Adaptive Leading Cruise Control in Mixed Traffic Considering Human Behavioral Diversity

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Abstract—This paper presents an adaptive leading cruise control strategy for the automated vehicle (AV) and first considers its impact on the following human-driven vehicle (HDV) with diverse driving characteristics in the unified optimization framework for improved holistic energy efficiency. The car-following behaviors of HDVs are statistically calibrated using the Next Generation Simulation dataset. In a typical single-lane car-following scenario where AVs and HDVs share the road, the longitudinal speed control of AVs can substantially reduce the energy consumption of the following HDV by avoiding unnecessary acceleration and braking. Moreover, apart from the objectives including car-following safety and traffic efficiency, the energy efficiencies of both AV and HDV are incorporated into the reward function of reinforcement learning (RL). The specific driving pattern of the following HDV is learned in real-time from historical speed information to predict its acceleration and power consumption in the optimization horizon. A comprehensive simulation is conducted to statistically verify the positive impacts of AV on the holistic energy efficiency of the mixed traffic flow with uncertain and diverse human driving behaviors. In freeway driving scenarios, simulation results indicate that the holistic energy efficiency is improved by an average of 6.03% and 6.41% compared to the reference control algorithms, respectively, RL without HDV consideration and model predictive control. These improvements highlight the significance of our approach in optimizing energy efficiency for mixed traffic on freeways.

Index Terms—Automated vehicles, eco-driving, mixed traffic, reinforcement learning, statistical analysis, energy consumption.

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THE transportation sector, which consumes 25% of global energy resources, is one of the main sources of greenhouse gas emissions and air pollution [1]. Extensive efforts have been made to improve vehicle efficiency and lower emissions of on-road vehicles in response to the increasingly stringent emission standards [2], [3], [4]. As a crucial technology in saving energy consumed by vehicles, eco-driving has been extensively discussed in [5], [6], [7], [8], [9], with the core idea of adjusting vehicle speed and maintaining an energy-efficient driving style [10]. More recently, the development automation technologies has provided another promising opportunity to further cut down energy consumption through the deployment of automated vehicles (AVs). With the assistance of wireless communication (e.g., vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) [11]) and sensor fusion techniques [12], AVs can take advantage of the rich information to optimize their operations, such as vehicle acceleration [13], motor torque regulation [14], path planning [15], etc.

Despite some promising results indicating that AVs can save energy, the impacts of connectivity and autonomy on the traffic efficiency and energy performance of neighboring vehicles have not been extensively studied, while this type of study can provide insights for policymakers and incentives to further promote CAVs. For example, Auld et al. [16] analyzed the mobility and energetic impacts introduced by AVs’ deployment. Results demonstrate that the traffic flow is improved with the increasing travel demand and decreasing travel time. Fakhrmoosavi et al. [17] explored the influences of a mixed traffic fleet on several aspects from a network level, indicating that AVs can enhance traffic safety, mobility, and emission reduction of the traffic system. Zhao and Kockelman [18] assessed the impacts of AVs under eight different testing scenarios with a travel demand model and simulation results indicate that the travel demand in Austin, Texas can increase by at least 20%.

Moreover, it is anticipated that AVs and human-driven vehicles (HDVs) will co-exist on the same road in the near future [19], [20]. Human drivers will still remain to be the majority who take charge of vehicle operations for a long period. Hence, it is imperative to develop eco-driving strategies for AVs in the mixed traffic flow in which AVs frequently interact with HDVs. Lu et al. [21] proposed an energy-efficient adaptive cruise control model for electric vehicles.
Autonomous vehicles (AVs) in a mixed traffic flow. Simulations are performed in a mixed single-lane traffic flow with different market penetration rates of AVs, indicating that the proposed method exhibits a superior performance in energy saving compared to other existing adaptive cruise control and cooperative adaptive cruise control methods. Zhu et al. [22] designed a novel model predictive control (MPC) method to enhance energy efficiency and keep driving safety for the AV in a mixed traffic flow. An integrated data-driven model of car-following is used in the MPC framework to predict the behaviors of HDVs. Simulation results validate its effectiveness in energy efficiency improvement and robustness. Li et al. [23] developed a cooperative controller for AVs in a mixed traffic platoon based on multi-agent reinforcement learning. Compared with MPC, the proposed strategy performs better in dampening traffic oscillations and reducing energy consumption. Ma and Wang [24] investigated the energy-saving potentials of the following human-driven platoon enabled by eco-driving control of AVs ahead. Especially, the influences of diverse characteristics of human behaviors are evaluated through extensive numerical analyses, which statistically show a positive influence of the proposed strategy on the subsequent platoon.

