Driver-Centric Data-Driven Model Predictive Vehicular Platoon with Longitudinal-Lateral Dynamics

Yanhong Wu, Zhiqiang Zuo, Senior Member, IEEE, Yijing Wang, Qiaoni Han, Ji Li, Member, IEEE, Hongming Xu

Abstract—This paper proposes a driver-centric data-driven model predictive control (DDMPC) strategy to improve driving comfort while maintaining driving safety of vehicular platoon. This strategy combines a data-driven model predictive controller and the driver-centric driving policy. The data-driven platoon model involving longitudinal-lateral dynamics is established with subspace identification to alleviate the adverse effects of uncertain dynamics. Then, a subspace predictor-based distributed data-driven model predictive controller is developed for vehicular platoon. To overcome the cutting-corner phenomenon on curved roads, the reference point is shifted from the preceding vehicle to an optimal corridor point behind it. In this way, a driver-centric driving policy is designed with a flexible spacing and soft control constraints to balance driving safety and driving comfort in terms of different driving styles. Finally, several experiments with sixty drivers are carried out on a self-developed vehicular platoon platform. The experimental results demonstrate the effectiveness of the proposed DDMPC strategy.

Index Terms—Vehicular platoon, driver-centric, data-driven model predictive control, longitudinal-lateral dynamics.

I. INTRODUCTION

The growing demand for transportation system is being hindered by the limited road capacity and the increasing concerns for traffic safety. Vehicular platoon has the concept of 'follow the leader', and it is realized by exchanging information among the vehicles [1]. In fact, platoon control with longitudinal-lateral dynamics involves complex dynamic models and ambiguous driving behavior. A suitable control strategy could ensure the safety and comfort of vehicular platoon, thereby the exploitation of the driver-centric longitudinal-lateral controller has triggered a widespread research upsurge.

Actually, the longitudinal-lateral controller is handled independently in [2], [3]. The longitudinal controller is developed to maintain constant spacing while utilizing a lane-keeping approach for the lateral one. Recently, the coupling between longitudinal controller and lateral controller has been studied in [4]–[7]. Tracking the reference path in intricate road conditions presents a formidable task, especially for curved roads.

To address the challenge of orientation tracking, one potential solution is the look-ahead method [8]. However, this method encounters the challenge of overcoming the cornering maneuver for vehicular platoon. To be more specific, the following vehicle may turn too early if there exists an orientation error between itself and the preceding vehicle, resulting in the cutting-corner phenomenon. To this end, Gehrig et al. [9] introduced the concept of extended look-ahead with longitudinal-lateral platoon controller to address the cutting-corner phenomenon. The forward-looking point, aligned perpendicularly to the course of the preceding vehicle, is viewed as a virtual leader. Subsequently, the history trajectory-based control method was developed in [10], [11]. The previous trajectory of the preceding vehicle is determined according to the stored position and motion parameters of the following vehicle. In this way, the cutting-corner phenomenon could be processed by shifting the reference point from the preceding vehicle to a static point behind it [12]. Although the above tracking methods have made some advance on the control performance of vehicular platoon, it also leads to a poor driving experience.

On the other hand, the drivers’ long-term regular driving behavior tendency constitutes special driving style. This style is characterized by individual differences and their consistency. For vehicular platoon, the driving behavior could affect a series of driving decisions such as steering, acceleration and braking. Therefore, several driver-centric policies of vehicular platoon have received extensive attention. A machine learning-based platoon tracking method was introduced to ensure driving safety while considering the acceptance of human drivers [13], [14]. The limited interpretability of the learning method may hinder the understanding of driver behavior. Then, some time-varying control schemes such as variable control gain [15], flexible spacing [16] and variable predictive step [17] provided reasonable solutions to achieve driver-centric control performance. However, there are few studies on the individual differences of drivers in the steering process to recognize driving behavior and adjust platoon spacing.

Among plenty of existing control schemes, the distributed model predictive control (MPC) has attracted considerable attention since it could explicitly model and constraint the control objectives [18]–[20]. For the distributed MPC scheme, each controller solves the individual optimal control problem within a finite horizon, and exchanges the results with communication network [21]. In certain intricate dynamic systems, the
analytical models inherently exhibit inaccuracies or pose challenges in their acquisition [22]–[24]. As a promising technique to comprehend the intricacies of vehicle structure, the data-driven modelling scheme appears [25], [26]. The underlying principle of this method focuses on examining the real-time input-output (I/O) trajectory to identify the black-box system [27], [28]. However, the involvement of complex network models causes a large computational burden. Therefore, it is necessary to develop a feasible algorithm to balance the computational efficiency and accuracy of vehicular platoon.

The aforementioned research in vehicular platoon modelling is focused on developing mechanism-based dynamic models. It presents a challenge in obtaining accurate dynamic parameters for the vehicular platoon. Furthermore, conventional longitudinal-lateral coupling control strategies cannot meet the requirement of driver-centric driving experience with different driving styles. The factors discussed previously have inspired the construction of an accurate platoon model and the development of a driver-centric control strategy for vehicular platoon. The principal contributions of this paper are outlined below.

i) A subspace-based data-driven modelling method is developed to characterize the platoon with longitudinal-lateral dynamics. The comprehensive investigation of longitudinal-lateral vehicular dynamics distinguishes it from existing studies focusing solely on individual longitudinal vehicular dynamics [29]. Each vehicle model involves the chassis model, the driving motor model and the steering motor model. Furthermore, these complex models are characterized by a data-driven model instead of the mechanism one [2], [5], [6].

ii) A driver-centric driving policy with a flexible spacing and soft constraints is proposed in terms of different driving styles. A projection twin support vector machine (PTSVM)-based driving style recognition method is developed in terms of the collected driving data. Then, different driving styles are implemented to design the driver-centric driving policy with flexible spacing and soft constraints for platoon. Here, the proposed policy could address the cutting-corner phenomenon and provide a better driving experience [22], [25].

iii) A driver-centric data-driven model predictive control (DDMPC) strategy is put forward, and its recursive feasibility and stability are proved. The application of existing data-driven control approaches [25], [27], [28], [30] to vehicular units is hindered by their computational burdens. The proposed distributed data-driven model predictive control algorithm could be employed directly in the predictive control without identifying the local state-space model.

