User-Centric Multi-Objective Predictive Control for Mixed Vehicular Platoon

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Abstract—The penetration rate of automated vehicles (AVs) will remain unsaturated for a long period, leading to the coexistence of AVs and human-driven vehicles (HDVs), namely, mixed vehicular platoon (MVP). This paper proposes a novel user-centric multi-objective predictive control (UMPC) strategy to address dynamics uncertainty and multi-objective conflict for MVP. A data-driven model is established with subspace identification to alleviate the adverse effects of the non-ideal driving behavior and complex powertrain structure of electric vehicles. To provide a personalized driving experience, soft constraints and a user-centric multi-objective cost function are formulated. Based on this, a multi-objective optimization scheme in terms of data-driven model predictive sequence is designed. It aims to mitigate conflicts among multiple optimization objectives involving driving safety, driving comfort and energy economy. Then, a grey wolf optimizer (GWO) is devised to navigate the search process, striving for globally optimal trade-offs among conflicting objectives. With the above preparations, a UMPC strategy is suggested. Then, a hardware-in-the-loop experiment platform with CarMaker software and driving simulator is constructed, and twenty drivers participate in the experiment. The experimental results demonstrate the effectiveness of the proposed UMPC strategy.

Index Terms—Mixed vehicular platoon, multi-objective optimization, data-driven model predictive control, user-centric.

I. INTRODUCTION

Intelligent transportation system has been hindered by the increasing concerns about traffic safety and limited road capacity. The unsaturated penetration rate of automated vehicles (AVs) would result in AVs sharing the road with human-driven vehicles (HDVs) [1]. In fact, mixed vehicular platoon (MVP) is an indispensible stage in the transition from fully manual driving to fully automated driving [2]. The key divergence between the pure automated vehicular platoon and MVP is that the latter involves HDVs whose behaviors are nonstandard and uncertain [3], [4]. In MVP, AVs should cooperate with HDVs, and their potential goal is to provide comfort, safety and economical driving experience for users. Therefore, the exploitation of the user-centric multi-objective control strategy for MVP has triggered a widespread research upsurge.

Amidst the abundance of platoon control schemes, the model predictive control (MPC) has attracted significant attention [5]–[7]. This method relies on an explicit model, such as Tampere model, optimal velocity model and intelligent driver model [8], [9]. However, human-driven electric vehicles involving different driving behaviors are elusive, and their chassis has a specialized powertrain structure. As an available technique for comprehending the intricacies of MVP, the data-driven control approach has emerged [10], [11]. Thus, the network-based MPC method has been widely adopted [12], [13]. Then, an extended data-driven MPC with reinforcement learning was developed to address the complex modelling issue [14], [15]. It should be pointed out that these schemes fail to be implemented in vehicular chips because of enormous computational burden. Thereafter, the Koopman operator-based strategy has been successfully applied to industrial processes [16], [17]. Note that the Koopman operator involves high-order terms and requires nonlinear transformation, resulting in increased complexity in the modelling. Therefore, it is necessary to develop an efficient data-driven predictive control scheme for MVP.

Actually, keeping safe spacing of MVP does not guarantee the achievement of operational performance. The energy efficiency and driving comfort are also essential criteria [18], [19]. These indicators affect the driving experience and the acceptance of autonomous driving technology in the transportation ecosystem. The essence of this phenomenon can be encapsulated as a multi-objective conflict challenge [20]. Afterward, a hierarchical multi-objective optimization scheme aiming at minimizing fuel consumption and enhancing traffic safety was developed in [21]. To simplify the multi-objective problem, the Pareto method and weighted-sum method provide potential solutions, facilitating the integration of diverse objectives into one unified objective [22]. Subsequently, several optimization algorithms such as particle swarm optimization [23], genetic optimization [24], ant colony optimization [25] and grey wolf optimization (GWO) [26] have been suggested. In this way, a non-dominated sorting genetic algorithm was utilized to find the Pareto optimal asymmetric degree regarding the overall performance of the platoon [27]. Moreover, an elite genetic-based interval optimization approach gave a feasible solution.
in balancing the multi-objective conflicts [28]. Among them, GWO demonstrates proficiency in capturing a comprehensive spectrum of trade-off solutions that has garnered significant attention. In this way, an improved GWO incorporating the support vector machine was given to enhance energy efficiency of electric vehicles [29]. It should be noted that different drivers pursue different optimization objectives of MVP [30]. Specifically, the conservative driver prefers to reduce energy consumption than keep inter-spacing and driving comfort. Conversely, the aggressive driver has a propensity for maintaining minimal inter-spacing, thereby prioritizing driving comfort and economy. Therefore, how to provide a user-centric multi-objective optimization scheme becomes a difficult task that needs to be tackled.