However, all the aforementioned studies only focus on the optimization of the AV, while neglecting its impact on the following HDV. Wang et al. first introduced the notion of leading cruise control (LCC) in [25] and [26]. The AV has two roles in the LCC framework, that is, following its predecessor while actively leading the motion of its following vehicles. However, LCC primarily seeks to smooth traffic flow and does not directly consider energy consumption issues. To achieve a higher holistic energy efficiency of the mixed traffic flow, this study first incorporates the HDV energy consumption in the optimization framework. In most existing studies, car-following models (e.g., optimal velocity model [27] and IDM [28]) are usually utilized to describe the behaviors of HDVs. In [29], five representative microscopic car-following models were used to calibrate the behaviors of drivers in Shanghai, and the IDM outperformed the other models from the perspectives of accuracy and stability. The parameters of these models indicating different driving styles are either set as constants [30], or assumed to follow some predefined uniform distribution [24]. However, in a dynamic traffic environment, the behaviors of HDVs are quite stochastic and do not follow deterministic patterns. It remains challenging to accurately predict the behaviors of HDVs, which are the necessary previews of most predictive control schemes.

More recently, model-free reinforcement learning (RL) algorithms have been widely applied in many areas such as autonomous driving [31], [32], [33], battery management [34], and eco-driving for electrified vehicles [35], [36]. One of the main advantages of model-free RL is that the agent can interact with the stochastic environment and try to maximize the accumulated reward in a learning manner. Instead of attempting to model the complicated environment with high stochasticity (e.g., uncertain human driving behaviors in this study), model-free methods directly improves system performance based on the explored samples [37].

Motivated by the discussion above, this study aims to design an adaptive leading cruise control strategy to reduce the holistic energy consumption of both AV and HDV by considering the diverse human driving behaviors in a reinforcement learning framework. The contributions and novelties of this study are summarized as follows:

1) In addition to car-following safety and traffic efficiency, the dynamics of both AV and the following HDV are considered in the optimization framework for improved holistic energy efficiency.
2) HDVs are calibrated into a joint distribution using the IDM based on the field-collected Next Generation Simulation (NGSIM) dataset to cover a wide range of stochastic and realistic driving behaviors.
3) The influences of diverse driving behaviors on the improvement of energy efficiency using the proposed control algorithm are quantitatively analyzed.

The rest of this paper is organized as follows. Section II presents the problem formulation including scenario description, vehicle dynamics, energy consumption model, the intelligent driver model as well as control objectives of this paper. In Section III, the stochastic behaviors of human drivers are developed and the detailed design process of reinforcement learning is given. Simulation results and performance analysis are provided in Section IV. Conclusions of this paper are presented in Section V.

II. Problem Formulation

A. Scenario Description

Similar to existing studies in [24] and [38], a common scenario of mixed traffic stream is investigated in this study, where there is a human-driven preceding vehicle (PV), an AV, and a following HDV, as shown in Fig. 1. Assume the AV can obtain velocity and gap distance information of both the PV and the following HDV through onboard sensors (e.g., millimeter-wave radars). There may exist more vehicles (AVs or HDVs) before the PV, which means this scenario is just a fraction of a long mixed traffic flow, while the traffic before the PV is not the focus of this study.

B. Vehicle Longitudinal Dynamics

Since this study emphasizes energy-efficient driving in a car-following scenario, only vehicle longitudinal dynamics is considered here, as described in Eq. (1).

\[
\dot{v} = \frac{F_d - mg \cos \alpha - mg \sin \alpha - 0.5 C_D A_f \rho v^2}{\delta m}
\]  

(1)

where \(v\) is the vehicle velocity, \(F_d\) denotes the driving force of the vehicle. \(m\) is vehicle mass and \(g\) denotes the gravitational
acceleration. $C_D$, $A_f$, and $\rho$ are aerodynamic drag coefficient, vehicle frontal area, and air density, respectively. $\delta$ is the rotational inertia coefficient. For simplicity, road slope is not considered here ($\alpha = 0$). Table I lists the critical parameters of the longitudinal dynamics model of the vehicle.

### C. Energy Consumption Model

Generally, an approximated and differentiable energy consumption model in a polynomial expression is sufficient to develop the eco-driving algorithm [39]. Targeting at electric vehicles, we employ the same in-wheel motor model as in our previous research [35], i.e., PD18 from Protean Electric [40]. The absence of a traditional powertrain curtails energy losses associated with transmission, thereby facilitating a more efficient power transfer. The electric power $P_m$ can be calculated as:

$$P_m = T_m \cdot \omega_m \cdot \eta_m^{-k} \quad (2)$$

where $T_m$ is the motor torque, $\omega_m$ is the rotating speed of the motor. $\eta_m$ is the electric-mechanical conversion efficiency and is described in Fig. 2. The superscript $k$ signifies the working status. When the torque is positive ($k = 1$), it works as a motor, converting electric power into mechanical power. Conversely, when the torque is negative ($k = -1$), it functions as a generator, recovering braking energy. It is worth noting that only the energy consumption map is considered and we assume no energy loss in other forms for simplicity. With the vehicle longitudinal dynamics and the efficiency map of the motor, we convert the energy consumption model to a function in terms of vehicle speed and acceleration. With acceptable accuracy, this model is free from heavy computation and complicated calibration. The detailed formation process is described in [41] and our fitted instantaneous energy consumption model is given as follows:

