Game Theory-Based Ramp Merging for Mixed Traffic With Unity-SUMO Co-Simulation

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***Abstract*—Ramp merging is considered to be one of the major causes of traffic accidents and congestion due to its inherent chaotic nature. With the development of the connected and automated vehicle (CAV) technology, CAVs can conduct cooperative merging using communication, and can also handle complicated situations even with legacy vehicles. In this article, a game theory-based ramp merging strategy has been developed for the optimal merging coordination of CAVs in mixed traffic, which can determine the dynamic merging sequence and corresponding longitudinal/lateral control. This strategy improves the safety and efficiency of the merging process by ensuring a safe intervehicle distance and harmonizing the speeds of CAVs in the traffic stream. To verify the proposed strategy, mixed traffic simulation runs under different penetration rates and different congestion levels have been carried out on an innovative Unity-SUMO integrated platform, which connects a game engine-based driving simulator with a state-of-the-art microscopic traffic simulator. The results show that the average speed of traffic flow can be increased up to 210%, while the fuel consumption can be reduced up to 53.9%. In addition, the driving volatility can be stabilized to a level with 0% extreme values.**

***Index Terms*—Connected and automated vehicles (CAVs), game theory, mixed traffic, ramp merging, unity-SUMO co-simulation.**

I. Introduction

TRAFFIC related issues, such as safety, efficiency, and environmental sustainability have drawn significant attention as transportation is more involved in people's daily lives. Stated by Statista [1] in 2015, there were 1.28 billion motor vehicles in-use in the world, and this number would likely grow to two billion within one or two decades. Further, as reported by the U.S. Department of Transportation, there were 36 560 people killed in traffic crashes on U.S. roadways in 2018 [2]. A survey from INRIX showed that traffic congestion cost each American nearly 100 h and U.S. $1400 in 2019, where the time lost in traffic jams had increased by 2 h compared to 2017 [3]. Among the factors leading to traffic congestion and accidents, ramp merging has a significant amount of impact [4], due to the chaotic nature of driving behaviors and the lack of coordination in the merging area. As emerging the connected and automated vehicle (CAV) technology enables vehicles to communicate with each other, many CAV-based algorithms and systems have been implemented to coordinate vehicle maneuvers or human driver behaviors in the merging area. However, most relevant studies, such as centralized optimal control-based ramp merging [5], [6], feedforward/feedback control-based ramp merging [7], and ramp merging speed guidance systems [8], have all relied on the strong assumption that all vehicles are CAVs (i.e., 100% CAV penetration rate).

Since CAVs are supposed to share the road with legacy vehicles for the foreseeable future, considering the mixed traffic environment is more pragmatic, though more challenging in terms of regulating the entire traffic stream. The well-planned merging sequence or speed trajectories for CAVs may be interrupted by legacy vehicles, hence the interaction between CAVs and legacy vehicles should not be ignored. Many researchers investigated this human–machine interaction from different angles. To name a few, Kumar *et al.* [9] investigated the digital-twin human–robot collaboration, Wang *et al.* [10] studied the human–machine interaction of the decision-making process of intelligent vehicles, and Xu *et al.* [11] presented an autonomous vehicle decision-making approach for lane changing and overtaking. Especially, in the circumstance that human behavior has significant impacts, game theory has been recognized as one of the effective methods for decision making. Game theory can model how human drivers decide to compete or cooperate with others, hence enabling the analysis of the interaction between them [12]. This article proposes a game theory-based ramp merging strategy with a decentralized algorithm, providing the optimal merging sequence and associated speed trajectory for each CAV in the mixed traffic.

Compared to other recent studies on cooperative ramp merging, the major contributions of this study are as follows.

1) For the mixed traffic scenario, a synthetic agent-based ramp merging strategy with both lateral and longitudinal control is proposed, including functions of conflict prediction, conflict avoidance, merging

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sequence determination, acceleration, and lane change control.

