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Switching Multi-Objective Receding Horizon Control for CACC of Mixed Vehicle Strings

XIULAN SONG^{ID}, KE WANG^{ID}, AND DEFENG HE^{ID}

College of Information Engineering, Zhejiang University of Technology, Hangzhou 310023, China

Corresponding author: Xiulan Song (songxl2008@zjut.edu.cn)

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ABSTRACT Vehicle safety, ride comfort, formation control and fuel economy are the main control objectives of cooperative adaptive cruise control (CACC) of vehicle strings. This paper considers the multi-objective CACC problem of a mixed vehicle string, i.e., the vehicle string is composed of CACC-, ACC- and human-driven vehicles. A new switching multi-objective receding horizon predictive control method is proposed for CACC of mixed vehicle strings. The longitudinal models of ACC- and human-driven vehicles are used to estimate the driving behaviors of the individual vehicles. Then three multi-objective predictive controllers are separately designed for different vehicle scenarios. According to different preceding vehicles, the multi-objective predictive controllers are switched online in the normal situation, and in the dangerous situation, the predictive controller is switched to the safety controller to ensure driving safety of vehicles in the string. To verify the effectiveness of the proposed control method, a mixed vehicle string consisting of six cars is used in the simulation experiment with complex traffic scenarios.

INDEX TERMS Multi-objective control, model predictive control, mixed vehicle strings, switching control.

I. INTRODUCTION

In the recent years, increasing vehicles cause many problems in most cities such as traffic jams, pollution and frequent traffic accidents [1]–[4]. Among many technologies to solve these problems, adaptive cruise control (ACC) is a widely adopted one in the context of current traffic infrastructure [5]–[8]. By on-board sensors (e.g. radars) measuring the spacing and relative speed of adjacent vehicles, the appropriate throttle or brake control actions of a host vehicle are calculated to adjust its following speed to keep a safe inter-vehicle distance (i.e. spacing) between the host vehicle and its predecessor [9]–[11]. Moreover, ACC can take less time from finding dangerous situation to reacting than human's driving, which greatly improves the driving safety of vehicles. In addition, ACC can quickly react to the traffic scenarios of front vehicles in advance and hence, it reduces the workloads of drivers and improves the ride comfort of cars [12]–[15].

In order to further increase the traffic capacity of roads, recently cooperative ACC (CACC) has been developed by the wireless Vehicle-to-Everything (V2X) communication network [16], [17]. By V2X, vehicles in the same traffic are

connected to share driving information (e.g. position, velocity, acceleration, etc.) among them. Due to sharing more driving information, CACC has shorter inter-vehicle distances, better comfort and safety performance than ACC, as well as the improved traffic efficiency of roads [17]–[19]. Many efforts have been made to develop CACC methods for connected and automated vehicles [10]–[19]. However, full automation of all connected vehicles on roads is not realistic under the current traffic conditions [20]–[22]. Hence, it is necessary to study CACC methods of mixed vehicle strings that are composed of human-driven vehicles and automated vehicles.

A mixed vehicle string generally includes human-driven vehicles, automated vehicles equipped with ACC systems (denoted as ACC-driven vehicles for simplicity) and automated vehicles with CACC systems (denoted as CACC-driven vehicles for simplicity), which run along a lane with safe inter-vehicle distances [23]–[25]. In mixed vehicle strings, the CACC-driven vehicles may not communicate with the human- and/or ACC-driven vehicles by V2X due to no full automation of the vehicles. This deteriorates the cooperative performance of the CACC systems designed for full connected and automated vehicles. The driving behaviors' uncertainties of front human-driven vehicles further

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degrade the following, comfort and safety performance of the CACC systems and hence, increase the accident risks of vehicles [26]–[31]. In CACC, formation is an important control objective of vehicle strings in order to guarantee the consistent following behaviors of the vehicle platoon and energy-saving is an also desired performance as reducing fuel consumption decreases pollution emissions of vehicles during travelling [32]–[37]. Consequently, how to ensure the control objectives of safety, ride comfort, formation and energy-saving is getting to be important and challenge task for the design of CACC systems in the mixed vehicle strings.

Compared with the abundant CACC results on fully connected and automated vehicles, there are few studies taking into account the aforementioned control objectives of mixed vehicle strings. For example, the authors [38] considered the ride comfort and safety objectives of CACC for mixed vehicle strings but ignored the fuel economy objective of vehicles. In [39], an eco-smart driving model was proposed to handle fuel-saving, ride comfort and formation control objectives for mixed vehicle strings and these control objectives were handled simultaneously for CACC-driven vehicles in [40]. But the method in [40] was not directly applied to mixed vehicle strings since the case of V2X intermittent transmission was not considered in CACC. The authors [41] adopted V2X communication to adjust the spacing between connected and non-connected vehicles in order to reduce congestion of mixed vehicle strings at T-junctions. In [42], the varying headway control strategy was proposed to improve the traffic efficiency of mixed vehicle strings, which was obtained through the spacing and relative speed of adjacent vehicles. Through V2X communication, the authors [43] proposed the distributed synchronous intersection protocol to improve the traffic efficiency and safety of mixed vehicle strings at intersections. To explicitly cope with the constraints on spacing, velocity and acceleration of vehicles, in [44] model predictive control (MPC) was used to develop CACC for mixed vehicle strings, where the formation control problem of the string was formulated as the finite horizon optimal control problem and was solved in manner of receding horizon.

This paper considers the multi-objective CACC problem of constrained mixed vehicle strings and proposes a new switching multi-objective receding horizon control approach for CACC of constrained mixed vehicle strings. To cope with the safety, ride comfort, formation and fuel economy objectives of CACC at the same time, the MPC strategy is used online for CACC-driven vehicles in the mixed string, where a set of longitudinal dynamic models is separately employed to predict the future driving behaviors of the human-driven and ACC-driven vehicles over a finite horizon window. Three multi-objective predictive controllers are designed for the CACC-driven vehicles to accommodate different traffic scenarios. Then these predictive CACC controllers are switched online according to overall consideration of front vehicles, normal situation and dangerous situation. To the best of our knowledge, there is no result on the switching receding horizon control approach for multi-objective CACC of constrained mixed

vehicle strings. The main contribution of this work is that the MPC and switching idea are combined to present a switching multi-objective predictive CACC approach of constrained mixed vehicle strings, such that the safety, ride comfort, formation and fuel economy objectives of the constrained mixed string are considered systematically in the framework of constrained optimal control. Finally, to illustrate the effectiveness of the proposed method, a mixed vehicle string consisting of six cars is used in the simulation experiment with complex traffic scenarios.

The rest of this paper is organized as follows. Section II presents models of mixed vehicle strings. In section III, three multi-objective predictive CACC controllers and a safety controller are designed to accommodate normal and dangerous driving situations, respectively. Section IV shows the simulation results of the proposed method and Section V concludes the paper.

II. MIXED VEHICLE STRINGS MODELING

Consider a mixed vehicle string consisting of M vehicles including human-, ACC- and CACC-driven vehicles, where the leading vehicle is a connected and automated car. Each vehicle cruises along a single lane with a safe inter-vehicle distance, where CACC-driven vehicles use the predecessor-following (PF) communication topology to obtain the information of position, velocity and acceleration of its front CACC-driven vehicle and the human- and ACC-driven vehicles in the string have no communication but can use onboard sensors to separately keep some safe inter-vehicle distances with their preceding vehicles. Due to the increasing adoption of 5G, in this paper, the V2X communication network-induced issues, e.g., time-varying delays, data-packet dropouts are not considered. Hence, it is assumed that the CACC-driven vehicles in the string can share their driving information among each other without time delays and packet dropouts and all vehicles can determine their own and other surrounding vehicles' information without errors.

Let $i = 1$ be leading vehicle and $i = 2, 3, \dots, M$ be the following vehicles in the mixed vehicle string. Labels I_H , I_A and I_C denote the index set of human-, ACC- and CACC-driven vehicles in the string, respectively. Let s_i , v_i and a_i be the position, speed, and acceleration of the i^{th} vehicle, respectively, and $\Delta t > 0$ be the sampling time for all vehicles in the string.