The above research in MVP modelling focuses on developing explicit dynamic models rather than data-driven ones. It poses a formidable difficulty in obtaining accurate dynamic parameters of the powertrain structure and characterizing non-ideal driving behavior. Furthermore, the existing multi-objective optimization algorithms cannot meet the requirement of personalized driving behavior. These factors motivate us to construct an appropriate platoon model and user-centric multi-objective optimization scheme for MVP. The main contributions of this paper are summarized below.

i) A subspace-based data-driven MVP model is developed to alleviate the adverse effects of uncertain dynamics. MVP involves electric vehicular models and driver models, and it is arduous to obtain these complex dynamic parameters. Then, the subspace identification method is utilized to construct the data-driven model.

ii) A user-centric multi-objective optimization scheme is designed. The corresponding user-centric cost function and soft constraints are constructed in terms of different driving styles. Such a treatment could provide a user-centric driving policy to balance conflicts among driving safety, driving comfort and energy economy.

iii) A user-centric multi-objective predictive control (UMPC) strategy is proposed with data-driven model predictive control and GWO. This strategy combines the predictive capability of MPC with the global optimization performance of GWO, thus it could enhance the robustness during solving the multi-objective issue.

This paper is organized as follows. Section II illustrates the MVP model. Section III gives the detailed process for the design of UMPC strategy. Field experiments with the corresponding analysis and discussions are carried out in Section IV. Experimental results are analyzed in Section V. Section VI draws the conclusion.

Notations: $\| \cdot \|_1$ stands for the Frobenius norm. The Moore-Penrose pseudo inverse of matrix $H$ is denoted as $H^\dagger$. $\Delta$ is the error between the current vector and the reference vector. $|.|$ denotes the absolute value. $\| \cdot \|_2$ represents the $L_2$ norm.

II. VEHICULAR PLATOON MODELLING

In the MVP, each electric autonomous vehicle is powered by the battery module, and its structure involves battery, motor, transmission and chassis. For HDV, the influence of the driver’s behavior is also taken into account. To alleviate the adverse effects of uncertain dynamics, the original mechanism model is transformed into a data-driven one.

A. Mechanism Model

Fig. 1 gives the powertrain structure of electric vehicle. The battery serves as the energy source, providing electrical power to the motor, where the electrical power is converted into mechanical force. The transmission system plays a crucial role in transferring the mechanical force to the tires, ultimately driving the vehicle forward. To derive a concise model, several reasonable hypotheses are given: 1) The vehicle is traveling on a dry and flat road, and the longitudinal slip of the tires is ignored. 2) The vehicle body is symmetric and rigid. 3) The yaw and pitch motions of the vehicle are neglected. 4) The influences of internal resistance, temperature variation and capacity degradation on the battery are ignored [31], [32].

According to the properties of electric vehicle’s powertrain from Refs. [3], [33], we can get

$$
\begin{align*}
\dot{a} &= \frac{T_d}{mr} \\
\dot{\text{SOC}} &= - \frac{T_d}{K_e C_{bat}}
\end{align*}
$$

where SOC stands for the state of charge of battery. $a$ denotes the acceleration of the vehicle. $T_d$ represents the demand torque. $i_k$ is the transmission ratio. $\eta_t$ stands for the transmission efficiency, $r$ represents the tire radius. $m$ stands for the mass of the vehicle. $C_{bat}$ denotes the capacity of the battery. $K_e$ is the anti-electromotive force coefficient.

Then, the optimal velocity model is employed to describe HDV [34]. Specifically,

$$
\begin{align*}
\dot{h}_1 &= v_0 - v_1 \\
\dot{v}_1 &= a_1 \\
\dot{a}_1 &= \frac{1}{h_1} (\alpha (V(h_1) - v_1) + \beta (v_0 - v_1) - a_1)
\end{align*}
$$

where $h$ denotes the spacing between adjacent vehicles, $v$ is the velocity of the vehicle. $\tau$ stands for the unknown propulsion time delay. $\alpha$ and $\beta$ represent the headway gain and the velocity gain. $V(h_1)$ denotes the spacing-dependent desired velocity function. All vehicles are expected to converge to the equilibrium state $(h^*, v^*, \text{SOC}^*)$. Here, $v^* = v_0$, $h^*$ satisfies
where $\Delta h_1(k)$ and $\Delta v_1(k)$ conform to the initial condition of the state of charge ($SOC_0$) [35].

Following the principle of Taylor formula, the HDV model has the form

$$x_1(k + 1) = A_1 x_1(k) + E_1 x_0(k),$$

with

$$A_1 = \begin{bmatrix}
1 & -T_s & 0 & 0 \\
0 & 1 & T_s & 0 \\
0 & 0 & T_s & 0 \\
0 & 0 & 0 & 1 \\
\end{bmatrix}, \quad E_1 = \begin{bmatrix}
\Delta h_1(k) \\
\Delta v_1(k) \\
a_1(k) \\
\Delta SOC_1(k) \\
\end{bmatrix},$$

where $T_s$ stands for the sampling period. $\Delta h_1(k) = h_1(k) - h^*$ and $\Delta v_1(k) = v_1(k) - v^*$ and $\Delta SOC_1(k) = SOC_1(k) - SOC^*$. Note that $x_0$ is the state vector of virtual leading the vehicle.