This paper is organized as follows. Section II illustrates the vehicular platoon model. Section III designs the DDMPC strategy. Field experiments are carried out in Section IV. Experimental results are analyzed in Section V. Section VI draws the conclusion.

Notations: \( \| \cdot \|_H \) denotes the Frobenius norm. \( \overline{M} \) represents the average value of \( M \). The Moore-Penrose pseudo inverse of matrix \( H \) is expressed as \( H^\dagger \). \( \triangle \) is the error between the current vector and the reference vector. \( \mathbb{R} \) represents the Euclidean space.

II. VEHICULAR PLATOON MODELING

The vehicular platoon is composed of one leading vehicle (LV) and \( M \) following vehicles (FVs). The predecessor-following (PF) communication topology is utilized between the preceding vehicle and the following one [31]. For each autonomous vehicle (AV), the longitudinal-lateral dynamics are influenced by the configuration of its chassis, motor and transmission. Here, a bicycle model and a two-track vehicle model are investigated. Among the existing complex models, there are several uncertain parameters. To address the issue of dynamics uncertainty, the mechanism model is transformed into a data-driven one.

A. Bicycle-based Mechanism Model

The vehicle kinematics model is employed to describe the characteristics of AV.

\[
\begin{align*}
\dot{x} &= v_x \cos \phi \\
\dot{y} &= v_x \sin \phi \\
\dot{\phi} &= \frac{v_y}{l}
\end{align*}
\]

where \( x \) and \( y \) represent the longitudinal position and lateral position, respectively. \( v_x \) denotes the center linear velocity. \( \phi \) is the heading angle. \( l \) is the wheelbase. \( \delta \) stands for the steering angle of the front wheel.

![Fig. 1. Schematic diagram of vehicle dynamics.](image)

The longitudinal dynamics of each vehicle involve gravitational force, tire friction and aerodynamic drag, etc. To deduce a succinct model, several reasonable hypotheses are needed, see Refs. [32], [33] for details. As shown in Fig. 1, the longitudinal movement of each vehicle is driven by the direct-current (DC) driving motor. Then, the longitudinal dynamic model can be expressed as

\[
\dot{v}_x = \frac{1}{m} (r \omega + \varsigma_l) 
\]

where \( r \) stands for the tire radius. \( m \) denotes the vehicle mass. \( \varsigma_l \) and \( \varsigma_l \) are the right and left wheel control torques.

In practical applications, the vehicle is regulated by the driving voltage \( \phi_d \) instead of the control torque \( \varsigma_l/\varsigma_r \) [34].
where, $\eta_i$ denotes the coefficient of torque, $\eta_e$ represents the coefficient of electric potential, $I_a$ is the speed ratio of motor, $L_a$ and $R_a$ represent the total inductance and the total resistance, respectively, $a$ is the longitudinal acceleration.

Furthermore, a permanent magnet synchronous motor (PMSM) of the steering execution module is responsible for the steering task. The modelling process of PMSM has been well addressed in [35], [36]. Thus, we have

$$\dot{\omega} = \frac{n_p n_f - C_s I_s - B_s}{J_s} \omega$$

$$\phi_s = R_s J_s + L_s \dot{I}_s + K_s \omega$$

where, $\omega$ is the rotational velocity, $n_p$ denotes the number of pole pairs, $n_f$ is the flux linkage, $C_s$ and $B_s$ represent the torque and viscous friction coefficient, respectively, $J_s$ stands for the moment of inertia, $\phi_s$ is the voltage of steering motor, $R_s$ denotes the stator resistance, $L_s$ corresponds to the equivalent inductance, $K_s$ is the back electromotive force coefficient.

To differentiate (2) and substitute it into (3) leads to

$$\dot{\phi}_s = \frac{L_s J_s}{n_p n_f - C_s} \dot{\omega} + \frac{R_s J_s + L_s}{n_p n_f - C_s} \dot{\omega} + (K_s + \frac{B_s R_s}{n_p n_f - C_s}) \omega.$$

According to the properties of forward Euler, the mechanism model of vehicle $i$ ($i \in [2, M]$) has a discrete state-space expression

$$\begin{aligned}
A_i(k) &= \begin{bmatrix}
1 & a_{13} & a_{14} & 0 & 0 & 0 & 0 \\
0 & 1 & a_{23} & a_{24} & 0 & 0 & 0 \\
0 & 0 & 1 & a_{34} & a_{35} & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & T_s & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & a_{57} \\
0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}, \\
B_i(k) &= \begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1
\end{bmatrix}, \\
C_i(k) &= \begin{bmatrix}
\Delta x_i(k) \\
\Delta y_i(k) \\
\Delta \phi_r(k) \\
\Delta v_x(k) \\
\Delta a(k) \\
\Delta \omega(k) \\
\Delta \sigma(k)
\end{bmatrix}, \\
U_i(k) &= \begin{bmatrix}
\Delta \phi_{u_r}(k) \\
\Delta \phi_{u_s}(k)
\end{bmatrix}^T,
\end{aligned}$$

with

$$\begin{aligned}
A(k) &= \begin{bmatrix}
1 & a_{13} & a_{14} & 0 & 0 & 0 & 0 \\
0 & 1 & a_{23} & a_{24} & 0 & 0 & 0 \\
0 & 0 & 1 & a_{34} & a_{35} & 0 & 0 \\
0 & 0 & 0 & 1 & T_s & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & T_s \\
0 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 0 & 0 & 0
\end{bmatrix}, \\
B(k) &= \begin{bmatrix}
1 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 1
\end{bmatrix}, \\
C(k) &= \begin{bmatrix}
\Delta x(k) \\
\Delta y(k) \\
\Delta \phi_r(k) \\
\Delta v_x(k) \\
\Delta a(k) \\
\Delta \omega(k) \\
\Delta \sigma(k)
\end{bmatrix}, \\
U(k) &= \begin{bmatrix}
\Delta \phi_{u_r}(k) \\
\Delta \phi_{u_s}(k)
\end{bmatrix}^T.
\end{aligned}$$

The two-track vehicle model presents significant advantages in capturing the dynamic interaction between tires and the road surface. This model has been widely used in vehicular modelling and control design [37], [38].