$$P_m(v, a) = \sum_{i=0}^{4} \sum_{j=0}^{4} p_{ij} v^i(t) a^j(t) \quad (3)$$

where $v(t)$ is the instantaneous vehicle speed; $a(t)$ is the instantaneous acceleration. $p_{ij}$ are fitting coefficients. Through trial-and-error, the polynomial order and coefficients are determined with the help of MATLAB Curve Fitting Toolbox. Fig. 3(a) presents the contour plot of the power consumption with respect to vehicle speed and acceleration, while the 0 kW contour line is emphasized by a red bold line. Fig. 3(b) demonstrates a satisfactory fitting result, characterized by residuals predominantly clustered around zero, and a root mean square error of 0.76 kW. The values of these coefficients are listed in Table II. The other coefficients, such as $p_{32}$, which are not given in Table II, equal to zero by default. Without loss of generality, the AV and HDV in the mixed traffic flow are assumed to follow the same energy consumption model.

### D. Intelligent Driver Model

The microscopic traffic model is utilized to simulate the car-following behaviors of HDVs in the transportation system. Inspired by the work in [29], the intelligent driver model (IDM) [42] is used in this study for its proven performance in accident-avoidance and generating realistic acceleration profiles. In addition, the parameters in the IDM capture diverse characteristics of drivers in virtually all single-lane traffic

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**Table I**

| Parameter                        | Value  |
|----------------------------------|--------|
| Vehicle mass $m$                | 2500 kg|
| Aerodynamic drag coefficient $C_D$ | 0.3    |
| Vehicle frontal area $A_f$      | 1.8 m$^2$|
| Rolling resistance coefficient $f$ | 0.015  |
| Air density $\rho$              | 1.206 kg/m$^3$ |
| Gravitational acceleration $g$  | 9.81 m/s$^2$ |
| Wheel radius $r$                | 0.3 m  |
| Rotational inertia coefficient $\delta$ | 1.02   |

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**Table II**

| Coefficient | Value  | Coefficient | Value  | Coefficient | Value  |
|-------------|--------|-------------|--------|-------------|--------|
| $p_{0}$     | 292.8  | $p_{10}$    | 734.5  | $p_{03}$    | 796.1  |
| $p_{20}$    | -23.52 | $p_{11}$    | 2492   | $p_{02}$    | 1656   |
| $p_{30}$    | 0.9413 | $p_{21}$    | 0.3535 | $p_{12}$    | -35.53 |
| $p_{31}$    | 84.57  | $p_{40}$    | -0.005 | $p_{31}$    | 0.0429 |
| $p_{22}$    | 2.577  | $p_{13}$    | 5.667  | $p_{04}$    | 214.4  |

Fig. 2. Efficiency map of the motor.

Fig. 3. (a) Contour plot of the fitted energy consumption model with respect to vehicle speed and acceleration. (b) Distribution of the fitting residuals.
scenarios, i.e. the car-following scenario [42]. Following is a brief description of the model:

\[ \dot{v} = a \left( 1 - \left( \frac{v}{v_0} \right)^\delta - \left( \frac{s^*(v, \Delta v)}{s} \right)^2 \right) \]  

(4)

\[ s^*(v, \Delta v) = s_0 + \max \left( 0, vT + \frac{v\Delta v}{2\sqrt{ab}} \right) \]  

(5)

where \( v \) is the instantaneous vehicle velocity; \( a \) denotes the maximum acceleration parameter; \( v_0 \) represents the desired velocity; \( \delta \) is the acceleration exponent; \( s^* \) and \( s \) denote the desired gap distance and the actual gap distance to the preceding vehicle; \( \Delta v \) is the speed difference to its preceding vehicle; \( s_0 \) is the minimum gap; \( T \) is the time gap to the preceding vehicle; and \( b \) is the comfortable deceleration parameter.

Each parameter in the IDM characterizes a specific aspect of human driving behaviors. For example, the maximum acceleration parameter \( a \) represents the driver’s aggressiveness in hitting the accelerator pedal. As the vehicle speed increases and approaches the desired speed \( v_0 \), the acceleration decreases accordingly and stabilizes around zero. The value of acceleration exponent \( \delta \) determines how fast the acceleration drops when approaching the desired speed. The time gap \( T \) defines the interval between the moment the rear bumper of the preceding vehicle passes an appointed location and the moment the front bumper of the following vehicle reaches the same location [43]. Intuitively, an aggressive driver tends to keep a relatively smaller time gap in comparison with a conservative driver. Overall, the IDM can produce smooth speed profiles and easily model various driving behaviors by tuning those parameters [42].