Consider the vehicle i and select the state vector $x_i = [s_i, v_i, a_i]^T$. For the vehicle $i \in I_H$ at sampling time k , the discrete-time prediction model of the human-driven vehicle can be described by [38]

$$x_i(k+1) = A_{i,i}x_i(k) + A_{i,i-1}x_{i-1}(k)$$

$$A_{i,i} = \begin{bmatrix} 1 & \Delta t & 0 \\ 0 & 1 & \Delta t \\ 0 & -2\alpha_i\Delta t/\mu_i & 1 + (2 - \alpha_i\mu_i)\Delta t/\mu_i \end{bmatrix}$$

$$A_{i,i-1} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 2\alpha_i\Delta t/\mu_i & -\alpha_i\Delta t \end{bmatrix} \quad (1)$$

where α_i is the sensitivity factor and μ_i is the driver's reaction time spent the response to the speed changes of the preceding vehicle. Moreover, consider the ACC-driven vehicle $i \in I_A$ at time k . The discrete-time prediction model of the closed-loop ACC system of the vehicle is represented by (2), as shown at the bottom of this page, where h_i is the headway of the ACC-driven vehicle, $\eta_i > 0$ is the lumped lag of the i^{th} vehicle's longitudinal dynamics and ω_i is the bandwidth of the system. Finally, consider the CACC-driven vehicle $i \in I_C$ and the prediction model of the open loop CACC system of the vehicle is represented by

$$x_i(k+1) = A_{i,i}x_i(k) + B_iu_i(k)$$

$$A_{i,i} = \begin{bmatrix} 1 & \Delta t & 0 \\ 0 & 1 & \Delta t \\ 0 & 0 & 1 - \Delta t/\zeta_i \end{bmatrix}, \quad B_i = \begin{bmatrix} 0 \\ 0 \\ \Delta t/\zeta_i \end{bmatrix} \quad (3)$$

where u_i is the acceleration command of the CACC-driven vehicle and $\zeta_i > 0$ is the lumped lag of the i^{th} vehicle's longitudinal dynamics.

By taking into account the control objectives of the safety, ride comfort, formation and fuel economy of the mixed vehicle strings, the goal of this paper is to design multi-objective optimal cruise controllers for the CACC-driven vehicles in (3) in the string. Here a set of multi-objective model predictive controllers and a safety controller will be designed for CACC-driven vehicles based on the prediction models (1)-(2). These controllers will be switched according to the different types of front vehicles and traffic scenarios in order to implement the control of CACC in the mixed vehicle string.

III. DESIGN OF SWITCHING CACC CONTROLLERS

The CACC objectives of mixed vehicle strings include vehicle safety, ride comfort, fuel economy and formation control. For each CACC objective of the vehicle string, the following constraints are used to ensure that these objectives are achieved.

Objective 1: Ride comfort. The ride comfort of a vehicle is affected by the acceleration and its variation of the vehicle [45]. Clearly, the excessive changes of acceleration of the vehicle will cause discomfort to passengers. Hence, the following acceleration constraints are used to ensure the ride comfort performance of vehicle $i \in I_C$:

$$\begin{cases} -a_{i,\max} \leq a_i(k) \leq a_{i,\max} \\ |a_i(k) - a_i(k-1)| \leq \Delta a_{i,\max} \Delta t \end{cases} \quad (4)$$

for $k \geq 0$, where $\Delta a_{i,\max} > 0$ and $a_{i,\max} > 0$ are the allowed maximum acceleration variation per second and the maximum acceleration, respectively. Let $a_{i,\min} = -a_{i,\max}$ for simplicity.

Objective 2: Driving safety. This objective can be measured by spacing and speed of vehicles. If the spacing of adjacent vehicles is too small, collisions may occur. Let $D_{i,i-1}(k) = s_{i-1}(k) - s_i(k) - L_i$ be the spacing between the vehicles i and $i-1$ at time k , where $s_i(k)$ and $s_{i-1}(k)$ are the position of vehicle i and vehicle $i-1$, respectively, and L_i is the length of vehicle i . Clearly, an excessively fast speed increases the possibility of traffic accidents. To guarantee driving safety, the following constraints should be satisfied for all times:

$$\begin{cases} D_{i,i-1}(t|k) \geq R_i, & v_{i,\min} \leq v_i(t|k) \leq v_{i,\max} \\ v_i^p(t|k) \geq 0, & v_{i-1}^a(t|k) \geq 0 \\ s_{i-1}^a(t|k) - s_i^p(t|k) - l_{i-1} \geq 0 \\ s_{i-1}^a(t|k) - s_i^p(t|k) - l_{i-1} + \frac{v_{i-1}^a(t|k)^2}{2a_{i-1,\min}} \geq \frac{v_i^p(t|k)^2}{2a_{i,\min}} \end{cases} \quad (5)$$

for $k \geq 0$ and $t > 0$, where $v_{i,\min} \geq 0$ and $v_{i,\max} > 0$ are the allowed minimum and maximum velocity of vehicle i , respectively, $s_i^p(t|k)$ and $v_i^p(t|k)$ are the predicted position and velocity of vehicle i at time $k + t\Delta t$, respectively, $s_{i-1}^a(t|k)$ and $v_{i-1}^a(t|k)$ are the assumed position and velocity of vehicle $i-1$ at time $k + t\Delta t$, respectively, $l_i = R_i + L_i$ is the virtual length of vehicle i , and R_i is the allowed minimum safe spacing of vehicle i . Note that here we focused on the CACC issue of constrained mixed vehicle strings travelling a single lane. Hence, the driving safety of vehicles changing lanes is out of scope of this work and will be studied in the future.

Objective 3: Formation control. This objective ensures that the following vehicles keep up with the preceding vehicles with some small spacing while avoiding accidents. To achieve the formation control objective of mixed vehicle strings, the following constraints are satisfied for all times [40]:

$$\begin{cases} \lim_{k \rightarrow \infty} D_{i,i-1}(k) = D_{i,i-1}^{st} \\ \lim_{k \rightarrow \infty} v_i(k) = v_0(k) = v_i^{st} \\ \lim_{k \rightarrow \infty} a_i(k) = 0 \end{cases} \quad (6)$$

where $D_{i,i-1}^{st} \geq R_i$ and v_i^{st} are desired spacing and velocity of vehicle i , respectively and $v_0(k)$ is the velocity of the leader.

$$x_i(k+1) = A_{i,i}x_i(k) + A_{i,i-1}x_{i-1}(k)$$

$$A_{i,i} = \begin{bmatrix} 1 & \Delta t & 0 \\ 0 & 1 & \Delta t \\ -\omega_i \Delta t / \eta_i & -(\omega_i^2 + \omega_i h_i) \Delta t / \eta_i & 1 - (1 + \omega_i^2 h_i) \Delta t / \eta_i \end{bmatrix}$$

$$A_{i,i-1} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ -\omega_i \Delta t / \eta_i & \omega_i^2 \Delta t / \eta_i & 0 \end{bmatrix} \quad (2)$$

Objective 4: Fuel economy. This objective ensures that fuel consumption of a CACC-driven vehicle is as small as possible over the prediction horizon $N > 1$ at each time k . Here the fuel economy objective of CACC-driven vehicle $i \in I_C$ is measured by the cost function

$$F_i(k) = \sum_{t=0}^{N-1} f_i^p(v_i^p(t|k), a_i^p(t|k)) \quad (7)$$

where $f_i^p(t|k)$ is the predicted fuel consumption rate of the vehicle at time $k + t\Delta t$ and is computed as [40]

$$f_i^p(v_i^p(t|k), a_i^p(t|k)) = \begin{cases} \frac{\tilde{f}_i(t|k)v_i^p(t|k)\Delta t}{\eta_{i,R}\zeta_{i,P}} + \tilde{f}_i\Delta t, & \text{if } \tilde{f}_i(t|k) > 0 \\ \tilde{f}_i\Delta t, & \text{otherwise} \end{cases} \quad (8)$$

where $\tilde{f}_i(t|k) = m_i g r_i + c_i v_i^p(t|k)^2 + m_i a_i^p(t|k)$ is the engine traction at time $k + t\Delta t$, terms $a_i^p(t|k)$ and $v_i^p(t|k)$ are the predicted acceleration and velocity of the vehicle at time $k + t\Delta t$, respectively, and m_i , g , r_i , c_i , $\eta_{i,R}$, $\zeta_{i,P}$, and \tilde{f}_i are the mass, gravity acceleration, rolling resistance coefficient, lumped aerodynamic drag coefficient, transmission efficiency, amount of work produced by 1g gasoline and idle fuel consumption rate of the vehicle, respectively.