According to Newton’s second law, the force equilibrium equations for vehicles along lateral, longitudinal and vertical axes are expressed as

$$\begin{aligned}
\dot{m}_v &= 2C_f (\delta - \frac{v_y + l_f \dot{\phi}}{v_x}) + 2C_l \dot{\phi} - v_y - m_v \dot{\phi} \\
\dot{m}_u &= 2C_f (\delta - \frac{v_y + l_f \dot{\phi}}{v_x}) + C_l \dot{\phi} - m_v \dot{\phi} \\
\dot{m}_t &= 2l_f C_f (\delta - \frac{v_y + l_f \dot{\phi}}{v_x}) - 2l_l C_f \dot{\phi} - v_y
\end{aligned}$$

where, $v_y$ and $v_x$ represent the lateral velocity and longitudinal velocity. $l_f$ and $l_l$ denote the centroid distances of rear axle and front axle, respectively. $C_f$ and $C_l$ are the front and rear cornering stiffness, respectively. $I_c$ stands for the vehicle inertia around the center of gravity.

Then, the motion behavior of vehicles in the global coordinate system can be described as

$$\begin{aligned}
\dot{y} &= v_x \sin \varphi + v_y \cos \varphi \\
\dot{x} &= v_x \cos \varphi + v_y \sin \varphi.
\end{aligned}$$

Based on (6)-(10), the ($i \in [2, M]$) two-track vehicle model has a discrete state-space form [37]

$$\begin{aligned}
\tilde{X}_i(k + 1) &= \tilde{A}_i(k) \tilde{X}_i(k) + \tilde{B}_i(k) \tilde{U}_i(k) \\
\tilde{Y}_i(k + 1) &= \tilde{C}_i \tilde{X}_i(k)
\end{aligned}$$

with

$$\begin{aligned}
\tilde{A}_i(k) &= \begin{bmatrix}
M_{11} & M_{12} & 0 & M_{14} & 0 & 0 \\
M_{21} & M_{22} & 0 & M_{24} & 0 & 0 \\
0 & 0 & 1 & 1 & 0 & 0 \\
M_{41} & M_{42} & 0 & M_{44} & 0 & 0 \\
\cos \varphi_i T_s & \sin \varphi_i T_s & M_{53} & 0 & 1 & 0 \\
-\sin \varphi_i T_s & \cos \varphi_i T_s & M_{53} & 0 & 0 & 1
\end{bmatrix}, \\
\tilde{B}_i(k) &= \begin{bmatrix}
2C_f \frac{T_r}{m} & M_{p1} & 0 & \frac{2C_f \frac{T_r}{m}}{\nu_{x_i}(k)} & 0 & 0
\end{bmatrix}, \\
\tilde{X}_i(k) &= \begin{bmatrix}
v_{x_i}(k) & v_{y_i}(k) & \varphi_i(k) & \dot{\phi}_i(k) & \dot{y}_i(k) & \dot{x}_i(k)
\end{bmatrix},
\end{aligned}$$

where

$$\begin{aligned}
M_{11} &= -2(C_f + C_l) T_s + M_{12} \dot{\varphi}_i(k) - 2C_f \dot{\delta}_i(k), \\
M_{12} &= 2(C_f (v_{x_i}(k) + l_f \dot{\phi}_i(k)) + 2C_l (v_{y_i}(k) - l_f \dot{\phi}_i(k)) - \dot{\varphi}_i(k) T_s, \\
M_{14} &= \frac{2(l_c C_r - l_f C_l) T_s}{\nu_{x_i}(k)}, \\
M_{22} &= \frac{2C_f \dot{\delta}_i(k) (v_{x_i}(k) + l_f \dot{\phi}_i(k)) T_s}{\nu_{x_i}(k)} + 1,
\end{aligned}$$

$$\begin{aligned}
M_{24} &= \frac{2l_f C_f \dot{\delta}_i(k) T_s}{\nu_{x_i}(k)} + 1,
\end{aligned}$$
Flexible Controller policy Vehicle

Flexible motor and tires such as C. Data-Driven Model behind this approach is to identify the linear dynamic system data-driven model with Hankel matrices [39]. The rationale for this policy is integrated into the DMPC algorithm to develop the driving policy. Then, the flexible spacing and soft constraints are calculated to construct the driver-centric driving policy. In this way, the optimal control sequence U(k) is obtained to steer the vehicular platoon.

III. DDMPC Strategy Design

In this part, the DDMPC strategy based on the driver-centric driving policy and the distributed data-driven model predictive control (DMPC) algorithm is put forward. Fig. 2 depicts the framework of the DDMPC strategy. More specifically, a projection twin support vector machine (PTSVM)-based driving style recognition methodology is devised to distinguish the different driving styles. According to the driver-centric driving style, the flexible spacing and soft constraints are calculated to construct the driver-centric driving policy. Then, this policy is integrated into the DMPC algorithm to develop the DDMPC strategy. In this way, the optimal control sequence U(k) is obtained to steer the vehicular platoon.

A. Driving Style Recognition

The driving style is a tending driving behavior over a long driving period, instead of a transient feature. Therefore, collected time serial vehicle characteristics are not directly applicable to train driving styles. To mitigate the adverse effects of transient driving behavior, the average, maximum and minimum vehicle characteristics have been extracted [40], [41]. With this in mind, we can obtain a dataset with 14 characteristic variables (see TABLE 1) to train the driving style.

To enhance computational efficiency, a PCA-based scheme is implemented to reduce the dimension of experiment data [42]. In this way, the dataset X with fourteen dimensions is transformed into Y with three dimensions.