Furthermore, a third-order vehicle kinematics model is applied to describe the characteristics of AV $i$ ($i \in [2, M]$). Thus, we have

$$\dot{v}_i = a_i - \frac{1}{2}(u_i - a_i)$$

where $u$ stands for the anticipated acceleration.

Similarly, the AV model could be deduced as

$$x_i(k + 1) = A_i x_i(k) + B_i u_i(k) + E_i x_{i-1}(k)$$

with

$$A_i = \begin{bmatrix}
1 & -T_s & 0 & 0 \\
0 & 1 & T_s & 0 \\
0 & 0 & T_s & 0 \\
0 & 0 & 0 & 1 \\
\end{bmatrix}, \quad B_i = \begin{bmatrix}
0 \\
i_s T_s / (mR) \\
0 \\
-T_s / (K_C C_{bat}) \\
\end{bmatrix},$$

$$E_i = \begin{bmatrix}
\Delta h_1(k) \\
\Delta v_1(k) \\
a_i(k) \\
\Delta SOC_1(k) \\
\end{bmatrix},$$

where $u_i(k) = T_d(k)$ denotes the input vector. $x_i(k)$ has a similar definition as HDV. $x_{i-1}$ is the state vector of ahead vehicle.

Based on (1) and (2), the MVP system with one HDV and $M - 1$ AVs admits

$$\begin{align*}
X(k + 1) & = \mathcal{A} X(k) + \mathcal{B} U(k) + \mathcal{E} W(k) \\
Y(k) & = C X(k)
\end{align*}$$

with

$$\mathcal{A} = \begin{bmatrix}
A_1 & 0 & \cdots & 0 \\
E_2 & A_2 & \cdots & 0 \\
\vdots & \ddots & \ddots & \vdots \\
0 & 0 & E_M & A_M \\
\end{bmatrix}, \quad \mathcal{B} = \begin{bmatrix}
0 & 0 & \cdots & 0 \\
0 & B_2 & \cdots & 0 \\
\vdots & \ddots & \ddots & \vdots \\
0 & 0 & 0 & B_M \\
\end{bmatrix},$$

$$\mathcal{E} = \begin{bmatrix}
E_1 & \cdots & 0 \\
0 & \cdots & u_2(k) \\
\vdots & \ddots & \vdots \\
0 & \cdots & u_M(k) \\
\end{bmatrix}, \quad \mathcal{U}(k) = \begin{bmatrix}
x_1(k) \\
x_2(k) \\
\vdots \\
x_M(k) \\
\end{bmatrix}, \quad \mathcal{W}(k) = \begin{bmatrix}
X(k) \\
X(k + 2) \\
\vdots \\
X(k + M) \\
\end{bmatrix}.$$
A. Driving Style Recognition

Actually, the driving style is a tending driving habit over a long period, instead of a transient feature. To alleviate the adverse effects of transient driving behavior, several quantitative indicators of collected data involving average, maximum and minimum are extracted to construct the dataset (see TABLE I). In this way, a comprehensive dataset $X \in \mathbb{R}^{(11 \times 20 \times 20)}$ with twenty drivers, nine variables and $z$ samples is obtained. The dataset requires normalization and dimensionality reduction processing to improve training effectiveness [37].

As shown in Fig. 3, the processed driving data is clustered into three driving styles involving aggressive ($S_1$), moderate ($S_2$) and conservative ($S_3$) using the K-means technique [38]. Twenty driving data samples are divided into two parts: three test sets and seventeen training sets. Based on the determined driving styles (see Fig. 3), the support vector machines (SVM) classification method is adopted to train the driving style classifier. This approach aims to search for the separating hyperplane in terms of the labeled data [39]. Its binary classification problem is described as an optimization problem

$$\min \left\{ \frac{1}{2} \| \psi \|^2 + \varrho \sum_{i=1}^{z} \xi_{i} \right\}$$

s.t. $S_j (\psi^T Y_j + b) \geq 1 - \xi_{j}$, $\xi_{j} > 0$

where $\psi$ stands for the vector of hyperplane $S$, $b$ denotes the bias, $\varrho$ is a penalty coefficient. $\xi_{j}$ stands for the slack variable.

Note that driving style recognition falls within the domain of multiclass classification issue, and the “one-against-all” approach is put forward in this paper, see Ref. [40] for details. With this in mind, different driving styles of drivers in the test set are recognized. Furthermore, several soft constraints and user-centric weight coefficients could be determined in terms of different driving styles.