In the vehicle string, the spacing error of vehicle i with respect to the desired spacing can be re-defined as

$$D_{i,i-1}(k) - D_{i,i-1}^{st} = s_{i-1}^p(t|k) - s_i^a(t|k) - L_i - d \quad (9)$$

where $s_{i-1}^p(t|k)$ and $s_i^a(t|k)$ are the predicted position of vehicle $i - 1$ and the assumed position of vehicle i at time $k + t\Delta t$, respectively, and d is the desired spacing. Assume that the string achieves the formation control objective at the terminal time $k + N\Delta t$. Then the desired position of vehicle i is computed as $s_{i,d}(N|k) = s_{i-1}^a(N|k) - L_i - d$, where $s_{i,d}(N|k)$ is the desired position of vehicle i at the terminal time. Then the position error between the desired position and the actual position can be computed as $\Delta s_i(N|k) = s_{i,d}(N|k) - s_i^p(N|k)$, where $s_i^p(N|k)$ is the predicted position of vehicle i at $k + N\Delta t$.

Now consider the i^{th} CACC-driven vehicle in the mixed string. At time k with the state $x_i(k)$, the multi-objective optimal CACC problem of vehicle $i \in I_C$ can be formulated as

$$a_i^*(:|k) = \underset{a_i^p(:|k)}{\operatorname{argmin}} J_i(x_i(k)) \quad (10)$$

subject to

$$\begin{cases} (4), (5), (9) \\ s_i^p(t+1|k) = s_i^p(t|k) + v_i^p(t|k)\Delta t \\ v_i^p(t+1|k) = v_i^p(t|k) + a_i^p(t|k)\Delta t \\ s_{i-1}^a(N|k) = s_{i-1}(k) + \Delta t \sum_{n=0}^{N-1} v_{i-1}^a(n|k) \\ v_{i-1}^a(t+1|k) = v_{i-1}^a(t|k) + \Delta t a_{i-1}^a(t|k) \\ a_i^p(N-1|k) = 0 \end{cases}$$

where $a_i^p(:|k)$ represents the optimal control input sequence, i.e., $a_i^p(:|k) = \{a_i^p(0|k), a_i^p(1|k), \dots, a_i^p(N-1|k)\}$, and the cost function $J_i(x_i(k)) = \beta_i F_i(k) + \gamma_i |\Delta s_i(N|k)|$ with weights $\beta_i > 0$ and $\gamma_i > 0$. Note that the penalty function on terminal spacing errors with its weight γ_i in J_i is used to ensure stability of predictive CACC controllers.

During the traveling of vehicles, it is necessary to obtain the real-time velocity and acceleration profiles of vehicles to calculate the fuel consumption of vehicles. In order to improve the computational efficiency, a fuel consumption table is established based on the velocity and acceleration profiles of vehicles. Therefore the fuel consumption of a vehicle is real-time obtained by online looking up the table. Here the speed and acceleration profiles are discretized as the form of [46], [47]

$$\begin{cases} a_i^{[l]} = -a_{i,\min} + (l-1)\delta_{i,a}, & l \in [1, L_{i,a}] \\ v_i^{[n]} = v_{i,\min} + (n-1)\delta_{i,v}, & n \in [1, L_{i,v}] \\ a_i^{[L_{i,a}]} = a_{i,\max}, & v_i^{[L_{i,v}]} = v_{i,\max} \end{cases} \quad (11)$$

where $\delta_{i,a}$ and $\delta_{i,v} = \delta_{i,a}\Delta t$ represent the acceleration and velocity resolutions of CACC-driven vehicle i , respectively, and integers $L_{i,a} > 1$ and $L_{i,v} > 1$ are the dimension of the table. Correspondingly, the fuel consumption table of the vehicle can be designed as [40]

$$f_i^{p[l,k]} = \begin{cases} \left(m_i g r_i + c_i \left(v_i^{[n]} \right)^2 + a_i^{[l]} m_i \right) v_i^{[n]} \Delta t / \eta_{i,R} \zeta_{i,P} + \tilde{f}_i \Delta t, & \text{condition 1} \\ \tilde{f}_i \Delta t, & \text{condition 2} \\ \inf, & \text{condition 3} \end{cases} \quad (12)$$

where

$$\begin{aligned} \text{condition 1 : } & \begin{cases} 0 < m_i a_i^{[l]} + m_i g r_i + c_i \left(v_i^{[n]} \right)^2 \leq \frac{\eta_{i,T} P_{i,\max}}{v_i^{[k]}} \\ v_{i,\min} \leq v_i^{[n]} + a_i^{[l]} \Delta t \leq v_{i,\max} \end{cases} \\ \text{condition 2 : } & \begin{cases} -B_{i,\max} \leq m_i a_i^{[l]} + m_i g r_i + c_i \left(v_i^{[n]} \right)^2 \leq 0 \\ v_{i,\min} \leq v_i^{[n]} + a_i^{[l]} \Delta t \leq v_{i,\max} \end{cases} \\ \text{condition 3 : } & \begin{cases} v_i^{[n]} + a_i^{[l]} \Delta t > v_{i,\max} \text{ or } v_i^{[n]} + a_i^{[l]} \Delta t < v_{i,\min} \\ \text{or } m_i a_i^{[l]} + m_i g r_i + c_i \left(v_i^{[n]} \right)^2 > \frac{\eta_{i,T} P_{i,\max}}{v_i^{[n]}} \\ \text{or } m_i a_i^{[l]} + m_i g r_i + c_i \left(v_i^{[n]} \right)^2 < -B_{i,\max}. \end{cases} \end{aligned}$$

Therefore, the constraints in the CACC problem (10) are converted into the following constraints:

$$\begin{cases} a_i^{[l]}(t|k) = a_i^{[l]} \\ |a_i^{[l]}(t+1|k) - a_i^{[l]}(t|k)| \leq \Delta a_{i,\max} \Delta t \\ a_i^{[l]}(N-1|k) = 0 \\ v_i^{[n]}(t+1|k) - v_i^{[n]}(t|k) = a_i^{[l]}(t|k) \Delta t \\ s_i^p(t+1|k) = s_i^p(t|k) + v_i^{[n]}(t|k) \Delta t \\ \sum_{m=1}^t v_i^{[n]}(m|k) \leq s_{i-1}^a(t|k) - s_i(k) - l_{i-1} \\ \frac{v_i^{[n]}(t|k)^2}{2a_{i,\min}} - \frac{v_{i-1}^a(t|k)^2}{2a_{i-1,\min}} - s_{i-1}^a(t|k) + s_i(k) + l_{i-1} \\ + \sum_{m=1}^t v_i^{[n]}(m|k) \Delta t \leq 0 \end{cases} \quad (13)$$

where $v_i^{[k]}(0|t)$ and $v_{i-1}^a(0|t)$ are the speed of vehicles i and $i-1$ at time t , respectively. Moreover, the cost function $J_i(x_i)$ in (10) is correspondingly reformulated as

$$J_i(x_i(k)) = \beta_i \sum_{t=0}^{N-1} f_i^{p[l,n]}(v_i^p(t|k), a_i^p(t|k)) + \gamma_i |\Delta s_i(N|k)| \quad (14)$$

In mixed vehicle strings, the information acquisition of CACC-driven vehicles varies with the preceding vehicles. When the preceding vehicle is a CACC-driven vehicle, the driving information can be directly obtained. However, the driving state information of an ACC-driven vehicle or human-driven vehicle for a certain time period cannot be directly obtained. As a result, it can only be predicted by the prediction models of these vehicles. Therefore, for different preceding vehicles, the cruise controllers of CACC-driven vehicles have to be switched among different controllers. In what follows, we present the switching cruise controller for a CACC-driven vehicle according to its preceding vehicle in the mixed string.