The self-organizing feature map (SOM) neural network is an effective unsupervised clustering method, which has been
TABLE I: CHARACTERISTIC VARIABLES OF PLATOON EXPERIMENTS

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
<th>Unit</th>
<th>Symbol</th>
<th>Description</th>
<th>Unit</th>
</tr>
</thead>
<tbody>
<tr>
<td>Δh</td>
<td>Average spacing error</td>
<td>m</td>
<td></td>
<td>a max</td>
<td>m/s²</td>
</tr>
<tr>
<td>h max</td>
<td>Maximum spacing error</td>
<td>m</td>
<td></td>
<td>a min</td>
<td>m/s²</td>
</tr>
<tr>
<td></td>
<td>Average absolute velocity error</td>
<td>m/s</td>
<td></td>
<td>δ max</td>
<td>rad</td>
</tr>
<tr>
<td></td>
<td>Maximum velocity</td>
<td>m/s</td>
<td></td>
<td>δ min</td>
<td>rad</td>
</tr>
<tr>
<td></td>
<td>Average absolute acceleration</td>
<td>m/s²</td>
<td></td>
<td>max</td>
<td>rad</td>
</tr>
<tr>
<td></td>
<td>Average absolute acceleration</td>
<td>m/s²</td>
<td></td>
<td>min</td>
<td>rad</td>
</tr>
</tbody>
</table>

| Δφ | Average absolute heading angle error | rad |
| Δδ | Average steering error | rad |

TABLE II: RESULTS OF DRIVING STYLE RECOGNITION

<table>
<thead>
<tr>
<th>Method</th>
<th>Fold</th>
<th>Train+Test Set</th>
<th>Precision</th>
<th>mAP</th>
</tr>
</thead>
<tbody>
<tr>
<td>SOM</td>
<td>1</td>
<td>42+18</td>
<td>88.8%</td>
<td></td>
</tr>
<tr>
<td>+SVM</td>
<td>2</td>
<td>44+16</td>
<td>87.5%</td>
<td>92.38%</td>
</tr>
<tr>
<td>SOM</td>
<td>3</td>
<td>45+15</td>
<td>93.3%</td>
<td>95.16%</td>
</tr>
<tr>
<td>+PTSVM</td>
<td>4</td>
<td>47+13</td>
<td>92.3%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>5</td>
<td>48+12</td>
<td>100%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>6</td>
<td>50+12</td>
<td>100%</td>
<td></td>
</tr>
</tbody>
</table>

TABLE II gives the recognition results of the trained PTSVM classifier with 5-fold cross-validation. Compared to the 92.38% mean Average Precision (mAP) of the traditional SVM method, our proposed PTSVM method achieves 95.16% mAP. This indicates that our proposed PTSVM method has better performance for driving style recognition.

B. Driver-Centric Driving Policy

To enhance the driving experience, a driver-centric driving policy with flexible spacing and soft constraints is developed in this subsection. Such an issue also comes from actual needs, see [40], [41]. As illustrated in Fig. 4, following vehicles track the preceding one and keep a flexible spacing in terms of the different driving styles.

The variable preview distance of drivers is defined as

$$ L_{i,k} = \frac{1}{2a_{max,i}} v_i^2 + T_s v_i + R_i $$

where $R_i$ is the minimum turning radius. $a_{max}$ denotes the maximum deceleration, and it depends on different driving styles. $T_s$ denotes the sample period.
Fig. 4. The framework of flexible spacing.

Based on (14), the flexible spacing of each vehicle is deduced as

\[ L_{f,i} = L_{i,k} + L_{\text{min,i}} \]

where \( L_{\text{min,i}} \) stands for the minimum safety spacing.

Furthermore, to overcome the cutting-corner phenomenon, the reference point is shifted from the preceding vehicle to an optimal corridor point \( C(C_{i,j}, C_{j,i}) \) behind it. With the preceding vehicle point \( P_{i-1}(P_{x,i-1}, P_{y,i-1}) \) as the center and \( L_{f,i} \) as the radius, we can get

\[ L_{f,i} = (C_{x,i,k} - P_{x,i-1,k})^2 + (C_{y,i,k} - P_{y,i-1,k})^2. \]

Now we aim to search for the intersection of \( C_i \) and the reference path \( P_{i,\text{ref}} \) such that

\[ J(P_i, P_{i,\text{ref}}) = \min \sum_{\mu \geq 1} \| C_i(k) - P_{i,\text{ref}}(\mu) \|^2. \]  

(15)

Then, the optimal sequence \( \mu(\mu \in \mathbb{Z}) \) of the reference path is obtained, and it will be utilized to construct the reference output trajectory \( \hat{Y}_{i,\text{ref}}(\mu) \).

For driving comfort, the output vector and input vector should be restricted within some control constraints. More specific,

\[ \hat{Y}_{\text{min},i,k} = [\Delta x_{\text{min},i,k}, \Delta x_{\text{min},i,k}, \ldots, \sigma_{\text{min},i,k}] \]
\[ \hat{Y}_{\text{max},i,k} = [\Delta x_{\text{max},i,k}, \Delta x_{\text{max},i,k}, \ldots, \sigma_{\text{max},i,k}] \]
\[ \hat{U}_{\text{min},i,k} = [\Delta \phi_{\text{min},i,k}, \Delta \phi_{\text{min},i,k}] \]
\[ \hat{U}_{\text{max},i,k} = [\Delta \phi_{\text{max},i,k}, \Delta \phi_{\text{max},i,k}] \]

Finally, the driver-centric driving policy is utilized to design the following DMPC algorithm.

C. Distributed DMPC Algorithm

The Hankel matrices described in (12) are derived as the subspace-based linear predictor equations. These equations can be directly employed to model predictive control without identifying local state-space models [45]. It could improve the computational efficiency of DDMPC algorithm without system identification process.

Then, the past state of predictor \( \hat{X}_i^p(k) \) is described as

\[ \hat{X}_i^p(k) = \Gamma_i^p(k)(\hat{Y}_i^p(k) - H_i(k)\hat{U}_i^p(k)). \]  

(17)

Substituting (17) into (12c) yields

\[ \hat{X}_i^p(k) = \mathcal{A}_i^p(k)(\hat{Y}_i^p(k)) + \Gamma_i^p(k)(\mathcal{Y}_i^p(k) - \hat{Y}_i^p(k))\hat{H}_i(k)\hat{U}_i^p(k). \]  

(18)

According to (18) and (12a), we can deduce

\[ \mathcal{Y}_i^p(k) = \mathcal{Y}_i^p(k) + \mathcal{H}_i^p(k)\mathcal{U}_i^p(k) \]
\[ + \mathcal{G}_i^p(k)(\hat{X}_i^p(k) - \mathcal{X}_i^p(k)\hat{H}_i(k)\hat{U}_i^p(k)). \]

Introducing the least square scheme to calculate \( L_{w,i}(k) \) and \( L_{u,i}(k) \), the optimization problem is stated as

\[ \min_{L_{w,i}(k), L_{u,i}(k)} \| \mathcal{Y}_i^p(k) - L_{w,i}(k) L_{u,i}(k)\mathcal{Y}_i^p(k) \|^2_2 \]  

(19)

where \( \mathcal{W}_i^p(k) = [\mathcal{Y}_i^p(k) \mathcal{U}_i^p(k)]^T \) stands for the subspace matrix that corresponds to the past I/O trajectory. \( L_{w,i}(k) \in \mathbb{R}^{L \times L_m} \) and \( L_{u,i}(k) \in \mathbb{R}^{L \times L_i + L_m} \) denote the subspace linear predictor coefficients. \( \mathcal{U}_i^p(k) \) stands for the subspace matrix associated with the future input trajectory.