2) A game theory-based ramp merging sequence decision-making method for CAVs is developed by considering different costs, such as safety, mobility, and comfort. Moreover, cooperative and noncooperative games are formed for different types of interaction.
3) A traffic flow-level simulation is carried out on a uniquely developed Unity-SUMO co-simulation platform to validate the algorithm and analyze the result.

The remainder of the article is organized as follows: Section II discusses the background and related work. Section III illustrates the workflow of the system and the developed game theory-based algorithm. Section IV presents the setup of the Unity-SUMO integrated platform and evaluates the system performance at the traffic flow level. Conclusions and future work are presented in Section V.

II. Background and Related Work

This section discusses the background and recent work on-ramp merging algorithms for CAVs, especially those with game theory-based strategies, the implemented acceleration control algorithms, and the state-of-the-art simulation platforms.

A. Ramp Merging Algorithms for CAVs

A number of ramp merging strategies have been developed to increase road safety and efficiency by the leveraging CAV technology [13]. Awal *et al.* [14] proposed a proactive optimal merging strategy based on V2V communication to optimize the on-ramp merging time and to reduce merging bottlenecks. Utilizing V2I communication, Scarinci *et al.* [15] developed a cooperative merging assistant control system based on the combination of macroscopic and microscopic traffic flow theories to create gaps to allow on-ramp vehicles to merge. Lu and Hedrick [16] introduced a concept of virtual platooning and developed a closed-loop adaptive longitudinal control algorithm to control the merging speeds of CAVs. Jain *et al.* [17] proposed an adaptive strategy to platoon merging with vehicle engine uncertainty, and by considering the bidirectional error, the merging vehicle can interact with both front and rear vehicles.

Apart from the aforementioned methodologies, game theory has also been widely adopted in ramp merging strategies for CAVs. Some researchers adopted game theory for decision-making in a complex environment. To get a global perspective and obtain the optimal solution, centralized optimization algorithms have been developed to coordinate the ramp merging maneuvers. Jing *et al.* [18] designed a cooperative game-based merging sequence coordination system to arrange CAVs into platoons, and used optimal control to guarantee the best sequence in terms of mobility and fuel consumption. Ramp merging can be seen as a mandatory lane change behavior, and many studies for mandatory lane change can be adopted to ramp merging management. To mitigate shockwaves caused by merging maneuvers, Akti *et al.* [19] proposed a game theory-based algorithm to organize the longitudinal and lateral movements for merging vehicles, in a fully connected environment. Wang *et al.* [20] combined receding horizon control with game theory to find an optimal acceleration control for both lane changing and car following. Based on a large amount of real-world vehicle trajectories, the game theory-based algorithm becomes more powerful with the support of human behavior estimation. By estimating surrounding vehicles' aggressiveness as their utilities, Zhang *et al.* [21] presented a game theory-based model predictive controller to find out the optimal gap to perform mandatory lane changing, by searching up to three gaps on the adjacent lane.

However, the majority of these studies rely on a strong assumption of 100% CAV penetration rate, allowing for a centralized complete game approach that can utilize full information [22]. In contrast, especially in mixed traffic with a low penetration rate, CAVs can only form an incomplete game with limited information from the legacy vehicles within the detection range of CAVs. Moreover, the advantage of CAVs' long-distance communication is diminished in the mixed traffic environment since long-distance communication includes higher uncertainty of the environment.

B. Cross-Platform Simulation

Simulation is a widely used method to implement and evaluate the algorithms due to its cost-effective, risk-free, and interactive characteristics. Microscopic traffic simulators, such as VISSIM and SUMO, provide high fidelity and continuous traffic simulation to model complex vehicle interactions in a specific traffic network [23]. In recent years, game engine-based driving simulators, such as LGSVL (Unity based) and CARLA (Unreal based) [24], have gained much momentum and attracted considerable attraction from researchers. They can simulate more realistic scenarios with a high degree of freedom, which enables the use of various vehicle models, customization of sensor suites and ambient environment, full control of all static and dynamic actors, and map generation.

