^{'}\mathbf{W}_{now}^{+} \\ &= \mathbf{Z}_{next}\mathbf{W}_{now}^T\mathbf{\Gamma}_{k+1} + \mathbf{z}_s(k+1)\mathbf{w}(k)^T\mathbf{\Gamma}_{k+1} \\ &= [\mathbf{A}_k \quad \mathbf{B}_k] + (\mathbf{z}_s(k+1) - [\mathbf{A}_k \quad \mathbf{B}_k]\mathbf{w}(k))\gamma(k+1)\end{aligned} \tag{24}$$

Figure 5 is the schematic diagram of Koopman online data-driven modelling method. The above method only needs to collect the current and previous system states and inputs during the modelling process, without storing the original data sequence of the system, significantly reducing the computational cost of online updates.

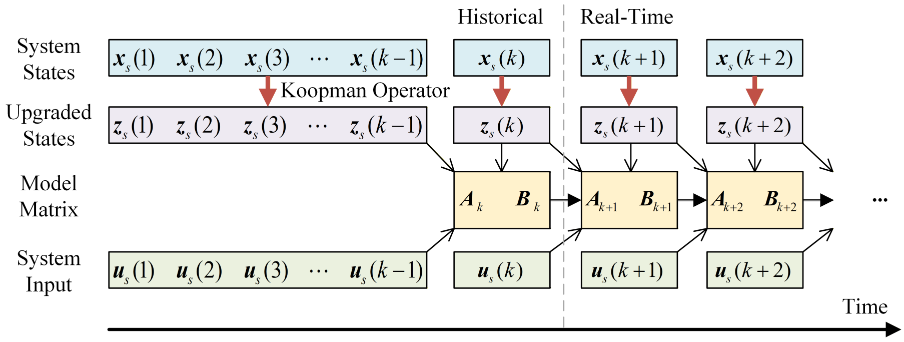

Figure 5: Schematic diagram of Koopman online data-driven modelling method.

4.2 Predictive Control Method Based on Online Data-Driven Model

For nonlinear systems such as suspension systems with multiple constraints, dynamic changes in system parameters and external disturbances, it is necessary to use finite time domain optimization methods to achieve dynamic optimization of the system. In order to achieve online optimization control of the suspension system, this section combines the Koopman data-driven model with model predictive control algorithm, and constructs the online control strategy of the suspension system using finite-time domain optimization method.

Consider the Koopman model of the suspension system

$$\begin{cases} \mathbf{z}_s(k+1) = \mathbf{A}_s\mathbf{z}_s(k) + \mathbf{B}_s\mathbf{u}_s(k) \\ \mathbf{x}_s(k+1) = \mathbf{C}_s\mathbf{z}_s(k+1) \end{cases} \tag{25}$$

The MPC optimization problem based on Koopman model is:

$$\min_{\bar{\mathbf{U}}_{sk}} \mathrm{J}_k = \frac{1}{2}\left[(\mathbf{C}_s\bar{\mathbf{Z}}_{sk} - \mathbf{X}_{ref})^T\mathbf{Q}_p(\mathbf{C}_s\bar{\mathbf{Z}}_{sk} - \mathbf{X}_{ref}) + \bar{\mathbf{U}}_{sk}^T\mathbf{R}_p\bar{\mathbf{U}}_{sk}\right] \tag{26}$$

$$\text{s.t.} \begin{cases} \mathbf{z} \in \bar{\mathbf{Z}}_{sk} \\ \mathbf{u} \in \bar{\mathbf{U}}_k \\ \mathbf{y}_{\min} \leq \mathbf{y} \leq \mathbf{y}_{\max} \\ \mathbf{u}_{\min} \leq \mathbf{u} \leq \mathbf{u}_{\max} \end{cases} \tag{27}$$

In formula (26) and (27), $\bar{\mathbf{Z}}_{sk}$ is the predicted value sequence of the system's dimensionality upgrade state, and $\mathbf{X}_{ref}$ is the reference state of the system. $\mathbf{Q}_p$ and $\mathbf{R}_p$ are the system's state weight matrix and input weight matrix, respectively. For suspension systems, the value of $\mathbf{Q}_p$ determines the optimized weight relationship of state variables: the larger the value of elements in the matrix, the higher the weight of the corresponding state variable, and the control algorithm prioritizes the indicator of that state variable. By solving the above optimization problem, the optimal control sequence $\bar{\mathbf{U}}^*_{sk}$ is obtained, and the first term of the sequence is taken as the control current, which is the control output at that time.

