

## Research Article

# Long Short-Term Memory-Based Model Predictive Control for Virtual Coupling in Railways

Ming Chai <sup>1,2</sup>, Haoxiang Su <sup>1</sup>, and Hongjie Liu <sup>1,2</sup>

<sup>1</sup>School of Electronics and Information Engineering, Beijing Jiaotong University, Beijing 100044, China

<sup>2</sup>National Engineering Research Center of Rail Transportation Operation and Control System, Beijing Jiaotong University, Beijing 100044, China

Correspondence should be addressed to Hongjie Liu; [hjliu2@bjtu.edu.cn](mailto:hjliu2@bjtu.edu.cn)

Received 5 October 2021; Revised 13 December 2021; Accepted 4 January 2022; Published 3 February 2022

Academic Editor: Andrej Hrovat

Copyright © 2022 Ming Chai et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

The increasing need for capacity has led the railway industry to explore new train control systems based on a concept called virtual coupling. Inspired by the platooning of autonomous vehicles, the safe operation of virtual coupling is guaranteed by a relative brake distance-based train separation method. This paper proposes a novel long short-term memory (LSTM)-based model predictive control (MPC) method for train operations. An MPC-based control design for virtual coupled train operations is presented. The LSTM is introduced to model the dynamics of the preceding train to approximate the actual train operations. With the train dynamics models, the operation trajectories of the preceding train are predicted based on planned control inputs. A study of a metro line in Chengdu was chosen to analyze the proposed control approach. The simulation results of different scenarios show that compared with the conventional MPC methods, the proposed LSTM-based MPC can reduce the speed differences and position differences of tracking trains by up to 35% and 25%, respectively.

## 1. Introduction

The ever-increasing railway transport demand of passengers and goods has been challenging infrastructure managers to continuously expand the capacity of existing networks. Therefore, the railway industry is looking into the adoption of advanced control systems. Virtual coupling is a novel train control systems concept [1]. It cancels mechanical couplers that maintain vehicles to move within the same train couple. In virtual coupling, the safe vehicle running distance is maintained by vehicle-to-vehicle communication-based train operation controls. This system uses a relative braking distance to separate trains [2]. This method can achieve a smaller train tracking distance. Without the mechanical coupler, trains can be dynamically coupled or decoupled during running. It can increase the line capacity by dynamically coupling two or more trains to form a new convoy. With virtual coupling, capacity can be flexibly adjusted on demand instead of based on a fixed schedule. Therefore, it can adapt to different transportation demands

[3]. Furthermore, the railway operations department can fulfill its demand of supporting optimum train operation.

One of the main challenges in virtual coupling is the synchronous operations of virtually coupled trains. With synchronous operations, a smaller tracking distance between trains can be achieved. Specifically, the following train needs to maintain a stable distance while moving between stations. An unstable tracking distance between trains results in a longer arrival time of virtually coupled trains at a station. This decreases the transport capacity.

Model predictive control is considered a feasible control method for virtual coupling. One of its advantages relies on its optimal control characteristics. Compared with road vehicles, a train is a large inertial body whose control capability is truly weaker. This results in a long time to change train operation states. In traditional train control, the train operates according to the preplanned speed curve and protection curve. However, in the virtual coupling, the distance between the preceding train and the following train needs to be kept small during the train operation. The

following train cannot synchronize with the preceding train by tracking the target curve. Therefore, the control target of the following train is a predicted operation state of the preceding train. In conventional control methods of virtual coupling, the approximation and prediction of the preceding train occur through the rule-based dynamics model of the train [4, 5]. Unfortunately, the prediction accuracy of these methods is limited, and they are unable to achieve ideal train convoy stability.

To solve this problem, we propose a long short-term memory (LSTM) based method to predict the operations of preceding trains. Train dynamics are modeled with an LSTM neural network trained from historical operation data. With this model, the operation of the preceding train is predicted with planned train control inputs. The prediction result is used to optimize the control of the following train in the MPC framework.

The existing literature studies the operation control of virtual coupling from different points of view. Some studies focus on control strategies for virtual coupling [6]. In virtual coupling, the extremely small distance may cause unstable train operation. For this reason, some studies present control systems that keep a constant distance [7, 8]. Liu et al. [9] proposed an optimal control method to maintain the speed of all trains in the virtual coupling consistent and safe distance. Ling and others [10] combined the dispatch operation in the virtual coupling scenario with the coordinated control of the train to determine the running route and the train order to optimize station operating time. Di Meo and others [11] defined a multiagent system control poly for virtual coupling. This approach aims to maintain the desired distance between trains and enrich the ERTMS/ETCS with virtual coupling without changing its working principles. Sliding mode control is used to achieve the same control effect [12].

The operation control method of virtual coupling can refer to recent developments in the field of safe platooning of autonomous vehicles and connected automated vehicle (CAV) platoons [13, 14]. The CAV platoon has an interconnection containing the leading vehicle (i.e., the leader) and the following vehicle (i.e., the follower). The leader is set to track a given trajectory, and the follower continues tracking the preceding vehicle with desired spacing and consistent speed. Compared with the CAV platoon, the virtual coupling control system has the same platoon concept due to the longitudinal movement of trains through the rail. The preceding train tracks the predefined speed profile and the following trains keep maintaining the minimum safe spacing and consistent speed. There are effective and available methods such as model predictive control [15] and feedback control [16] in linear and nonlinear CAV platoon control problems. These methods can maintain platoon cohesion. These methods have brought some inspiration to virtual coupling controller design.

Many existing kinds of research realize adaptive control through neural networks [17–19]. Neural networks require relatively less information about the dynamics of the system. It also has been maturely proved to be effective in addressing the control problem of nonlinear systems with unknown

dynamics. Moreover, it has been widely used to propose control for various nonlinear systems. Many existing studies are dedicated to combining control algorithms such as MPC and deep learning. Deep learning and MPC use their advantages to compensate for their shortcomings to achieve better control. The research results also prove that the control performance can be improved by adopting such a method. Wang et al. [20] proposed a deep learning-based model predictive control to model and control the continuous stirred-tank reactor system. The convergence and stability of this control method are analyzed and show better performance in modeling, tracking, and antidisturbance. Zhang et al. [21] use a recurrent neural network as the prediction model in model predictive control to control multiple unmanned quadrotor formation flights. A recurrent neural network (RNN) is used to separately model the two subsystems in quadrotor flight. The system model established through deep learning achieves accurate control. A collision avoidance control method was proposed in [22]. Through deep learning technology and an MPC controller, the automatic driving of vehicles was realized under the premise of considering maneuverability, vehicle dynamics, and traffic rules. There are also some theoretical analyses on the combination and application of MPC and deep learning [23, 24]. However, most of the existing work is to improve the control accuracy as possible under the premise that the control target is known. In virtual coupling, it is also important to set the control target of the following train based on precise predictions of the preceding train.

Based on the previous research, we proposed an LSTM-based model predictive control method. Model predictive control is used as the control architecture, and LSTM is used to predict control target in the following train to achieve more accurate tracking to achieve the stability of the train convoy. Our main contributions are as follows:

- (1) An MPC control framework is presented for the following train in the virtual coupling, according to the metro infrastructures and their communication architectures. The preceding train continuously sends status information and control information to the following train. Based on the control architecture, the LSTM-based model predictive control method is proposed to make successive trains drive while keeping a desired stable distance.
- (2) LSTM neural network is used to predict the preceding train state and serve as the control target of the following train. More accurate control targets improve the stability of the control. Simulations are conducted, and the traditional prediction method is compared with the method proposed in this paper. A section of one metro line in Chengdu is used as the background to verify the validity of the method.
- (3) The following train dynamics are modeled by deep learning. Conventional controlled objects are established by formulas, which cannot entirely reflect the actual dynamics characteristics of the train. Through deep learning, a dynamics model closer to

the actual train is established using a large amount of historical data, which can better reflect the accuracy and practicability of the control algorithm.

The rest of this paper is organized as follows. In Section 2, the problem of virtual coupling train operations is formulated. Section 3 presents the entire MPC methodology. Section 4 explains the design of the train dynamics model by LSTM networks and the overall control structure. Section 5 presents different tests, simulations, and results. Finally, the conclusions are drawn in Section 6.

## 2. Problem Statement

**2.1. Communication Structure of Trains in Virtual Coupling.** Wireless communications and distributed computing have promoted the development of vehicle-monitoring systems to reduce railway system maintenance and inspection requirements while maintaining safety and reliability [25]. The typical virtual coupling communication framework is shown in Figure 1. Centralized traffic control (CTC) directs the train convoy operation. CTC generates a route request command according to the train's operation plan and sends it to the interlocking system. The interlocking system ensures that the train route is safe and useable by controlling the wayside infrastructure. After a route is set, the interlocking sends the route information to the radio block center (RBC). The RBC calculates the train movement authorization (MA). An MA is a succession of railway sections in which a train can safely operate. During train operation, continuous radio communication exchanges train control information between trains and wayside equipment [26].

In the traditional train control architecture, the following train passively follows the preceding train through the coupler force control and maintains a stable running state with the preceding train. In virtual coupling, trains are supposed to move together, similar to physical coupling. The following train can achieve a comparable control effect to the coupler through active control. The control strategies for the preceding train and the following train are different. The preceding train tracks the desired speed profile of the MA area. The following train tracks the speed of the preceding train while maintaining a stable distance. Virtual coupling entails convoys of trains linked via vehicle-to-vehicle communication to synchronize the speed with the train ahead to maintain a safety margin in between. In the virtual coupling system, vehicle-to-vehicle communication becomes essential to maximize the probability of message delivery compared to train-to-track communication only (i.e., fully infrastructure-based communication). Virtual coupling requires extremely low reaction times and, hence, latency to synchronize multivehicle behaviors.