Oh [25] built a virtual reality (VR)-in-the-loop simulator by connecting VISSIM and Unity with VR and created an immersive driving environment. To further explore the vehicle-to-anything (V2X) communication in large-scale traffic, Jia *et al.* [26] integrated three popular open-source simulators SUMO (traffic simulator), OMNeT++ (network simulator), and Webots (3-D robot simulator), providing the information of large-scale network in addition to traffic simulation. However, compared to the aforementioned game engine-based simulators, Webots in this work lacks a high-fidelity simulation environment and vehicle models. Biurrun-Quel *et al.* configured a driver-centric simulator by connecting Unity and SUMO through traffic control interface (TraCI) protocol to present a driver view for one of the SUMO controlled background vehicles [27], which only allows one-way communication from SUMO to Unity. To better simulate the mixed traffic environment and implement the algorithm for CAVs, two-way communication needs to be set up.

In this research, we fuse the game engine Unity with the microscopic traffic simulator SUMO to verify the proposed

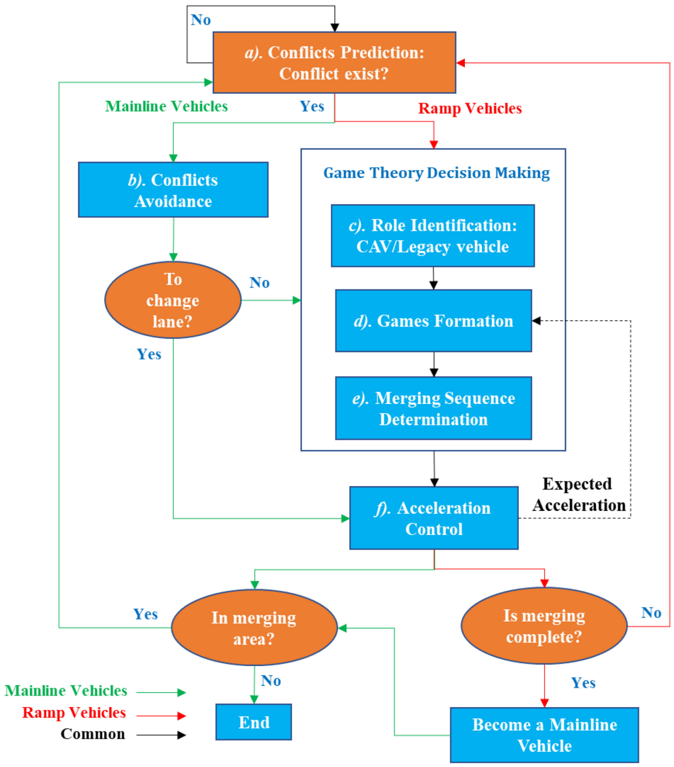

Fig. 1. System workflow of the mixed traffic ramp merging strategy for CAVs.

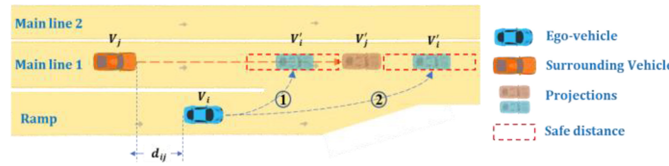

Fig. 2. Conflict prediction module.

strategy. In this Unity-SUMO integrated platform, CAVs are not only modeled with more realistic vehicle dynamics, but also equipped with customized radar systems and wireless communication modules. A real-world ramp merging area is mapped and synchronized in both the Unity world terrain and SUMO traffic network, where simulation is conducted to evaluate the performance of our proposed strategy, with different penetration rates and different traffic congestion levels. Drivers with different driving behaviors are also generated by SUMO to set up a more realistic mixed traffic environment.

III. Methodology

This section presents the proposed ramp merging strategy for CAVs in mixed traffic. The system architecture and strategy workflow are introduced in Section I, followed by the elaboration of the game theory algorithm and decision-making process.