It should be noted that the orthogonal projection offers a viable solution to the least square problem described in (19). Thus,

\[ \hat{Y}_i(k) = \mathcal{Y}_i^p(k)[\mathcal{W}_i^p(k) \mathcal{U}_i^p(k)]^T. \]  

(20)

By incorporating the attributes of the QR-decomposition into equation (20), one obtains

\[ \hat{Y}_i(k) = \mathcal{Y}_i^p(k) \left[ \begin{array}{c} \mathcal{W}_i^p(k) \\ \mathcal{U}_i^p(k) \end{array} \right]^T \]  

(21)

Based on (15) and (21), the local optimal control problem is given as

\[ J_i^p(k) = \min_{\tau=0}^{K_i-1} \sum_{\tau=0}^{K_i-1} \xi(\hat{Y}_i(k + \tau | k), \hat{U}_i(k + \tau | k)) \]  

(22a)

\[ = \min_{\tau=0}^{K_i-1} \left\{ \| \hat{Y}_i(k + \tau | k) - \hat{Y}_{\text{ref},i}(\mu + \tau) \|^2_{F_i} + \| \hat{U}_i(k + \tau | k) - \hat{U}_{\text{ref},i}(\mu + \tau) \|^2_{G_i} \right\} \]

s.t. \( \hat{Y}_i(k + N | k) \in \mathcal{Y} \)

\[ \hat{U}_i(k + N | k) \in \mathcal{U} \]  

(22b)

where \( F_i \) and \( G_i \) denote positive definite weight matrices. The terminal constraints (22a) and (22b) are used to enforce that vehicular platoon has the same output as \( \hat{Y}_{\text{ref},i} \) at the end of prediction horizon. The sets \( \mathcal{Y} \) and \( \mathcal{U} \) correspond to terminal constraints. Note that the control horizon is configured to be consistent with the prediction horizon in this paper.

Furthermore, the DMPC algorithm offers a significant benefit in effectively addressing operational constraints of the cost function, as pointed out in [46]. Based on the driver-centric driving policy, several soft constraints in equation (16) are integrated into the process of optimizing the control problem.
(22). That is,
\[ Y_{ix}^{\min} \leq \hat{Y}_i(k + \tau | k) \leq Y_{ix}^{\max}. \]
\[ U_{ix}^{\min} \leq \hat{U}_i(k + \tau | k) \leq U_{ix}^{\max}. \]

Subsequently, the feedforward control law of DDMPC is derived as
\[
\hat{U}_i(k) = \left( F_i^T L_{u,i} F_i \Gamma_i L_{u,i} + G_i \right)^{-1} \left( \Gamma_i L_{u,i} \right)^T \left( F_i Y_{ix,f}(k) - L_{u,i} \hat{Y}_i(k) \right). \tag{23}
\]

Let us define a vector \( \mathcal{L}_i = [L_{u,i}, L_{u,i}] \), and the singular value decomposition method is introduced into \( \mathcal{L}_i \). Then, we can get
\[
\mathcal{L}_i = \mathcal{U}_i \mathcal{Y}_i^T \tag{24}
\]
where \( \mathcal{U}_i \) and \( \mathcal{Y}_i \) are unitary matrices. \( \mathcal{L}_i \) stands for the diagonal matrix.

Substituting (24) into (23) yields
\[
\hat{U}_i(k) = \left( L_{u,i}^T F_i \Gamma_i L_{u,i}^T + G_i \right)^{-1} \left( L_{u,i} \right)^T \mathcal{U}_i \mathcal{Y}_i^T X_i(k)
= K_i X_i(k) \tag{25}
\]
where \( K_i \) denotes the control gain.

In practice, the first element of control law (25) is implemented to steer the vehicular platoon.

D. Stability Analysis

Theoretical analysis is essential as it could provide the guidance for the selection of system parameters, thereby ensuring the stability of vehicular platoon.

**Lemma 1:** [27] System (11) is characterized by the controllability of \((A_i, B_i)\) and the observability of \((A_i, C_i)\). If system (11) is input-output-to-state stability, there exists a matrix \( R \) and positive constants \( \varepsilon_0, \varepsilon_1, \gamma_0 \) such that
\[
W_i(k + 1) - W_i(k) \leq -\varepsilon_0 \| X_i(k) \|_2^2 + \varepsilon_1 \| \mathcal{Y}_i(k), \mathcal{U}_i(k) \|_2^2 \tag{26}
\]
with the ISS Lyapunov function \( W_i(k) \leq \gamma_0 \| X_i(k) \|_2^2 \).

By combining the quadratic stage cost with an exponential controllability argument, it guarantees the infinite horizon cost is bounded, i.e.,
\[
J_i^*(k) \leq \gamma_s \| X_i(k) \|_2^2 \tag{27}
\]
with \( \gamma_s > 0 \).

Then, a local Lyapunov function candidate \( V_i(k) \) is defined as
\[
V_i(k) = J_i^*(k) + W_i(k). \tag{28}
\]

**Theorem 1:** Suppose that \( \{ U_i^0, \mathcal{U}_i^0 \} \) is persistently exciting of order \( N + 2n \). For any constant \( \gamma > 0 \), there exists a sufficiently long prediction horizon \( N_m > 0 \) such that for all \( N > N_m \) and any initial condition satisfying \( V_i(0) < \gamma \), the DMPC problem (22) is recursively feasible. Then, the closed-loop system is exponentially stable if the function \( V_i(k) \) admits
\[
\varepsilon_0 \| X_i(k) \|_2^2 \leq V_i(k) \leq \gamma_s \| X_i(k) \|_2^2
\]
\[
\gamma_s (\gamma_s - \gamma_0) - \varepsilon_0 \leq 0.
\]

The proof for Theorem 1 is provided in Appendix A.