The train control system controls the train speed based on the target speed curve. The system uses various control algorithms to adjust the train speed to make it as consistent as possible with the target speed in the target speed curve. A typical train speed curve and target speed curve are shown in Figure 2. The greatest recommended speed (GRS) is a speed curve calculated by the train control system based on the

current line speed limit, used to prevent the train from overspeeding. The train operation process can be divided into three phases: traction phase, cruise phase, and braking phase. The control algorithm designed in this paper aims to control the following train in the cruise phase.

**2.2. Dynamics Model of Virtual Coupling Trains.** First, we consider the dynamic model of a single train. The external forces that a train is subject to include tractive or braking forces and additional operational resistances. The basic equation of train movement can be described by the following:

$$m \frac{d^2 s_i}{dt^2} = u_i - r(v_i) - mg \sin(\theta(x_i)), \quad (1)$$

$$\frac{ds_i}{dt} = v_i, \quad (2)$$

$$\frac{dv_i}{dt} = a_i, \quad (3)$$

where  $m$  is the train mass.  $s_i$  and  $v_i$  are the train position and speed at the current instant  $i$ , respectively.  $u_i$  is the external tractive or braking force at the current instant  $i$ .  $r(v_i)$  is the basic operational resistance, generally described by the Davis equation  $r(v_i) = a + bv_i + cv_i^2$  [27].  $a$ ,  $b$ , and  $c$  are the empirical coefficients accounting for the mass resistance, mechanical resistance, and air resistance, respectively.  $mg \sin(\theta_i)$  is one kind of operational resistance caused by gravity, where  $g$  is the gravitational acceleration and  $\theta(x_i)$  is the angle between the rail slope and the horizontal reference line.

Under the actuation of external forces on a train, speed series  $v_i$  depicts train movements. The running distance can be described by the following:

$$D = \sum v_i \Delta t, \quad (4)$$

where  $\Delta t$  is the time step between instants  $i + 1$  and  $i$ .

For a virtual coupling train control system, the state of the train can be defined as  $x = (s, v, a)^T$ , where  $s, v, a$  represent the position, speed, and acceleration, respectively. The control input of the train can be expressed as  $u$ . Therefore, equations (1)–(3) can be written compactly as follows:

$$x_{i+1} = f(x_i, u_i), \quad (5)$$

where  $i$  denotes the time step.

Then, to investigate the virtual coupling train control system control problem, we consider a virtual coupling train control system composed of two trains moving along a railway line. The preceding train sends state information (e.g., position, velocity, and acceleration) to the following train. The preceding train circulates at a velocity  $v_t^l$ , and the following train circulates at  $v_t^f$ . The superscript denotes the train ( $l$  for the leader and  $f$  for the follower). The subscript denotes the time. The distance between trains is calculated by means of the following:

$$d = s_t^l - s_t^f + L, \quad (6)$$

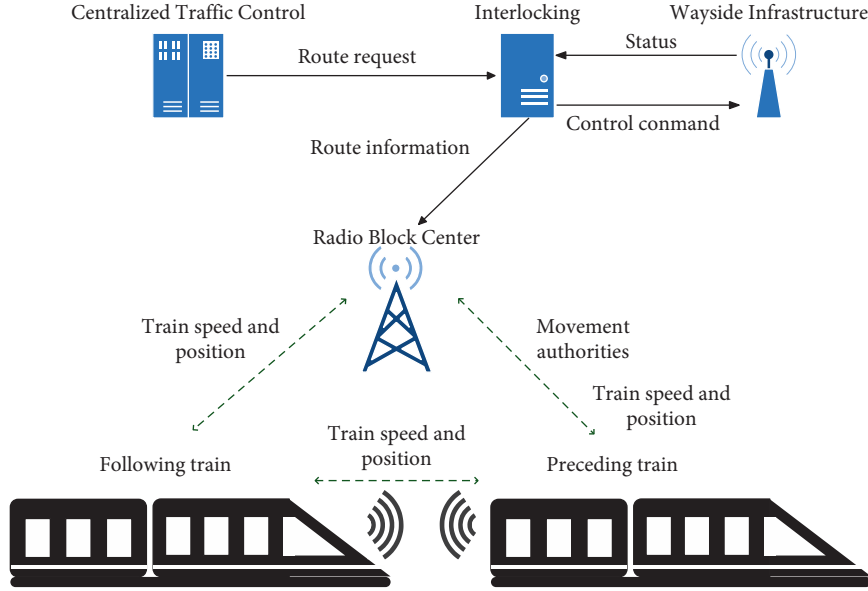


FIGURE 1: Illustration of the virtual coupling communication topology.

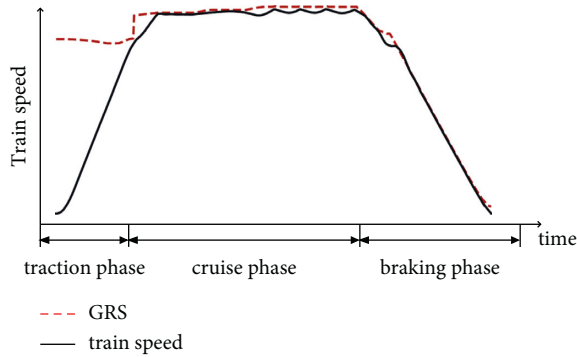


FIGURE 2: Illustration of the train operation phase.

where  $L$  is the safety margin.

In the designed virtual coupling train control system, our control objective is to maintain the speed of the preceding train and the following train consistently while maintaining a safe distance (safe margin). If the following train has a location tracking error of  $e_s$ , we can express the control objective of the following train as follows:

$$\begin{aligned} v_t^f &= v_t^l, \\ d &= L + e_s. \end{aligned} \quad (7)$$

### 3. Model Predictive Control Construction

We consider a decentralized virtual coupling control with two trains, one for the front or preceding train and the other for the following train. We propose a model predictive control approach for the following train. The controller is nonlinear, and the constraints are explicitly handled.

Model predictive control is a control algorithm that relies on the iterative solution of an optimal control problem. The control input is calculated at each sampling time

based on the predicted state [28, 29]. One of the advantages of MPC is that the resulting operating strategy respects all the system and problem constraints. In this paper, an MPC feedback control system is designed for the following train in Figure 3.

*3.1. Design of the MPC.* For the formulation of the MPC, a prediction horizon  $[t, t + N_p]$  is considered at time  $t$ . According to the receding horizon principle, at each time, the MPC solver computes the optimal control  $u = \{u_t, u_{t+1}, \dots, u_{t+N_p}\}$ . The first input is applied to the control system before the next time step. At the next time step  $t + 1$ , a new optimization problem is raised based on a new state measurement [30].

We express the control optimization problem as follows:

$$\min_u J_N = \sum_{k=0}^{N_p-1} l(x_k), \quad (8)$$

where  $l$  is the cost function and  $N_p$  is the prediction horizon. We discuss the setting of the cost function  $l$  in the next section. Then, the controller needs to find the best control input at the cost of minimizing  $J$ , subject to the following:

$$x_{t+1} = f(x_t, u_t), \quad (9)$$

$$0 < v_t < v_{\text{lim}},$$

$$a_{\text{min}} < a_t < a_{\text{max}},$$

$$u_{\text{min}} < u_t < u_{\text{max}},$$

$$d > d_{\text{min}},$$

(10)

where  $v_{\text{lim}}$  is the line speed limit, which is set according to actual line data.  $a_{\text{min}}$  and  $a_{\text{max}}$  are the maximum deceleration and acceleration of the train,  $u_{\text{min}}$  and  $u_{\text{max}}$  are the maximum and minimum values of the control input. These are set

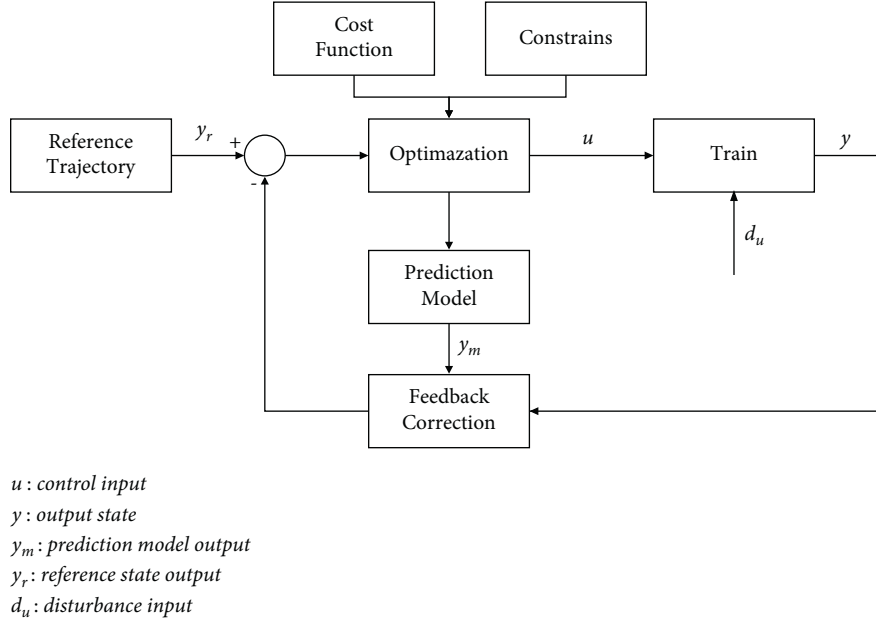


FIGURE 3: Flowchart of typical MPC.

according to the actual performance parameters of the train.  $d$  is the distance between trains, and  $d_{\min}$  is the safe margin. We refer to the illustration of the safety margin in the Shift2Rail technical report [31], and the safety margin used is set according to the train speed and line conditions in the simulation.