A. Strategy Workflow

Our strategy is designed from a decentralized agent-based model perspective, allowing vehicles to act independently. The strategy workflow is shown in Fig. 1, where every vehicle goes through this process at each time step. Six major modules are functioning to support the strategy.

1) Conflict Prediction Module: Based on the information from the radar system or other CAVs, this module projects the ego vehicle and its surrounding vehicles into the future to see whether conflicts exist in the next time step. As Fig. 2 illustrates, when the projected surrounding vehicle V_j' is out of the safe distance of the projected ego vehicle V_i', there is no conflict; otherwise, this surrounding vehicle will be classified as a potential conflict and added to the conflict list. The analytical form of projection and conflict prediction can be expressed in (1). As the conflict state can be an instant condition and be too sensitive, a hysteresis controller considering historical information is implemented to filter the conflict state results [28]

$$\begin{cases} \text{No conflict}, & \begin{cases} v_i \times \Delta t + D_{\text{safe}} - d_{ij} \le v_j \times \Delta t \\ \qquad or \\ v_i \times \Delta t - D_{\text{safe}} - d_{ij} \ge v_j \times \Delta t \end{cases} \\ \text{Potential conflict}, & \text{else} \end{cases} \quad (1)$$

where v_i is the speed of ego vehicle; v_j is the speed of its surrounding vehicle; $d_{ij} = x_i - x_j$ is the current clearance; Δt is the simulation time step length; D_{safe} is the safe clearance, which is a speed-variant term depending on both the minimum static clearance and safe time headway of the ego vehicle.

2) Conflict Avoidance Module: Avoiding the conflict is the preferred option taken by mainline vehicles, who can change to another lane to avoid the conflict with ramp vehicles. This module takes time-to-collision (TTC) and intervehicle gap into account, urging mainline vehicles to change lanes for larger intervehicle gaps and TTCs. When the mainline vehicle cannot avoid conflict by changing lanes, mainline vehicle activates the *Game Formation Module* and initiates the game for determining the merging sequence with ramp vehicles.

3) Role Identification Module: This module is developed to classify ego vehicle's potential competitors into either CAV or legacy vehicle, which determines the game type in *Module d)*. Basically, the vehicle type (CAV or legacy vehicle) can be identified based on the signal association from both the radar detection and wireless communication.

4) Game Formation Module: The game formulation process is triggered once it receives a conflict notice from *Conflict Prediction Module*, where the ego vehicle forms an individual (two player) game with each of its competitors (i.e., each potentially conflicting vehicle). If the competitor is CAV, the game will be a cooperative one. Otherwise, it is a noncooperative game. In each game, each player may choose to be a follower or a leader. The corresponding expected acceleration and costs are calculated for each leader-follower combination, and the acceleration rates are computed by *Acceleration Control Module* to be introduced later. To dynamically adapt to the mixed traffic environment, a game is played in each time step, if a conflict exists. The game starts when the conflict emerges and ends until this conflict is solved.

5) Merging Sequence Determination Module: The merging sequence determination module is the last part of the game theory-based algorithm. The purpose of this module is responsible for coordinating the merging sequence dynamically by utilizing results from the game formation module. Each vehicle will obtain its role with respect to its competitor (i.e., leader or follower), as well as an optimal longitudinal acceleration that satisfies the safety constraints. If two competitors are both CAVs, they will share respective costs with each other and make a game-wise optimal decision together. Details of the game theory-based algorithm will be introduced in the next section.

6) Acceleration Control Module: This module is responsible for two main goals. The first one is to ensure ego vehicle can run at the desired longitudinal speed and track the lane. The second one is to perform the lane change maneuver safely, once the lane change condition is satisfied. Liu *et al.* [29] presented the vehicle longitudinal motion with a standard vehicle kinematic, where the longitudinal jerk of the vehicle was the control input. Since our algorithm focuses on acceleration control, we formulate the model as (2), where the longitudinal acceleration is used as the control input

$$\begin{bmatrix} s(k+1) \\ v(k+1) \end{bmatrix} = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} s(k) \\ v(k) \end{bmatrix} + \begin{bmatrix} \Delta t^2/2 \\ \Delta t \end{bmatrix} a(k) \tag{2}$$

where s v, and a represent the displacement, speed, and acceleration of the vehicle, respectively.