When the preceding vehicle is a CACC-driven vehicle, the driving information of the preceding vehicle can be directly obtained through the network. In this scenario, the driving information of the preceding vehicle can be directly obtained through V2X network, i.e.

$$\begin{cases} a_{i-1}^a(t|k) = u_{i-1}^*(t+1|k-1) \\ s_{i-1}^a(t+1|k) = s_{i-1}(k) + \Delta t v_{i-1}^a(t|k) \\ v_{i-1}^a(t+1|k) = v_{i-1}^a(t|k) + \Delta t a_{i-1}^a(t|k) \end{cases} \quad (15)$$

where $u_{i-1}^*(t+1|k-1)$ is the optimal control input at time $k-1$ of the preceding vehicle. Then the multi-objective cruise controller of the CACC-driven vehicle i is computed as

$$a_i^*(:|k) = \arg \min_{a_i^p(:|k)} \{J_i(x_i(k)) \text{ s.t. } (13), (15)\} \quad (16)$$

where $J_i(x_i)$ is given by (14) and solution $a_i^*(:|k)$ the optimal acceleration command sequence. According to the receding horizon principle of MPC, the CACC controller is selected the first element of $a_i^*(:|k)$, i.e., $u^*(k) = a_i^*(0|k)$.

In what follows, we consider the scenario where the preceding one of CACC-driven vehicle i is an ACC-driven vehicle $i-1$. The prediction model of the ACC-driven vehicle in (2) can be used to estimate the information of the ACC-driven vehicle, i.e.

$$\begin{cases} s_{i-1}^a(t+1|k) = s_{i-1}(k) + v_{i-1}^a(t|k) \Delta t \\ v_{i-1}^a(t+1|k) = v_{i-1}^a(t|k) + a_{i-1}^a(t|k) \Delta t \\ a_{i-1}^a(t|k) = a_{i-1}^a(t-1|k) + a_{i-1,a}(k-1) \Delta t \\ a_{i-1,a}(k) = \frac{\omega_{i-1}^2}{\eta_{i-1}} v_{i-2}^a(t|k) - \frac{\omega_{i-1}^2 + \omega_{i-1} h_{i-1}}{\eta_{i-1}} v_{i-1}^a(t|k) \\ + \frac{\omega_{i-1}}{\eta_{i-1}} (s_{i-2}^a(t|k) - s_{i-1}^a(t|k)) \\ - \frac{\omega_{i-1}^2 + 1}{\eta_{i-1}} a_{i-1}^a(t|k) \end{cases} \quad (17)$$

where $s_{i-2}^a(t|k)$ and $v_{i-2}^a(t|k)$ are the assumed position and speed at the time $k+t\Delta t$ of the preceding vehicle of the ACC-driven vehicle, respectively. If the preceding vehicle of the ACC-driven vehicle is a CACC-driven vehicle, the CACC-driven vehicle information can be directly obtained through communication, and then the ACC-driven vehicle information is predicted. If it is other types of vehicles, the prediction model is continuously used for prediction. In this scenario, the multi-objective controller of the CACC-driven vehicle can be computed as

$$a_i^*(:|k) = \arg \min_{a_i^p(:|k)} \{J_i(x_i(k)) \text{ s.t. } (13), (17)\} \quad (18)$$

where $J_i(x_i)$ is given by (14) and solution $a_i^*(:|k)$ the optimal acceleration command sequence. According to the receding horizon principle of MPC, the CACC controller is selected the first element of $a_i^*(:|k)$, i.e., $u^*(k) = a_i^*(0|k)$.

Now we consider the scenario where the preceding vehicle is a human-driven vehicle. The vehicle driving information is also unknown for a certain time period. Then the prediction model in (1) is used to estimate the driving information of the human-driven vehicle, i.e.

$$\begin{cases} s_{i-1}^a(t+1|k) = s_{i-1}(k) + v_{i-1}^a(t|k) \Delta t \\ v_{i-1}^a(t+1|k) = v_{i-1}^a(t|k) + a_{i-1}^a(t|k) \Delta t \\ a_{i-1}^a(t|k) = a_{i-1}^a(t-1|k) + a_{i-1,m}(k-1) \Delta t \\ a_{i-1,m}(k) = \frac{2\alpha_i}{\mu_i} (v_{i-2}^a(t|k) - v_{i-1}^a(t|k)) \\ - \alpha_i a_{i-2}^a(t|k) - \frac{2 - \alpha_i \mu_i}{\mu_i} a_{i-1}^a(t|k) \end{cases} \quad (19)$$

In this scenario, the multi-objective cruise controller of the CACC-driven vehicle i is computed as

$$a_i^*(:|k) = \arg \min_{a_i^p(:|k)} \{J_i(x_i(k)) \text{ s.t. } (13)(19)\} \quad (20)$$

where $J_i(x_i)$ is given by (14) and solution $a_i^*(:|k)$ the optimal acceleration command sequence. According to the receding horizon principle of MPC, the CACC controller is selected the first element of $a_i^*(:|k)$, i.e., $u^*(k) = a_i^*(0|k)$.

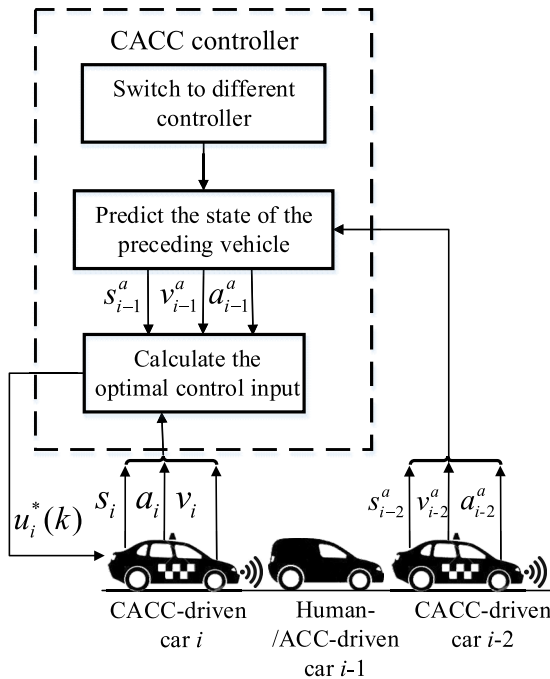


FIGURE 1. Control scheme structure.

According to the type of the preceding vehicles of the CACC-driven vehicles, three multi-objective predictive controllers are separately obtained by (16), (18) and (20). Note that when the CACC-driven vehicle is in the normal situation, one controller is activated among the three cruise controllers according to the type of the preceding vehicles. However, if the CACC-driven vehicle is in a dangerous situation in which the CACC problems have no solution, it is first required to ensure driving safety of the vehicle. Once emerging dangerous situations, the CACC-driven vehicle is needed to be switched to some safety controller to ensure the driving safety of the vehicle. Here according to practical operations, the safety controller of the CACC-driven vehicle i is designed as

$$u_{i,s}(k) = \begin{cases} -a_{i,\min} & \text{If } v_i(k) - a_{i,\min}\Delta t \geq v_{i,\min} \\ \frac{v_{i,\min} - v_i(k)}{\Delta t} & \text{Otherwise} \end{cases} \quad (21)$$

which also ensures formation and safety of the mixed string.

The control scheme structure of mixed vehicle strings is shown in Fig.1, which shows the interactive information between the CACC vehicles and the operation mechanism of the CACC controller. With the received information of the preceding CACC-driven vehicle, the controller is switched and the position, velocity and acceleration are predicted. Then, the control input of the CACC-driven car is computed based on all information. The procedure of implementing the multi-objective receding horizon optimal control for CACC of mixed vehicle strings is summarized as follows.