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>$\Delta h$</td>
<td>Average spacing error</td>
<td>$m$</td>
<td>$[J_k]$</td>
<td>Average absolute jerk</td>
<td>$m/s^2$</td>
</tr>
<tr>
<td>$h_{max}$</td>
<td>Maximum spacing error</td>
<td>$m$</td>
<td>$\triangle \text{SOC}$</td>
<td>Average state of charge error</td>
<td>$%$</td>
</tr>
<tr>
<td>$</td>
<td>\Delta v</td>
<td>$</td>
<td>Average absolute velocity error</td>
<td>$m/s$</td>
<td>$a_{max}$</td>
</tr>
<tr>
<td>$v_{max}$</td>
<td>Maximum velocity</td>
<td>$m/s$</td>
<td>$</td>
<td>a_{min}</td>
<td>$</td>
</tr>
<tr>
<td>$</td>
<td>\bar{a}</td>
<td>$</td>
<td>Average absolute acceleration</td>
<td>$m/s^2$</td>
<td>$T_{d,max}$</td>
</tr>
<tr>
<td>$</td>
<td>T_d</td>
<td>$</td>
<td>Average absolute torque</td>
<td>$Nm$</td>
<td></td>
</tr>
</tbody>
</table>

B. Subspace Predictor Design

The data-driven model mentioned in (2) is used to construct the linear subspace predictor equations. These equations allow for the prediction procedure without identifying the local state-space model [41]. The elimination of the system identification procedure has the advantages of enhancing the computational efficiency of the UMPC algorithm.

With the least squares method calculating $L_n(k)$, $L_o(k)$ and $L_s(k)$, the optimization problem can be formulated as

$$\min \| \mathbf{y}^f(k) - [L_n(k) \ L_o(k) \ L_s(k)] \begin{bmatrix} Q^p(k) \\ U^p(k) \\ W^p(k) \end{bmatrix} \|^2_2$$

(5)
where $Q^R(k) = [Y^R(k) \ U^R(k) \ \mathbf{W}^R(k)]^T$ stands for the subspace prediction matrix corresponding to the past I/O trajectory. $L_o(k)$, $L_v(k)$ and $L_e(k)$ denote the subspace predictor coefficients.

Then, the orthogonal projection technique is applied to calculate the optimization problem in (5). Thus,

$$\hat{Y}(k) = Y^f(k)\left[Q^R(k) \ U^R(k) \ W^R(k)\right]^T.$$  

According to the properties of QR-decomposition, we can obtain

$$\hat{Y}(k) = Y^f(k)\left[Q^R(k) \ U^R(k) \ W^R(k)\right]^T = \left[L_o(k) L_v(k) L_e(k)\right]\left[Q^R(k) \ U^R(k) \ W^R(k)\right]^T \tag{6}$$

To reflect the individualized driving styles, several soft constraints of UMPC strategy are imposed, i.e.,

$$\begin{align*}
Y^f_{\text{min}} & \leq \hat{Y}_k(k + \tau|k) \leq Y^f_{\text{max}} \\
U^f_{\text{min}} & \leq \hat{U}_k(k + \tau|k) \leq U^f_{\text{max}}.
\end{align*}$$

Therefore, the corresponding soft constraints with different driving styles are given in TABLE II. With the above preparations, the optimal sequence $\{\hat{Y}, \hat{U}\}$ will be applied to design the following multi-objective cost function directly.

**TABLE II: SOFT CONSTRAINTS OF UMPC STRATEGY.**

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Aggressive</th>
<th>Moderate</th>
<th>Conservative</th>
</tr>
</thead>
<tbody>
<tr>
<td>$T_d(N/m)$</td>
<td>[-70,80]</td>
<td>[-65,75]</td>
<td>[-60,70]</td>
</tr>
<tr>
<td>$\omega$</td>
<td>[0,5,0,2,0,3]</td>
<td>[0,4,0,3,0,3]</td>
<td>[0,2,0,3,0,5]</td>
</tr>
<tr>
<td>$\Delta h(m)$</td>
<td>[-5,5]</td>
<td>[-8,8]</td>
<td>[-12,12]</td>
</tr>
<tr>
<td>$\Delta v(m/s)$</td>
<td>[-5,5]</td>
<td>[-3,3]</td>
<td>[-1,1]</td>
</tr>
<tr>
<td>$a(m/s^2)$</td>
<td>[-4,4]</td>
<td>[-2,2]</td>
<td>[-1,1]</td>
</tr>
<tr>
<td>$\Delta \text{SOC} (%)$</td>
<td>[0,0,01]</td>
<td>[0,0,008]</td>
<td>[0,0,005]</td>
</tr>
</tbody>
</table>

**C. Multi-Objective Optimization**

In addition to ensuring driving safety and economic efficiency, it is essential to guarantee a satisfactory driving experience for MVP [42]. To achieve the balance among multiple conflicting objectives, a multi-objective cost function is developed in terms of the prediction sequence.