Due to the high requirement for model accuracy in MPC, the aforementioned recursive update step is introduced on the basis of the above method to perform online updates on the Koopman model. Compared to ordinary MPC methods based on fixed parameter models, the above method reduces the impact of system model mismatch on optimization calculations and improves the optimization performance of predictive control.

To better compare the proposed predictive control strategies, LQR feedback control method (k-LQR) and MPC control method (k-MPC) were designed based on data-driven offline models, and the two methods were used as baseline methods to compare with the suspension system predictive control method (o-MPC) based on Koopman online model proposed in this paper.

Take $\mathbf{Q}_p = [50000, 1000]$, $\mathbf{R}_p = 10^{-5}$, the prediction step range is 10, the upper and lower bounds of the suspension gap are 0.002˜0.016 m, and the upper and lower bounds of the control current are 0˜70 A.

Consider the parameter changes that occur during the operation of the train, after the suspension system stabilizes, the operating conditions shown in Table 1 are introduced through simulation software to simulate the changes in system parameters.

Situation number	Trigger time	Name of parameter	Value before trigger	Value after trigger
1	2.5s	Pole area of half-magnet	0.115 m^2	0.100 m^2
2	5.0s	Load mass	2000 kg	2500 kg
3	7.5s	Stiffness of secondary suspension	2.0×10^5 N/m	2.2×10^5 N/m

Table 1: System parameter changes during simulation.

Figure 6 and Table 2 shows the response comparison of different control methods. The k-LQR control method using the static Koopman model exhibits steady-state errors in control response after changes in system parameters, while the two sets of steady-state errors using the MPC control method are smaller, indicating that MPC has better adaptability to system changes. Compared with the k-MPC control method based on offline models, the dynamic model established by adopting online update strategy can capture the parameter changes of the system, gradually converge the model parameters used in the optimization calculation process to the actual system

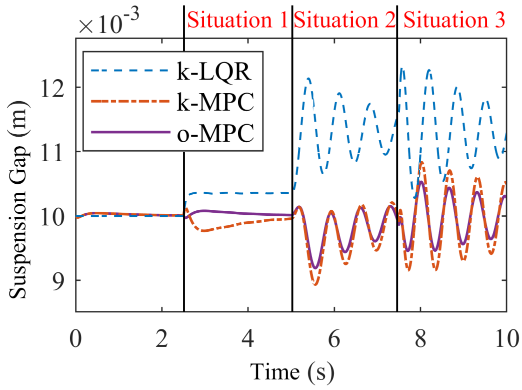

Figure 6: Schematic diagram of Koopman online data-driven modelling method.

parameters, improve the accuracy of optimization calculation, and further improve the performance indicators such as response speed and fluctuation amplitude of suspension control, which can meet the stable control under the time-varying conditions of suspension system parameters.

Situation number	Item	k-LQR	k-MPC	o-MPC
1	Maximum absolute error	0.350 mm	0.050 mm	0.010 mm
2	Maximum fluctuation amplitude	2.131 mm	1.052 mm	0.799 mm
3	Maximum fluctuation amplitude	2.270 mm	0.830 mm	0.530 mm

Table 2: Comparison of the system response.

5 Concluding remarks

This paper proposes a data-driven modelling and predictive optimization control method suitable for the long-term service conditions of high-speed maglev trains. Experimental results show that the proposed online Koopman-MPC control framework can adapt to parameter perturbations during the operation of the suspension system, reduce steady-state errors and fluctuations in the suspension system response, and provide a practical and effective technical solution for the debugging and engineering application of the suspension system of high-speed maglev trains.

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