**E. Control Objectives**

As shown in Fig. 4, in such a mixed traffic flow, only AV is fully controllable and it has an impact on the energy performance of following HDV. The control objective of this paper is to improve the potential energy-saving benefits enabled by vehicle autonomy through dedicated control of AV while taking into account the diverse behaviors of the HDV. The control objectives are given by:

\[ a^*_i(t) = \arg \min_{a_i(t)} \left( J \right) \quad t \in [t_0, t_f] \]  

(6a)

with

\[ J(a_i(t)) = \int_{t_0}^{t_f} \left( P_{AV}(t) + P_{HDV}(t) \right) dt \]  

(6b)

subject to

\[ \text{TTC}(t) > \text{TTC}_{\text{min}} \]  

(6c)

\[ \text{TG}(t) < \text{TG}_{\text{max}} \]  

(6d)

\[ a_{\text{min}} \leq a_i(t) \leq a_{\text{max}} \]  

(6e)

where \( a_1 \) is the acceleration of AV and is also the control variable of the system; \( a^*_i(t) \) represents the acceleration profile with the optimal energy-saving performance within the time interval \([t_0, t_f]\). \( J \) is the total cost function including both AV’s and HDV’s trip energy consumption; and \( P_{AV} \) and \( P_{HDV} \) are the instantaneous energy consumption rate of AV and HDV as illustrated in Eq. (3). Besides, some constraints are imposed for collision avoidance and traffic efficiency purposes. Time-to-collision (TTC) indicates how much time remains before two vehicles collide and time gap (TG) here is the time headway of AV to the preceding vehicle [44].

### III. Adaptive Leading Cruise Control

In this section, a RL-based adaptive leading cruise control strategy is developed. First, in order to better model the stochastic human driving behaviors, the least squares method (LSM) is utilized to find the optimal parameters in the IDM. The formulation of the longitudinal speed control strategy for the AV will then be given. Different from previous research where only AV is considered, we aim to improve the energy efficiency of both AV and the following HDV by leveraging the predictive dynamics of HDV. The formulated optimal control problem is solved in a learning manner based on a RL framework. In the rest of this section, the detailed formulation of the reward function will be presented.

#### A. Stochastic Driver Behaviors

To model and calibrate the realistic human driving behaviors, the field-test vehicle trajectory data from the NGSIM project is utilized [45]. The trajectory data were collected on eastbound I-80 in Emeryville, California using an array of synchronized digital video cameras and then transcribed into the format of vehicle trajectory with a customized software named NGVIDEO. The original dataset encompasses abundant information such as a buildup of traffic congestion, semi-congested state, and full congestion during peak hours. A car-following extraction filter proposed in [46] was applied to extract the car-following episodes. A total of 761 car-following episodes at a sampling rate of 10 Hz were extracted and used in our study. Each car-following episode consists of four-column data, which are gap distance, following vehicle’s speed, relative speed, and lead vehicle’s speed. The car-following trajectory data of different human drivers in the NGSIM dataset is applied to calibrate the IDM, as introduced in Section II. In the realm of car-following model calibration, the choice of measurement of performance (MoP) plays a pivotal role in determining the accuracy and reliability of the model. Punzo et al. [47] have highlighted the limitations of using speed as a MoP due to its integral relationship with spacing, leading to overlooked gap errors. This insight, further detailed in [48], underscores that zero gap errors inherently imply zero speed errors. Given these findings, the
Objective function is defined as minimizing the root mean square percentage error (RMSPE) of spacing difference:

$$\min \sqrt{\frac{\sum_{i=1}^{N} (s_{i}^{\text{sim}} - s_{i}^{\text{obs}})^2}{\sum_{i=1}^{N} (s_{i}^{\text{obs}})^2}}$$  \hspace{1cm} (7)$$

where $N$ denotes the total number of car-following episodes ($N = 761$); $s_{i}^{\text{obs}}$ is the actual spacing of the $i$th car-following episode; and $s_{i}^{\text{sim}}$ is the simulated spacing of the IDM.

The driving preference parameters in the IDM are optimized using the LSM for its simplicity and faster convergence. In order to balance the optimization performance and computational efficiency, instead of directly optimizing all parameters $(a, v_0, s_0, T, b)$ in the IDM, only two parameters $(v_0, T)$ are optimized while the others are set as constants. The sensitivity analysis reveals that the time headway $T$ and the desired velocity $v_0$ are the most influential parameters in the IDM, with sensitivity indices of approximately 0.61 and 0.37, respectively. These values are orders of magnitude greater than the sensitivity indices of the other parameters $(s_0, a, b)$, which are fall below 0.001. This significant discrepancy highlights the dominant role of $T$ and $v_0$ in shaping the behavior of the IDM, whereas the remaining parameters have minimal impact. The choice of $T$ and $v_0$ as the main features is further supported by the calibration results. The distributions of $(v_0, T)$ share a similar pattern with that of the maximum driving speed of human drivers in the NGSIM dataset, while the other parameters cluster around boundary values. The results also align with the intuitive understanding of car-following behavior, where both the time gap and the desired speed are primary determinants of a driver’s actions. As shown in Fig. 5, the boxplot gives the distribution of the RMSPE under two groups with different parameter settings. The global group means all the five driving preference parameters are optimized simultaneously, while in the local group, only $v_0$ and $T$ are optimized with other parameters set as constants. The blue diamond symbols indicate the average computation time for each episode. With acceptable sacrifice in optimization performance (mean value of RMSPE increasing from 6.3 % to 8.6 %), the average computation time drops from 516.45 ms to 174.38 ms for each optimization process.