The notation  $x_{t+k|t}$  represents the state vector at time  $t+k$ , predicted at time  $t$ . In the designed control system, the optimal state and control input obtained are as follows:

$$\begin{aligned} x_t &= \{x_{t|t}, x_{t+1|t}, \dots, x_{t+N_p|t}\}, \\ u_t &= \{u_{t|t}, u_{t+1|t}, \dots, u_{t+N_p|t}\}. \end{aligned} \quad (11)$$

For closed-loop control, we apply the first input to system (9) in the time interval  $[t, t+1)$ .

$$u_t = u_{t|t}. \quad (12)$$

In the next step, a new optimal problem based on a new state measurement is solved over a shifted horizon, yielding a moving receding horizon control strategy with control law.

**3.2. Cost Function Design in the MPC Framework.** The tracking capability is usually specified in terms of speed error and distance error. The consistency of speed and the maintenance of the distance between trains are issues we care about in designing control algorithms. For speed, the control objective is divided into the following three parts:

- (i) (A1) The speed of the train cannot exceed the current line speed limit
- (ii) (A2) When the preceding train is at a steady-state, the speed difference between the preceding train and the following train should be minimized

(A3) When the preceding train accelerates or decelerates, the acceleration error should converge to small values

For the distance between trains, the control objective is to (B1) minimize the speed difference between the preceding and the following train while maintaining a steady, safe distance between the two trains.

In those subobjectives, we attempt to quantify them under the MPC framework. The subobjective (A1) is formulated as linear constraints. The subobjectives (A2) and (A3) are quantified to be cost functions. In particular, subobjective B1 is reflected in both the cost function and constraints. Together, they yield a tractable model predictive optimization problem.

A 1-norm function of tracking errors is adopted as the MPC cost function in [32], and a 2-norm function is used in [33]. The former gives equal consideration to tracking errors of different degrees, while the latter tends to penalize larger errors and neglect smaller errors. Actually, the following train should only respond to sufficiently large tracking errors and should not be sensitive to tiny tracking errors. Therefore, it is more reasonable to employ the 2-norm of tracking errors to quantify (A3):

$$l_{ae} = (a - a^{\text{ref}})^2, \quad (13)$$

where  $a^{\text{ref}}$  is the target acceleration.

Similarly, when the speed of the preceding train is not much different from that of the following train. The acceleration of the preceding train does not change much. The subobjective (A2) is also defined as a 2-norm function of desired speed

$$l_{ve} = (v - v^{\text{ref}})^2, \quad (14)$$

where  $v^{\text{ref}}$  is the target speed.

For two moving trains, the positions of the preceding train and the following train can never coincide, and the difference is large. Nevertheless, the position of the preceding train is always one of the targets of the following train's tracking. Therefore, the subobjective (B1) can be defined as a 1-norm function

$$l_{se} = (s - s^{\text{ref}}), \quad (15)$$

where  $s^{\text{ref}}$  is the preceding train's position.

The three cost functions (13)–(15) are not combined but are set in different operating scenarios to obtain a tractable predictive optimization problem.

#### 4. LSTM-Based Model Predictive Control

In virtual coupling, it is necessary to predict the preceding train state for the following train. The predicted state is used as the control objective of the following train, and it is also used for the optimal control of MPC. As an effective tool for mining large amounts of data, neural networks are widely used in data-driven trajectory prediction research. A long short-term memory (LSTM) neural network, a type of RNN, is more efficient than an RNN [34, 35]. LSTM network can capture the characteristics of time series in a longer time span and achieve better results than RNN in traffic prediction. In this section, LSTM is used to model the dynamics of the preceding train and predict the state of the preceding train for MPC due to its superiority compared to other conventional modeling methods [36].

*4.1. Train Dynamics Model.* Due to the complex environment and disturbances, train dynamics are challenging to describe with formulas accurately. Therefore, a deep learning modeling method is adopted to solve this problem. The LSTM network is used as one of the neural network components to obtain a more accurate preceding train dynamics model.

The upper part of Figure 4 is the calculation unit of LSTM. The middle part of Figure 4 demonstrates the framework of the LSTM neural network we build to approximate the train dynamics model. The lower part of Figure 4 represents the closed-loop control process of the physical movement of a train. We use the data from train operation records for neural network training. Our developed LSTM model is a feed-forward artificial neural network structured with an input layer at the bottom, stacked hidden layers, and an output layer. The LSTM network is always connected to the fully connected (FC) network in the hidden layers. The input of one neuron in the  $l$ th hidden layer is defined as  $x_l^{(t)}$ , and the output as  $h_l^{(t)}$ . The forward calculation method of the overall network at time  $t$  can be described as the following expression. The first is the calculation inside LSTM:

$$\begin{aligned} f^{(t)} &= \sigma(W_f \cdot [h_l^{(t-1)}, x_l^{(t)}] + b_f) \\ C^{(t)} &= f^{(t)}C^{(t-1)} + i^{(t)}\tilde{C}^{(t)} \\ o^{(t)} &= \sigma(W_o \cdot [h_l^{(t-1)}, x_l^{(t)}] + b_o) \\ h_l^{(t)} &= o^{(t)}\tanh(C^{(t)}). \end{aligned} \quad (16)$$

Then, the calculation that is output to the fully connected layer is as follows:

$$\begin{aligned} h_l^{(t)} &= x_{l+1}^{(t)}, \\ h_{l+1}^{(t)} &= \tanh(x_{l+1}^{(t)}w_{l+1} + b_{l+1}), \end{aligned} \quad (17)$$

where  $w_{l+1}$  and  $b_{l+1}$ , respectively, denote the neural weight matrix and bias of the  $l + 1$ -th hidden layer.

If the neural network is well trained with the train operation data, we can use the neural network model to reflect the actual train's operating status. That is, the actual operation of the train can be reflected through the input and output to the neural network.

We designed a planning-based prediction, that is, the following train predicts the future state of the preceding train under the premise that the preceding train's control input is known. The advantage of this is that the following train can more accurately know the behavior of the preceding train, avoiding the unpredictable situation of the train in front, such as emergency braking due to particular circumstances. A mapping function is established from the current train state and input control commands to the next state through the LSTM network.

$$\{s_{t+1}, v_{t+1}\} = \varphi\{s_t, v_t, u_t\}. \quad (18)$$

*4.2. Control Structure Based on LSTM.* The composite control structure based on LSTM and MPC is proposed in Figure 5 for the following train. The control structure consists of three main parts: the state prediction model based on LSTM, the MPC framework, and the train dynamics model.

For the following train, at each time horizon, the control input  $u$  is optimally determined by comparing the following train state and the reference state. The LSTM prediction model obtains the reference state. The preceding train state is the input of the LSTM prediction model. Based on that, the following train state is obtained by the dynamics model. Meanwhile, the next time horizon starts and the train state and reference state are updated. The whole process is online iterative until the following train state reaches the reference.

### 5. Simulations and Analysis

*5.1. Test Environment.* We record the detailed train operation data of the Chengdu Metro Line 8. The field data are collected from the onboard computers. These data are used for training and testing the accuracy of the trained networks. In addition, we established the dynamic model of the following train as the controlled object of the control algorithm through deep learning in advance. Another state prediction model of the preceding train is also generated through deep learning as a comparison. The difference is that the prediction of the preceding train state does not require the control input of the preceding train. We trained the dynamics model of the preceding train under two operating scenarios. In scenario 1, the train operation is subject to the speed limit of the curve and then accelerates to a normal