Step 1): Initialize the parameters of the CACC controllers β_i and γ_i with $i \in I_C$; let $k = 0$.

Step 2): The CACC-driven vehicle i obtains the position, velocity and acceleration information of the preceding CACC-driven vehicle from time k to $k + N\Delta t$.

Step 3): If there is no other type of vehicles between the two CACC-driven vehicles, then the controller from (16) is activated. In the scenario, the desired position of vehicle i at time $k + N\Delta t$ is calculated by (9) and the information is obtained in Step 2). Then, from the fuel consumption table, the vehicle i selects the control input that satisfies the constraint (13). The position error Δs_i between actual position and the desired position is calculated, which together with the fuel consumption are brought into the cost function, and then the optimal control sequence is computed as $a_i^p(:,t)$ by minimizing the cost function value. If the problem (16) has no solution, it is judged that the vehicle is in a dangerous situation. Then the CACC controller of vehicle i is switched to (21) to ensure the driving safety of the vehicle.

Step 4): If there is an ACC-driven vehicle between the vehicles, then the CACC controller from (18) is activated. From the CACC-driven vehicle information obtained in Step 2) and the position and velocity of the ACC-driven vehicle, the state information of the ACC-driven vehicle from time t to $k + N\Delta t$ is predicted. In (9), the position error is calculated using the obtained information of ACC-driven vehicle. Similarly, by the fuel consumption table, the CACC-driven vehicle computes the control input that satisfies the constraint (13) and the total fuel consumption over the time window $N\Delta t$ is obtained. The calculated position error and fuel consumption are brought into the cost function. The control input that minimizes the cost function value is the optimal control sequence $a_i^p(:,t)$. If the problem (18) has no solution, then the CACC controller of vehicle i is switched to (21) to ensure the driving safety of the vehicle.

Step 5): If the preceding vehicle is a human-driven vehicle, then the CACC controller from (20) is activated. If the problem (20) has no solution, then the CACC controller of vehicle i is switched to (21) to ensure driving safety of the vehicle.

Step 6): Implement the first element of $a_i^p(:,t)$ to the CACC-driven vehicle (3); let $k = k+1$ and go back to Step 2).

IV. SIMULATION AND RESULTS DISCUSSION

In this section, a mixed vehicle string with six cars, shown in Fig. 2, is used to illustrate the effectiveness of the proposed method. In this vehicle string, the leading vehicle is an automated car that broadcasts its information to the other vehicles through the V2X network, the second, fourth and

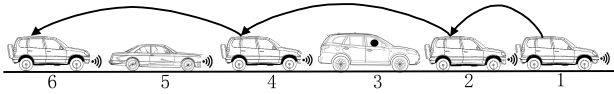


FIGURE 2. Schematic of a mixed vehicle string with six cars.

TABLE 1. Parameters of CACC-driven vehicles.

Car index	m_i (kg)	L_i (m)	$P_{i,max}$ (kW)	$B_{i,max}$ (N)	r_i
2	1235	4.0	130	6400	0.035
4	1167	4.5	128	6600	0.044
6	1180	4.4	120	6300	0.040

Car index	c_i ($N \cdot s^2 \cdot m^{-2}$)	$\eta_{i,R}$	$\zeta_{i,P}$ (J/g)
2	1.15	0.84	14000
4	1.12	0.89	13000
6	1.14	0.82	14000

sixth vehicles are the CACC-driven cars, the third vehicle is a human-driven car, and the fifth vehicle is an ACC-driven car.

The CACC-driven vehicles communicate with their nearest front CACC-driven vehicles while the ACC-driven vehicle and the human-driven vehicle do not have the ability to communicate with the other cars. It is assumed that the ACC- and human-driven vehicles keep a safe inter-vehicle distance following their preceding vehicle. The initial positions of six cars are set to be 113 m, 90 m, 68 m, 45 m, 23 m, and 0 m, respectively. The initial velocities of all cars are set to be 22 m/s. The acceleration of the leader is given by

$$a_1(t) = \begin{cases} 1\text{m/s}^2, & \text{if } 8 \text{ s} \leq t \leq 11 \text{ s} \\ -4 \text{ m/s}^2, & \text{if } 24 \text{ s} < t < 25 \text{ s} \\ 0, & \text{else} \end{cases}$$

In this simulation experiment, the vehicle’s parameters used to compute the fuel cost function (7) include mass m_i , length L_i , maximum engine power $P_{i,max}$, maximum braking force $B_{i,max}$, rolling resistance coefficient r_i , lumped aerodynamic drag coefficient c_i , efficiency of automatic mechanical transmission $\eta_{i,R}$, and efficiency of fuel to work $\zeta_{i,P}$ for $i \in I_C$. Refer to [40], the values of these parameters are listed as Table 1. Moreover, the lumped lag of vehicle’s longitudinal dynamics, time headway, and bandwidth are set as $\varsigma_j = \eta_j = 0.38$, $h_j = 1.3$, and $\omega_j = 1.6$ for $j \in I_A$ and $j \in I_C$, respectively [38] and the sensitivity factor and response time are $\alpha_i = 0.98$ and $\mu_i = 3.62$ for $i \in I_H$, respectively [48].

To ensure driving safety of vehicles in the string, the minimum allowable inter-vehicle distance R_i is 1.5 m and the desired spacing d is 18.5 m. Moreover, the weights of the fuel consumption and position error are $\beta_{i,c} = 1$ and $\gamma_{i,c} = 7.6$, respectively, the minimum acceleration interval and minimum velocity interval are $\delta_{i,a} = 0.2 \text{ m/s}^2$ and $\delta_{i,v} = 0.02 \text{ m/s}$, respectively [40]. The velocity of each car is subject to $19 \text{ m/s} \leq v_i \leq 28 \text{ m/s}$ in order to satisfy the velocity constraints of roads. To guarantee ride comfort of

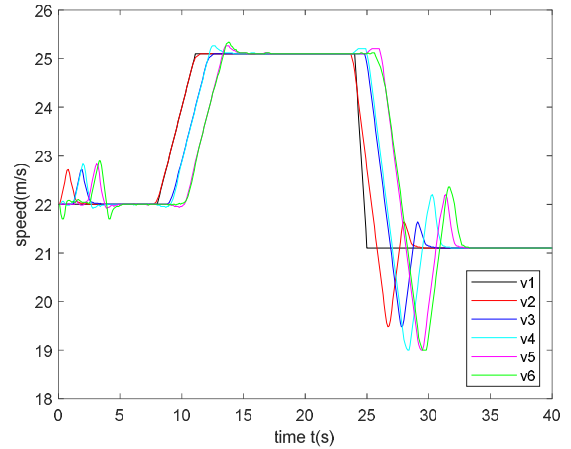


FIGURE 3. Velocity evolutions obtained by the proposed method.

cars, the acceleration constraint and the maximum change in acceleration per second are set to $-2 \text{ m/s}^2 \leq a_i \leq 2 \text{ m/s}^2$ and $\Delta a_{i,max} = 10 \text{ m/s}^3$, respectively. Let the sampling time interval be $\Delta t = 0.1 \text{ s}$ and the prediction horizon be $N = 5$ for each multi-objective optimal CACC problem of vehicle $i \in I_C$.