**B. Preliminaries of Reinforcement Learning**

This subsection introduces the fundamentals of RL. The modeling basis of RL is the markov decision process, where an agent interacts with a stochastic environment [49]. At each time step $t$, the agent observes the state $s_t$ from its surrounding environment and then selects an action $a_t$ to execute based on the current policy $\pi(a_t|s_t)$. The environment returns a scalar reward $r_t$ to the agent and transits to a new state $s_{t+1}$. The goal of the agent is to obtain a policy that maximizes the discounted total reward. The optimal policy can be written as:

$$\pi^* = \arg \max_{\pi} \mathbb{E} \left( \sum_{t=0}^{T} y^t r(s_t, a_t) \right)$$  \hspace{1cm} (8)$$
where $\gamma \in (0, 1]$ denotes the discount factor. Combined with deep learning, deep reinforcement learning (DRL) uses neural networks to approximate the Q-value function [50], policy $\pi(a_t|s_t)$ [51] or system model. Since the selected control variable (i.e., acceleration of AV) is continuous, the deep deterministic policy gradient (DDPG) algorithm is utilized for its capability of dealing with continuous action spaces [51]. The policy-network, parameterized by $\theta^\pi$, is used to deterministically map the state into the action as $a_t = \pi(s_t|\theta^\pi)$. The Q-value network, parameterized by $\theta^Q$, is used for value function approximation. The Q-value network is updated by minimizing the loss function as follows:

$$L = \frac{1}{N} \sum_i \left( y_i - Q(s_i, a_i | \theta^Q) \right)^2$$

(9)

where $y_i = r_i + \gamma Q'(s_{i+1}, \mu'(s_{i+1} | \theta^\mu) | \theta^Q)$. Then the gradients $\nabla_\theta Q(s, a)$, calculated by the Q-value network, are passed to the policy-network to update the weights and biases using stochastic gradient descent (SGD):

$$\nabla_\theta J = \frac{1}{N} \sum_i \nabla_a Q(s, a | \theta^Q) \nabla_\theta \mu(s | \theta^\mu)$$

(10)

C. Design of Reinforcement Learning Algorithm

As inputs into the agent, the state space should provide enough information about the current traffic situation. Here we design two kinds of state space and investigate their impact on the training results. The state space $A$ (SS-A) includes seven state variables, including the speeds of three vehicles, their relative speed and their gap distances, which can be expressed as $S_A = \{v_0, v_1, v_2, \Delta v_{01}, \Delta v_{12}, \Delta d_{01}, \Delta d_{12}\}$. The state space $B$ (SS-B) only includes independent variables, which is defined as $S_B = \{v_1, \Delta v_{01}, \Delta v_{12}, \Delta d_{01}, \Delta d_{12}\}$. The control input, i.e., AV’s acceleration, makes up the action space, which is written as: $A = \{a_t\}$. The physical meaning of these variables can be found in Fig. 4. The objective of this study is to design an adaptive leading cruise control strategy to regulate the AV and achieve four sub-objectives: car-following safety, traffic efficiency, energy economy of AV, and energy economy of HDV. By incorporating the energy economy of the following HDV into the reward function for the first time, we aim to improve the overall energy efficiency from a statistical perspective. The reward function capturing the four sub-objectives, as listed below, is adopted.

1) Car-following Safety: The highest priority should always be given to safety to avoid collisions. TTC, which indicates how much time remains before collision, is treated as the metric for safety, as given by:

$$TTC(t) = \frac{\Delta d_{01}(t)}{\Delta v_{01}(t)}$$

(11)

where 0 is the index for preceding vehicle and 1 is the index for AV; $\Delta d_{01}$ denotes their gap distance and $\Delta v_{01}$ represents their relative speed ($\Delta v_{01} = v_0 - v_1$). A smaller TTC value is associated with higher crash risk, and vice versa [44]. The lower bound of TTC, as a critical boundary differentiating ‘safe driving’ and ‘dangerous driving’, should be clearly stated. The literature offers divergent views on the appropriate value to set as a safety limit, with suggestions varying from 1.5 to 5 seconds [44]. A final value of 4s is selected which leads to the best overall performance [52]. If TTC is smaller than 4s, the corresponding negative reward will be given. Intuitively, a smaller TTC value comes with a bigger penalty. Therefore, the reward corresponding to car-following safety is given as follows:

$$R_{safe} = \begin{cases} \log \left( \frac{TTC}{4} \right) & 0 \leq TTC \leq 4 \\ 0 & \text{otherwise} \end{cases}$$

(12)

