# Distributed MPC-Based String Stable Platoon Control of Networked Vehicle Systems

Jiange Wang<sup>®</sup>, Xiaolei Li<sup>®</sup>, *Member, IEEE*, Ju H. Park<sup>®</sup>, *Senior Member, IEEE*, and Ge Guo<sup>®</sup>, *Senior Member, IEEE* 

Abstract—In this paper, the string stable platoon control problem of discrete-time networked vehicle systems is considered by using distributed model predictive control (MPC) based method. An optimization problem is established to minimize the cost function associated to the system trajectories. The last-step shifting method is applied to set the local optimal solution as the assumed solution and send it to the neighbor vehicles. By using the sum of the cost function as Lyapunov function, the stability of the closed-loop platoon system is studied. Comparing with existing results, the string stability, which is the unique characteristics of the platoon system, is guaranteed under the bidirectional-based structure as well as the predecessor-followerbased information flow structure. Finally, several simulations are presented to demonstrate the effectiveness of the proposed algorithms.

*Index Terms*—Platoon control, MPC-based method, string stable, networked vehicle.

## I. INTRODUCTION

**I** N THE past decades, traffic jam has become increasingly serious [1], [2]. How to ensure the vehicle runs fast and safely on the road has attracted the attention of many researchers. Platoon control is one of the most promising solutions to this issue and has achieved many remarkable results, see [3], [4], [5] and the references therein. Vehicle platoon control aims to ensure the specified distance between each vehicle, with all vehicles in the system having the same speed and acceleration as the (virtual) leader vehicle's [6], [7], [8].

The platoon system includes four elements, including vehicle dynamics (VD), information flow topology (IFT),

Jiange Wang and Xiaolei Li are with the School of Electrical Engineering, Yanshan University, Qinhuangdao 066004, China (e-mail: jg\_wang@163.com; xiaolei@ysu.edu.cn).

Ju H. Park is with the Department of Electrical Engineering, Yeungnam University, Gyeongsan 38541, South Korea (e-mail: jessie@ynu.ac.kr).

Ge Guo is with the State Key Laboratory of Synthetical Automation for Process Industries, Northeastern University, Shenyang 110819, China, and also with the School of Control Engineering, Northeastern University at Qinhuangdao, Qinhuangdao 066004, China (e-mail: geguo@yeah.net).

Digital Object Identifier 10.1109/TITS.2022.3221382

formation geometry (FG) [9], [10] and distributed controller (DC). The IFT structures are mainly divided into predecessorfollowing-based [9], [11], [12], [13] and bidirectional-based structure [5], [6]. FG represents the distance strategy between the vehicles in the platoon [14]. Intuitively, the design of DC is closely related to VD, IFT, and FG. In recent years, some advanced control methods, which can improve the performance of the connected vehicle platoon system are proposed, such as adaptive control method [15], sliding mode control method [16], and robust control method [17]. Specifically, a two-layer distributed control scheme is proposed to ensure the closed-loop stability for the platoon system moving in one-dimension space with constant vehicle spacing being guaranteed [15]. In [16], the sliding mode control is introduced into the vehicle platoon control to solve the distributed trajectory optimization problem for the heterogeneous platoon system. A cooperative adaptive cruise control scheme is proposed for the vehicle platoon system and the distributed observer is used to estimate the lump disturbance in [17]. However, most of these methods fail to consider the discrete vehicle model as well as the string stability, which is a peculiar property of vehicle platoon.

To solve the trajectory optimization problem with discrete vehicle dynamics, model predictive control (MPC) is introduced into vehicle platoon systems by solving the formulated optimization problems within the predictive horizon to update the control signals. By setting current states as the initial states in each sampling moment, the MPC method can predict the next-step state by using the current one [18]. Since the MPC method can solve complex problems such as disturbance reduction and delay tolerance issues, it is popular in practical applications. In [19], the traffic control problem on highways is considered, but the centralized MPC's calculation time scales poorly. Due to the limitations of collecting all vehicle information and the challenges of calculation complexity of the optimization problems, the centralized MPC is not suitable for an actual vehicle platoon system [20], [21], [22]. However, the majority of the applications are used in a centralized approach, which means the controllers are designed by assuming that all of the states in the system are known. For this issue, the distributed MPC method is proposed for the vehicle platoon systems, which means only the local information can be used to each local controller to solve the MPC problem [23]. In [24], a distributed iteration control approach based on the feasible direction method is proposed for multi-agent systems

This work is licensed under a Creative Commons Attribution-NonCommercial-NoDerivatives 4.0 License. For more information, see https://creativecommons.org/licenses/by-nc-nd/4.0/

Manuscript received 15 November 2021; revised 14 June 2022 and 1 November 2022; accepted 7 November 2022. Date of publication 21 November 2022; date of current version 1 March 2023. This work was supported in part by the National Natural Science Foundation of China under Grant 62103352, Grant 61903319, Grant 62033011, Grant 62271437, Grant 62173079, and Grant U1808205. The work of Ju H. Park was supported by the National Research Foundation of Korea (NRF) Grant through the Korea Government [Ministry of Science and Information and Communications Technology (ICT)] under Grant 2019R1A5A8080290. The Associate Editor for this article was M. Wang. (*Corresponding author: Ju H. Park.*)

to solve the distributed MPC optimization problems. The distributed MPC method removes the requirement on all states of the vehicles are known and, however, how to ensure the string stability of the platoon system is also one of the most challenging problems and still not well explored.

String stability is a special characteristic of the vehicle platoon system [25], [26], [27], [28]. Generally, there are two different stability definitions in vehicle platoon, i.e., individual stability and string stability. The former one, which is also known as Lyapunov stability, means that each vehicle in platoon system can be stabilized on some specific trajectories, while the latter one means the disturbances are not being magnified downstream along the vehicle platoon [28], [29], [30]. If the string stability is not guaranteed, a small disruption can be amplified and produce traffic congestion as the platoon length grows, such as stop-and-go phenomenon [31], [32]. Intuitively, VDs, FGs as well as IFTs of the platoon system will all affect the string stability [13], [29], [33]. In [29], the authors proved that since the complementary sensitivity integral constraint, the system is string unstable under the PF topology and CD policy. Under BD structure, the string stability of the platoon system is limited under the linear controller by some assumptions [33]. Some detailed comprehensive comparison between different types of string stability definitions under different analysis methods can be found in [26] and the reference therein. The existing results show that changing the forward communication structure of IFTs or the FGs between vehicles does not affect the string stability of the system. It should be noted that, to our best knowledge, how to ensure the string stability for a discrete platoon system by using distributed MPC method is still an open problem and not well explored.

In this paper, the distributed MPC string stable platoon control of discrete networked vehicle systems is considered. An optimization problem is considered to minimize the cost function associated to the system trajectories. A distributed MPC scheme is proposed, including the last-step shifting method, which is applied to set the local optimal solution as the assumed solution and send it to its neighbor vehicles. By using the sum of the cost function as Lyapunov function, the individual stability as well as the string stability of the closed-loop platoon system are studied. The effective of the proposed method is verified by the simulation results and the simulation results show that the proposed distributed MPC method can be applied to many different topology structures of vehicle platoon system. The contributions of the paper are summarized as follows:

- A distributed MPC-based method is proposed for a realistic discrete vehicle platoon systems by using the last-step shifting method. Comparing with [34], the proposed algorithm removes the requirement on all states of the platoon system be known.
- 2) Both the individual stability and the string stability are considered for predecessor-follower-based and bidirectional-based vehicle platoon structure. Comparing with [35] and [36], not only the individual stability but also the string stability of the closed-loop system are considered under the proposed controller. Also

unlike [37], rigorous proof is presented to guarantee the string stability under the bidirectional-based structure as well as the predecessor-follower-based vehicle platoon structure.

The outline of this paper is given as follows: the preliminaries and problem formulation are given in Section II. The distributed MPC-based method for the discrete vehicle platoon system and the prove processing is given in Section III. Section V presents the simulation results and the conclusion of the paper is given in Section VI.

## II. PRELIMINARIES

#### A. Vehicle Model for Platoon Control

The dynamics of the networked vehicle is the basis for designing a DC. Many existing results on vehicle platoon systems focus on the linear system model, such as the first-order integral model [3] and the second-order integral model [38]. In recent years, the third-order integral model has been studied, but these continuous models are harsh for real vehicle systems.

The vehicle model is defined as follows:

$$p_{i}(t+1) = p_{i}(t) + v_{i}(t)\tau,$$
  

$$v_{i}(t+1) = v_{i}(t) + a_{t}(t)\tau,$$
  

$$a_{i}(t+1) = a_{i}(t) + (f_{i}(t) + q_{i}(t)c_{i}(t))\tau,$$
 (1)

where  $p_i(t)$ ,  $v_i(t)$ ,  $a_i(t)$  represents the *i*-th vehicle's position, velocity and acceleration, respectively.  $c_i$  is the engine input representing the desired driving or braking torque.  $\tau$  represents the sampling time.  $f_i(t) = -\frac{1}{\Delta_s}(a_i + m_a c_a c_g v_i^2/2m_i + f_{c_g}/m_i) - m_a c_a c_g v_i a_i/m_i$  and  $q_i(t) = \frac{1}{\Delta_s m_i}$  with  $m_a$ ,  $m_i$ ,  $\Delta_s$ ,  $c_a$  and  $c_g$  being the specific air mass, the vehicle mass, the time lag, the area of cross-sectional, and the drag coefficient, respectively. Based on [39], the engine input is given as follows:

$$c_i(t) = m_i u_i + m_a c_a c_g v_i^2 / 2 + f_{c_g} + m_a c_a c_g v_i a_i, \qquad (2)$$

where  $u_i$  is the designed control input. For each vehicle, the state is defined as  $\Phi_i(t) = [p_i(t), v_i(t), a_i(t)]^T \in \mathbb{R}^{3 \times 1}$ . Then, the vehicle model can be rewritten as follows:

$$\Phi_i(t+1) = A_i(\Phi_i(t)) + B_i u_i(t),$$
(3)

where

$$A_i(\Phi_i(t)) = \begin{bmatrix} p_i(t) + v_i(t)\tau \\ v_i(t) + a_i(t)\tau \\ a_i(t) - \frac{1}{\Delta s}a_i(t)\tau \end{bmatrix}, B_i = \begin{bmatrix} 0 \\ 0 \\ \frac{1}{\Delta s}\tau \end{bmatrix}.$$

## B. Control Objectives

As mentioned above, the stability definition for the platoon system includes individual stability and string stability. The control objective is to design a DC for a platoon system modeled by (1) and to ensure system stability in both senses, where the distances between vehicles are identical to the desired distance, and the vehicle velocities and accelerations in the platoon system are equal to the leader's ones. The control objective are described as follows. The desired position of  $i_{th}$  vehicle is  $\lim_{t\to\infty} p_i(t) = p_i^* = p_0 + l_{i,0}$ , the desired velocity is  $\lim_{t\to\infty} v_i(t) \to v_i^* = v_0$ , the desired acceleration is  $\lim_{t\to\infty} a_i(t) \to a_i^* = a_0$ , where  $l_{i,0}$  is the desired distance between the leader vehicle and the *i*-th vehicle,  $p_0$ ,  $v_0$  and  $a_0$ are the (virtual) leader's position, velocity and acceleration, respectively. Based on [37], the definition of the platoon system's string stability is that all state errors of the system are converged to zero and the following condition should also be satisfied:

$$\max \|p_i - p_0 - l_{i,0}\| \le k_i \max \|p_{i-1} - p_0 - l_{i-1,0}\|, \quad (4)$$

where  $0 < k_i < 1$ , i = 1, 2, ..., N. This equation means that the disturbance is propagate downstream along the vehicle platoon system without being magnified, then the system is string stability.