Fig. 3 shows the velocity evolutions of the mixed vehicle string obtained by applying the proposed CACC method. According to the position and velocity information of the first vehicle, the second vehicle is driven by its CACC controller such that the actual spacing of the vehicle is greater than the desired spacing. In order to keep up with the preceding vehicle, the second vehicle starts to accelerate at $0 \sim 1 \text{ s}$. After a time period, the spacing between the vehicles 2 and 1 reaches the desired spacing, and the second vehicle begins to decelerate to the same velocity as the first vehicle. The third vehicle is a human-driven vehicle. Clearly, the human-driven vehicle has generally a reaction time and hence the state cannot be changed immediately according to the state of the preceding vehicle. At time $t = 8 \text{ s}$, the acceleration of the first vehicle becomes 1 m/s^2 , the second vehicle is immediately accelerated by the obtained optimal control input based on the information transmitted from the first vehicle, and the third vehicle begins to accelerate at time $t = 9 \text{ s}$. The fourth vehicle predicts the third vehicle motion state according to the information of the second vehicle and the prediction model of the human-driven vehicle and then accelerates immediately after the velocity of the third vehicle changes since the reaction time of automated vehicle is less than the human reaction time. The fifth vehicle is driven by an ACC controller and its movement state cannot be changed quickly according to the state of the preceding vehicle. At time $t = 9 \text{ s}$ the fourth vehicle has started to accelerate but the fifth vehicle starts to accelerate until time $t = 10 \text{ s}$. The sixth car is driven by the designed CACC controller and its preceding vehicle is an ACC-driven car. Once the state information of the fourth car is obtained, the optimal control input of the sixth car is computed by the multi-objective CACC controller according to the motion state predicted by the prediction model of the

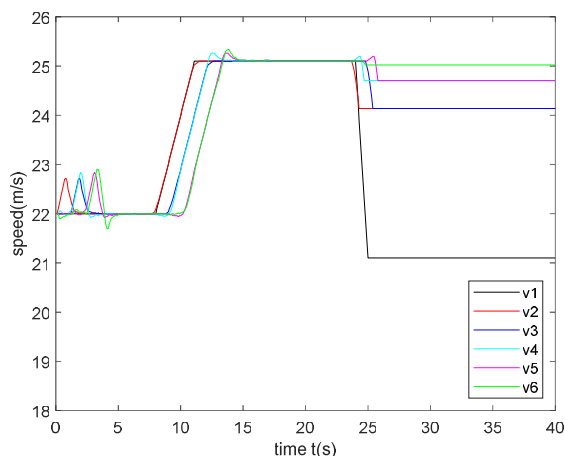


FIGURE 4. Velocity evolutions without switching safety controller.

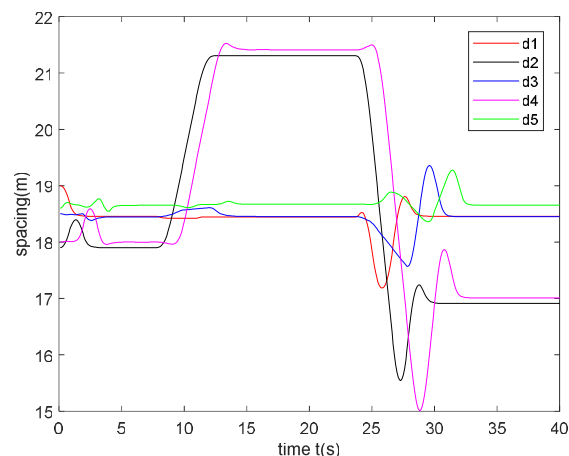


FIGURE 5. Spacing evolutions obtained by the proposed method.

ACC-driven car. As a result, the sixth vehicle keeps up with the preceding vehicle in a short time.

Moreover, when the first vehicle stops to accelerate, the second vehicle can quickly stop to accelerate accordingly. From the information transmitted by the first vehicle, the fourth vehicle switches to the safety controller (21) such that it can keep a safe spacing with the third vehicle being driven by human. When the velocity of the first vehicle reaches a steady state, the rear vehicle can quickly reach the same steady state as the first vehicle. At $t = 24$ s, the first vehicle encounters an unexpected situation, where the acceleration becomes -4 m/s^2 , which exceeds the allowable the range of acceleration. Then the second vehicle obtains the information of the first vehicle’s abnormal deceleration, and its CACC controller is switched to the safety controller immediately. As a result, the second vehicle decelerates at the maximum acceleration to prevent collisions but the human-driven car has a reaction time such that it decelerates 1 s later than the second vehicle. The fourth vehicle predicts the state of the human-driven car according to information of the second car, and then it switches to the safety controller to ensure safety. At $t = 25$ s, the first vehicle stops to decelerate, the rear vehicles also gradually stop to decelerate and tend to be in the same stable state as the preceding vehicle. On the contrary, Fig. 4 shows the velocity evaluations of the mixed vehicle string without switching safety controller (21). From Fig. 4, if the vehicle does not switch to the safety controller when the preceding vehicle in dangerous situation, the first vehicle tends to be in a steady state but the rear vehicle cannot be in the same stable state as the first vehicle. The velocity of the second vehicle is always greater than the velocity of the first vehicle and eventually, the vehicles will collide.

Fig. 5 pictures the spacing curves of adjacent cars in the entire mixed vehicle string. As seen from Fig. 5, the spacing between the first and second vehicles is larger than the desired spacing. Hence, the velocity of the second vehicle changes immediately to achieve the desired spacing. When the first car accelerates or decelerates, the spacing between the two vehicles only slightly changes. Note that as the third vehicle

is a human-driven car, it does not accelerate immediately when the second car accelerates to keep up with the first car. Hence, the spacing of the adjacent vehicles increases to the stable spacing. When the acceleration becomes 1 m/s^2 from $t = 8$ s to $t = 11$ s, the first car starts to accelerate and its acceleration information is transmitted to the second car through V2X network. The second vehicle computes the CACC input by the controller (16) to immediately catch up the first car, where the spacing varies between 18 m and 19 m. The fourth vehicle also computes the CACC input based on the information of the second vehicle by the CACC controller whose preceding vehicle is human-driven vehicle, and then the variation of the spacing changes in a small range. Moreover, at $t = 24$ s, the first vehicle suddenly decelerates at -4 m/s^2 . The second vehicle switches to the safety controller (21) from the information of the first vehicle, which can ensure the safety of the second vehicle. It can be seen from Fig. 5 that the spacing between the second vehicle and the first vehicle varies in 17~19 m at this time period and the variation significantly reduces in the sixth car. However, if the CACC controller is not switched to the safety controller in this dangerous situation, the position of the second vehicle exceeds the position of the first vehicle and a collision accident occurs. Note that the desired spacing of CACC-driven cars is set to be more than the others’ in some time intervals to verify the proposed method in various traffic scenarios. Fig. 6 shows the spacing evolutions when the safety controller is used online. These illustrate that the switching CACC controller proposed in this paper can guarantee driving safety of the whole string.

Fig. 7 shows the acceleration curves of each vehicle in the mixed string. It can be seen from Fig. 7 that the acceleration of each car is within the range of acceleration and the acceleration variation per second for each vehicle is smaller than the maximum one, which ensures ride comfort of the CACC-driven vehicles.

Table 2 lists the fuel consumption per 100 kilometers of three CACC-driven cars in the mixed vehicle strings. It is observed from Table 2 that for a given β_i , the fuel

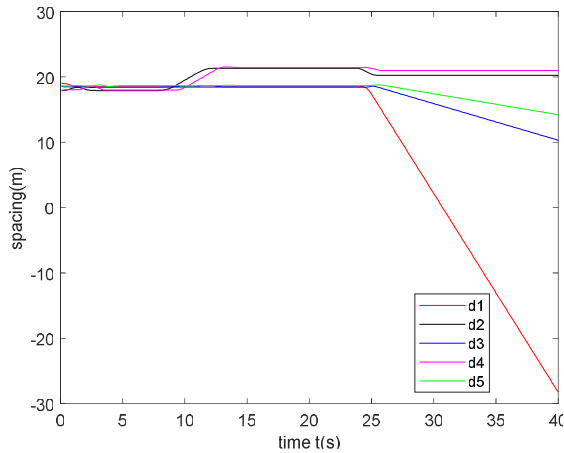


FIGURE 6. Spacing evolutions without switching safety controller.