The sum cost function involving driving safety $J_s$, driving comfort $J_c$ and energy economy $J_e$ becomes

$$J^*(k) = w_s J_s(k) + w_c J_c(k) + w_e J_e(k)$$ \tag{7}

$$= \min_{k=0}^{N-1} \sum (w_s \| \Delta h(k + \tau|k) \|^2 + w_c (\| \Delta v(k + \tau|k) \|^2)$$

$$+ \| a(k + \tau|k) \|^2 + \| T_d(k + \tau|k) \|^2)$$

$$+ w_e \| \Delta \text{SOC}(k + \tau|k) \|^2$$

where $w_s$, $w_c$ and $w_e$ denote the weight coefficients corresponding to three objectives with $w_s + w_c + w_e = 1$. $Q$, $R$ and $F$ are positive definite weight matrices. Note that these weight coefficients are defined according to different driving styles. Such a treatment has been well addressed and shows its efficiency in [43].

Actually, GWO algorithm has found wide applications in addressing the global multi-objectives optimization issue [44]. By simulating the cooperative and independent behaviors exhibited by grey wolves, GWO preserves a broad spectrum of solutions within the optimization problem. Therefore, the sum cost function (7) is solved by the GWO algorithm. TABLE III gives the detailed solving process.

**TABLE III: ALGORITHM FLOW OF MULTI-OBJECTIVE OPTIMIZATION.**

**Algorithm: GWO-based Multi-objective Optimization**

1: Initialize the grey wolves population of $\alpha$, $\beta$, $\delta$
2: Assign the initial positions of grey wolves for MVP
3: While ($t < N_g$)
4: Calculate the prediction sequence $\hat{Y}$ (6)
5: Construct the multi-objective cost function $J^*$ (7)
6: Obtain the variables $\alpha'$, $\beta'$
7: Get the positions ($P_a$, $P_b$ and $P_d$) of grey wolves with best fitness (8)
8: Update the positions of grey wolves
9: End
10: Output the global optimal solution $T_d$

The encircling prey behavior of grey wolves could be modeled as

$$\begin{align*}
D(t) &= |\alpha P_p(t) - P(t)|, \quad t \in [1, N_g] \\
P(t + 1) &= P_p(t) - \alpha' D(t) \\
s.t. \quad \alpha' = (2 - \frac{2t}{N_g})(2\vartheta_1 - 1), \quad \beta = 2\vartheta_2
\end{align*}$$ \tag{8}

where $P(t)$ and $P_p(t)$ are the position of grey wolves and the prey at the iteration step $t$, respectively. $N_g$ stands for the maximum number of iterations. $D(t)$ denotes the distance between wolf $\omega$ and the prey. $\vartheta_1$ and $\vartheta_2$ represent random vectors confined to the interval $[0, 1]$. $\alpha'$ and $\beta$ are the coefficient vectors, which remain within the range of $[-2, 2]$ and $[0, 2]$, respectively.

During the hunting phase, the leading wolves ($\alpha$, $\beta$ and $\delta$) would track the prey and guide wolf $\omega$ to hunt. The term "score" signifies the fitness value of each individual solution in the optimization issue. Note that a lower score represents a better solution. As shown in Fig. 4, the scores of wolves $\alpha$, $\beta$ and $\delta$ could converge within 6 iterative steps. This indicates that the proposed strategy executes effective performance in addressing multi-objective optimization problems.

**D. Stability Analysis**

The stability of the proposed strategy is proven in this subsection.

**Lemma 1:** [10] Let system (3) satisfying the stabilizability of pair $(A, B)$ and the detectability of pair $(A, C)$. If system (3)
is stable, there exists a Lyapunov function $W(k)$ such that

$$W(k + 1) - W(k) \leq -\varepsilon_0\|X(k)\|^2 + \xi \left( Y(k), \mathcal{U}(k) \right)$$

(9)

s.t. $W(k) \leq \gamma_0\|X(k)\|^2, W^\infty(k) = \sum_{t=0}^{N-1} W(k + \tau | k)$

where $\varepsilon_0$ and $\gamma_0$ are positive constants.