IV. Experiments Design

In this section, two experimental platforms involving physical experimental platform and co-simulation experimental platform are constructed. Then, several comparative experiments are carried out to verify the advantage of the proposed DDMPC strategy.

![Fig. 5. Hardware framework of vehicular platoon platform.](image)

**A. Physical Experimental Platform**

The physical experiment is carried out on a vehicular platoon platform (see Fig. 5) comprising of three vehicles, a driving simulator, a WiFi router, seven ultra wide band (UWB) positioning modules and three host computers. Each vehicle is equipped with ROS system and Nano processing unit. This specific type of vehicles has been widely applied in vehicular platoon modelling and control studies [47]–[49]. The proposed DDMPC strategy is deployed with Matlab language on each host computer, enabling the generation of an optimal control sequence (voltage). Then, the voltage control sequence is transformed to the Nano processing unit with the WiFi router to drive the DC motors of vehicles. This forms a closed-loop structure.

![Fig. 6. Driving simulator.](image)

As illustrated in Fig. 6, the driving simulator is operated by different drivers. To provide a better driving experience, a control monitor is developed in Simulink software. It could provide all vehicle states to compensate for the driver’s vision...
TABLE III: DRIVERS’ ATTRIBUTES

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Number</th>
<th>Attributes</th>
<th>Number</th>
<th>Attributes</th>
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<td>Age</td>
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<td>&gt;42</td>
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<td></td>
<td></td>
<td>&gt;42</td>
<td>16</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Profession</td>
<td>Teacher</td>
<td>22</td>
<td></td>
<td>Student</td>
<td>20</td>
<td>Others</td>
<td>28</td>
</tr>
</tbody>
</table>

blind spot when the vehicles are away from the driver. Then, the steering angle and pedal travel are converted into voltage signals to control the leading vehicle $L_1$. Accordingly, all vehicles’ information could be exchanged under the PF topology.

![Fig. 7. Experimental scenarios.](image)

The vehicular platoon configuration with three vehicles traveling on a $Z$-curved road, see Fig. 7. The width and length of the reference trajectory are 1m and 6m, respectively. Following vehicle 2 ($F_2$) and following vehicle 3 ($F_3$) track $L_1$ with 0.35m/s. $h_1$ and $h_2$ stand for the flexible spacing. The experiment entails the recruitment of sixty drivers to participate in the study. The attributes of these drivers including gender, age, driving age and profession, are enumerated in TABLE III. Several key experimental parameters have been listed in TABLE IV.

TABLE IV: EXPERIMENTAL PARAMETERS

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Value</th>
<th>Symbol</th>
<th>Value</th>
<th>Symbol</th>
<th>Value</th>
</tr>
</thead>
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<tr>
<td>$m$</td>
<td>3.87kg</td>
<td>$N$</td>
<td>16</td>
<td>$R$</td>
<td>0.8m</td>
</tr>
<tr>
<td>$L_{min}$</td>
<td>0.35m</td>
<td>$I$</td>
<td>0.35m</td>
<td>$n$</td>
<td>30</td>
</tr>
<tr>
<td>$T_s$</td>
<td>20Hz</td>
<td>$N_m$</td>
<td>13</td>
<td>$L$</td>
<td>12</td>
</tr>
</tbody>
</table>

B. Co-Simulation Experimental Platform

Several experiments are also carried out on a co-simulation platform (see Fig. 8) with Matlab® software, IPG-CarMaker® software, a driving simulator and high-performance computer.

![Fig. 8. The framework of co-simulation platform](image)

IPG-CarMaker® details vehicle dynamics including chassis, battery, motor, clutch, engine and tire models.

All strategies are deployed with Matlab language on the host computer, and it could generate the optimal control sequence. In this way, each vehicle is driven via brake, acceleration and steering wheel. These algorithms are compiled into C++ code and plugged in the IPG-CarMaker® software. In addition, the real-time information of vehicular platoon could be exchanged through the SimNet module.

![Fig. 9. Co-simulation experimental scenarios](image)

As shown in Fig. 9, the platoon configuration with three vehicles traveling on a 2km urban traffic road. Three default vehicle models are chosen from IPG-CarMaker®, and their average velocity is 20m/s. Here, the desired safe spacing of platoon is set to 80m.

C. Experimental Procedures

The physical experiment process consists of two stages: data collection and strategy verification. Initially, the leading vehicle is operated by drivers, while the remaining vehicles are AVs. The collected experimental data $D \in \mathbb{R}^{7 \times 3}$ from one single driver has 7 I/O trajectories of 3 vehicles. sixty drivers participate in this experiment, then we can obtain a dataset with (60 × 7) items. Note that this dataset is used to construct the data-driven model. Moreover, it is quantified into
14 variables (see TABLE I) to train the driving style. For the second stage, \( L_1 \) is regarded as a virtual leader, and different control strategies are embedded into the following vehicles. Furthermore, the co-simulation experiment also follows a similar experimental procedure to the physical one.

Five different experiments are conducted to train the driving styles and verify the advantage of our proposed DDMPC strategy. The following outlines the detailed experimental procedures.

- **Exp1.** \( F_2 \) and \( F_3 \) with the MPC strategy [18] track \( L_1 \) which are controlled by sixty drivers.
- **Exp2.** The proposed driver-centric driving policy is integrated into the mechanism-based MPC, namely, DMMPC strategy [50] to steer \( F_2 \) and \( F_3 \) to track \( L_1 \).
- **Exp3.** The DMPC strategy without the driver-centric method in [29] is applied to each following vehicle to track \( L_1 \).
- **Exp4.** \( F_2 \) and \( F_3 \) use the proposed DDMPC strategy to follow \( L_1 \).
- **Exp5.** The DDMPC strategy with three driving styles is carried out in \( F_2 \) and \( F_3 \) to follow \( L_1 \).
- **Exp6.** Following the procedure of **Exp4**, a two-track vehicle model [38] is applied to the DMMPC strategy, which generates a DMPC\(_M\) strategy.
- **Exp7.** The distributed robust control (DRC) strategy [51] is employed to each following vehicle to track \( L_1 \).