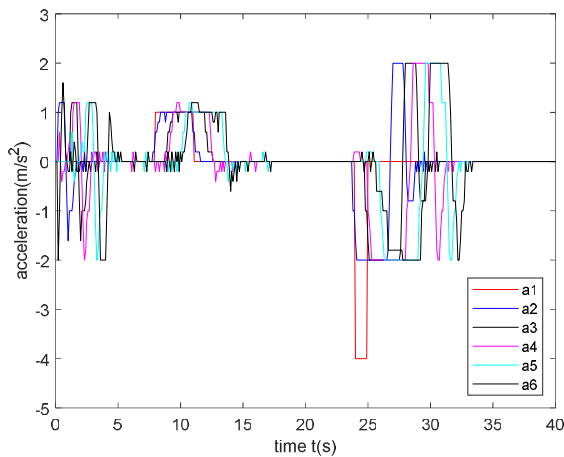


FIGURE 7. Acceleration curves of the mixed vehicle string.

TABLE 2. Fuel consumption (g/100km).

N	β_i	Car index		
		2	4	6
3	0	14598	15889	16793
	1	10426	11477	12417
4	0	14016	14996	15817
	1	11323	12419	12978
5	0	13857	14526	14707
	1	13842	14483	14617
6	0	13792	14472	14573
	1	13751	14403	14469
7	0	13723	14413	14428
	1	13654	14343	14317
8	0	13689	14385	14289
	1	13616	14273	14167

consumption per 100 kilometers of each CACC-driven car will decrease when the prediction horizon increases. Moreover, for a fixed N , the fuel consumption per 100 kilometers

of each CACC-driven car at $\beta_i = 1$ is less than that at $\beta_i = 0$. This is caused from the fact that the fuel cost function is considered explicitly during the computation of the CACC controllers. Moreover, this fuel-saving at a small N is more than that at a large N . However, a too small N may cause that the CACC controllers do not drive the vehicles to keep a stabilizing formation of the string. Hence, the prediction horizon can be appropriately selected by making a trade-off among these concerns.

V. CONCLUSION

To ensure safety, ride comfort, formation and fuel economy of constrained mixed vehicle strings, this paper proposed the switching multi-objective receding horizon CACC for the string. Combing the prediction models of human- and ACC-driven vehicles, three multi-objective predictive CACC controllers were separately designed for different traffic scenarios. According to different preceding vehicles, the CACC controllers were switched online in normal and dangerous situations such that the CACC controller was switched to the safety controller to ensure driving safety of the whole mixed vehicle string. The simulation results verified the effectiveness of the control method proposed in this paper. The issues of stability and V2X communication network, e.g., time-varying delays and data-packet dropouts, will be pursued along the proposed method in future work.

REFERENCES

- [1] K. C. Dey, L. Yan, X. Wang, Y. Wang, H. Shen, M. Chowdhury, L. Yu, C. Qiu, and V. Soundararaj, "A review of communication, driver characteristics, and controls aspects of cooperative adaptive cruise control (CACC)," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 2, pp. 491–509, Feb. 2016.
- [2] A. Vahidi and A. Eskandarian, "Research advances in intelligent collision avoidance and adaptive cruise control," *IEEE Trans. Intell. Transp. Syst.*, vol. 4, no. 3, pp. 143–153, Sep. 2003.
- [3] D. He, Y. Shi, and X. Song, "Weight-free multi-objective predictive cruise control of autonomous vehicles in integrated perturbation analysis and sequential quadratic programming optimization framework," *J. Dyn. Syst., Meas., Control*, vol. 141, no. 9, pp. 1–15, Sep. 2019.
- [4] M. A. S. Kamal, M. Mukai, J. Murata, and T. Kawabe, "Model predictive control of vehicles on urban roads for improved fuel economy," *IEEE Trans. Control Syst. Technol.*, vol. 21, no. 3, pp. 831–841, May 2013.
- [5] R. C. Zhao, P. K. Wong, Z. C. Xie, and J. Zhao, "Real-time weighted multi-objective model predictive controller for adaptive cruise control systems," *Int. J. Automot. Technol.*, vol. 18, no. 2, pp. 279–292, Apr. 2017.
- [6] D. Moser, R. Schmied, H. Waschl, and L. del Re, "Flexible spacing adaptive cruise control using stochastic model predictive control," *IEEE Trans. Control Syst. Technol.*, vol. 26, no. 1, pp. 114–127, Jan. 2018.
- [7] R. Rajamani and C. Zhu, "Semi-autonomous adaptive cruise control systems," *IEEE Trans. Veh. Technol.*, vol. 51, no. 5, pp. 1186–1192, Sep. 2002.
- [8] Mark Vollrath, S. Schleicher, and C. Gelau, "The influence of cruise control and adaptive cruise control on driving behaviour—A driving simulator study," *Accident Anal. Prevention*, vol. 43, no. 3, pp. 1134–1139, May 2011.
- [9] D. He and B. Peng, "Gaussian learning-based fuzzy predictive cruise control for improving safety and economy of connected vehicles," *IET Intell. Transp. Syst.*, vol. 14, no. 5, pp. 346–355, May 2020, doi: 10.1049/iet-its.2019.0452.
- [10] D. He, Y. Shi, H. Li, and H. Du, "Multiobjective predictive cruise control for connected vehicle systems on urban conditions with InPA SQP," *Optim. Control Appl. Methods*, vol. 40, no. 3, pp. 479–498, May 2019.
- [11] K. Ma and H. Wang, "Influence of exclusive lanes for connected and autonomous vehicles on freeway traffic flow," *IEEE Access*, vol. 7, pp. 50168–50178, 2019.