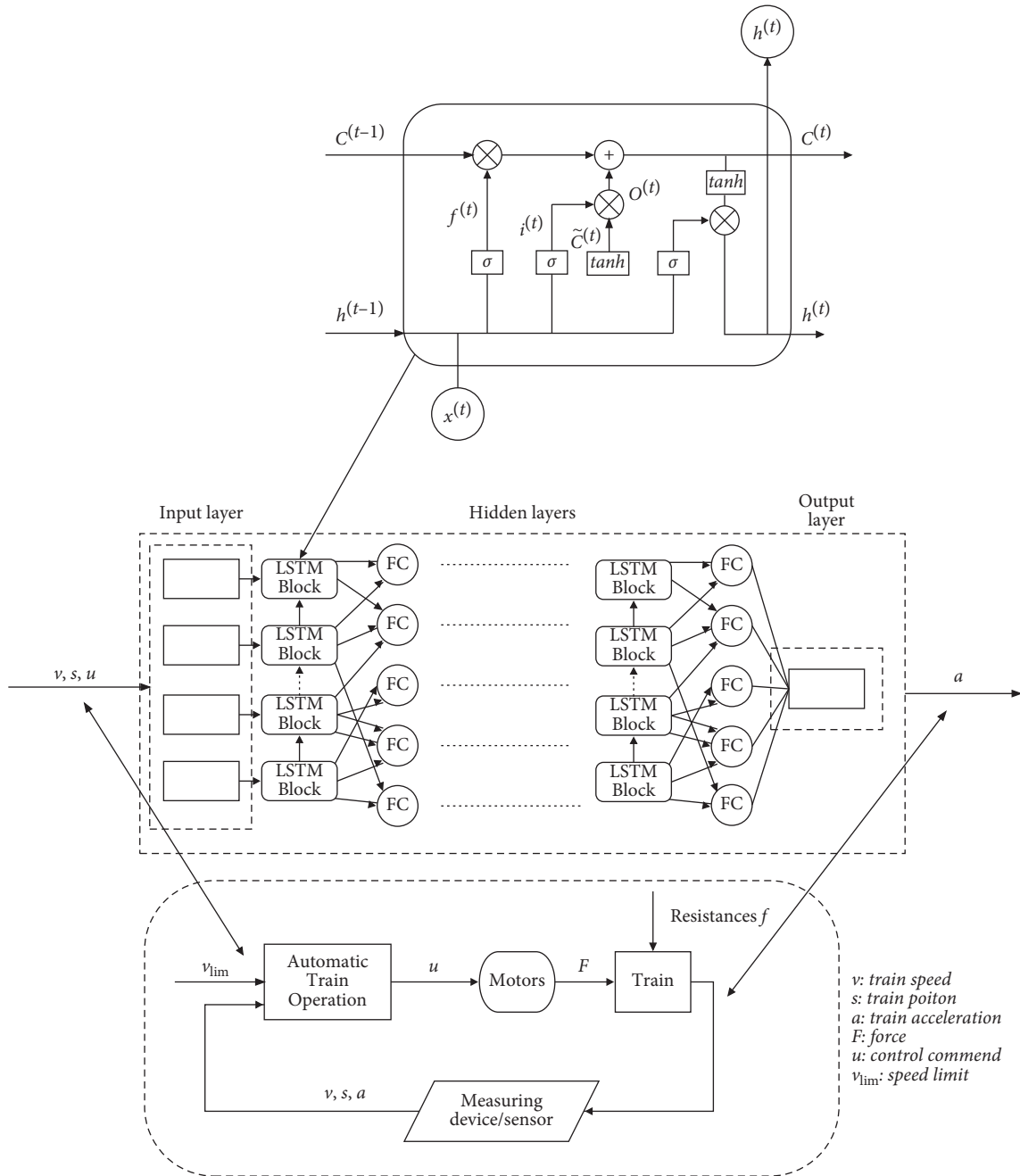


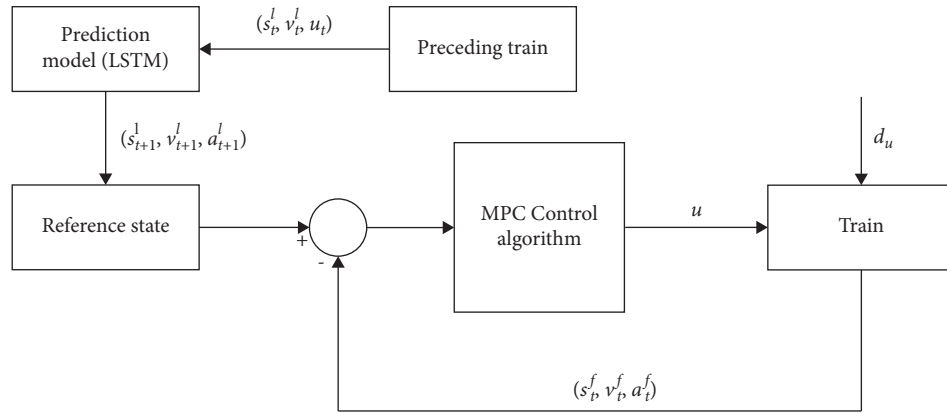
FIGURE 4: Illustration of LSTM neural network for leading train dynamics.

operating speed with small fluctuations. In scenario 2, the train adjusts its speed before entering the curve.

**5.2. Training the Neural Network Model.** This study adopts the backpropagation algorithm with Adam. Set the loss function of the neural network to MSE. We adjust the number of layers and nodes of the neural network to reduce the loss function value after training.

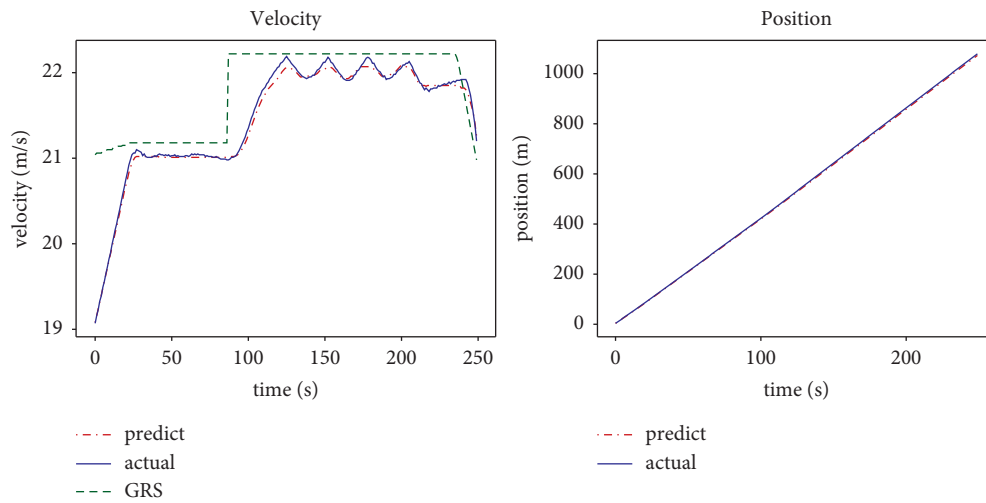
To evaluate the accuracy and performance of the model obtained by deep learning, we use field data to test the model accuracy. Figure 6(a) demonstrates the field data and the train velocities and positions predicted by the LSTM

network, corresponding to operating scenario 1 in the model training experiments. The LSTM network achieves great predictive performance. The position and velocity curves predicted by the deep neural network are very close to the field data. The results by operating scenario 2 in Figure 6(b) also obtained the same conclusion. At the same time, we separately recorded the acceleration calculation error of the dynamics model, the predicted position, and the velocity error in Figure 7. The average error of acceleration prediction does not exceed 0.02, and the average error of velocity prediction does not exceed 0.5. The position error increases with time, and the cumulative error increases, approaching 4. Verifying these data demonstrates its

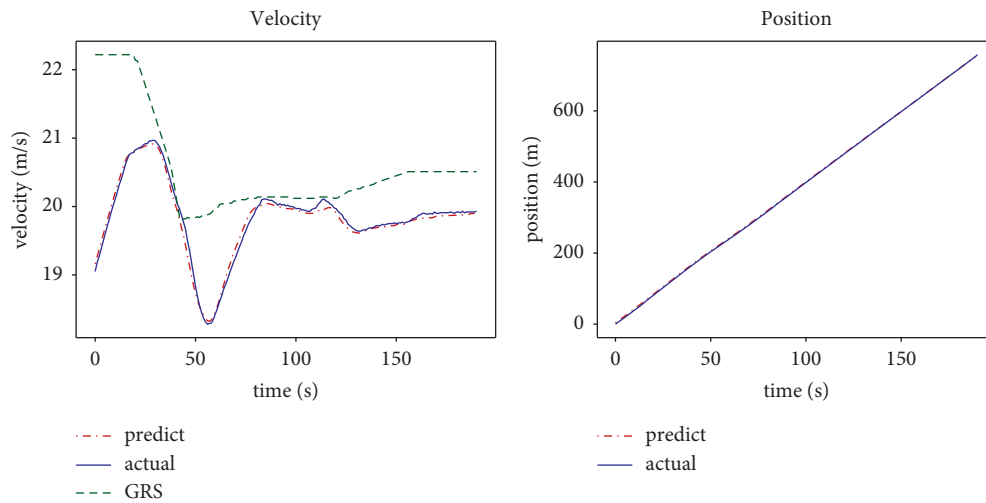


$u$  : control input  
 $s$  : train position  
 $v$  : train speed  
 $a$  : train acceleration  
 $d_u$  : disturbance input

FIGURE 5: LSTM-based MPC structure for the following train.



(a)



(b)

FIGURE 6: Field data and predicted train states by LSTM neural network in different scenarios. (a) Comparison of train velocity and position curves in scenario 1. (b) Comparison of train velocity and position curves in scenario 2.



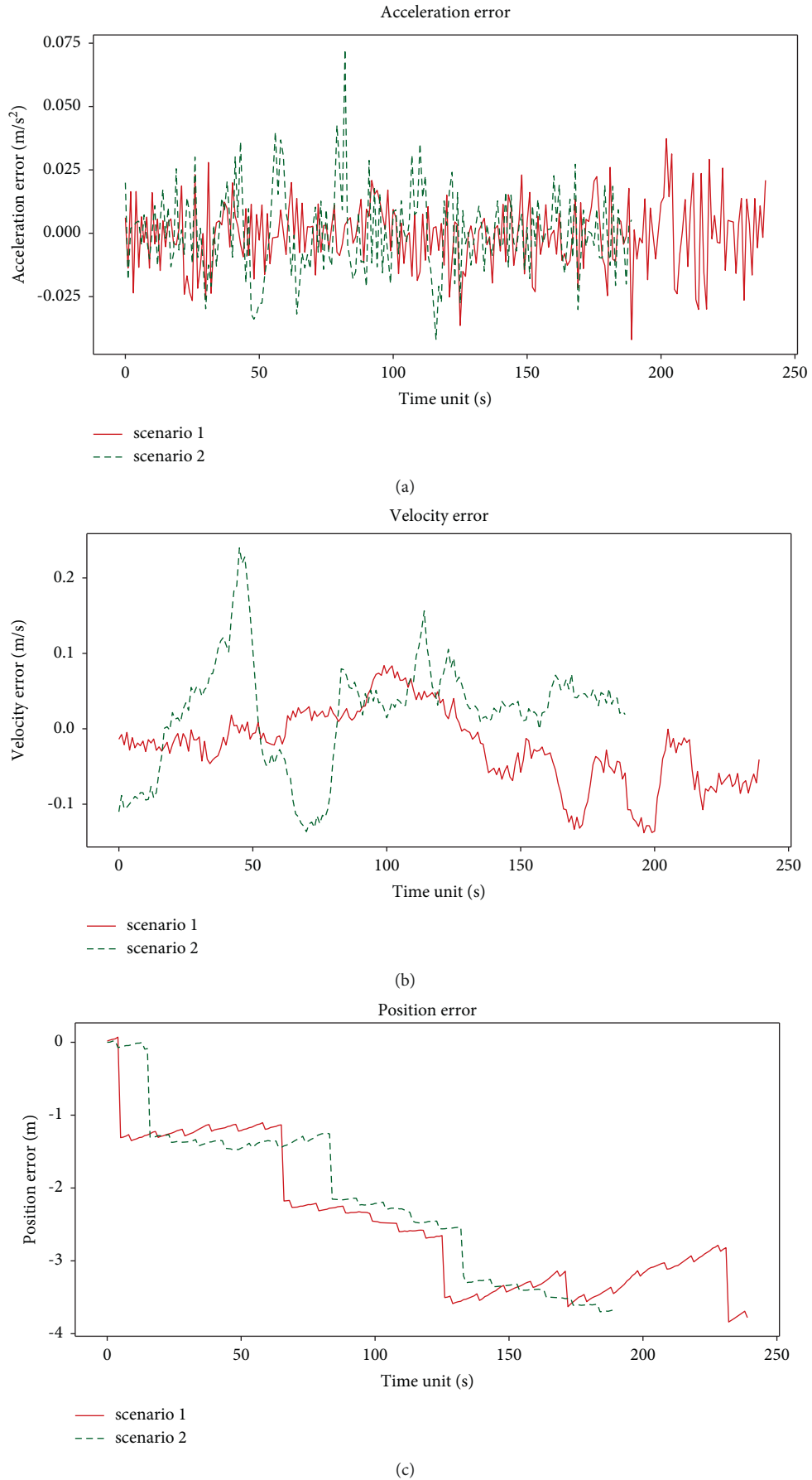


FIGURE 7: Train dynamics model error of different scenarios. (a) Acceleration error. (b) Velocity error. (c) Position error.

capability to model the train dynamics in practice and the prediction accuracy.