Remark 1: The desired distance among the vehicles in platoon system can be either constant or time-varying, which is referred as the CD or CTH policy in a platoon system [26]. In [40], the result shows that the vehicle platoon systems with CTH policy by using MPC algorithm can be converged. In this paper, we focus on the networked vehicle platoon system's stability by using the distributed MPC-based approach and the CD policy is considered in platoon system.

#### C. Communication Topology

In this paper, both the BD information flow structure in platoon system are considered. The communication topology can be described by a undirected graph  $\mathcal{G}_N = \{\mathcal{V}_N, \mathcal{E}_N\}$ , where  $\mathcal{V}_N = \{1, 2, \dots, N\}$  is the vehicle index set, and  $\mathcal{E}_N \in \mathcal{V}_N \times \mathcal{V}_N$ is the set of edges between vehicles. Note that the leader is indexed by 0. The vehicle *i* can communicate with the vehicles j if  $e_{i,j} = (i, j) \in \mathcal{E}_N$ . The adjacency matrix is given as  $\mathcal{A} = [a_{i,j}] \in \mathbb{R}^{N \times N}$ , where  $a_{i,j} = 1$  if  $(i, j) \in \mathcal{E}_N$ , otherwise  $a_{i,i} = 0$ . The neighbor set of vehicle *i* is defined as  $\mathcal{N}_i =$  $\{j \in \mathcal{V}_N, a_{i,j} = 1\}$ . The Lapiacian matrix  $\mathcal{L}$  of  $\mathcal{G}_N$  is defined as  $\mathcal{L} = \mathcal{D} - \mathcal{A}$ , where the degree matrix  $\mathcal{D}$  is given as  $\mathcal{D} =$  $diag\{d_1, d_2, \ldots, d_N\}$  with  $d_i = \sum_{i \in \mathcal{N}_i} a_{ij}$ . If *i*-th vehicle can communicate with the leader, the pinning gain  $q_i = 1$ . The pinning matrix is given as  $\mathcal{P} = diag\{q_1, q_2, \dots, q_N\}$ . The leader accessible set for vehicle i is given as  $Q = \{0\}$  if  $q_i = 1$ , otherwise  $Q = \emptyset$ . Obviously only the information of vehicle j in the set  $\mathcal{I}_i = \mathcal{N}_i \cup Q$  can be used for the designed controller of *i*-th vehicle. The following assumption is given for the communication topology.

Assumption 1: The platoon system communication topology  $G_N$  contains at least one spanning tree rooting at the leader vehicle and the self-loop does not exist in  $G_N$ .

The following well-known lemma for graph  $\mathcal{G}_N$  is also given. Lemma 1: [41] Under the Assumption 1, if  $\mathcal{G}_N$  contains a spanning tree rooting at the leader, then  $\mathcal{D} + \mathcal{P}$  is invertible and  $\lambda_{(\mathcal{D}+\mathcal{P})^{-1}\mathcal{A}} < 1$ .

## III. DISTRIBUTED MODEL PREDICTIVE BASED METHOD

In this section, the distributed MPC-based method for networked vehicle platoon systems is proposed. The local optimization problem is firstly proposed and a solution algorithm is given. Then rigorous proof is given to demonstrate that both the Lyapunov stability and string stability can be guaranteed.

#### A. Distributed Local Optimization Control Problem

Although all the information for vehicle *j* in set  $\mathcal{I}_N$  can be used for control design of the  $i_{th}$  vehicle, the local optimal problem is established only used the information from the  $(i-1)_{\text{th}}$  and  $(i+1)_{\text{th}}$  vehicle in the platoon system. In this subsection, the following definitions are used.  $N_p$  is defined as the predictive horizon,  $\delta$  is the updating period in distributed MPC algorithm, s represents the predicted time at time t, the predicted state is  $\Phi_i^p(s,t)$  with  $s = 0, 1, 2, \dots, Np$ , i.e., s = 1 means  $s = t_0 + \delta$ , which represent the predicted value of the state  $\Phi_i^p$  of the time  $t + \delta$  at the time t. The optimal predicted state is defined as  $\Phi_i^*(s, t)$ , the assumed state is denoted by  $\hat{\Phi}_i(s, t)$ , the predicted control input is  $u_i^p(s,t)$ , the optimal control input is  $u_i^*(s,t)$ , the assumed control input is  $\hat{u}_i(s, t)$ . The state variable  $\Phi_i^p(s, t)$  is used to parameterizes the optimal control problem,  $\Phi_i^*(s, t)$  is defined as an optimal solution to the optimal control problems.  $\hat{\Phi}_i(s, t)$ is the trajectory communicated to its neighbours  $(i + 1) \in \mathcal{I}_i$ and  $(i-1) \in \mathcal{I}_i$ . In the proposed algorithm, the shifted last-step optimal trajectory of vehicle *i* is used and it will be implemented within the update period  $[t, t + \delta]$ . It should be noted that  $\Phi_i^p(s,t) = \Phi_i^*(s,t) = \hat{\Phi}_i(s,t)$  at the initial moment.

The optimization control problem for vehicle  $i \in \{1, 2, ..., N\}$  in platoon system at time t is established as follows:

$$\Gamma_{i}(t): J_{i}(t) = \min_{u_{i}^{p}(s,t)} J_{i}(\Phi_{i}^{p}, u_{i}^{p}, \hat{\Phi}_{i}, \hat{\Phi}_{j})$$
  
$$= \sum_{s=0}^{N_{p}-1} g_{i}(\Phi_{i}^{p}(s,t), u_{i}^{p}(s,t), \hat{\Phi}_{i}(s,t), \hat{\Phi}_{j}(s,t))$$
(5)

subject to

$$\Phi_i^p(s+1,t) = A(\Phi_i^p(s,t)) + Bu_i^p(s,t), s < N_p,$$
 (6)

where  $u_i^p(s,t) \in U_i$  is the control input with  $U_i$ being the feasible set of  $u_i^p(s,t)$ ,  $\Phi_i^p(s_{N_p},t)$ =  $\frac{1}{\|\mathcal{I}_i\|} \left( \sum_{j \in \mathcal{I}_i, j > i} (\hat{\Phi}_j(s_{N_p}, t) + L_{i,j}) + \sum_{j \in \mathcal{I}_i, j < i} (\hat{\Phi}_j(s_{N_p}, t) - L_{i,j}) \right)$  $L_{j,i}$ ) with  $s_{N_p}$  means  $s = N_p$ . The cost function  $g_i(\Phi_i^p, u_i^p, \hat{\Phi}_i, \hat{\Phi}_j)$  in (5) is given as (7), shown at the bottom of the next page, where  $L_{i,i-1} = [l_{i,i-1}, 0, 0]^T$ ,  $L_{i,i+1} = [l_{i,i+1}, 0, 0]^T$ .  $K_i \ge 0$  denotes the penalized strength from the desired trajectory to the predicted state trajectory. For the vehicles that can not access to the leader,  $K_i = 0$ .  $R_i \geq 0$  denotes the control input weight.  $F_i \geq 0$  is the weight coefficient for the moving suppression term, in which the assumed state trajectory is the shifted last-step optimal state.  $G_i \ge 0$  denotes the weight of predecessor relative error term, which means the vehicle *i* try to ensure the predicted trajectory as close to the assumed trajectory of the neighbor vehicle i - 1 and i + 1. In addition, this paper doesn't consider the effects of the communication and actuation delays in the platoon control. Theoretically, the proof is still valid in the presence of communication delays, since the last-step shifting method is applied to set the local optimal

solution as the assumed solution, where the optimal predictive process is independent of the communication delay. However, as mentioned in [42], the communication and actuation delays are detrimental to string stability. How to ensure the string stability under both the communication and actuation delays in a distributed MPC scheme for networked vehicle systems is still an open problem, which will be considered in the future.

Remark 2: Note that Problem  $\Gamma_i(t)$  only needs the neighboring information thus be fully distributed. Comparing with the results in [34], where the leader information being used in each subsystems, this paper removes the requirements on any prior information of the leaders. In addition, the proposed distributed MPC based method in this paper can ensure both the asymptotic stability and string stability, which is also different the one in [36], where the string stability isn't considered. Rigorous proof and discussions will be given in Section IV.

#### B. Distributed MPC-Based Algorithm

In this subsection, the distributed MPC-based algorithm is summarized as follows:

# IV. STABILITY ANALYSIS FOR THE VEHICLE Platoon System

In this section, since the particularity of the vehicle platoon system, both the closed-loop stability and the string stability of the system are analyzed by using the Lyapunov function theory and mathematical induction, respectively. The terminal equality constraint is also proved to ensure that the predicted terminal state will converge to the desired state.