2) Traffic Efficiency: High traffic efficiency defined in this study indicates a small and safe TG from the AV to the preceding vehicle. A small TG within the safe range usually means a higher roadway capacity [53]. There are slight differences regarding the legal or recommended safety distances in different countries. For instance, several driver training programs in the United States claim that it is hard for human drivers to safely follow a preceding car within a time gap of less than 2s [54]. In Germany, a headway of larger than 1.8s is recommended. A time gap of 3s is recommended by the Swedish National Road Administration in rural areas [44]. In this study, in order not to sacrifice the potential in energy saving, only an overlarge time gap will be penalized and its boundary value is set as 2.5s. The reward in terms of traffic efficiency is constructed as follows:

$$TG(t) = \frac{\Delta d_{01}(t)}{v_1(t)}$$

(13)

$$R_{eff} = \begin{cases} -1 & TG \geq 2.5 \\ 0 & \text{otherwise} \end{cases}$$

(14)
3) **Energy Economy of AV:** One major objective of eco-driving is to save as much energy as possible. We aim to find an optimal speed trajectory leading to the minimum energy consumption by controlling vehicle acceleration. Using the instantaneous energy consumption model introduced in Section II, the immediate energy consumption in each step can be estimated. The reward in terms of the energy economy of AV can be described as:

$$ R_{AV} = -\frac{P_{AV}}{20000} \times \Delta t $$

(15)

where the constant value of 20000 is used to scale the reward value into the range of $[-1, 1]$, and $\Delta t$ is time step and equals to 0.1s.

4) **Energy Economy of HDV:** Since the HDV is not controllable, we can only improve its energy economy by leveraging the interaction between the HDV and the regulated AV. However, it is challenging to precisely predict how the HDV reacts to the surrounding traffic due to the uncertain and diverse human driving behaviors. To this end, the HDV behavior will be learned and predicted through onboard sensors, the reward in terms of the HDV speed $v$, the gap distance $d$, and HDV speed. The expected acceleration of the HDV can be calculated as follows:

$$ v(t + 1) = v(t) + a(t) \times \Delta t $$

(19a)

$$ v_2(t + 1) = v_2(t) + (a_2(t) \times (1 + \xi)) \times \Delta t $$

(19b)

$$ \Delta d_{12}(t + 1) = \Delta d_{12}(t) + \frac{\Delta v_{12}(t) + \Delta v_{12}(t + 1)}{2} \times \Delta t $$

(19d)

where $\xi$ is the random noise ranging from 0% to 5%.

B. Reference Control Algorithms

For the purpose of comparison, two reference strategies that did not consider the following HDV in the optimization were also developed.

1) **RL without HDV:** The reward function of this reference strategy includes car-following safety, traffic efficiency, and the ego benefit of AV, serving as a typical RL-based energy-saving adaptive cruise control method [55]. Specifically, the state space in this reference strategy is $S = [v_0, v_1, \Delta v_{101}, \Delta d_{101}]$, the action space is defined as $A = \{a_1\}$. The reward function can be described as follows:

$$ r_{ref} = R_{safe} + R_{eff} + R_{AV} $$

(20)

2) **MPC:** MPC is prevalently employed in adaptive cruise control due to its proficiency in handling multi-objective

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**TABLE III**

| Hyperparameter | Value     | Description                  |
|----------------|-----------|------------------------------|
| $\gamma$       | 0.9       | Discount factor              |
| $N$            | 1024      | Number of samples for SGD update |
| $D$            | 20000     | Number of samples in replay buffer |
| $\text{LR}_A$  | 0.001     | Learning rate for policy network |
| $\text{LR}_C$  | 0.001     | Learning rate for Q-value network |

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**IV. SIMULATION RESULTS**

A. Simulation Setup

A car-following episode with a time length of 30s is sampled from the NGSIM dataset, and we assign the lead vehicle’s speed to the PV. The initial speed of the following vehicle in this episode is used to initialize $v_1$ and $v_2$. The initial gap distance in this episode is used to initialize $\Delta d_{101}$ and $\Delta d_{12}$. With the sampling rate being 0.1s, there are 300 steps in each training episode and each step equals 0.1s in real life. All the state variables are fed into the policy network and it outputs the acceleration of AV directly $a_1(t)$. The inputs of the Q-value network are the state and action and it outputs a scalar Q-value $Q(s_1, a_1)$.

A variety of DDPG models were trained in this stochastic mixed traffic environment to find out the suitable network structure. Finally, a structure of three fully connected hidden layers (200-100-50 neurons in each layer) with rectified linear unit (ReLU) activations is adopted. The output layer of the policy network is activated by a $tanh$ function to map into range $[-1, 1]$. After that, a linear mapping is applied to transform the outputted acceleration between $[-3, 3] m/s^2$. An overview of the hyperparameters is given in Table III. Besides, in order to compensate for the optimization error in Fig. 5 and better consider the randomness in human driving behaviors, a random noise $\xi$ is added to the outputted acceleration of HDV. A kinematic point-mass model is used to update the environment state:

$$ v_1(t + 1) = v_1(t) + a_1(t) \times \Delta t $$

(19a)

$$ v_2(t + 1) = v_2(t) + (a_2(t) \times (1 + \xi)) \times \Delta t $$

(19b)

$$ \Delta d_{12}(t + 1) = \Delta d_{12}(t) + \frac{\Delta v_{12}(t) + \Delta v_{12}(t + 1)}{2} \times \Delta t $$

(19d)

where $\xi$ is the random noise ranging from 0% to 5%.
optimization problems and constraints [52]. Since the primary objective of an adaptive cruise controller is to maintain a desired gap distance to the preceding vehicle, we adopt a constant time headway here:

\[ \tilde{d}_{AV} = t_{hw} \times v_{AV} \]  
\hspace{2cm} (21)

where \( t_{hw} \) is the average time headway in Fig. 6 (\( t_{hw} = 1 \) s), \( \tilde{d}_{AV} \) is the desired gap distance of the AV.