**Theorem 1:** Given that $\{\mathcal{U}^p, \mathcal{U}^f\}$ is persistently exciting of order $N + 2L$. There exists a prediction horizon $N_m > 0$ such that for all $N > N_m$, the UMPC problem (7) is recursively feasible. Then, the closed-loop system achieves stable if the function $V(k)$ fulfills

$$\varepsilon_0\|X(k)\|^2 \leq V(k) \leq \gamma_s\|X(k)\|^2$$

$$\frac{\gamma_s(\gamma_s - \gamma_0)}{\varepsilon_0(N_m - 1)} - \varepsilon_0 \leq 0.$$  

**Proof:** A local Lyapunov function candidate $V(k)$ is defined as

$$V(k) = J'(k) + W(k).$$

According to the exponential controllability argument, the lower bound and upper bound of $V(k)$ can be derived as

$$\sum_{k=1}^{N-1} \left( \varepsilon_0\|X(k + \tau | k)\|^2 \right) \leq \gamma_s\|X(k)\|^2 + \gamma_0\|X(k)\|^2.$$  

(10)

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

$$\|X(k)\|^2 \leq \frac{\gamma_s + \gamma_0}{\varepsilon_0(N_m - 1)}\|X(k)\|^2.$$  

Denote the standard candidate solution being $\{Y(k + 1), \mathcal{U}(k + 1)\}$, then one gets

$$J'(k + 1) = \sum_{t=k+1}^{N-1} \xi \left( Y(k + \tau + 1 | k + 1), \mathcal{U}(k + \tau + 1 | k + 1) \right)$$

$$= J'(k) - \xi \left( Y'(k | k), \mathcal{U}'(k | k) \right).$$

Then, the optimal cost of the candidate solution over the horizon $N_m$ satisfies

$$J'(k + 1) \leq J'(k) - \xi \left( Y'(k | k), \mathcal{U}'(k | k) \right)$$

$$\leq J'(k) - \frac{\gamma_s + \gamma_0}{\varepsilon_0(N_m - 1)}\|X(k)\|^2 - \xi (Y(k | k), \mathcal{U}(k | k)).$$

(11)

Based on (10) and (11), the Lyapunov function candidate admits

$$V(k + 1) - V(k) \leq \frac{\gamma_s + \gamma_0}{\varepsilon_0(N_m - 1)}\|X(k)\|^2$$

$$\leq \frac{\gamma_s + \gamma_0}{\varepsilon_0(N_m - 1)} - \varepsilon_0\|X(k)\|^2.$$  

To guarantee the monotonic decreasing of $V(k)$, it requires a sufficiently long horizon $N_m$, such that

$$N \geq N_m \geq \frac{\gamma_s + \gamma_0}{\varepsilon_0} + 1.$$  

Now the UMPC scheme guarantees the stability of the closed-loop system, thus achieving vehicular platoon tracking. This completes the proof.

**IV. Experiments**

In this part, a hardware-in-the-loop experimental platform is designed with a driving simulator and an IPG-CarMaker® software. Then, several experiments are conducted to evaluate the performance of the proposed UMPC strategy.

**A. Experimental Platform**

The experiment is carried out on the hardware-in-the-loop platform (see Fig. 5) with a IPG-CarMaker® software, the driving simulator and a host computer. IPG-CarMaker® could provide comprehensive vehicle dynamics and testing scenarios. This computer is equipped with an Intel i7-14700KF (3.4GHz) CPU and an RTX4060 GPU, which meets the computational requirements for the actual vehicle applications [45]. The Logitech G29 driving simulator with the resolution of 65536 deg/count is presented in Fig. 6. Such a driving simulator includes a pedal, a steering wheel and three monitors. The pedal is designed to be nonlinear and allows for the adjustment of pressure sensitivity according to individual preferences.

The control signals of MVP are generated from the host computer and the driving simulator. To be more specific, the proposed strategy is deployed with Matlab language on the host computer, and it could generate the optimal control sequence. Then, a PID-based lower-level controller is designed to drive each AV via brake and acceleration. Furthermore, all algorithms are compiled into C++ code and plugged in the IPG-CarMaker® software. In addition, the real-time...
information of vehicles is exchanged through the SimNet module. This forms a closed-loop structure.

Fig. 6. Driving simulator.

As illustrated in Fig. 7, the MVP consists of one virtual leading vehicle, two AVs and one HDV. All vehicles travel on a 7.8km straight road. Four default vehicle models including Beetle (VLV), NIO (HDV), Tesla (AV2) and Toyota (AV3) are chosen from IPG-CarMaker®. A drive cycle source block (WLTC Class3) from Simulink is regarded as the reference velocity of VLV, and the desired inter-vehicle spacing of platoon is set to 50m.

Fig. 7. Configurations of MVP.

B. Experimental Procedure and Participants

Twenty drivers participated in the experiments, and their attributes involving sex, age, driving age and profession are presented in Fig 8. The experiment process is divided into data collection stage and strategy verification stage. In the first stage, twenty drivers take turns controlling HDV, while AVs are driven by the default control module of IPG-CarMaker®. The collected experimental dataset \( D \in \mathbb{R}^{95000 \times 5 \times 4} \) from one single driver has 95000 samples and five I/O trajectories of four vehicles. Twenty drivers participate in this experiment, thereby we can obtain a dataset with \( (95000 \times 5 \times 4) \times 20 \) items. The collected platoon dataset is utilized to construct the data-driven model and train driving styles. Then, four experiments are carried out to validate the performance of our proposed UMPC strategy. Detailed experimental procedure is described as follows.