## A. Terminal Equality Constraint

Define the terminal state error as follows:

$$E_{\Phi_i}(s_{N_p}, t+1) = \Phi_0(s_{N_p}, t+1) - \Phi_i^*(s_{N_p}, t+1) - L_{0,i}$$
(8)

Based on the distributed MPC-based algorithm, we have

$$\Phi_{i}^{p}(s_{N_{p}}, t+1) = \frac{1}{\|I_{i}\|} (\sum_{j \in \mathcal{I}_{i}, j > i} (\hat{\Phi}_{j}(s_{N_{p}}, t+1) + L_{i,j}) + \sum_{j \in \mathcal{I}_{i}, j < i} (\hat{\Phi}_{j}(s_{N_{p}}, t+1) - L_{j,i}))$$
$$= \frac{1}{\|I_{i}\|} (\sum_{j \in \mathcal{I}_{i}, j > i} (A(\Phi_{j}^{*}(s_{N_{p}}, t)) + L_{i,j}))$$

$$+ \sum_{j \in \mathcal{I}_{i}, j < i} (A(\Phi_{j}^{*}(s_{N_{p}}, t)) - L_{j,i}))$$

$$= \frac{1}{\|I_{i}\|} (\sum_{j \in \mathcal{I}_{i}, j > i} (\mathcal{Z}\Phi_{j}^{*}(s_{N_{p}}, t) + L_{i,j})$$

$$+ \sum_{j \in \mathcal{I}_{i}, j < i} (\mathcal{Z}\Phi_{j}^{*}(s_{N_{p}}, t) - L_{j,i}))$$

$$= \mathcal{Z}\Phi_{i}^{*}(s_{N_{p}}, t),$$
(9)

where  $\mathcal{Z}$  is given as follows

$$\mathcal{Z} = \begin{bmatrix} 1 \ \tau & 0 \\ 0 \ 1 & \tau \\ 0 \ 0 \ 1 - \frac{1}{\Delta s} \tau \end{bmatrix}.$$
 (10)

Then, we have  $\Phi_i^p(s_{N_p}, t+1) = \Phi_i^*(s_{N_p}, t+1)$ , and one can know that the predicted state trajectory will converge to the optimal state trajectory.

Substituting (9) into (8), it yields

$$E_{\Phi_{i}}(s_{N_{p}}, t+1) = \Phi_{0}(s_{N_{p}}, t+1) - \frac{1}{\|I_{i}\|} (\sum_{j \in \mathcal{I}_{i}, j > i} (\hat{\Phi}_{j}(s_{N_{p}}, t+1) + L_{i,j}) + \sum_{j \in \mathcal{I}_{i}, j < i} (\hat{\Phi}_{j}(s_{N_{p}}, t+1) - L_{j,i})) - L_{0,i}$$
$$= \frac{1}{\|I_{i}\|} \sum_{j \in \mathcal{I}_{i}} (\Phi_{0}(s_{N_{p}}, t+1) - \hat{\Phi}_{j}(s_{N_{p}}, t+1) - L_{0,j})$$
$$= \frac{1}{\|I_{i}\|} \mathcal{Z} \sum_{j \in \mathcal{I}_{i}} (E_{\Phi_{j}}(s_{N_{p}}, t))$$
(11)

Rewriting (11) as an matrix form as

$$E_{\Phi}(s_{N_p}, t+1) = (\mathcal{D} + \mathcal{P})^{-1} \mathcal{A} \otimes \mathcal{Z} E_{\Phi}(s_{N_p}, t).$$
(12)

According to the definition of  $\mathcal{Z}$ , we have  $\lambda_{\mathcal{Z}} = 1$  and  $\lambda_{\mathcal{Z}} = 1 - \frac{1}{\Delta s}\tau$ . Then, we can get that  $\max(\lambda_{\mathcal{Z}}) = 1$ . Based on the Assumption1 and Lemma1, the self-loop does not exist in the  $\mathcal{G}_N$  for vehicle platoon systems and the eigenvalues of  $(\mathcal{D} + \mathcal{P})^{-1}\mathcal{A}$  are all located within a unit circle. Then, we can know that  $\lambda_{(\mathcal{D} + \mathcal{P})^{-1}\mathcal{A} \otimes \mathcal{Z})} < 1$ , thus the terminal state error are converged to zero at  $t = t + N_p$ .

## B. Stability Analysis for Closed-Loop Stability

The main results are given as follows.

Theorem 1: Under Assumption 1 and the proposed distributed MPC controller, the closed-loop vehicle platoon system

$$g_{i}(\Phi_{i}^{p}, u_{i}^{p}, \hat{\Phi}_{i}, \hat{\Phi}_{j}) = \left\| K_{i}(\Phi_{i}^{p}(s, t) - \Phi_{i}^{*}(s, t)) \right\| + \left\| R_{i}u_{i}^{p}(s, t) \right\| \\ + \left\| F_{i}(\Phi_{i}^{p}(s, t) - \hat{\Phi}_{i}(s, t)) \right\| \\ + \sum_{j \in \mathcal{I}_{i}, j > i} \left\| G_{i}(\Phi_{i}^{p}(s, t) - \hat{\Phi}_{j}) \right\| \\ + \sum_{j \in \mathcal{I}_{i}, j < i} \left\| G_{i}(\Phi_{i}^{p}(s, t) - \hat{\Phi}_{j}(s, t) + L_{j,i})) \right\|$$
(7)

Algorithm 1 The distributed MPC-based method for vehicle platoon system

**1. Initialization**: Set vehicle i = 1 as the leader and broadcast the desired velocity to other vehicles. We assumed that the leader vehicle i will solve the optimal problem  $\Gamma_i(t)$  by setting  $F_i = G_i = 0$  before t = 0, and that the other vehicles in the platoon system will solve the optimal problem  $\Gamma_i(t)$  by setting  $F_i = 0$  before t = 0, implying that the assumed trajectories are unnecessary in the initialization.

Initialize  $\Phi_i^p(s, 0)$  and  $u_i^p(s, 0)$  as:

$$\Phi_i^p(s,0) = \begin{cases} \Phi_i(0), s = 0\\ A(\Phi_i^p(s-1,0)) + Bu_i^p(s-1,0), others\\ u_i^p(s,0) = 0 \end{cases}$$

**2. Iteration**: For any  $0 \le t < t + N_p$ , implementing the following process:

(1) Transmit the assumed state trajectories  $\hat{\Phi}_i(s, t)$ , which is derived by solving the optimal problem  $\Gamma_i(t)$ , to the neighbor vehicle  $j \in \mathcal{I}_i$ ;

(2) Solve the optimal problem  $\Gamma_i(t)$  and obtain the optimal control  $u_i^*(t)$  and

$$\Phi_i^*(t+1) = A_i(\Phi_i^*(t)) + B_i u_i^*(t);$$

(3) Compute  $\hat{\Phi}_i(s, t+1)$  and  $\hat{u}_i(s, t+1)$  as:

$$\hat{\Phi}_i(s, t+1) = \begin{cases} \Phi_i^*(s+1, t), \ s \le Np - 1\\ A_i(\Phi_i^*(s_{N_p}, t)), \ others \end{cases}$$

where  $s_{N_p}$  means  $s = N_p$ .

$$\hat{u}_i(s,t+1) \begin{cases} u_i^*(s+1,t), \ s \le Np-1 \\ 0, \ others \end{cases}$$

(4) Transmit  $\hat{\Phi}_i(s, t+1)$  to its neighbour vehicles i + 1 and i-1. Also the vehicle *i* receive  $\hat{\Phi}_{i+1}(s, t+1)$  and  $\hat{\Phi}_{i-1}(s, t+1)$ 1) from its neighbours, respectively;

(5) Solve the optimal problem  $\Gamma_i(t)$  for  $u_i^*(s, t+1)$  and set s = s + 1 and go back to step (1).

is stable under if the following conditions are satisfied, i.e.

$$u_i^*(s_0, t) = 0, \qquad (13)$$

$$\Phi_i^*(s_0, t) - \hat{\Phi}_i(s_0, t) = 0, \qquad (14)$$

$$(\Phi_i^*(s_0, t) - \Phi_j(s_0, t) - L_{i,j})_{j \in I_i, j > i} = 0,$$
(15)

$$(\Phi_i^*(s_0, t) - \Phi_j(s_0, t) + L_{j,i})_{j \in I_i, j < i} = 0.$$
(16)

*Remark 3: The above conditions are the constraints on the* assumed states of the system at s = 0, which means the initial assumed states of the system. It requires that the assumed states of the system equal to the desired states of the system at the initial moment, this is consistent with the previous definition of the expected value and predicted value of the system.

*Proof:* Consider the sum of the local cost function as an candidate Lyapunov function, then the difference function is

$$\Delta V = \sum_{i=1}^{N} (J_i^*(t+1) - J_i^*(t)), \qquad (17)$$

where  $J_i^*(t) = \sum_{s=0}^{N_p - 1} g_i(\Phi_i^*(s, t), u_i^*(s, t), \hat{\Phi}_i(s, t), \hat{\Phi}_j(s, t)).$ Then rewriting (17) as

$$\Delta V = \sum_{i=1}^{N} (\sum_{s=0}^{N_p-1} g_i(\Phi_i^*(s,t+1), u_i^*(s,t+1), \hat{\Phi}_i(s,t+1), \hat{\Phi}_j(s,t+1), \hat{\Phi}_j(s,t+1)) - \sum_{s=0}^{N_p-1} g_i(\Phi_i^*(s,t), u_i^*(s,t), \hat{\Phi}_i(s,t), \hat{\Phi}_j(s,t))).$$
(18)

Next, we will prove that the difference function  $\Delta V$  is strictly monotonically decreasing such that the asymptotic stability can be ensured.