### 5.3. MPC Control Algorithm Simulations

**5.3.1. Real Line Simulation.** After verifying the predictive performance of the neural network, a real metro line simulation has been analyzed. The railway line corresponds to Line 8 of Metro of Chengdu in China. Our simulations are based on the following assumptions. The train convoy is formed by two trains. The initial conditions include that the initial gap between tracking trains is 20 m and the tracking trains have the same initial speed. The communication delay is not considered. In the simulations, we add the established train dynamic model to the control algorithm and use model predictive control to simulate the operation control of the following train in the virtual coupling during the cruise phase. In addition, in order to verify the robustness of the control algorithm, Gaussian white noise is added as input interference in the experiment.

The performance of the proposed LSTM-Based MPC algorithm is illustrated in two aspects in the simulation, including the speed of the trains and the distance between trains. Figure 8 shows the simulation results under the two scenarios. Figure 8(a) corresponds to the speed profile of virtually coupled trains in scene 1, Figure 8(b) corresponds to scene 2, and Figure 8(c) shows the distance changes between trains in two scenarios. From the figure, the following train can track the speed of the preceding train with a small margin of error. The maximum speed difference between the two trains appears in scene 2, reaching 0.24 m/s. Benefiting from accurate speed tracking and maintenance, the distance between the two trains varies within a tiny range and always remains within the set safety margin (10 m).

**5.3.2. Influence of the Length of the Prediction Horizon.** Several simulations were also run to study the influence of different prediction horizons on control performance. Simulation is carried out in both operating scenarios, and we changed the prediction horizon  $N_p$  from 5 to 15. As expected, the computation time increases when the prediction horizon increases. Another effect is that the distance between trains increases when the prediction horizon increases. We recorded and analyzed the changes in distance between trains. These results are shown in Table 1.

**5.4. Comparison and Discussion.** In order to further verify the performance of the proposed control algorithm, first, we compare the proposed control algorithm with the traditional train control architecture. The following train operates according to the preplanned speed curve and protection curve. The design of the controller is that the following train tracks the target's speed curve and maintains a safe distance from the preceding train. The controller does not predict the behavior of the preceding train. Denote this control method as no prediction (NP). The proposed control method in this paper is denoted as PBP (Planning-Based Prediction). The

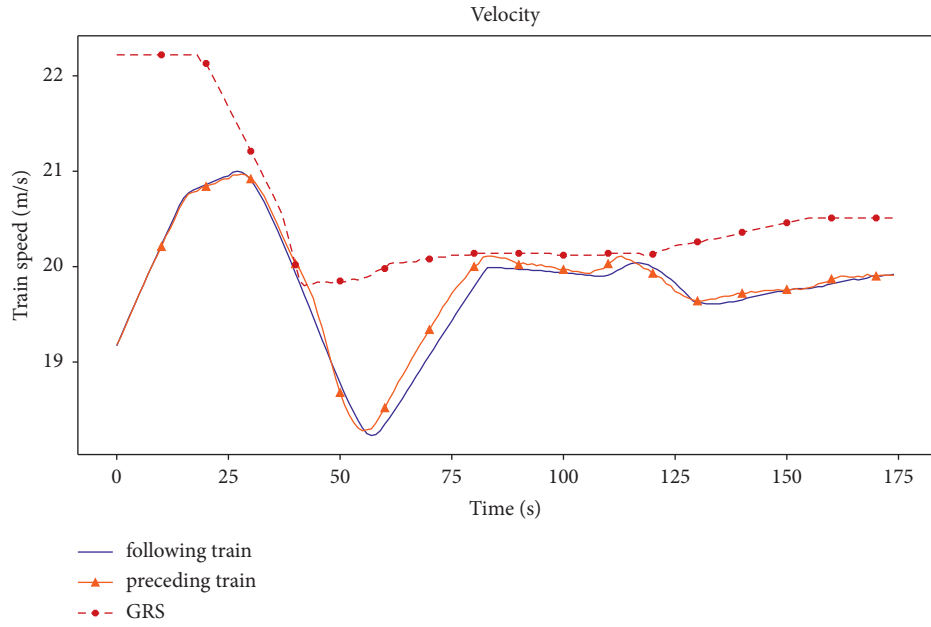
two methods were compared under the same conditions, and the experimental results were shown in Figure 9 under the two scenarios mentioned above.

In scenario 1, where the operation scene is relatively single, both methods can achieve speed tracking and distance stability of the following train to the preceding train. Since the following train does not consider the synchronous operation with the preceding train, but as far as possible to achieve the target speed, so the distance between the two trains is less than the proposed PBP method. Nevertheless, this is not what we expect, and there will still be sharp changes in the distance. However, in scenario 2, due to frequent acceleration and deceleration and the change of the speed limit in the interval, it is difficult for the following train to accurately track the speed of the preceding train only by tracking the target speed curve, resulting in a sharp change in the distance between the two trains. In this case, the algorithm proposed in this paper has a good performance. In the two methods, the average speed difference between the following train and the preceding train is 0.075 m/s (NP) and 0.370 m/s (PBP), respectively. Therefore, in the virtual coupling, it is unacceptable for the following train not to predict the state of the preceding train.

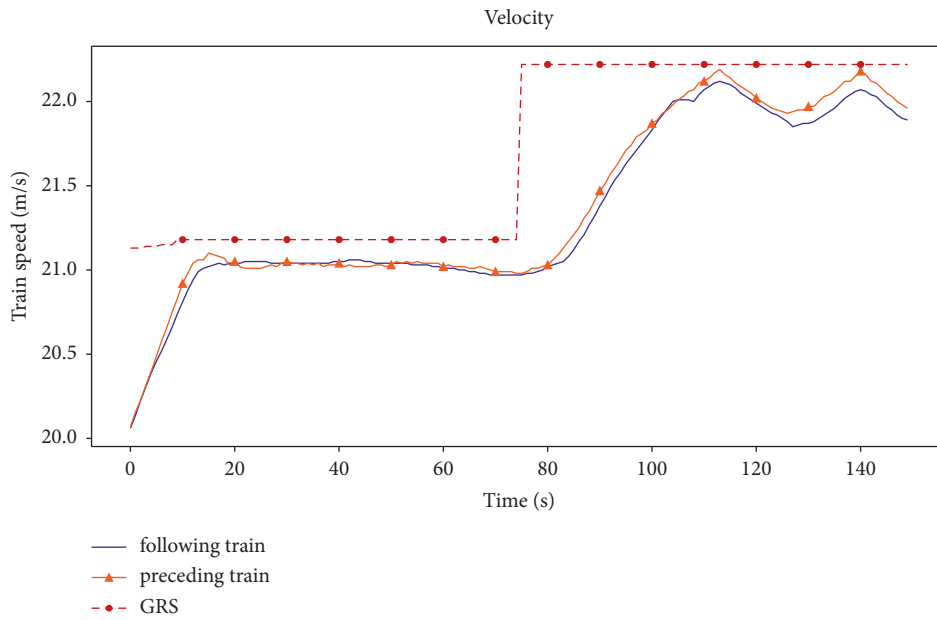
Then, we compared and analyzed the influence of different prediction methods on controlling the following train in the virtual coupling. We divide the prediction methods into planned-based and unplanned methods. Among them, the planning-based method is divided into the calculation of the dynamics model obtained by deep learning and the calculation of the traditional dynamics formulas. Calculation by dynamics formula is a classical conventional method adopted in articles [4, 5]. We refer to the calculation method mentioned in these articles and make some changes. The unplanned method is to build a state prediction model of the preceding train through deep learning. Trajectory prediction based on LSTM neural network is also used in [37]. Compared with the Kalman filter model, this method has been verified to have higher accuracy. However, the predicted input does not include the control input of the preceding train. The deep learning prediction model (DLP), planning-based prediction model (PBP), and train dynamics formula (TDF) are the three considered prediction strategies. We set the prediction horizon to 5, comparing different prediction methods' control performances in two operating scenarios. Figure 10 presents these results.

In Figure 10, we can see how the distance between the trains is maintained within the set safety margin (10 meters) for the two test conditions. Compared with the TDF strategies, the neural network prediction method enables the following train to achieve more accurate speed tracking. Moreover, the velocity plot shows that the PBP method can achieve better speed tracking. The following train's speed is close to the preceding train's speed and has no significant speeding.