Note that **Exp6** and **Exp7** are carried out on the co-simulation experimental platform, and others are conducted on the physical experimental platform. Furthermore, the effectiveness of different driving styles on vehicular platoon has also been analyzed in **Exp5**. Typical performance example can be viewed in online supplementary video (https://youtu.be/geyk2lhp13U).

V. RESULTS AND DISCUSSIONS

In this part, the results of different strategies will be analyzed in terms of driving safety, driving comfort and comprehensive performance for EVP. Several indexes involving Euclidean spacing, velocity, heading angle and their errors are applied to characterize the platoon performance. Then, some assessment methods such as absolute maximum error (AMAXE), root mean square error (RMSE) and correlation coefficient can be utilized to evaluate the effectiveness of the proposed DDMPC strategy.

Fig. 10. Results of Exp1.

A. Results of Physical Experiments

Several key variables collected from **Exp1** involving position information, velocity information and heading angle information are presented in Fig. 10. These normalized results satisfy the characteristics of a normal distribution, indicating the validity of the experimental data.

It is clear to see the superiority of our proposed DDMPC strategy from Figs. 11-13. According to the results of **Exp2**, an obvious heading and velocity oscillation of the DMMPC strategy is executed in Figs. 11(b)-11(c). Therefore, it could perform a tracking error for the platoon in Fig. 11(a). Furthermore, the DMPC strategy without the driver-centric method fails to track the road trajectory but only the ahead vehicle in **Exp3**. To be more specific, both \( F_2 \) and \( F_3 \) could track the velocity and heading of \( L_1 \) in 12(b) and Fig. 12(c). Note that a large lateral position error is executed in Fig. 12(a), and it could cause the vehicle to deviate from the road boundary. Fig.13 illustrates the proposed DDMPC strategy could track the velocity and heading of \( L_1 \) within \( 2\sigma \), and keep a stable tracking in **Exp4**.

The evaluation indicators for driving comfort are different for individual driving styles. Therefore, three driving styles are investigated to demonstrate driving comfort in **Exp5**. As we can see from Fig. 14, the platoon with aggressive style exhibits the earliest turning behavior and most unstable
velocity tracking, resulting in an excessive tight spacing. Conversely, the latest steering behavior and stable spacing are demonstrated for the conservative one. In this case, the vehicular platoon prefers to guarantee the string stability rather than the driving experience. The moderate style exhibits a relatively conventional driving experience and string stability compared to the aggressive and conservative ones.

B. Results of Co-Simulation Experiments

The results of Exp6 and Exp7 are demonstrated in Figs. 15-16. According to Fig. 15, $F_2$ with the DRC strategy exhibits a bigger Euclidean spacing, and its peak reaches about 110m. Accordingly, the velocity error and heading angle error perform obvious oscillations, especially in 250s. Comparatively, $F_2$ with the DDMPC$_M$ strategy exhibits more stable Euclidean spacing, velocity and heading tracking capability. Note that the proposed DDMPC strategy has similar performance to DDMPC$_M$ one, indicating the data-driven model could characterize the dynamics of vehicles. A similar result is also obtained for $F_3$ in Fig. 16. To conclude, the results indicate that the proposed DDMPC strategy is capable of capturing the complex dynamics of actual vehicles and exhibit superior platoon tracking stability compared to the DRC one.

C. Comprehensive Analysis

To provide a more detailed explanation of the merits inherent in our proposed DDMPC strategy, the absolute maximum error (AMAXE) and root mean square error (RMSE) assessment methods are introduced. In TABLE V, the Euclidean spacing error ($\Delta E$), velocity error ($\Delta v$) and heading error ($\Delta \phi$) for different strategies are evaluated. According to the physical experimental results, the proposed DDMPC strategy has the minimum Euclidean spacing error and velocity error, which implies that satisfactory string stability could be fulfilled for the platoon. Although the DMPC strategy demonstrates superior heading tracking performance, it cannot guarantee the road constraint. Note that the co-simulation experiments follow a similar conclusion to the physical one. Therefore, these results illustrate that the DDMPC strategy has better performance for driving safety.

The computational efficiency of algorithms is also critical for platoon, affecting the capacity of real-time platoon control. To this end, the average computational time of each sampling interval among three strategies is presented in Fig. 17. In terms of the results of physical experiments, $F_2$ and $F_3$ with the DMMPC strategy spend the utmost computational time about 10.7ms and 10.8ms, respectively. The DRC strategy achieves minimal computational time of 9.2ms and 9.1ms. Meanwhile, the computational time of the DDMPC strategy falls between the two mentioned above. The average computational time of co-simulation experiments also conforms to the similar conclusion. This implies that despite a marginal compromise
Fig. 14. Results of Exp5.

Fig. 15. Results of Exp6.

In this paper, we have developed a DDMPC strategy to improve a driver-centric driving experience on curved roads. According to the analysis above, it can be concluded that the proposed DDMPC strategy provides safe and satisfactory driving experience for different drivers.

VI. CONCLUSION

In this paper, we have developed a DDMPC strategy to improve a driver-centric driving experience on curved roads.
The subspace identification method has been employed to construct the data-driven model, and it replaces the mechanism to solve the optimization problem. The issue of cutting corners has been tackled through the creation of a driver-centric driving policy, which was designed based on data...
gathered from experiments. Then, the DMPC algorithm and driver-centric driving policy are integrated to develop the DDMPC strategy, and its feasibility and stability have been proved. Compared with the existing MPC-based strategies, the proposed DDMPC strategy in this paper maintains more stable velocity and spacing tracking, which shows its superiority in driving safety. And the experimental results have demonstrated that our proposed DDMPC strategy could recognize the driving style and provide satisfactory driving experience for drivers. Our future work will be dedicated to reducing the computational burden of the proposed strategy and testing it in actual vehicles.