According to the local optimal theory, we have

$$\Delta V \leq \sum_{i=1}^{N} (\sum_{s=0}^{N_{p}-1} g_{i}(\hat{\Phi}_{i}(s,t+1),\hat{u}_{i}(s,t+1),\hat{\Phi}_{i}(s,t+1), \hat{\Phi}_{i}(s,t+1), \hat{\Phi}_{j}(s,t+1)) \\ - \sum_{s=0}^{N_{p}-1} g_{i}(\Phi_{i}^{*}(s,t),u_{i}^{*}(s,t),\hat{\Phi}_{i}(s,t),\hat{\Phi}_{j}(s,t))) \\ \leq \sum_{i=1}^{N} (-g_{i}(\Phi_{i}^{*}(s_{0},t),u_{i}^{*}(s_{0},t),\hat{\Phi}_{i}(s_{0},t),\hat{\Phi}_{j}(s_{0},t)) \\ + \sum_{s=1}^{N_{p}-1} (g_{i}(\Phi_{i}^{*}(s,t),u_{i}^{*}(s,t),\Phi_{i}^{*}(s,t),\Phi_{j}^{*}(s,t)) \\ - \sum_{s=1}^{N_{p}-1} g_{i}(\Phi_{i}^{*}(s,t),u_{i}^{*}(s,t),\hat{\Phi}_{i}(s,t),\hat{\Phi}_{j}(s,t)))).$$
(19)

where the definitions of  $\Phi_i^*(s,t), u_i^*(s,t), \hat{\Phi}_i(s,t), \hat{\Phi}_i(s,t)$ are given previously. Combining (7) and (19), it yields

$$\begin{split} \Delta V &\leq \sum_{i=1}^{N} (-g_{i}(\Phi_{i}^{*}(s_{0},t),u_{i}^{*}(s_{0},t),\hat{\Phi}_{i}(s_{0},t),\hat{\Phi}_{j}(s_{0},t)) \\ &+ \sum_{s=1}^{N_{p}-1} ((\|K_{i}(\Phi_{i}^{*}(s,t) - \Phi_{i}^{*}(s,t))\| \\ &+ \|R_{i}(u_{i}^{*}(s,t))\| + \|F_{i}(\Phi_{i}^{*}(s,t) - \Phi_{i}^{*}(s,t))\| \\ &+ \sum_{j\in I_{i},j>i} \|G_{i}(\Phi_{i}^{*}(s,t) - \Phi_{j}^{*}(s,t) - L_{i,j})\| \\ &+ \sum_{j\in I_{i},j>i} \|G_{i}(\Phi_{i}^{*}(s,t) - \Phi_{j}^{*}(s,t) + L_{j,i})\| ) \\ &- (\|K_{i}(\Phi_{i}^{*}(s,t) - \Phi_{i}^{*}(s,t))\| + \|R_{i}(u_{i}^{*}(s,t))\| \\ &+ \|F_{i}(\Phi_{i}^{*}(s,t) - \hat{\Phi}_{i}(s,t))\| \\ &+ \sum_{j\in I_{i},j>i} \|G_{i}(\Phi_{i}^{*}(s,t) - \hat{\Phi}_{j}(s,t) - L_{i,j})\| \\ &+ \sum_{j\in I_{i},j>i} \|G_{i}(\Phi_{i}^{*}(s,t) - \hat{\Phi}_{j}(s,t) + L_{j,i})\|)))$$
(20)

Furthermore, according to the properties of the matrix norm, we have

$$\Delta V \leq \sum_{i=1}^{N} (-g_i(\Phi_i^*(s_0, t), u_i^*(s_0, t), \hat{\Phi}_i(s_0, t), \hat{\Phi}_j(s_0, t)) + \sum_{s=1}^{N_p - 1} (\sum_{j \in I_i} \left\| G_i(\Phi_j^*(s, t) - \hat{\Phi}_j(s, t)) \right\| - \left\| F_i(\Phi_i^*(s, t) - \hat{\Phi}_i(s, t)) \right\|))$$
(21)

Since  $\sum_{i \in I_i} G_i - F_i \leq 0$ , it derives that  $(\Phi_i^*(s,t) - \hat{\Phi}_i(s,t))^T (\sum_{j \in I_i} G_i - F_i) (\Phi_i^*(s,t) - \hat{\Phi}_i(s,t)) \leq 0$ . In addition,

$$\sum_{j \in I_i} \left\| G_i(\Phi_i^*(s,t) - \hat{\Phi}_i(s,t)) \right\| \\ - \left\| F_i(\Phi_i^*(s,t) - \hat{\Phi}_i(s,t)) \right\| \le 0 \quad (22)$$

Then substituting (22) into (21), we have

$$\Delta V \leq \sum_{i=1}^{N} (-g_i(\Phi_i^*(s_0, t), u_i^*(s_0, t), \hat{\Phi}_i(s_0, t), \hat{\Phi}_j(s_0, t)))$$
  
$$\leq -\sum_{i=1}^{N} (\|K_i(\Phi_i^*(s_0, t) - \Phi_i^*(s_0, t))\| + \|R_i u_i^*(s_0, t)\| + \|F_i(\Phi_i^*(s_0, t) - \hat{\Phi}_i(s_0, t))\| + \sum_{j \in I_i, j > i} \|G_i(\Phi_i^*(s_0, t) - \hat{\Phi}_j(s_0, t) - L_{i,j})\| + \sum_{j \in I_i, j < i} \|G_i(\Phi_i^*(s_0, t) - \hat{\Phi}_j(s_0, t) + L_{j,i})\|). (23)$$

According to the conditions in (13)-(16), one has

$$\Delta V \leq -\sum_{i=1}^{N} (\|K_{i}(\Phi_{i}^{*}(s_{0}, t) - \Phi_{i}^{*}(s_{0}, t))\| + \|R_{i}u_{i}^{*}(s_{0}, t)\| + \|F_{i}(\Phi_{i}^{*}(s_{0}, t) - \hat{\Phi}_{i}(s_{0}, t))\| + \sum_{j \in I_{i}, j > i} \|G_{i}(\Phi_{i}^{*}(s_{0}, t) - \hat{\Phi}_{j}(s_{0}, t) - L_{i,j})\| + \sum_{j \in I_{i}, j < i} \|G_{i}(\Phi_{i}^{*}(s_{0}, t) - \hat{\Phi}_{j}(s_{0}, t) + L_{j,i})\|) < 0$$
(24)

Then asymptotical stability of the closed-loop platoon system is guaranteed. This completes the proof.  $\Box$ 

Remark 4: In this paper, the last-step shifting method is used to constructed the assumed states in the proposed distributed MPC algorithm. The similar strategies are also used in [35], [36]. In contrast to these results, asymptotical stability of the closed-loop platoon system can be guaranteed under both PF and BD information flow structures. In addition, another potential benefit is that the proposed algorithm removes the requirement on all states of the platoon system be known such as the leader's one, which is different from [34].

#### C. String Stability Analysis

The string stability is suggested and thoroughly investigated to ensure that the disturbance between each vehicle does not amplify along the string when the number of vehicles is increasing in the system [26], [27], [28]. The string stability of the vehicle platoon systems is analyzed in this section.

Theorem 2: Under Assumption 1 and Theorem 1, the proposed distributed MPC-based algorithm ensures the string stability of the vehicle platoon system if the following conditions are satisfied:

1. The optimal problem  $\Gamma_i$  is solved by using the proposed distributed MPC algorithm for each vehicle  $i \ge 2$  under the following conditions:

$$p_{i}^{P}(s_{0},t) - p_{0}(s_{0},t) - l_{0,i}| \leq \alpha_{i} \left| p_{i-1}^{P}(s_{0},t) - p_{0}(s_{0},t) - l_{0,i-1} \right|$$
(25)

where  $0 < \alpha_i \leq 1$ .

2. Problem  $\Gamma_i(t)$  will be solved by the proposed distributed MPC algorithm with the following constraints: For the leader vehicle:

$$\begin{vmatrix} p_1^p(s,t+1) - p_0(s,t+1) - l_{0,1} \\ -(\hat{p}_1(s,t+1) - p_0(s,t+1) - l_{0,1}) \\ \leq k_{(1,s)} | p_1^p(s,t+1) - p_0(s,t+1) - l_{0,1} | \end{aligned} (26)$$

where  $k_{(1,s)} > 0$ ;

For the other vehicles:  

$$\begin{vmatrix} p_i^p(s,t+1) - p_0(s,t+1) - l_{0,i} \\ -(\hat{p}_i(s,t+1) - p_0(s,t+1) - l_{0,i}) \\ \leq k_{(i,s)} \max | p_i^p(s,t+1) - p_0(s,t+1) - l_{0,i} | \quad (27) \end{aligned}$$

where  $k_{(i,s)} > 0$ .

3. In addition, the following condition is satisfied:

$$k_{i,s}(k_{i-1,s}+1) + \alpha_i \prod_{j=1}^{s} (k_{i-1,j}+1) + \sum_{j=1}^{s-1} (k_{i,j} \prod_{\beta=1}^{s} (k_{i-1,\beta}+1)) < 1, \text{ for } i \ge 2.$$
(28)

*Proof:* Based on the definition of the string stability, if the following condition is satisfied:

$$\max_{t \ge 0} \left| p_i - p_0 - l_{0,i} \right| \le k_s \max_{t \ge 0} \left| p_{i-1} - p_0 - l_{0,i-1} \right|, \quad (29)$$

where  $k_s \leq 1$ , then the vehicle platoon system is string stable. To verify this condition, the mathematical induction method is used.

**For** s = 0: We will firstly prove that the condition (29) is satisfied for the case that s = 0. Since  $F_i = G_i = 0$  at initialization for the leader vehicle i = 1,  $p_i^p(s_0, t) - p_0(s_0, t) - l_{0,i} = p_i^*(s_0, t) - p_0(s_0, t) - l_{0,i}$  at initialization, based on (25), we have

$$\begin{aligned} \left| p_{i}^{*}(s_{s},t) - p_{0}(s_{0},t) - l_{0,i} \right| \\ &\leq \alpha_{i} \left| p_{i-1}^{*}(s_{0},t) - p_{0}(s_{0},t) - l_{0,i} \right|. \end{aligned} (30)$$

Then, we have

$$\max \left| p_i^*(s_0, t) - p_0(s_0, t) - l_{0,i} \right| \\\leq \alpha_i \max \left| p_{i-1}^*(s_0, t) - p_0(s_0, t) - l_{0,i} \right| \quad (31)$$

Thus the condition (29) is satisfied for the case that s = 0.

also satisfied for the case that s = 1. By using the triangle inequality, we have

$$\begin{aligned} & \left| p_{i}^{*}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i} \right| \\ & \leq \left| p_{i}^{*}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i} - \left( \hat{p}_{i}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i} \right) \right| \\ & + \left| \hat{p}_{i}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i} \right|. \end{aligned}$$
(32)

Since  $p_i^p$  is the predicted position trajectory and  $p_i^*$  is the optimal predicted position trajectory, we have

$$\left| p_i^*(s_1, t) - p_0(s_1, t) - l_{0,i} \right| \le \left| p_i^p(s_1, t) - p_0(s_1, t) - l_{0,i} \right|.$$
(33)

Substituting (33) into (32), we can obtain

$$\begin{aligned} \left| p_{i}^{*}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i} \right| \\ &- (\hat{p}_{i}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i}) \right| \\ &+ \left| \hat{p}_{i}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i} \right| \\ &\leq \left| \begin{array}{c} p_{i}^{p}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i} \\ - (\hat{p}_{i}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i}) \right| \\ &+ \left| \hat{p}_{i}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i} \right|. \end{aligned}$$
(34)