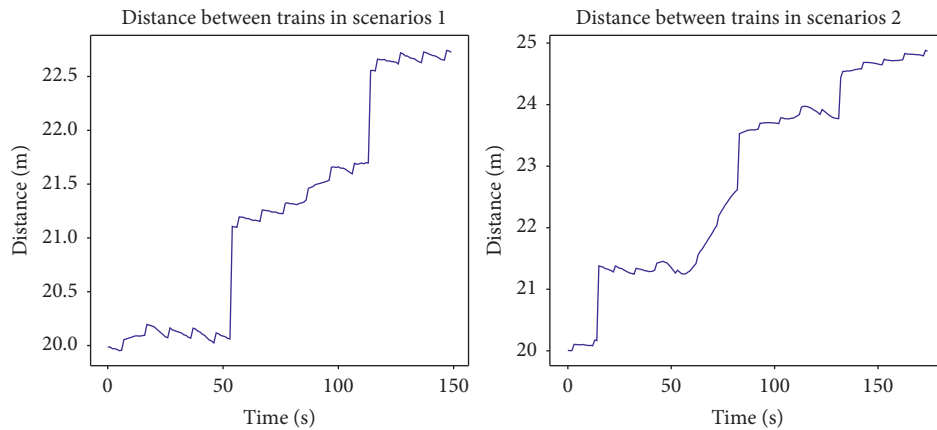
Through specific numerical analysis, the differences of different prediction methods are more directly reflected. In scenario 2, these differences are more prominent, which is embodied in the average speed errors of the preceding train and the following train under the three algorithms are 0.075



(a)



(b)



(c)

FIGURE 8: Simulation results of velocity and distance. (a) The speed profile of train convey in scenario 1. (b) The speed profile of train convey in scenario 2. (c) The distance between trains in different scenarios.

TABLE 1: The influence of different prediction horizons on tracking distances.

Scenario	$N_p$	Average value	Standard deviation
1	5	21.68	1.22
	10	21.84	1.36
	15	21.94	1.44
2	5	22.95	1.68
	10	23.13	1.61
	15	22.96	1.88

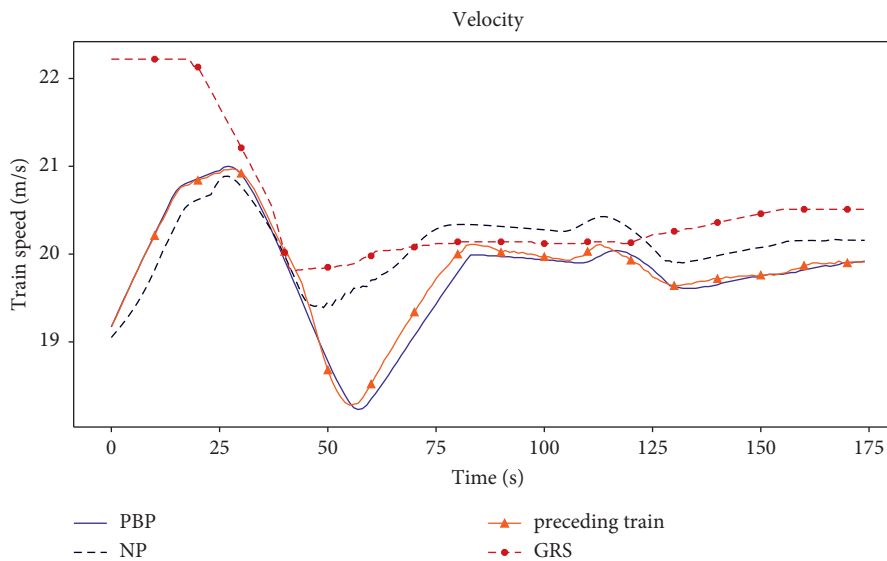
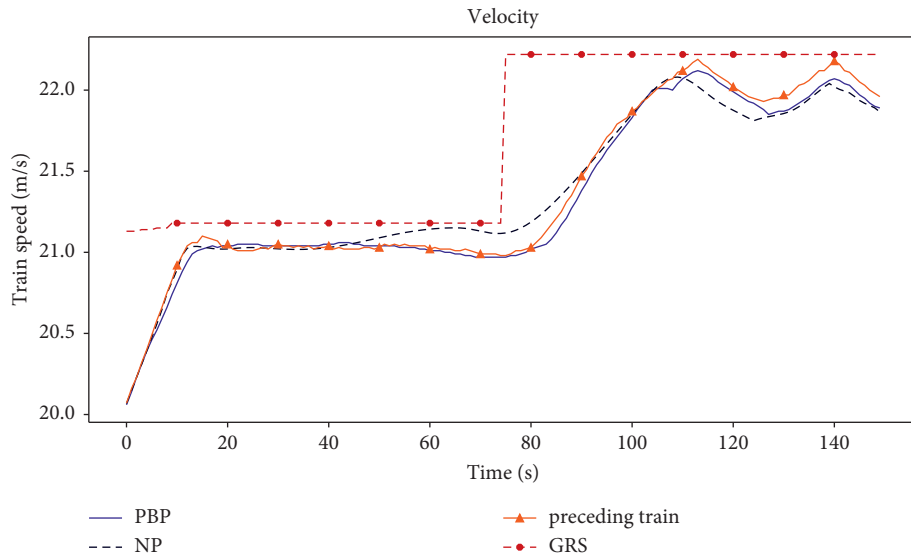


FIGURE 9: Continued.

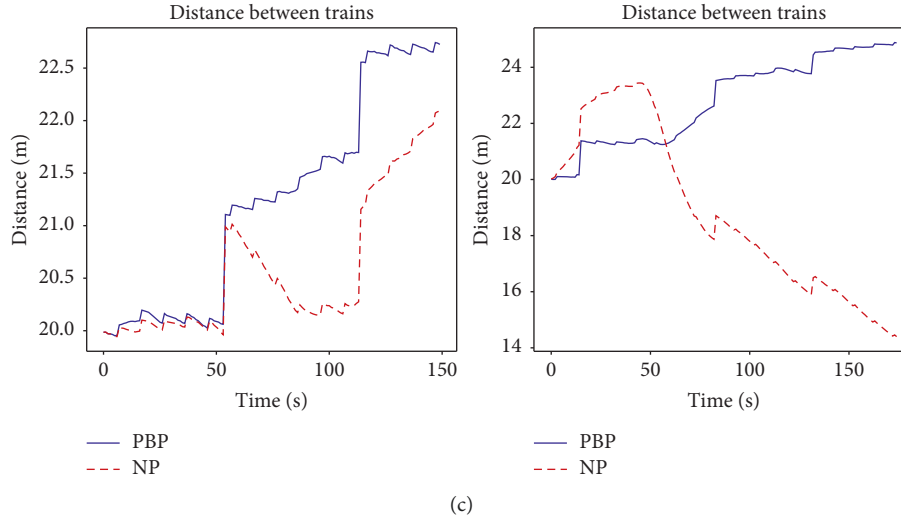


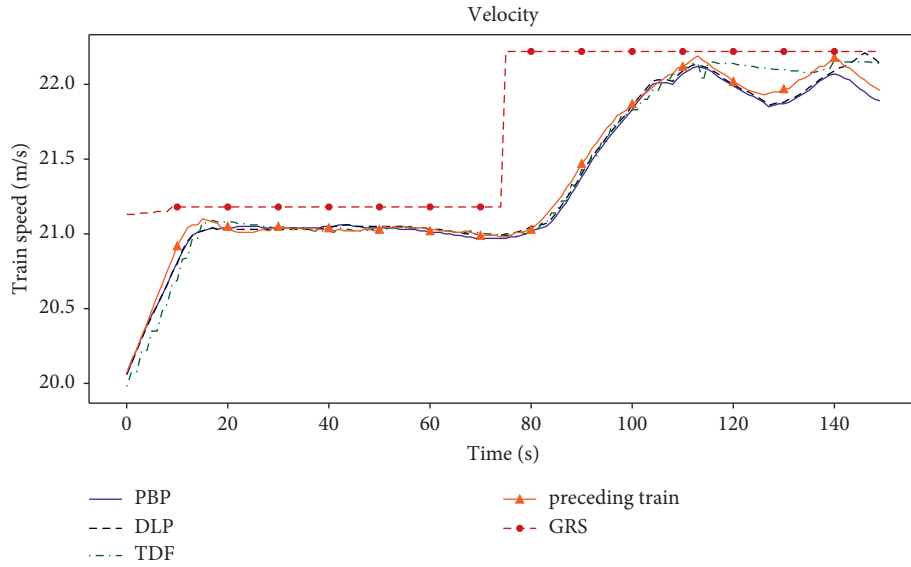
FIGURE 9: Comparison of different control strategies. (a) The speed of the following train under different control strategies in scenario 1. (b) The speed of the following train under different control strategies in scenario 2. (c) The distance between trains in different scenarios.

(PBP), 0.11 (DLP), and 0.12 (TDF), respectively. We calculate the variance of distance variation under different prediction methods are 1.56 (PBP), 1.58 (DLP), and 2.14 (TDF), respectively. The results show that, compared with the conventional TDF method, the PBP method achieves 35 % and 25 % improvement of velocity and distance, respectively.