- **Exp1.** Following vehicles \( (AV_2, AV_3) \) with the mechanism-based MPC (MMPC) strategy [46] track HDV. In this case, the dynamic parameters of MVP have uncertainties.
- **Exp2.** The LQR-based multi-objective predictive control (LMPC) strategy [47] is applied to each following vehicle.
- **Exp3.** Following vehicles are driven by the proposed UMPC strategy with different driving styles.
- **Exp4.** The UMPC strategy with different platoon configurations is deployed to the following vehicles. Among **Exp1**, **Exp2** and **Exp4**, HDV is controlled by the same driver with moderate driving style under configuration 1.

V. RESULTS AND DISCUSSIONS

In this section, the results of different strategies are analyzed in terms of three indicators involving safety, comfort and economy. Moreover, the effects of different platoon configurations are also detailed.

A. Driving Safety Analysis

As illustrated in Fig. 9(a), \( AV_2 \) with MMPC strategy and LMPC strategy perform an obvious spacing error and their peaks are about 63m and 68m. Comparatively, the proposed

![Fig. 8. Drivers’ attributes.](image)

To investigate the effects of HDV in complex traffic environments, two platoon configurations are designed in this paper. As shown in Fig. 7, HDV is allocated to different positions within MVP, and each following vehicle could receive information from both HDV and ahead vehicles. TABLE IV lists several key experimental parameters.

**TABLE IV: EXPERIMENTAL PARAMETERS.**

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( N )</td>
<td>15</td>
</tr>
<tr>
<td>( N_m )</td>
<td>11</td>
</tr>
<tr>
<td>( L )</td>
<td>10</td>
</tr>
<tr>
<td>( T_s )</td>
<td>10Hz</td>
</tr>
<tr>
<td>( SOC_0 )</td>
<td>70%</td>
</tr>
<tr>
<td>( h^* )</td>
<td>50m</td>
</tr>
<tr>
<td>( N_g )</td>
<td>30</td>
</tr>
</tbody>
</table>

![Fig. 9. Platoon configurations.](image)
UMPC strategy exhibits more stable spacing tracking capability than the others, which implies that more satisfactory string stability of MVP could be guaranteed. A similar result is obtained for $AV_3$ in Fig. 9(b). They both illustrate the superiority of UMPC strategy over MMPC and LMPC in terms of driving safety. To investigate the effectiveness of user-centric approach, the performance of spacing tracking with different driving styles is plotted in Fig. 10. Both $AV_2$ and $AV_3$ with conservative strategy have bigger spacing than other styles, which implies the most stable driving condition could be kept. Relatively, the minimum spacing of platoon is conducted by the aggressive one.

![Fig. 9. Results of the spacing with different driving styles.](image)

To investigate the distinctions of the above experimental results, a histogram with normal distribution and variance is presented in Fig. 11. These results conform to the normal distribution, indicating the validity of the strategies. In addition, a larger variance may lead to significant spacing error of MVP while a smaller variance implies relative stability. $AV_2$ with the proposed UMPC strategy exhibits the minimum variance compared with MMPC and LMPC ones, and the UMPC strategy with aggressive driving style shows the minimum variance in contrast to moderate and conservative ones. A similar result is also obtained for $AV_3$. To sum up, these results illustrate that the UMPC strategy with aggressive driving style exhibits the desirable spacing tracking capability over others.

**B. Driving Comfort Analysis**

The driving comfort of MVP is analyzed in terms of velocity and acceleration. As shown in Fig. 12, the MMPC strategy exhibits an obvious oscillation during velocity tracking, especially in the process of rapid deceleration. This results in an uncomfortable driving experience. Compared to the MMPC strategy and the LMPC strategy, the UMPC strategy has the capability to maintain the stable tracking of desired velocity. Moreover, Fig. 13 gives the assessment of acceleration including mode, interquartile range (IQR) and median. The UMPC strategy executes the minimum acceleration compared to other strategies, meaning the most stable driving operation.

Furthermore, the velocity errors of the UMPC strategy with different driving styles are depicted in Fig. 14. Both $AV_2$ and $AV_3$ with aggressive driving style perform a significant fluctuation while keeping the minimum spacing. It is clear that the conservative style keeps the most stable velocity tracking, and the moderate one is situated between the above two driving styles. Moreover, the result of acceleration also yields a similar conclusion, see Fig. 15. In light of the analysis above, the proposed UMPC strategy could provide a desirable driving experience for users.