Then substituting (27) into (34), one can get

$$\begin{aligned} \left| p_{i}^{p}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i} \right. \\ \left. - (\hat{p}_{i}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i}) \right| \\ \left. + \left| \hat{p}_{i}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i} \right| \\ \left. \le k_{i,1} \max \left| \hat{p}_{i-1}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i-1} \right| \\ \left. + \left| \hat{p}_{i}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i} \right| \end{aligned}$$
(35)

Furthermore, substituting (35) into (32), we can obtain

$$\begin{aligned} \left| p_{i}^{*}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i} \right| \\ &\leq \left| p_{i}^{p}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i} \right| \\ &- (\hat{p}_{i}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i}) \right| \\ &+ \left| \hat{p}_{i}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i} \right| \\ &\leq k_{i,1} \max \left| \hat{p}_{i-1}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i-1} \right| \\ &+ \left| \hat{p}_{i}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i} \right|. \end{aligned}$$
(36)

From the results with s = 0, it yields

$$\begin{aligned} \left| p_i^*(s_0, t) - (p_0(s_0, t)) - l_{0,i} \right| \\ &\leq \alpha_i \left| p_{i-1}^*(s_0, t) - (p_0(s_0, t)) - l_{0,i} \right| \quad (37) \end{aligned}$$

Then, one can get

$$\begin{aligned} \left| \hat{p}_{i}(s_{1}, t+1) - p_{0}(s_{1}, t+1) - l_{0,i} \right| \\ &\leq \alpha_{i} \left| \hat{p}_{i-1}(s_{1}, t+1) - p_{0}(s_{1}, t+1) - l_{0,i} \right|. \end{aligned}$$
(38)

By combining (36), (37), and (38), the following result is derived

$$\begin{aligned} \left| p_{i}^{*}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i} \right| \\ &\leq k_{i,1} \max \left| \hat{p}_{i-1}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i-1} \right| \\ &+ \alpha_{i} \left| \hat{p}_{i-1}(s_{1},t) - p_{0}(s_{1},t) - \hat{l}_{0,i} \right|. \end{aligned}$$
(39)

For s = 1: Next, we will prove that the condition (29) is Similarly, the following inequality can be yielded by using the triangle inequality,

$$\left| \begin{array}{c} \hat{p}_{i}(s,t+1) - p_{0}(s,t+1) - l_{0,i} \\ - \left| \begin{array}{c} p_{i}^{*}(s,t+1) - p_{0}(s,t+1) - l_{0,i} \\ \end{array} \right| \\ \leq \left| \begin{array}{c} p_{i}^{p}(s,t+1) - p_{0}(s,t+1) - l_{0,i} \\ - (\hat{p}_{i}(s,t+1) - p_{0}(s,t+1) - l_{0,i}) \end{array} \right|.$$

$$(40)$$

Then according to (27) and (40), the following result is derived by defining i = i - 1,

$$\hat{p}_{i-1}(s,t+1) - p_0(s,t+1) - l_{0,i-1} | \\ \leq k_{i-1,s} \max \left| p_{i-1}^*(s,t+1) - p_0(s,t+1) - l_{0,i-1} \right| \\ + \left| p_{i-1}^*(s,t+1) - p_0(s,t+1) - l_{0,i-1} \right|.$$
(41)

Substituting s = 1 into (41), we have

$$\begin{aligned} \left| \hat{p}_{i-1}(s_1, t) - p_0(s_1, t) - l_{0,i-1} \right| \\ &\leq k_{i-1,1} \max \left| p_{i-1}^*(s_1, t) - p_0(s_1, t) - l_{0,i-1} \right| \\ &+ \left| p_{i-1}^*(s_1, t) - p_0(s_1, t) - l_{0,i-1} \right| \end{aligned}$$
(42)

Substituting (42) into (39), one can get

$$\begin{aligned} \left| p_{i}^{*}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i} \right| \\ &\leq k_{i,1} \max(k_{i-1,1} \max \left| p_{i-1}^{*}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i-1} \right| \\ &+ \left| p_{i-1}^{*}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i-1} \right| \\ &+ \alpha_{i} \cdot (k_{i-1,s} \max \left| p_{i-1}^{*}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i-1} \right| \\ &+ \left| p_{i-1}^{*}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i-1} \right| \\ &\leq (k_{i,1}(k_{i-1,1}+1) + \alpha_{i}k_{i-1,1} + \alpha_{i}) \\ \max \left| p_{i-1}^{*}(s_{1},t) - p_{0}(s_{1},t) - l_{0,i-1} \right|. \end{aligned}$$
(43)

Thus the following result can be derived,

$$\max \left| p_i^*(s_1, t) - p_0(s_1, t) - l_{0,i} \right| \\\leq (k_{i,1}(k_{i-1,1} + 1) + \alpha_i k_{i-1,1} + \alpha_i) \\\cdot \max \left| p_{i-1}^*(s_1, t) - p_0(s_1, t) - l_{0,i-1} \right|.$$
(44)

Then the condition in (29) is proved.

For s = 2: Similarly, by following the process for the case s = 1, we will prove that the condition (29) is also satisfied for the case that s = 2. By using the triangle inequality theory, we have

$$\begin{aligned} \left| p_{i}^{*}(s_{2},t) - p_{0}(s_{2},t) - l_{0,i} \right| \\ &\leq \left| p_{i}^{*}(s_{2},t) - p_{0}(s_{2},t) - l_{0,i} \right| \\ &- \left( \hat{p}_{i}(s_{2},t) - p_{0}(s_{2},t) - l_{0,i} \right) \right| \\ &+ \left| \hat{p}_{i}(s_{2},t) - p_{0}(s_{2},t) - l_{0,i} \right| \end{aligned}$$

$$(45)$$

Similarly, by following the process of (33)-(35) and substituting it into (45), we have

$$|p_i^*(s_2, t) - p_0(s_2, t) - l_{0,i}| \leq k_{i,2} \max |\hat{p}_{i-1}(s_2, t) - p_0(s_2, t) - l_{0,i}| + |\hat{p}_i(s_2, t) - p_0(s_2, t) - l_{0,i}|$$
(46)

By using the triangle inequality theory, we have

$$\left| \begin{array}{l} \hat{p}_{i}(s,t+1) - p_{0}(s,t+1) - l_{0,i} \\ - \left| \begin{array}{l} p_{i}^{*}(s,t+1) - p_{0}(s,t+1) - l_{0,i} \\ \le k_{i,s} \max \left| p_{i}^{p}(s,t+1) - p_{0}(s,t+1) - l_{0,i} \right| \end{array} \right|$$

$$(47)$$

Then, the following result will be derived by defining i = i - 1 and s = 2,

$$\begin{aligned} \left| \hat{p}_{i-1}(s_{2},t) - p_{0}(s_{2},t) - l_{0,i} \right| \\ &\leq k_{i-1,2} \max \left| p_{i-1}^{p}(s_{2},t) - p_{0}(s_{2},t) - l_{0,i-1} \right| \\ &+ \left| p_{i-1}^{*}(s_{2},t) - p_{0}(s_{2},t) - l_{0,i-1} \right| \\ &= k_{i-1,2} \max \left| p_{i-1}^{*}(s_{2},t) - p_{0}(s_{2},t) - l_{0,i-1} \right| \\ &+ \left| p_{i-1}^{*}(s_{2},t) - p_{0}(s_{2},t) - l_{0,i-1} \right| \end{aligned}$$
(48)

Substituting (48) into (46), we have

$$\begin{aligned} \left| p_{i}^{*}(s_{2}, t) - p_{0}(s_{2}, t) - l_{0,i} \right| \\ &\leq k_{i,2}(k_{i-1,2} + 1) \max \left| p_{i-1}^{*}(s_{2}, t) - p_{0}(s_{2}, t) - l_{0,i-1} \right| \\ &+ \left| \hat{p}_{i}(s_{2}, t) - p_{0}(s_{2}, t) - l_{0,i} \right| \end{aligned}$$
(49)

From the results with s = 1, it yields

$$\begin{aligned} \left| p_{i}^{*}(s_{1}, t) - p_{0}(s_{1}, t) - l_{0,i} \right| \\ &\leq (k_{i,1}(k_{i-1,1} + 1) + \alpha_{i}k_{i-1,1} + \alpha_{i}) \\ &\max \left| p_{i-1}^{*}(s_{1}, t) - p_{0}(s_{1}, t) - l_{0,i-1} \right| \end{aligned}$$
(50)

Then, one can obtain

$$\begin{aligned} \left| \hat{p}_{i}(s_{2}, t+1) - (p_{0}(s_{2}, t+1)) - l_{0,i} \right| \\ &\leq (k_{i,1}(k_{i-1,1}+1) + \alpha_{i}k_{i-1,1} + \alpha_{i}) \\ &\max \left| \hat{p}_{i-1}(s_{2}, t+1) - (p_{0}(s_{2}, t+1)) - l_{0,i-1} \right| \end{aligned}$$
(51)

By combining (48)-(51), the following result is derived,

$$\begin{aligned} \left| p_{i}^{*}(s_{2}, t) - p_{0}(s_{2}, t) - l_{0,i} \right| \\ &\leq k_{i,2}(k_{i-1,2} + 1) \max \left| p_{i-1}^{*}(s_{2}, t) - p_{0}(s_{2}, t) - l_{0,i-1} \right| \\ &+ (k_{i,1}(k_{i-1,1} + 1) + \alpha_{i}k_{i-1,1} + \alpha_{i}) \\ &\max(k_{i-1,2} \max \left| p_{i-1}^{*}(s_{2}, t) - p_{0}(s_{2}, t) - l_{0,i-1} \right| \\ &+ \left| p_{i-1}^{*}(s_{2}, t) - p_{0}(s_{2}, t) - l_{0,i-1} \right| \end{aligned}$$
(52)

The following result can be derived,

$$\max \left| p_i^*(s_2, t) - p_0(s_2, t) - l_{0,i} \right| \\\leq (\alpha_i (k_{i-1,1} + 1)(k_{i-1,2} + 1) + k_{i,1}(k_{i-1,1} + 1)(k_{i-1,2} + 1) \\+ k_{i,2}(k_{i-1,2} + 1)) \\\cdot \max \left| p_{i-1}^*(s_2, t) - p_0(s_2, t) - l_{0,i-1} \right|.$$
(53)

Next, suppose that the following condition is hold for the case s = n.

$$\begin{aligned} \left| p_{i}^{*}(s_{n}, t) - p_{0}(s_{n}, t) - l_{0,i} \right| \\ &\leq (k_{i,n}(k_{i-1,n} + 1) + \alpha_{i} \prod_{j=1}^{n} (k_{i-1,j} + 1)) \\ &+ \sum_{j=1}^{n-1} (k_{i,j} \prod_{\beta=1}^{n} (k_{i-1,\beta} + 1))) \\ &\cdot \max \left| p_{i-1}^{*}(s_{n}, t) - p_{0}(s_{n}, t) - l_{0,i-1} \right|. \end{aligned}$$

Based on this condition, we will prove that the condition (29) is still satisfied under the proposed distributed MPC-based algorithm.