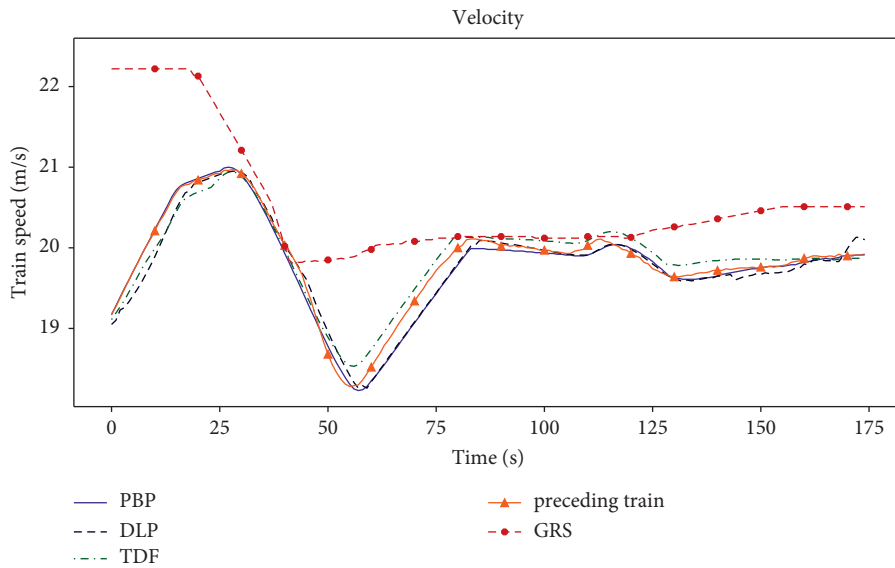
The simulation also verified a particular scenario in which the preceding train is running abnormally and brakes at a certain part of the line, the control problem of the following train. At this point, there is a clear difference between the three prediction methods. Since the control input of the preceding train is known, the (PBP) method can correctly predict the state of the preceding train due to the change in the control input when the preceding train is braking. However, due to the unknown control input of the preceding train, the (DLP) method will have a significant deviation in the predicted state in this scenario. In spite of the control input of the preceding train is known in the TDF method, the prediction accuracy is limited, and the stability of the train convoy is still difficult to maintain. Due to the constraint of the safety distance between trains, the following train will still brake and slow down under the other two prediction strategies. However, due to untimely deceleration, the distance between trains will still suddenly decrease. The result is shown in Figure 11. As can be seen from the figure, the distance between the two trains corresponding to the three control strategies decreases instantly after braking. The two planning-based prediction methods (PBP) and (TDF) achieve more accurate speed tracking in the case of emergency braking of the preceding train, thus making the distance change between the two trains relatively small. The small degree of distance change is helpful to maintain the stability of the whole train convoy. More accurate speed tracking also helps keep the convoy running after emergency braking.

**5.5. Experimental Results and Discussion.** In this paper, model predictive control and deep learning methods are used to design the following train controller in virtual coupling to realize the stable operation of the virtual coupling convoy. First, by comparing with the traditional train control architecture, we think it is necessary to predict the operation state of the preceding train for the following train. Through simulations in two scenarios and comparing the control effects of different prediction methods, it can be proven that the method used in this paper can achieve a more stable convoy operation. In scenario 1, the maximum speed tracking error of the PBP case is 0.11, while the tracking errors of the other two methods are 0.17 and 0.20, respectively. In scenario 2, the maximum speed tracking error of the PBP method is 0.24, better than 0.31 and 0.32 in the other methods. The PBP method proposed in this paper can maintain minor distance change under the premise of achieving better speed tracking. Furthermore, the planning-based prediction method achieves more accurate speed tracking, whether a normal operation scenario or an unconventional situation of the preceding train's emergency braking. The PBP method can respond more quickly to the abnormal braking of the preceding train so that the distance between the two trains will not change sharply. The simulation proves its application effect in special scenes.

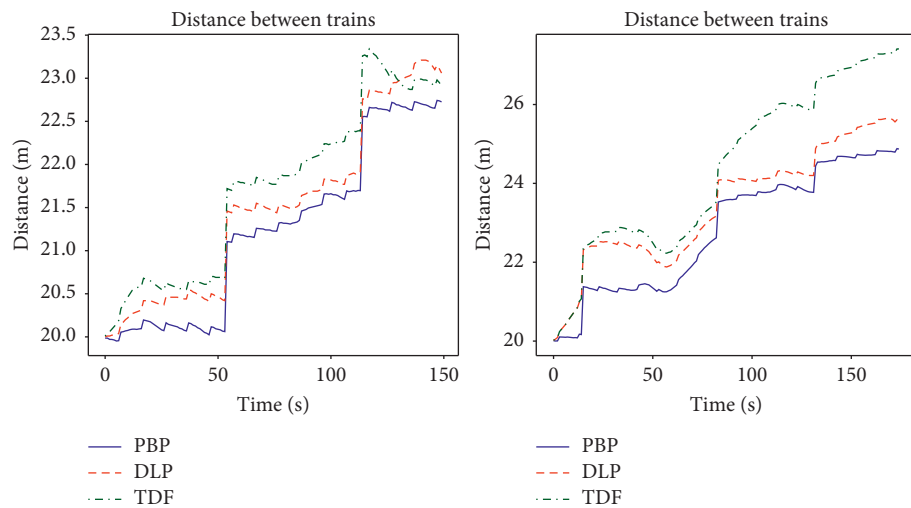
The experiment provides new insight into virtual coupling. The neural network predicts the control target of the following train in the virtual coupling. Previous control studies have mainly focused on the control effect of the control algorithm under ideal conditions. However, in this paper, we use field data to train the neural network and compare the field data with the control results. The experimental results also verify the effectiveness of this method. The planning-based prediction method proposed in this paper is more effective. However, the method proposed in this paper is limited to the condition in which the line



(a)



(b)



(c)

FIGURE 10: Comparison of different prediction strategies. (a) The speed of the following train under different control strategies in scenario 1. (b) The speed of the following train under different control strategies in scenario 2. (c) The distance between the trains under different prediction strategies.

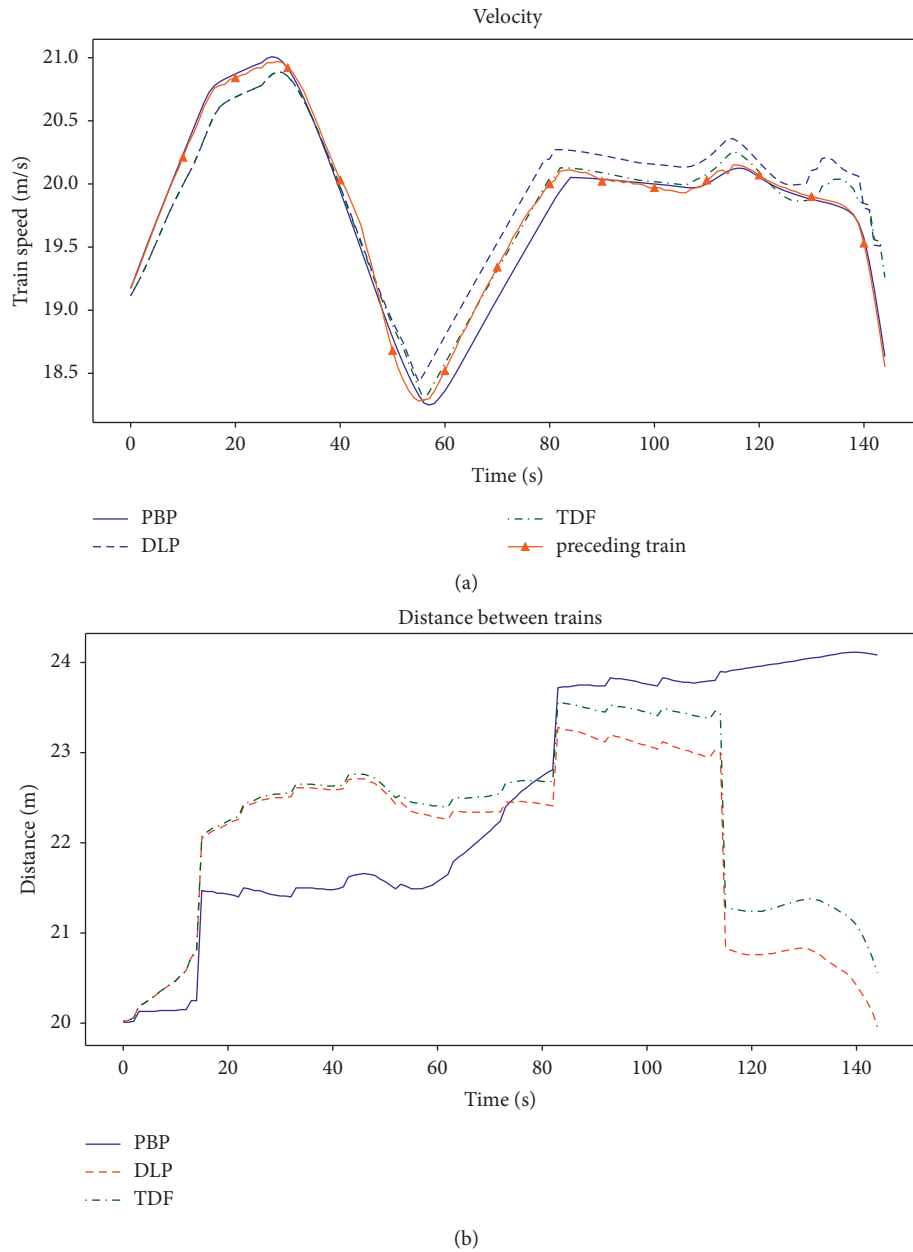


FIGURE 11: An abnormal braking scenario. (a) The speed of the following train under different prediction strategies in an abnormal braking scenario. (b) The distance between trains under different prediction strategies in an abnormal braking scenario.

conditions do not change significantly. Thus, the following train can accurately predict the state of the preceding train. To some extent, this is also the limitation of neural networks. The currently feasible solution is to update the neural network model through field data in time.

## 6. Conclusion

This paper relies on deep learning and model predictive control (MPC) to propose a virtual coupling control solution for the following train. The solution first uses deep learning to model the dynamics of the preceding train. Subsequently, several prediction strategies were developed for model predictive control, and simulation comparisons were carried

out based on one metro line. The results show that different prediction strategies have significant differences in control effects. Compared with the conventional dynamics formula, the model established by deep learning achieves better predictive performance and a better control effect. Furthermore, a planning-based prediction model more accurately predicts the preceding train's operation state. Such a prediction strategy can also deal with unexpected scenes during operation (e. g., abnormal braking). Therefore, the simulation results demonstrate better performance and benefits of this prediction strategy and control architecture.