**C. Energy Economy Analysis**

The economic objective of MVP aims to enhance battery efficiency by minimizing the degradation of SOC. From Figs. 16-17, the initial condition of SOC is set to 70%,
and it gradually diminishes with the increasing mileage of the vehicle. AV2 and AV3 with the UMPC strategy execute lower decline rate compared to other strategies. After the completion of journey, their remaining SOC are 62.8% and 61.4%. Furthermore, the aggressive driving strategy exhibits a fast decline rate of SOC, and the final SOC reaches 58.5% and 61.2%. This is attributed to the aggressive driving habits of frequent acceleration, resulting in higher battery consumption.

D. Comprehensive Configuration Analysis

To provide a more detailed explanation of the merits of our proposed UMPC strategy, the absolute maximum error (AMAXE) and root mean square error (RMSE) assessment indexes are introduced. With this in mind, the average spacing (AMAXE) and root mean square error (RMSE) assessment indexes are introduced. With this in mind, the average spacing
TABLE VI: CORRELATION COEFFICIENT OF EXPERIMENTAL RESULTS.

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Safety ( (h) )</th>
<th>Comfort ( (a + v + T_d) )</th>
<th>Economy ( \text{SOC} )</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( HDV )</td>
<td>( AV_2 )</td>
<td>( AV_3 )</td>
</tr>
<tr>
<td>Config 1</td>
<td>0.5227</td>
<td>0.6648</td>
<td>0.6257</td>
</tr>
<tr>
<td>Config 2</td>
<td>0.5681</td>
<td>0.6137</td>
<td>0.7011</td>
</tr>
</tbody>
</table>

Fig. 16. Results of the SOC with different strategies.

Fig. 17. Results of the SOC with different driving styles.

error \( (\Delta h) \), velocity error \( (\Delta v) \), acceleration \( (a) \) and SOC of \( AV_2 \) and \( AV_3 \) are analyzed in TABLE V. The UMPC strategy has the minimum AMAXE and RMSE, which implies that a desirable string stability could be ensured for MVP. Compared to LMPC and MMPC, the UMPC strategy with conservative style executes the maximum spacing error, the minimum velocity error and SOC. This means that the conservative style pays more attention to the energy economy and driving comfort than driving safety. Similar results can also be obtained for moderate and aggressive ones. Therefore, these results illustrate that the UMPC strategy is superior to the MMPC and LMPC ones. And it could provide a satisfactory driving experience for users.

The results of MVP with different platoon configurations are demonstrated in the online supplementary file (https://docs.google.com/document/d/1i4kdqugibx17H-TcN-fnOHAT_7d35gh4h-Z2gkSIM/edit). Furthermore, these results are analyzed with the correlation coefficient method in TABLE VI. The higher the correlation coefficient value, the stronger the tracking capability. The correlation coefficients of \( AV_2 \) with two configurations are 0.6648 and 0.6257 while they become 0.6137 and 0.7011 for \( AV_3 \). In addition, similar results can be acquired regarding the comfort and economy. This phenomenon may come from the relaxed feeling for the driver while acting as a leader, causing a more comfortable driving experience. Comparably, the driver will be concerned about the potential risk of collision with the ahead vehicle while acting as a follower, and then the driver will drive the vehicle more carefully.

To sum up, it can be concluded that our proposed UMPC strategy provides safe, economical and comfortable driving experience for users. Furthermore, the configuration of MVP has certain impact on MVP that it contributes to ensuring the string stability of MVP while the HDV serves as a following vehicle.

VI. Conclusion

In this paper, a UMPC strategy has been developed to handle dynamic uncertainty and multi-objective conflicts of MVP. The subspace identification method has been utilized to establish the data-driven model. It has the potential to alleviate the adverse effects caused by non-ideal driving behavior and dynamic uncertainty of the complex powertrain structure. The optimal prediction sequence generated from the subspace predictor has been utilized to construct a multi-objective cost function. Then, the GWO scheme has been introduced to
solve the optimal solution amidst conflicting objectives. Based on this, the UMPC strategy has been designed in terms of different driving styles. Finally, the experimental results demonstrate that our proposed UMPC strategy could provide safe, economical and comfortable driving conditions for users. It is found that HDV would execute a more satisfactory driving performance while acting as the follower than the leader. In this paper, limited experimental scenarios and datasets make it challenging to validate the generalizability of the proposed strategy on complex scenarios. Therefore, exploring the application of our proposed strategy to actual vehicles will constitute a distinct research task. In the future, we will focus on reducing the computational burden of the proposed strategy and testing it in actual vehicles.

## References


[3] Y. Cui, L. Peng, and H. Li, “Filtered probabilistic model predictive control for complex scenarios. Therefore, exploring the application of our proposed strategy to actual vehicles will constitute a distinct research task. In the future, we will focus on reducing the computational burden of the proposed strategy and testing it in actual vehicles.

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