For s = n + 1: By using the triangle inequality, we have

$$\begin{aligned} \left| p_{i}^{*}(s_{n+1}, t) - p_{0}(s_{n+1}, t) - l_{0,i} \right| \\ &\leq \left| p_{i}^{*}(s_{n+1}, t) - p_{0}(s_{n+1}, t) - l_{0,i} \right| \\ &- (\hat{p}_{i}(s_{n+1}, t) - p_{0}(s_{n+1}, t) - l_{0,i}) \right| \\ &+ \left| \hat{p}_{i}(s_{n+1}, t) - p_{0}(s_{n+1}, t) - l_{0,i} \right| \\ &\leq k_{i,n+1} \max \left| \hat{p}_{i-1}(s_{n+1}, t) - p_{0}(s_{n+1}, t) - l_{0,i} \right| \\ &+ \left| \hat{p}_{i}(s_{n+1}, t) - p_{0}(s_{n+1}, t) - l_{0,i} \right|. \end{aligned}$$
(55)

Following the previous process, it yields

$$\begin{aligned} \left| \hat{p}_{i}(s,t+1) - p_{0}(s,t+1) - l_{0,i} \right| \\ - \left| p_{i}^{*}(s,t+1) - p_{0}(s,t+1) - l_{0,i} \right| \\ \leq k_{i,s} \max \left| p_{i}^{p}(s,t+1) - p_{0}(s,t+1) - l_{0,i} \right|. \end{aligned}$$
(56)

Defining i = i - 1 and substituting it into (56), one can get

$$\begin{aligned} \left| \hat{p}_{i-1}(s_{n+1}, t+1) - p_0(s_{n+1}, t+1) - l_{0,i-1} \right| \\ &\leq k_{i-1,n+1} \max \begin{vmatrix} p_{i-1}^p(s_{n+1}, t+1) \\ + p_0(s_{n+1}, t+1) - l_{0,i-1} \end{vmatrix} \\ &+ \left| p_{i-1}^*(s_{n+1}, t+1) - p_0(s_{n+1}, t+1) - l_{0,i} \right| \\ &\leq k_{i-1,n+1} \max \begin{vmatrix} p_{i-1}^*(s_{n+1}, t+1) \\ + p_0(s_{n+1}, t+1) - l_{0,i-1} \end{vmatrix} \\ &+ \left| p_{i-1}^*(s_{n+1}, t+1) - p_0(s_{n+1}, t+1) - l_{0,i} \right|. \end{aligned}$$
(57)

Substituting (57) into (55), it yields

$$\begin{aligned} \left| p_{i}^{*}(s_{n+1},t) - p_{0}(s_{n+1},t) - l_{0,i} \right| \\ &\leq k_{i,n+1} \max(k_{i-1,n+1} \max \left| \begin{array}{c} p_{i-1}^{*}(s_{n+1},t+1) \\ + p_{0}(s_{n+1},t+1) - l_{0,i-1} \right| \\ &+ \left| p_{i-1}^{*}(s_{n+1},t+1) - p_{0}(s_{n+1},t+1) - l_{0,i} \right| \\ &+ \left| \hat{p}_{i}(s_{n+1},t) - p_{0}(s_{n+1},t) - l_{0,i} \right| \\ &\leq k_{i,n+1}(k_{i-1,n+1}+1) \max \left| \begin{array}{c} p_{i-1}^{*}(s_{n+1},t+1) \\ + p_{0}(s_{n+1},t+1) - l_{0,i-1} \right| \\ &+ \left| \hat{p}_{i}(s_{n+1},t) - p_{0}(s_{n+1},t) - l_{0,i} \right|. \end{aligned}$$
(58)

Based on the condition (54), we have

$$\begin{aligned} \left| p_i^*(s_n, t) - p_0(s_n, t) - l_{0,i} \right| \\ &\leq (k_{i,n}(k_{i-1,n} + 1) + \alpha_i \prod_{j=1}^n (k_{i-1,j} + 1)) \\ &+ \sum_{j=1}^{n-1} (k_{i,j} \prod_{\beta=1}^n (k_{i-1,\beta} + 1))) \\ &\cdot \max \left| p_{i-1}^*(s_n, t) - p_0(s_n, t) - l_{0,i-1} \right|. \end{aligned}$$

Then, we can obtain

$$\begin{aligned} \left| \hat{p}_{i}(s_{n+1}, t+1) - p_{0}(s_{n+1}, t+1) - l_{0,i} \right| \\ &\leq (k_{i,n}(k_{i-1,n}+1) + \alpha_{i} \prod_{j=1}^{n} (k_{i-1,j}+1)) \\ &+ \sum_{j=1}^{n-1} (k_{i,j} \prod_{\beta=1}^{n} (k_{i-1,\beta}+1))) \\ &\max \left| \hat{p}_{i-1}(s_{n+1}, t+1) - p_{0}(s_{n+1}, t+1) - l_{0,i-1} \right|. \end{aligned}$$
(59)



(a) The initial position and the end positions of each vehicle, (b) The spacing errors of each vehicle, where  $SE_i$  represents where  $P_{Vi}$  represents the position of vehicle *i*.  $p_{i-1} - p_i - l_{i-1,i}$ .



(c) The velocities of each vehicle, where  $V_{Vi}$  represents the(d) The accelerations of each vehicle, where  $A_{Vi}$  represents velocity of vehicle *i*. the acceleration of vehicle *i*.

Fig. 1. The results for vehicle platoon system under BD structure.

Then substituting (59) into (58), one can get

$$\begin{aligned} \left| p_{i}^{*}(s_{n+1}, t) - p_{0}(s_{n+1}, t) - l_{0,i} \right| \\ &\leq k_{i,n+1}(k_{i-1,n+1} + 1) \\ \max \left| p_{i-1}^{*}(s_{n+1}, t + 1) + p_{0}(s_{n+1}, t + 1) - l_{0,i-1} \right| \\ &+ ((k_{i,n}(k_{i-1,n} + 1) + \alpha_{i} \prod_{j=1}^{n} (k_{i-1,j} + 1)) \\ &+ \sum_{j=1}^{n-1} (k_{i,j} \prod_{\beta=1}^{n} (k_{i-1,\beta} + 1)))(k_{i-1,n+1} + 1)) \\ &\cdot \max \left| p_{i-1}^{*}(s_{n+1}, t + 1) + p_{0}(s_{n+1}, t + 1) - l_{0,i-1} \right| \\ &= (k_{i,n+1}(k_{i-1,n+1} + 1) + \alpha_{i} \prod_{j=1}^{n+1} (k_{i-1,j} + 1)) \\ &+ \sum_{j=1}^{n} (k_{i,j} \prod_{\beta=1}^{n+1} (k_{i-1,\beta} + 1))) \\ &\cdot \max \left| p_{i-1}^{*}(s_{n+1}, t + 1) + p_{0}(s_{n+1}, t + 1) - l_{0,i-1} \right|. \end{aligned}$$
(60)

From (60), the following condition can be derived.

$$\max \left| p_{i}^{*}(s_{n+1}, t) - p_{0}(s_{n+1}, t) - l_{0,i} \right|$$

$$\leq (k_{i,n+1}(k_{i-1,n+1}+1) + \alpha_{i} \prod_{j=1}^{n+1} (k_{i-1,j}+1))$$

$$+ \sum_{j=1}^{n} (k_{i,j} \prod_{\beta=1}^{n+1} (k_{i-1,\beta}+1)))$$

$$\max \left| p_{i-1}^{*}(s_{n+1}, t+1) + p_{0}(s_{n+1}, t+1) - l_{0,i-1} \right|. (61)$$

Then according to the available condition (54), it yields

$$\max \left| p_i^*(s,t) - p_0(s,t) - l_{0,i}^* \right| \\ \leq k_s \max \left| p_{i-1}^*(s,t) - p_0(s,t) - l_{0,i} \right|.$$
(62)

where  $k_s = (k_{i,s}(k_{i-1,s} + 1) + \alpha_i \prod_{j=1}^{s} (k_{i-1,j} + 1) + \sum_{j=1}^{s-1} (k_{i,j} \prod_{\beta=1}^{s} (k_{i-1,\beta} + 1)))$ . Since  $k_{i,s}(k_{i-1,s} + 1) + \alpha_i \prod_{j=1}^{s} (k_{i-1,j} + 1) + \sum_{j=1}^{s-1} (k_{i,j} \prod_{\beta=1}^{s} (k_{i-1,\beta} + 1)) \le 1$  and the condition in (29) is hold, one can get that  $k_s \le 1$ . Then, the string stability of the platoon system is guaranteed.

Remark 5: Under the proposed distributed MPC algorithm, the string stability of the discrete-time platoon system is always guaranteed under the both BD and PF structures. This is different from the results in [35] and [36], where the string stability is not considered. The string stability can be proved by the Laplacian transformation of position errors for linear continuous system. However, the system's position error cannot be directly Laplace transformed for discretetime systems. Compared with the string stability analysis of linear continuous system in [43], the string stability analysis of discrete system is more challenging. The string stability analysis for nonlinear discrete system is also one of our future works.

## V. SIMULATION

## A. Simulation Parameters Settings

In this subsection, a vehicle platoon system with 10 vehicles modeled by the discrete model (1) is considered. The first vehicle is considered as a leader while the others are considered as followers. The initial position of the virtual leader is  $X_0 = 100$  and the virtual leader is moving as a constant velocity of  $v_0 = 5m/s$ . The desired distance between each vehicle is considered as  $l_{i,i-1} = 5m$ . In this paper, the horizon



(a) The initial position and the end positions of each vehicle, (b) The spacing errors of each vehicle, where  $SE_i$  represents where  $P_{Vi}$  represents the position of vehicle *i*.  $p_{i-1} - p_i - l_{i-1,i}$ .



(c) The velocities of each vehicle, where  $V_{Vi}$  represents the(d) The accelerations of each vehicle, where  $A_{Vi}$  represents velocity of vehicle *i*. the acceleration of vehicle *i*.

Fig. 2. The results for vehicle platoon system under PF structure.