However, the control scheme proposed in this paper only considers the simplified scenario of two trains. The virtual coupling scenario of multiple trains, which is more

widely used in practical applications, is not considered. More evolved studies are necessary considering essential issues such as uncertainties in time delays or even communication failure that may appear in the reception of positional information. These aspects are the subject of ongoing research.

## Data Availability

The experimental data used to support the findings of this study are included within the article.

## Conflicts of Interest

The authors declare that they have no conflicts of interest.

## Acknowledgments

This research was funded by the Fundamental Research Funds for the Central Universities under grant 2020JBZD002, Beijing Natural Science Foundation (L201004), National Railway Administration of the People's Republic of China funding program (KF2021-004); Beijing Laboratory of Urban Rail Transit and Frontiers Science Center for Smart High-speed Railway System.

## References

- [1] U. Bock and G. Bikker, "Design and development of a future freight train concept - virtually coupled train formations," *IFAC Proceedings Volumes*, vol. 33, no. 9, pp. 395–400, 2000.
- [2] F. Flammini, M. Stefano, N. Roberto, P. Alberto, S. Stefania, and V. Valeria, "Towards railway virtual coupling," in *Proceedings of the 2018 IEEE International Conference on Electrical Systems for Aircraft, Railway, Ship Propulsion and Road Vehicles International Transportation Electrification Conference (ESARS-ITEC)*, November 2018.
- [3] T. Schumann, "Increase of Capacity on the Shinkansen High-Speed Line Using Virtual Coupling," *International Journal of Transport Development and Integration*, vol. 1, no. 4, pp. 666–676, 2016.
- [4] X. Luo, "An Adaptive Model Predictive Control System for Virtual Coupling in Metros," in *Actuators*, vol. 10, no. 8, 2021.
- [5] J. Felez, Y. Kim, and F. Borrelli, "A model predictive control approach for virtual coupling in railways," *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 7, pp. 2728–2739, 2019.
- [6] Qi Wang, "Optimized control of virtual coupling at junctions: a cooperative game-based approach," *Actuators*, vol. 10, Multidisciplinary Digital Publishing Institute, 2021 No. 9.
- [7] G. Shi-Gen, "Cooperative adaptive bidirectional control of a train platoon for efficient utility and string stability," *Chinese Physics B*, vol. 24, no. 9, Article ID 090506, 2015.
- [8] W. Bai, Z. Lin, H. Dong, and B. Ning, "Distributed cooperative cruise control of multiple high-speed trains under a state-dependent information transmission topology," *IEEE Transactions on Intelligent Transportation Systems*, vol. 20, no. 7, pp. 2750–2763, 2019.
- [9] Y. Liu, Y. Zhou, S. Su, J. Xun, and T. Tang, "An analytical optimal control approach for virtually coupled high-speed trains with local and string stability," *Transportation Research Part C: Emerging Technologies*, vol. 125, Article ID 102886, 2021.
- [10] L. Ling, "Intelligent dispatching and coordinated control method at railway stations for virtually coupled train sets," in *Proceedings of the 2019 IEEE Intelligent Transportation Systems Conference (ITSC)*, IEEE, Auckland, New Zealand, October 2019.
- [11] C. Di Meo, "Ertms/etcs virtual coupling: proof of concept and numerical analysis," *IEEE Transactions on Intelligent Transportation Systems*, vol. 21, no. 6, pp. 2545–2556, 2019.
- [12] J. Park, B.-H. Lee, and Y. Eun, "Virtual Coupling of Railway Vehicles: Gap Reference for Merge and Separation, Robust Control, and Position Measurement," *IEEE Transactions on Intelligent Transportation Systems*, pp. 1–12, 2020.
- [13] C. Wang, S. Gong, A. Zhou, T. Li, and S. Peeta, "Cooperative adaptive cruise control for connected autonomous vehicles by factoring communication-related constraints," *Transportation Research Procedia*, vol. 38, pp. 242–262, 2019.
- [14] G. Orosz, "Connected cruise control: modelling, delay effects, and nonlinear behaviour," *Vehicle System Dynamics*, vol. 54, no. 8, pp. 1147–1176, 2016.
- [15] Y. Zhou, M. Wang, and S. Ahn, "Distributed model predictive control approach for cooperative car-following with guaranteed local and string stability," *Transportation Research Part B: Methodological*, vol. 128, pp. 69–86, 2019.
- [16] S. Feng, Y. Zhang, S. E. Li, Z. Cao, H. X. Liu, and L. Li, "String stability for vehicular platoon control: definitions and analysis methods," *Annual Reviews in Control*, vol. 47, pp. 81–97, 2019.
- [17] C. Sun, W. He, and J. Hong, "Neural network control of a flexible robotic manipulator using the lumped spring-mass model," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 47, no. 8, pp. 1863–1874, 2016.
- [18] W. He, X. Mu, L. Zhang, and Y. Zou, "Modeling and trajectory tracking control for flapping-wing micro aerial vehicles," *IEEE/CAA Journal of Automatica Sinica*, vol. 8, no. 1, pp. 148–156, 2020.
- [19] L. Kong, W. He, Y. Dong, L. Cheng, C. Yang, and Z. Li, "Asymmetric bounded neural control for an uncertain robot by state feedback and output feedback," *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 51, no. 3, 2019.
- [20] G. Wang, Q.-S. Jia, J. Qiao, J. Bi, and M. Zhou, "Deep learning-based model predictive control for continuous stirred-tank reactor system," *IEEE Transactions on Neural Networks and Learning Systems*, vol. 32, no. 8, pp. 3643–3652, 2021.
- [21] B. Zhang, X. Sun, S. Liu, and X. Deng, "Recurrent neural network-based model predictive control for multiple unmanned quadrotor formation flight," *International Journal of Aerospace Engineering*, vol. 2019, pp. 1–18, 2019.
- [22] J. Pei, Y. Su, D. Zhang, Y. Qi, and Z. Leng, "Velocity forecasts using a combined deep learning model in hybrid electric vehicles with V2V and V2I communication," *Science China Technological Sciences*, vol. 63, no. 1, pp. 55–64, 2019.
- [23] K. Bieker, S. Peitz, S. L. Brunton, J. N. Kutz, and M. Dellnitz, *Deep Model Predictive Control with Online Learning for Complex Physical Systems*, arXiv preprint arXiv:1905.10094, 2019.
- [24] S. Chen, Z. Wu, D. Rincon, and P. D. Christofides, "Machine learning-based distributed model predictive control of nonlinear processes," *AIChE Journal*, vol. 66, no. 11, 2020.
- [25] G. M. Shafiqullah, A. Gyasi-Agyei, and P. Wolfs, "Survey of Wireless Communications Applications in the Railway industry," in *Proceedings of the 2nd International Conference on Wireless Broadband and Ultra Wideband Communications (AusWireless 2007)*, IEEE, Sydney, NSW, Australia, August 2007.



- [26] M. Chai, H. Wang, T. Tang, and H. Liu, "Runtime verification of train control systems with parameterized modal live sequence charts," *Journal of Systems and Software*, vol. 177, Article ID 110962, 2021.
- [27] B. P. Rochard and F. Schmid, "A review of methods to measure and calculate train resistances," *Proceedings of the Institution of Mechanical Engineers - Part F: Journal of Rail and Rapid Transit*, vol. 214, no. 4, pp. 185–199, 2000.
- [28] M. Morari and J. H. Lee, "Model predictive control: past, present and future," *Computers & Chemical Engineering*, vol. 23, no. 4-5, pp. 667–682, 1999.
- [29] S. J. Qin and T. A. Badgwell, "A survey of industrial model predictive control technology," *Control Engineering Practice*, vol. 11, no. 7, pp. 733–764, 2003.
- [30] D. Q. Mayne, "Model predictive control: recent developments and future promise," *Automatica*, vol. 50, no. 12, pp. 2967–2986, 2014.
- [31] Shift2Rail, *Application Roadmap for the Introduction of Virtual Coupling*, pp. 1–74, MOVINGRAIL, European: Maastricht, The Netherlands, 2020.
- [32] D. Corona, "A hybrid MPC approach to the design of a Smart adaptive cruise controller," in *Proceedings of the 2006 IEEE Conference on Computer Aided Control System Design, 2006 IEEE International Conference on Control Applications, 2006 IEEE International Symposium on Intelligent Control*, October 2006.
- [33] D. Corona and B. De Schutter, "Adaptive cruise control for a SMART car: a comparison benchmark for MPC-PWA control methods," *IEEE Transactions on Control Systems Technology*, vol. 16, no. 2, pp. 365–372, 2008.
- [34] A. Sherstinsky, "Fundamentals of recurrent neural network (RNN) and long short-term memory (LSTM) network," *Physica D: Nonlinear Phenomena*, vol. 404, Article ID 132306, 2020.
- [35] R. C. Staudemeyer and E. R. Morris, *Understanding LSTM—A Tutorial into Long Short-Term Memory Recurrent Neural Networks*, arXiv preprint arXiv:1909.09586, 2019.
- [36] X. Bao, Z. Sun, and N. Sharma, "A recurrent neural network based mpc for a hybrid neuroprosthesis system," in *Proceedings of the 2017 IEEE 56th Annual Conference on Decision and Control (CDC)*, pp. 4715–4720, IEEE, Melbourne, VIC, Australia, 2017 December.
- [37] Y. He, J. Lv, D. Zhang et al., "Trajectory prediction of urban rail transit based on long short-term memory network," in *Proceedings of the 2021 IEEE International Intelligent Transportation Systems Conference (ITSC)*, pp. 3945–3950, IEEE, Indianapolis, IN, USA, September 2021.