**Appendix A**

The proof of Theorem 1

Substituting (26) and (27) into (28), the lower bound of \( V_i(k) \) yields

\[
V_i(k) \geq J_i^*(k) + \sum_{\tau=0}^{N-1} \xi(\mathcal{Y}_{i(k \tau+k+1)}^*, \mathcal{U}_i(k \tau+k+1)) + W_i(k+1) + \varepsilon_0 \| X_i(k) \| ^2
\]

(29)

\[
-\varepsilon_1 \xi(\mathcal{Y}_i(k), \mathcal{U}_i(k))
\geq \varepsilon_0 \| X_i(k) \| ^2.
\]

Furthermore, the upper bound of \( V_i(k) \) admits

\[
V_i(k) \leq \gamma_i \| X_i(k) \| ^2 + \gamma_0 \| X_i(k) \| ^2.
\]

(30)

Based on (30), we can get

\[
\sum_{k=1}^{N-1} \left( \varepsilon_0 \| X_i(k) \| ^2 \right) \leq \sum_{k=0}^{N-1} \left( \varepsilon_0 \| X_i(k) \| ^2 \right)
\]

\[
\leq V_i(k) \leq (\gamma_i + \gamma_0) \| X_i(k) \| ^2.
\]

Thus, there exists an integer \( N_m \in \{1, 2, ..., N-1\} \) such that

\[
\| X_i(k) \| ^2 \leq \frac{\gamma_i + \gamma_0}{\varepsilon_0 (N_m - 1)} \| X_i(k) \| ^2.
\]

Denote the standard candidate solution being \( \{ \mathcal{Y}_i^*(k+1), k \}, \mathcal{U}_i^*(k+1) \), then one derives

\[
J_i^*(k+1) = \sum_{\tau=0}^{N-1} \xi(\mathcal{Y}_i^*(k+\tau+1), \mathcal{U}_i^*(k+\tau+1))
\]

\[
= \sum_{\tau=1}^{N-1} \xi(\mathcal{Y}_i^*(k+\tau), \mathcal{U}_i^*(k+\tau))
\]

\[
= J_i^*(k) - \xi(\mathcal{U}_i^*(k), \mathcal{U}_i^*(k)).
\]

Hence, it follows that

\[
J_i^*(k+1) \leq J_i^*(k) - \xi(\mathcal{U}_i^*(k), \mathcal{U}_i^*(k)).
\]

Then, the cost of the candidate solution over the horizon \( N_m \) satisfies

\[
J_i^*(k+1) + \xi(\mathcal{Y}_i(k), \mathcal{U}_i(k))
\]

(31)

\[
\leq \sum_{k=0}^{N-1} \xi(\mathcal{Y}_i(k), \mathcal{U}_i(k)) + J_i^*(k+1)
\]

\[
\leq \gamma_i \| X_i(k) \| ^2 + J_i^*(k)
\]

\[
\leq J_i^*(k) + \frac{\gamma_i + \gamma_0}{\varepsilon_0 (N_m - 1)} \| X_i(k) \| ^2.
\]

According to (29) and (31), the Lyapunov function candidate becomes

\[
V_i(k+1) - V_i(k)
\]

\[
J_i^*(k+1) - J_i^*(k) + W_i(k+1) - W_i(k).
\]

\[
\leq \left( \frac{\gamma_i + \gamma_0}{\varepsilon_0 (N_m - 1)} \| X_i(k) \| ^2.\right.
\]

To ensure the local Lyapunov function candidate \( V_i(k) \) is decreased monotonically, a sufficiently long horizon \( N_m \) should be satisfied, such that

\[
N \geq N_m \geq \frac{\gamma_i + \gamma_0}{\varepsilon_0} + 1.
\]

Now it is found that the DDMPC scheme is exponentially stable, thus achieving the vehicular platoon tracking objective. This completes the proof.

**References**


**Yanhong Wu** received the M.S. degree in vehicle engineering from Chongqing Jiaotong University, Chongqing, China, in 2020. He is currently pursuing the Ph.D. degree with the School of Electrical Automation and Information Engineering, Tianjin University, Tianjin, China. He is now a visiting Ph.D. with the University of Birmingham, U.K.

His research interests include data-driven modelling, model predictive control, and their applications on connected and autonomous vehicles.

**Zhiqiang Zuo** (M’04 - SM’18) received the M.S. degree in control theory and control engineering from Yanshan University, Qinhuangdao, China, in 2001, and the Ph.D. degree in control theory from Peking University, Beijing, China, in 2004.

In 2004, he joined the School of Electrical Automation and Information Engineering, Tianjin University, Tianjin, China, where he is a Full Professor. From 2008 to 2010, he was a Research Fellow with the Department of Mathematics, City University of Hong Kong, Hong Kong. From 2013 to 2014, he was a Visiting Scholar with the University of California at Riverside, Riverside, CA, USA. His current research interests include nonlinear control, robust control, model predictive control, and multiagent systems.

Prof. Zuo is an Associate Editor of the Journal of the Franklin Institute.

**Yijing Wang** received the M.S. degree in control theory and control engineering from Yanshan University, Qinhuangdao, China, in 2000, and the Ph.D. degree in control theory from Peking University, Beijing, China, in 2004.

In 2004, she joined the School of Electrical Automation and Information Engineering, Tianjin University, Tianjin, China, where she is a Full Professor. Her current research interests include analysis and control of switched/hybrid systems and robust control.

**Qiaoni Han** received the B.S. and M.S. degrees from the Institute of Electrical Engineering, Yanshan University, China, in 2010 and 2013, respectively, and the Ph.D. degree from the School of Electronic and Electric Engineering, Shanghai Jiao Tong University, Shanghai, China, in 2017. From 2017 to 2019, she was an Assistant Professor with Qingdao University and selected for the Young Talents Program.

She is currently an Associate Professor with the Department of Automation, Tianjin University, Tianjin, China. Her research interests include modelling and optimization of wireless networks, transmission and control of network systems.

**Ji Li** (Member, IEEE) received the Ph.D. degree in mechanical engineering from the University of Birmingham, U.K., in 2020.

He is currently an Assistant Professor and works on the Connected and Autonomous Systems for Electrified Vehicles (CASE-V) at the Birmingham CASE-V Automotive Research and Education Centre. His current research interests include computational intelligence, data-efficient modelling, feature selection, man-machine system, and their applications on connected and autonomous vehicles.

**Hongming Xu** received the Ph.D. degree in mechanical engineering from Imperial College London, London, U.K., in 1995.

He is a Professor of energy and automotive engineering at the University of Birmingham, Birmingham, U.K., and the Head of Vehicle and Engine Technology Research Centre. He has six years of industrial experience with Jaguar Land Rover, Coventry, U.K. He has authored and coauthored more than 500 journals and conference publications on advanced vehicle powertrain systems involving both experimental and modelling studies.