- [12] T. Andreas, "Vehicle trajectory effects of adaptive cruise control," *J. Intell. Transp. Syst.*, vol. 16, no. 1, pp. 36–44, Jun. 2012.
- [13] L. D. Baskar, B. De Schutter, and H. Hellendoorn, "Model-based predictive traffic control for intelligent vehicles: Dynamic speed limits and dynamic lane allocation," in *Proc. IEEE Intell. Vehicles Symp.*, Eindhoven, The Netherlands, Jun. 2008, pp. 174–179.
- [14] S. E. Li, R. Li, J. Wang, X. Hu, B. Cheng, and K. Li, "Stabilizing periodic control of automated vehicle platoon with minimized fuel consumption," *IEEE Trans. Transport. Electric.*, vol. 3, no. 1, pp. 259–271, Mar. 2017.
- [15] M. Vajedi and N. L. Azad, "Ecological adaptive cruise controller for plug-in hybrid electric vehicles using nonlinear model predictive control," *IEEE Trans. Intell. Transp. Syst.*, vol. 17, no. 1, pp. 113–122, Jan. 2016.
- [16] B. van Arem, C. J. G. van Driel, and R. Visser, "The impact of cooperative adaptive cruise control on traffic-flow characteristics," *IEEE Trans. Intell. Transp. Syst.*, vol. 7, no. 4, pp. 429–436, Dec. 2006.
- [17] 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)*, Seoul, South Korea, Jun. 2015, pp. 286–291.
- [18] A. Firooznia, J. Ploeg, N. van de Wouw, and H. Zwart, "Co-design of controller and communication topology for vehicular platooning," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 10, pp. 2728–2739, Oct. 2017.
- [19] H. Rakha and R. K. Kamalanathsharma, "Eco-driving at signalized intersections using V2I communication," in *Proc. 14th Int. IEEE Conf. Intell. Transp. Syst. (ITSC)*, Washington, DC, USA, Oct. 2011, pp. 341–346.
- [20] C. Anayor, W. Gao, and A. Odekunle, "Cooperative adaptive cruise control of a mixture of human-driven and autonomous vehicles," in *Proc. SoutheastCon*, Petersburg, FL, USA, Apr. 2018, pp. 1–3.
- [21] M. A. Goodrich and E. R. Boer, "Designing human-centered automation: Trade-offs in collision avoidance system design," *IEEE Trans. Intell. Transp. Syst.*, vol. 1, no. 1, pp. 40–54, Mar. 2000.
- [22] B. Asadi and A. Vahidi, "Predictive cruise control: Utilizing upcoming traffic signal information for improving fuel economy and reducing trip time," *IEEE Trans. Control Syst. Technol.*, vol. 19, no. 3, pp. 707–714, May 2011.
- [23] A. Bose and P. Ioannou, "Mixed manual/semi-automated traffic: A macroscopic analysis," *Transp. Res. C, Emerg. Technol.*, vol. 11, no. 6, pp. 439–462, Dec. 2003.
- [24] Y. Liu, H. Gao, H. Cheng, G. Liu, and B. Xu, "Autonomous coordinated control of a platoon of vehicles with multiple disturbances," *IET Control Theory Appl.*, vol. 8, no. 18, pp. 2325–2335, Dec. 2014.
- [25] A. Talebpoor and H. S. Mahmassani, "Influence of connected and autonomous vehicles on traffic flow stability and throughput," *Transp. Res. C, Emerg. Technol.*, vol. 71, pp. 143–163, Oct. 2016.
- [26] V. Milanés, S. E. Shladover, J. Spring, C. Nowakowski, H. Kawazoe, and M. Nakamura, "Cooperative adaptive cruise control in real traffic situations," *IEEE Trans. Intell. Transp. Syst.*, vol. 15, no. 1, pp. 296–305, Feb. 2014.
- [27] 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.
- [28] M. Barth and K. Boriboonsomsin, "Energy and emissions impacts of a freeway-based dynamic eco-driving system," *Transp. Res. D, Transp. Environ.*, vol. 14, no. 6, pp. 400–410, Aug. 2009.
- [29] S. Li, K. Li, R. Rajamani, and J. Wang, "Model predictive multi-objective vehicular adaptive cruise control," *IEEE Trans. Control Syst. Technol.*, vol. 19, no. 3, pp. 556–566, May 2011.
- [30] P. Ioannou and Z. Xu, "Throttle and brake control systems for automatic vehicle following," *IVHS J.*, vol. 1, no. 4, pp. 345–377, 1994.
- [31] H. Yang and W.-L. Jin, "A control theoretic formulation of green driving strategies based on inter-vehicle communications," *Transp. Res. C, Emerg. Technol.*, vol. 41, pp. 48–60, Apr. 2014.
- [32] S. Tsugawa, "An overview on energy conservation in automobile traffic and transportation with ITS," in *Proc. IEEE Int. Vehicle Electron. Conf. (IVEC)*, Tottori, Japan, 2001, pp. 137–142.
- [33] J. Zhang and P. Ioannou, "Longitudinal control of heavy trucks in mixed traffic: Environmental and fuel economy considerations," *IEEE Trans. Intell. Transp. Syst.*, vol. 7, no. 1, pp. 92–104, Mar. 2006.
- [34] P. A. Ioannou and M. Stefanovic, "Evaluation of ACC vehicles in mixed traffic: Lane change effects and sensitivity analysis," *IEEE Trans. Intell. Transp. Syst.*, vol. 6, no. 1, pp. 79–89, Mar. 2005.
- [35] M. S. Rahman and M. Abdel-Aty, "Longitudinal safety evaluation of connected vehicles' platooning on expressways," *Accident Anal. Prevention*, vol. 117, pp. 381–391, Aug. 2018.
- [36] B. Sakhdari and N. L. Azad, "A distributed reference governor approach to ecological cooperative adaptive cruise control," *IEEE Trans. Intell. Transp. Syst.*, vol. 19, no. 5, pp. 1496–1507, May 2018.
- [37] A. A. Alam, A. Gattami, and K. H. Johansson, "An experimental study on the fuel reduction potential of heavy duty vehicle platooning," in *Proc. 13th Int. IEEE Conf. Intell. Transp. Syst.*, Funchal, Portugal, Sep. 2010, pp. 306–311.
- [38] F. Li and Y. Wang, "Cooperative adaptive cruise control for string stable mixed traffic: Benchmark and human-centered design," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 12, pp. 3473–3485, Dec. 2017.
- [39] C. Lu, J. Dong, L. Hu, and C. Liu, "An ecological adaptive cruise control for mixed traffic and its stabilization effect," *IEEE Access*, vol. 7, pp. 81246–81256, Jun. 2019.
- [40] C. Zhai, Y. Liu, and F. Luo, "A switched control strategy of heterogeneous vehicle platoon for multiple objectives with state constraints," *IEEE Trans. Intell. Transp. Syst.*, vol. 20, no. 5, pp. 1883–1896, May 2019.
- [41] H. Furukawa, M. Saito, Y. Tokunaga, and R. Kiyohara, "Vehicle control method at T-junctions for mixed environments containing autonomous and non-autonomous vehicles," in *Proc. IEEE 32nd Int. Conf. Adv. Inf. Netw. Appl. (AINA)*, Krakow, Poland, May 2018, pp. 79–85.
- [42] J. Chen, Y. Zhou, and H. Liang, "Effects of ACC and CACC vehicles on traffic flow based on an improved variable time headway spacing strategy," *IET Intell. Transp. Syst.*, vol. 13, no. 9, pp. 1365–1373, Sep. 2019.
- [43] S. Aoki and R. Rajkumar, "V2V-based synchronous intersection protocols for mixed traffic of human-driven and self-driving vehicles," in *Proc. IEEE 25th Int. Conf. Embedded Real-Time Comput. Syst. Appl. (RTCSA)*, Hangzhou, China, Aug. 2019, pp. 1–11.
- [44] H. Chin, H. Okuda, Y. Tazaki, and T. Suzuki, "Model predictive cooperative cruise control in mixed traffic," in *Proc. 41st Annu. Conf. IEEE Ind. Electron. Soc.*, Yokohama, Japan, Nov. 2015, pp. 3199–3205.
- [45] U. Munir and Z. Junzhi, "Weight changing model predictive controller for adaptive cruise control with multiple objectives," in *Proc. IEEE Int. Conf. Mechatronics, Robot. Autom. (ICMRA)*, Hefei, China, May 2018, pp. 62–66.
- [46] H. Yang, H. Rakha, and M. V. Ala, "Eco-cooperative adaptive cruise control at signalized intersections considering queue effects," *IEEE Trans. Intell. Transp. Syst.*, vol. 18, no. 6, pp. 1575–1585, Jun. 2017.
- [47] A. Stevanovic, J. Stevanovic, K. Zhang, and S. Batterman, "Optimizing traffic control to reduce fuel consumption and vehicular emissions," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2128, no. 1, pp. 105–113, Jan. 2009.
- [48] R. E. Chandler, R. Herman, and E. W. Montroll, "Traffic dynamics: Studies in car following," *Oper. Res.*, vol. 6, no. 2, pp. 165–184, Apr. 1958.



XIULAN SONG was born in Hangzhou, Zhejiang, China, in 1982. She received the B.S. degree in communication engineering from the Zhejiang University of Technology, in 2005, the M.S. degree in electronic and communication engineering from Zhejiang University, in 2008, and the Ph.D. degree in control theory and control engineering from the Zhejiang University of Technology, in 2015.

Since 2008, she has been a Lecturer with the Information Engineering Institute, Zhejiang University of Technology. She is the author of one book, more than 20 articles, and more than five inventions. Her research interests include vehicle control networks and wireless multimedia communication.



KE WANG received the bachelor's degree in communication engineering from the Zhejiang University of Technology, Hangzhou, China, in 2018, where he is currently pursuing the master's degree. His main research interests include autonomous vehicle control and cooperative control.



DEFENG HE was born in Yiwu, China, in 1979. He received the B.S. degree in energy engineering from Central South University, Changsha, China, in 1997, and the Ph.D. degree in control science and engineering from the University of Science and Technology of China, Hefei, China, in 2008.

From 2014 to 2015, he was a Visiting Scholar with the University of Michigan, Ann Arbor, MI, USA. From 2008 to 2010, he was a Lecturer with the College of Information Engineering, Zhejiang University of Technology, Hangzhou, China. From 2010 to 2015, he was an Assistant Professor with the Zhejiang University of Technology. Since 2015, he has been a Full Professor with the Zhejiang University of Technology. He is the author of more than 60 articles and holds more than 30 patents. His research interests include model predictive control and distributed control of interconnected systems.

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