A constrained linear-quadratic MPC formulation is given as:

\[
\min_{a} \sum_{t=0}^{N-1} \left[ \left( \frac{d_{AV} - \tilde{d}_{AV}}{d_{max}} \right)^2 + \left( \frac{P_{AV}}{P_{max}} \right)^2 \right] 
\]  
\hspace{2cm} (22)

where \( N \) is the prediction horizon (\( N = 10 \) in this study), \( P_{AV} \) is the motor power of AV, \( d_{max} \) and \( P_{max} \) are constants for normalization (\( d_{max} = 15 \) m, \( P_{max} = 200 \) kW in this study.)

C. Training Results

Considering that stochasticity significantly affects training performance, the training was repeated eight times with different random seeds. Each training consists of 3000 episodes. At the beginning of each episode, the driving preference set \((v_0, T)\) of HDV is randomly sampled with replacement from the joint distribution as shown in Fig. 6. This is to replicate the driving diversity of human drivers in real traffic. Fig. 7 gives the trajectories of rolling mean episode reward with respect to the training process under the two state space design. The solid and dashed lines are the rolling mean episode rewards, while the translucent area indicates a 95% confidence interval over eight runs. A steep increase can be observed within the first 500 episodes. As the training progresses, the reward trajectory starts to converge, thereby proving that the designed reward function is stable and effective. It can also be clearly observed that the solid line converges to a higher level than the dashed line, which proves that the inclusion of dependent state variables offers a depth of information that aids the agent’s learning capabilities.

As depicted in Fig. 8, a randomly sampled car-following episode simulated by DDPG displays the speed and acceleration profiles of three vehicles, in addition to the trajectories of the two gap distances, within the mixed traffic flow. It is obvious that the acceleration amplitudes of the AV and the HDV are substantially lower than that of the PV. Consequently, by implementing the proposed leading cruise control algorithm, both the AV and the HDV can avoid extreme maneuvers such as drastic acceleration and hard braking. The similar phenomenon can also be observed in the speed trajectories where the speed profiles of the AV and the HDV are smoother than that of the PV. The standard deviation of vehicle’s acceleration and speed are employed as the measure of traffic stability in this study [19], [56]. The acceleration standard deviations for the PV, AV and HDV are 0.8348 m/s², 0.2890 m/s², 0.1924 m/s² and the speed standard deviations are 1.3268 m/s, 1.3218 m/s, and 1.3032 m/s, respectively.

In the direction of the traffic flow, there’s a noticeable decline in standard deviations. Vehicles with lower standard deviations demonstrate more consistent and stable behaviors, contributing to traffic stability. Besides, both two gap distances are maintained within a safe and reasonable range, indicating the safe car-following process.

To investigate the energy economy performance of the proposed algorithm, we conduct a Monte Carlo analysis to compare the trip energy consumption of HDV under two scenarios, as shown in Fig. 9. In scenario A, the AV drives after the human-driven PV and the HDV follows the AV, where the AV is actively regulated to lead the HDV. In scenario B, the HDV directly follows after the PV. The characteristic parameters of the HDV are sampled from the joint distribution in Fig. 6 for 761 times without replacement. Then we employ histograms to represent the distribution of energy consum-
As shown in Fig. 10, the trip energy consumption of all the 761 HDVs under two different driving scenarios (i.e., with and without AV) is compared. The x-axis shows how much energy is consumed and the y-axis indicates the counts, i.e., the frequency. It can be observed that the columns in Scenario A move towards the left when compared with those in Scenario B. The average energy consumption of HDV is 203.11 kJ for Scenario A and 254.26 kJ for Scenario B, i.e., a reduction of average energy consumption by up to 20.12%. The lower part in Fig. 10 presents a point-to-point comparison of energy efficiency improvement in percentage, with a minimum improvement of 10.15% and a maximum improvement of 37.80%. It can be interpreted that the HDVs with diverse characteristics can all benefit from the adaptive leading cruise control. The AV in this traffic flow can be regarded as a virtual controller that optimizes the driving decisions of the AV to positively interact with the following HDV. As shown in Fig. 8, AV has smoother speed and acceleration profiles than those of PV and leads the HDV to behave similarly, i.e., eco-driving manner.