TABLE I The Mass and Initial States of Each Vehicle

The Mass and initial states of each vehicle in platoon system				
No./State	Mass	Position	Velocity	Acceleration
	(kg)	( <i>m</i> )	(m/s)	$(m/s^2)$
Vehicle <sub>0</sub>	5	100	5	0
Vehicle <sub>1</sub>	5.6557	90	3	0
Vehicle <sub>2</sub>	5.0357	81	2	0
Vehicle <sub>3</sub>	5.8791	73	1	0
Vehicle <sub>4</sub>	5.9340	66	0.7	0
Vehicle <sub>5</sub>	5.6787	60	0.7	0
Vehicle <sub>6</sub>	5.7577	55	0.1	0
Vehicle <sub>7</sub>	5.7431	51	0.3	0
Vehicle <sub>8</sub>	5.3922	47	2	0
Vehicle <sub>9</sub>	5.6555	45	3	0

is set as T = 10s, the predictive horizon is set as  $N_p = 15$ , and the update period is set as  $\tau = 0.1s$ , respectively. The model parameters are  $\Delta s = 0.5s$ ,  $m_a = 1$ ,  $c_a = 0.98m^2$ ,  $c_g = 0.01$ , and  $f_{cg} = 0.5N$ . All of the vehicles in the platoon system moving in the positive direction of X-axis. The initial states of each vehicle are given in Table I. The simulation results are given as follows to verify the effectiveness of the proposed algorithm.

#### B. The Simulation Results Under BD Structure

The platoon control using the proposed distributed MPC-based method under the BD structure is presented in this subsection. The initial conditions and control setting are given in previous subsection. The main results are shown in Fig.1. Under the BD structure, both the front vehicle  $(i - 1)_{\text{th}}$  and the following vehicle  $(i + 1)_{\text{th}}$  can be affect by the vehicle  $i_{\text{th}}$  in the platoon system. Fig.1(a) shows the position of each vehicle. Since a constant velocity is defined to the leader vehicle's,

the final slopes of each vehicle's position is the same as that of the virtual leader. Fig.1(b) shows the spacing errors of each vehicle in the platoon system, which satisfy the system's string stability. Fig.1(c) and Fig.1(d) show the velocity and acceleration, respectively. It can be seen that the spacing errors of each vehicle are all converged to zero, the velocity and the acceleration of each vehicle are converged to the leader's velocity and acceleration, respectively. It can be seen that under the proposed distributed MPC-based algorithm, both the asymptotical stability and the string stability are guaranteed.

## C. The Simulation Results Under PF Structure

Fig.2 shows the results by using the proposed distributed MPC-based method under a PF platoon structure, which means the vehicle  $i_{th}$  only contact to the front vehicle  $(i - 1)_{th}$  in the system. The simulation setting is same to the ones in Subsection A. According to the PF structure, the local cost function will change as  $J_i(t) = \sum_{s=0}^{N_p-1} (\|K_i(\Phi_i^p(s,t) - \Phi_i^*(s,t))\| + \|R_i u_i^p(s,t)\| + \|F_i(\Phi_i^p(s,t) - \hat{\Phi}_i(s,t)\| + \sum_{i \in I_i} \|G_i(\frac{1}{2}(\Phi_i^p(s,t) - \hat{\Phi}_{i-1}(s,t) + L_{i,i-1}))\|)$ . Fig.2(a) shows the position of each vehicle. Since the virtual leader runs with a constant velocity, the final slopes of each vehicle's position is the same as it. The spacing errors are shown in in Fig.2(b), which

same as it. The spacing errors are shown in in Fig.2(b), which can be seen that the string stability of the platoon system is guaranteed. The velocities and accelerations are shown in Fig.2(c) and Fig.2(d), respectively. Fig.4 shows the cost of each vehicle under the BD structure and the PF structure. From Fig.1 and Fig.2, we can know that the proposed distributed MPC-based method can guarantee the close-loop stability of the system both under the BD structure and the PF



(a) The initial position and the end positions of each vehicle, (b) The spacing errors of each vehicle, where  $SE_i$  represents where  $P_{Vi}$  represents the position of vehicle *i*.  $p_{i-1} - p_i - l_{i-1,i}$ .



(c) The velocities of each vehicle, where  $V_{Vi}$  represents the(d) The accelerations of each vehicle, where  $A_{Vi}$  represents velocity of vehicle *i*.

Fig. 3. The results for vehicle platoon system under BD structure with CMPC.



(a) The cost of the platoon system under BD(b) The cost of the platoon system under PF struc-(c) The cost of the platoon system under BD structure. structure with CMPC.

Fig. 4. The cost of the platoon system under BD structure and PF structure.

structure. The string stability of the platoon system also can be guarantee under the proposed method. The cost functions converge to zero under the distributed MPC algorithm, which is shown in Fig.4.

# D. Comparison Results Under BD Structure With Centralized MPC

In this subsection, comparison results with the centralized MPC algorithm proposed in [34] are presented. Based on [34], the cost function and constraints in  $\Gamma_i(t)$  are aggregated and replace  $\hat{\Phi}_j(s, t)$  with  $\Phi_j^p(s, t)$  in the MPC method. Since global information in the platoon system can be used in the centralized MPC method, the real-time predicted trajectory  $\Phi_j^p(s, t)$  is used to avoid the local optimum instead of the assumed trajectory  $\hat{\Phi}_j(s, t)$  in it. From Fig.3, it can be seen that even though the system can be converged, the string stability cannot be guaranteed. Fig.4 shows the cost of each vehicle under the BD structure and the PF structure.

## VI. CONCLUSION

The distributed MPC algorithm is proposed for a discrete-time platoon system in this paper. The method can

be applied not only to the PF-based vehicle platoon structures but also to the BD-based one. By considering the sum of the local cost function as the candidate Lyapunov function, the asymptotical stability is guaranteed. In addition, rigorous proof is also presented for the string stability issue of the platoon system. Finally, simulation results as well as comparison results are presented to show the effectiveness of the proposed control scheme. How to ensure the effectiveness of the proposed control method for some complicated cases, such as the nonlinear discrete vehicle platoon system under communication failure/delays, traffic oscillations and emergency braking, will be considered in future works.

#### REFERENCES

- Y. Li, K. Li, T. Zheng, X. Hu, H. Feng, and Y. Li, "Evaluating the performance of vehicular platoon control under different network topologies of initial states," *Phys. A, Stat. Mech. Appl.*, vol. 450, pp. 359–368, May 2016.
- [2] T. Tank and J. P. M. G. Linnartz, "Vehicle-to-vehicle communications for AVCS platooning," *IEEE Trans. Veh. Technol.*, vol. 46, no. 2, pp. 528–536, May 1997.
- [3] J. Wang, X. Luo, W. Wong, and X. Guan, "Specified-time vehicular platoon control with flexible safe distance constraint," *IEEE Trans. Veh. Technol.*, vol. 68, no. 11, pp. 10489–10503, Nov. 2019.

- [4] G. Antonelli and S. Chiaverini, "Kinematic control of platoons of autonomous vehicles," *IEEE Trans. Robot.*, vol. 22, no. 6, pp. 1285–1292, Dec. 2006.
- [5] P. Barooah, P. G. Mehta, and J. P. Hespanha, "Mistuning-based control design to improve closed-loop stability margin of vehicular platoons," *IEEE Trans. Autom. Control*, vol. 54, no. 9, pp. 2100–2113, Sep. 2009.
- [6] Y. Zheng, S. Li, K. Li, and L.-Y. Wang, "Stability margin improvement of vehicular platoon considering undirected topology and asymmetric control," *IEEE Trans. Control Syst. Technol.*, vol. 24, no. 4, pp. 1253–1265, Jul. 2016.
- [7] J. Wang, W.-C. Wong, X. Luo, X. Li, and X. Guan, "Connectivitymaintained and specified-time vehicle platoon control systems with disturbance observer," *Int. J. Robust Nonlinear Control*, vol. 31, no. 16, pp. 78440–7861, 2021.
- [8] J. Wang, X. Luo, X. Li, and X. Guan, "Robust predefined-time platoon control of networked vehicles with uncertain disturbances," *Int. J. Syst. Sci.*, vol. 52, no. 15, pp. 3128–3140, 2021.
- [9] Y. Zheng, S. E. Li, J. Wang, L. Y. Wang, and K. Li, "Stability and scalability of homogeneous vehicular platoon: Study on the influence of information flow topologies," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 1, pp. 14–26, Jan. 2016.
- [10] S. E. Li, Y. Zheng, K. Li, and J. Wang, "An overview of vehicular platoon control under the four-component framework," in *Proc. IEEE Intell. Vehicles Symp. (IV)*, Jul. 2015, pp. 286–291.
- [11] S. Sheikholeslam and C. A. Desoer, "Longitudinal control of a platoon of vehicles with no communication of lead vehicle information: A system level study," *IEEE Trans. Veh. Technol.*, vol. 42, no. 4, pp. 546–554, Nov. 1993.
- [12] S. S. Stankovic, M. J. Stanojevic, and D. D. Siljak, "Decentralized overlapping control of a platoon of vehicles," *IEEE Trans. Control Syst. Technol.*, vol. 8, no. 5, pp. 816–832, Sep. 2000.
- [13] R. H. Middleton and J. H. Braslavsky, "String instability in classes of linear time invariant formation control with limited communication range," *IEEE Trans. Autom. Control*, vol. 55, no. 7, pp. 1519–1530, Jul. 2010.
- [14] S. E. Li et al., "Dynamical modeling and distributed control of connected and automated vehicles: Challenges and opportunities," *IEEE Intell. Transp. Syst. Mag.*, vol. 9, no. 3, pp. 46–58, Fall 2017.
- [15] J. Hu, P. Bhowmick, F. Arvin, A. Lanzon, and B. Lennox, "Cooperative control of heterogeneous connected vehicle platoons: An adaptive leader-following approach," *IEEE Robot. Autom. Lett.*, vol. 5, no. 2, pp. 977–984, Apr. 2020.
- [16] S. Wen and G. Guo, "Distributed trajectory optimization and sliding mode control of heterogenous vehicular platoons," *IEEE Trans. Intell. Transp. Syst.*, vol. 23, no. 7, pp. 7096–7111, Jul. 2022.
- [17] J. Sawant, U. Chaskar, and D. Ginoya, "Robust control of cooperative adaptive cruise control in the absence of information about preceding vehicle acceleration," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 9, pp. 5589–5598, Sep. 2021.
- [18] M. A. Rodrigues and D. Odloak, "MPC for stable linear systems with model uncertainty," *Automatica*, vol. 39, no. 4, pp. 569–583, 2003.
- [19] J. R. D. Frejo and E. F. Camacho, "Global versus local MPC algorithms in freeway traffic control with ramp metering and variable speed limits," *IEEE Trans. Intell. Transp. Syst.*, vol. 13, no. 4, pp. 1556–1565, Dec. 2012.
- [20] S. Riverso, M. Farina, and G. Ferrari-Trecate, "Plug-and-play decentralized model predictive control for linear systems," *IEEE Trans. Autom. Control*, vol. 58, no. 10, pp. 2608–2614, Oct. 2013.
- [21] G. Mantovani and L. Ferrarini, "Temperature control of a commercial building with model predictive control techniques," *IEEE Trans. Ind. Electron.*, vol. 62, no. 4, pp. 2651–2660, Apr. 2015.
- [22] S. Di Cairano, H. E. Tseng, D. Bernardini, and A. Bemporad, "Vehicle yaw stability control by coordinated active front steering and differential braking in the tire sideslip angles domain," *IEEE Trans. Control Syst. Technol.*, vol. 21, no. 4, pp. 1236–1248, Jul. 2013.
- [23] R. R. Negenborn and J. M. Maestre, "Distributed model predictive control: An overview and roadmap of future research opportunities," *IEEE Control Syst.*, vol. 34, no. 4, pp. 87–97, Aug. 2014.
- [24] E. Camponogara and L. B. De Oliveira, "Distributed optimization for model predictive control of linear-dynamic networks," *IEEE Trans. Syst.*, *Man, Cybern. A, Syst. Humans*, vol. 39, no. 6, pp. 1331–1338, Jun. 2009.
- [25] H. Hao, P. Barooah, and P. G. Mehta, "Stability margin scaling laws for distributed formation control as a function of network structure," *IEEE Trans. Autom. Control*, vol. 56, no. 4, pp. 923–929, Apr. 2011.

- [26] 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," *Annu. Rev. Control*, vol. 47, pp. 81–97, Mar. 2019.
- [27] M. Treiber and A. Kesting, "Traffic flow dynamics," *Traffic Flow Dynamics: Data, Models and Simulation.* Berlin, Germany: Springer, 2013.
- [28] X. Guo, J. Wang, F. Liao, and R. S. H. Teo, "Distributed adaptive integrated-sliding-mode controller synthesis for string stability of vehicle platoons," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 9, pp. 2419–2429, Apr. 2016.
- [29] P. Seiler, A. Pant, and K. Hedrick, "Disturbance propagation in vehicle strings," *IEEE Trans. Autom. Control*, vol. 49, no. 10, pp. 1835–1842, Oct. 2004.
- [30] J. Ploeg, D. P. Shukla, N. Van De Wouw, and H. Nijmeijer, "Controller synthesis for string stability of vehicle platoons," *IEEE Trans. Intell. Transp. Syst.*, vol. 15, no. 2, pp. 854–865, Apr. 2014.
- [31] D. Swaroop and J. K. Hedrick, "String stability of interconected systems," *IEEE Trans. Autom. Control*, vol. 41, no. 3, pp. 1806–1810, Mar. 1996.
- [32] M. Burkhardt, H. Yu, and M. Krstic, "Stop-and-go suppression in two-class congested traffic," *Automatica*, vol. 125, Mar. 2021, Art. no. 109381.
- [33] P. Barooah and J. P. Hespanha, "Error amplification and disturbance propagation in vehicle strings with decentralized linear control," in *Proc.* 44th IEEE Conf. Decis. Control, Dec. 2005, pp. 4964–4969.
- [34] J.-Q. Wang, S. E. Li, Y. Zheng, and X.-Y. Lu, "Longitudinal collision mitigation via coordinated braking of multiple vehicles using model predictive control," *Integr. Comput.-Aided Eng.*, vol. 22, no. 2, pp. 171–185, 2015.
- [35] K. Li, Y. Bian, S. E. Li, B. Xu, and J. Wang, "Distributed model predictive control of multi-vehicle systems with switching communication topologies," *Transp. Res. C, Emerg. Technol.*, vol. 118, Sep. 2020, Art. no. 102717.
- [36] Y. Zheng, S. E. Li, K. Li, F. Borrelli, and J. K. Hedrick, "Distributed model predictive control for heterogeneous vehicle platoons under unidirectional topologies," *IEEE Trans. Control Syst. Technol.*, vol. 25, no. 3, pp. 899–910, Dec. 2017.
- [37] W. B. Dunbar and D. S. Caveney, "Distributed receding horizon control of vehicle platoons: Stability and string stability," *IEEE Trans. Autom. Control*, vol. 57, no. 3, pp. 620–633, Mar. 2012.
- [38] Y. Liu, H. Gao, C. Zhai, and W. Xie, "Internal stability and string stability of connected vehicle systems with time delays," *IEEE Trans. Intell. Transp. Syst.*, vol. 22, no. 10, pp. 6162–6174, Oct. 2021.
- [39] Y. Liu, C. Pan, H. Gao, and G. Guo, "Cooperative spacing control for interconnected vehicle systems with input delays," *IEEE Trans. Veh. Technol.*, vol. 66, no. 12, pp. 10692–10704, Dec. 2017.
- [40] H. Ma, L. Chu, J. Guo, J. Wang, and C. Guo, "Cooperative adaptive cruise control strategy optimization for electric vehicles based on SA-PSO with model predictive control," *IEEE Access*, vol. 8, pp. 225745–225756, 2020.
- [41] B. Hu and M. D. Lemmon, "Distributed switching control to achieve almost sure safety for leader-follower vehicular networked systems," *IEEE Trans. Autom. Control*, vol. 60, no. 12, pp. 3195–3209, Dec. 2015.
- [42] Y. Zhang, Y. Bai, J. Hu, D. Cao, and M. Wang, "Memory-anticipation strategy to compensate for communication and actuation delays for strings-stable platooning," *IEEE Trans. Intell. Vehicles*, early access, Feb. 16, 2022, doi: 10.1109/TIV.2022.3152047.
- [43] Y. Zhou, M. Wang, and S. Ahn, "Distributed model predictive control approach for cooperative car-following with guaranteed local and string stability," *Transp. Res. B, Methodol.*, vol. 128, pp. 69–86, Jan. 2019.



**Jiange Wang** received the M.S. and Ph.D. degrees in control science and engineering from Yanshan University, Qinhuangdao, China, in 2017 and 2020, respectively.

From July 2018 to September 2020, she was an exchange Ph.D. student at the National University of Singapore, Singapore. From 2021 to 2022, she was a Research Fellow at the Department of Electrical Engineering, Yeungnam University, South Korea. She is currently a Faculty Member with the School of Electrical Engineering, Yanshan University. Her

research interests include cooperative control for multi-agent systems and intelligent transportation systems.



Xiaolei Li (Member, IEEE) received the B.Eng. and Ph.D. degrees in control engineering from Yanshan University, China, in 2012 and 2018, respectively. From September 2018 to July 2022, he was a Research Fellow at the School of Electrical and Electronic Engineering, Nanyang Technological University, Singapore. He joined the Yanshan University, in August 2022, where he is currently an Associate Professor. He received the Best Paper Award of the 16th Conference on Industrial Electronics and Applications ICIEA 2021. His current research inter-

ests include localization and formation control of robotic systems and cyber security of cyber-physical systems.



Ge Guo (Senior Member, IEEE) received the B.S. and Ph.D. degrees from Northeastern University, Shenyang, China, in 1994 and 1998, respectively. From May 2000 to April 2005, he was a Professor at the Lanzhou University of Technology, China, and the Director of the Institute of Intelligent Control and Robots. He then joined as a Professor with the Department of Automation, Dalian Maritime University, China. Since 2018, he has been a Professor with Northeastern University and the Dean of the School of Control Engineering at Qinhuangdao Campus.

He has published more than 150 international journal articles within his areas of interest. His research interests include intelligent transportation systems and cyber-physical systems. He was an Honoree of the New Century Excellent Talents in University, Ministry of Education, China, in 2004, and a Nominee for Gansu Top Ten Excellent Youths by the Gansu Provincial Government in 2005. He received the CAA Young Scientist Award in 2017 and the First Prize of Natural Science Award of Hebei Province in 2020. He is an Associate Editor of the IEEE TRANSACTIONS ON INTELLIGENT TRANSPORTATION SYSTEMS, the IEEE TRANSACTIONS ON INTELLIGENT VEHICLES, the *Information Sciences*, the *IEEE Intelligent Transportation Systems Magazine*, the ACTA Automatica Sinica, the China Journal of Highway and Transport, and the Journal of Control and Decision.



**Ju H. Park** (Senior Member, IEEE) received the Ph.D. degree in electronics and electrical engineering from the Pohang University of Science and Technology (POSTECH), Pohang, South Korea, in 1997.

From May 1997 to February 2000, he was a Research Associate at the Engineering Research Center-Automation Research Center, POSTECH. He joined Yeungnam University, Kyongsan, South Korea, in March 2000, where he is currently the Chuma Chair Professor. He is a coauthor of the

monographs Recent Advances in Control and Filtering of Dynamic Systems with Constrained Signals (New York, NY, USA: Springer-Nature, 2018) and Dynamic Systems With Time Delays: Stability and Control (New York, NY, USA: Springer-Nature, 2019). He has published a number of articles in his research areas. His research interests include robust control and filtering, neural/complex networks, fuzzy systems, multiagent systems, and chaotic systems. He is a fellow of the Korean Academy of Science and Technology (KAST). Since 2015, he has been a recipient of the Highly Cited Researchers Award by Clarivate Analytics (formerly, Thomson Reuters) and listed in three fields, engineering, computer sciences, and mathematics, from 2019 to 2022. He is an Editor of the International Journal of Control, Automation and Systems and is an Editor of an edited volume Recent Advances in Control Problems of Dynamical Systems and Networks (New York: Springer-Nature, 2020). He is also a Subject Editor/an Advisory Editor/an Associate Editor/an Editorial Board Member of several international journals, including IET Control Theory and Applications, Applied Mathematics and Computation, Journal of The Franklin Institute, Nonlinear Dynamics, Engineering Reports, Cogent Engineering, the IEEE TRANSACTION ON FUZZY SYSTEMS, the IEEE TRANSACTION ON NEURAL NETWORKS AND LEARNING SYSTEMS, and the IEEE TRANSACTION ON CYBERNETICS.