In addition, the impact of AVs on the following HDV regarding energy efficiency is further justified by quantitatively comparing the proposed strategy (with consideration of HDV in the optimization) and the reference strategies (without consideration of HDV in the optimization) when uncertain and diverse human driving behaviors are present. The total energy consumption for comparison is calculated as follows:

$$\sum_{j=1}^{N} \left( \int_{t_0}^{t_f} P_i dt_j \right)$$

where $i = 1$ refers to AV and $i = 2$ refers to HDV, as depicted in Fig. 4. $N$ is the number of HDVs (761 in this study). As shown in Fig. 11, by taking into account the energy economy of HDV in the proposed strategy, the total energy consumption of two vehicles is remarkably reduced for most scenarios with diverse human driving behaviors, when compared to the two reference strategies. A similar analysis of point-to-point percentage improvement is also conducted and shown in Fig. 11(b) and (c). The proposed strategy achieves positive improvement in most scenarios. With the proposed adaptive leading cruise control strategy, the holistic energy efficiency can witness an increase of up to 19.99%, with an average improvement of 6.03% in comparison to the RL without HDV strategy. When benchmarked against the MPC strategy, the improvement becomes even more pronounced, registering a peak enhancement of 20.09% and an average of 6.41%. However, it is worth noting that there is still a small portion of cases (85 out of 761 drivers, about 11%) with more energy consumed by two vehicles when compared to the RL without HDV strategy. These negative improvement cases mainly correspond to more aggressive HDVs, of which the preference parameters are clustered in the upper left corner of the joint distribution in Fig. 6. That is, these HDVs desire to maintain a higher speed and simultaneously keep a small time headway, leading to frequent and significant changes in acceleration. In these cases, the HDV does not have enough space to save energy, nor can it offset the energy efficiency that the AV has sacrificed. Note that the proposed adaptive leading cruise control strategy can statistically improve the
TABLE IV
ENERGY CONSUMPTION OF THE MIXED TRAFFIC FLOW UNDER DIVERSE DRIVING CHARACTERISTICS

|               | Proposed Strategy | RL without HDV | MPC |
|---------------|-------------------|----------------|-----|
|               | HDV (kJ) | AV (kJ) | Sum (kJ) | HDV (kJ) | AV (kJ) | Sum (kJ) | Improvement | HDV (kJ) | AV (kJ) | Sum (kJ) | Improvement |
| Most Improvement | 174.34 | 252.82 | 427.16 | 282.42 | 251.43 | 533.85 | 19.99% | 283.10 | 251.43 | 534.53 | 20.09% |
| Least Improvement | 122.63 | 263.00 | 385.63 | 119.81 | 251.43 | 371.24 | -3.88% | 117.61 | 251.43 | 369.04 | -4.50% |
| Mean Improvement | 202.15 | 258.19 | 460.34 | 238.45 | 251.43 | 489.88 | 6.03% | 240.46 | 251.43 | 491.88 | 6.41%  |

Fig. 12. Corresponding comparison of energy consumption of HDV and AV under three different strategies.

energy efficiency (i.e., an expectation of positive results) and most HDVs will benefit from it.

Fig. 12 further gives the distributions of energy consumption of HDV and AV under three different strategies. Both in the RL without HDV strategy and the MPC strategy, the energy consumption of AV remains constant. The reason is that, in both strategies, the AV only considers its own benefits, resulting in a deterministic solution when following after the same PV. In contrast, in the proposed strategy, with a slight sacrifice in the energy economy of AV, the average energy consumption of HDV drops from 238.45 kJ to 202.15 kJ (i.e., 15.22% reduction). Therefore, it is further demonstrated that by considering the HDV in the reward function, the overall energy efficiency can be improved from a statistical perspective, despite of the diverse driving preferences of HDVs. The numerical summary is given in Table IV.

D. Generalization Test

To evaluate the generalization capability of the adaptive leading cruise control strategy, four different speed profiles for the PV are randomly sampled from the NGSIM dataset, which are not encountered during training. The same Monte Carlo analyses are performed to reveal the energy-saving potential. As shown in Fig. 13, similar conclusions can be obtained that the proposed strategy helps improve the overall energy efficiency in most cases with average improvements of 7.00%, 8.04%, 9.35% and 4.62% for the four cases. Simulation results demonstrate a good generalization capability of the proposed control algorithm under different driving scenarios.

V. CONCLUSION

This study proposes an adaptive leading cruise control strategy for AV while considering the diverse characteristics of following HDV in a mixed traffic flow scenario. The diversity of human drivers’ behaviors is modeled using the IDM and the NGSIM dataset is used to calibrate the IDM to reflect a realistic distribution of human driving preferences. In addition to the objectives including car-following safety, traffic efficiency, and the energy economy of AV, the energy economy of the following HDV is also incorporated into the reward function design, aiming at improving the overall energy efficiency of this mixed traffic flow. Historical speed information of HDV is utilized to learn its driving patterns and predict its acceleration of the next step. Through a Monte Carlo simulation, the proposed adaptive leading cruise control strategy exhibits an average improvement of 6.03% and 6.41% in terms of traffic energy efficiency when compared against two reference algorithms under the uncertain driving environment with diverse human driving behaviors. With a little sacrifice in the energy economy of AV, it can help the following HDV save energy substantially. Moreover, similar statistically positive results can be observed during testing scenarios.

Our future research will look at: 1) how to more accurately model the stochasticity in human driving behaviors to reflect...
the realistic traffic environment; 2) how to generalize our proposed framework to traffic flows including various types of powertrains (electric vehicles, internal combustion engine vehicles, and hybrid vehicles).

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