Once the ego vehicle confirms its target vehicle and the associated states, the consensus control algorithm [30] from our previous research is adopted to compute the acceleration. This allows the ego vehicle i to maintain a desired intervehicle gap and the same speed with its target vehicle j

$$a_{ref}(k+1) = -\alpha_{ij}\beta_{ij}\cdot\Big[\big(s_i(k) - s_j(k) + l_j + v_i(k) \cdot\big(t_{ij}^g(k) + \tau_{ij}(k)\big)\big) + \gamma_i\cdot(v_i(k) - v_j(k)\Big] \tag{3}$$

where α_{ij} denotes the value of adjacency matrix; β_{ij} and γ_i are control gains; $\tau_{ij}(t)$ denotes the time-varying communication delay between two vehicles; and $t_{ij}^g(t)$ is the time-varying desired time gap between two vehicles.

The string stability of this algorithm is well discussed in [30]. For a platoon of CAVs, this consensus-based control algorithm guarantees that the error signals are not amplified upstream along with the platoon, ensuring the string stability in a pure CAV environment.

B. Game Theory-Based Merging Sequence Determination

During the merging process, complex conflict can be summarized with three types of scenarios, including the interactions between 1) two legacy vehicles; 2) two CAVs; and 3) a CAV and a legacy vehicle. This article will only discuss the CAV(s) involved conflicts, since the conflicts between two legacy vehicles cannot be coordinated directly by CAVs. Hereafter, this article will analyze the merging strategy from the perspective of the ego vehicle (CAV). Assumptions and specifications that are generally common in related literature are made as follows.

1) The proposed algorithm aims to control the longitudinal speed to provide a safe merging space, and low-level control of the steering angle is outside the scope of this article.
2) All CAVs that are involved in conflicts act cooperatively to achieve an optimal goal.
3) The communication module and perception system of CAVs in the platform are assumed to be ideal. Therefore, no communication delay and packet loss are considered, and CAVs are capable of acquiring perfect information.
4) The proposed algorithm guarantees the string stability within a pure CAV platoon instead of the whole mixed traffic flow. Since the string stability of mixing two car-following models is a complicated problem, it is still an open topic and out of our research interest.

1) Game Formulation: When a potential conflict exists in the merging area, at least one of mainline vehicles and ramp vehicles needs to adjust its speed for a certain merging sequence. For the decision-making purpose, *Game Theory* is adopted for CAVs to evaluate their situation and then figure out the optimal merging strategy. A two-player nonzero-sum game is used in this article to handle each conflict by providing a merging sequence for each player in the game.

In such a game, ego vehicle is named *Player 1* (hereafter "P1"), while its competitor is named *Player 2* (hereafter "P2"). Both P1 and P2 can choose either to be a leader or a follower, with the action set given as $A(P1) = \{1\text{: To be the leader},\ 2\text{: To be the follower}\}$ and $A(P2) = \{1\text{: To be the leader},\ 2\text{: To be the follower}\}$.

The motivations of mainline vehicles and ramp vehicles may be different: mainline vehicles attempt to drive safely without compromising in travel speed, while ramp vehicles have to worry about the remaining distance to the end of the merging area. As the remaining distance decreases, the merging intention of ramp vehicles may grow, and this anxiety can be expressed as the risk value in the cost function.

2) Cost Function: Safety is always the first priority to be considered. For each action of ego vehicle in the game, a corresponding suggested acceleration $\hat{a}$ is calculated by the control algorithm. Therefore, we can predict the TTC in next time step of each action. From the perspective of ego vehicle, the predicted TTC for any pair of players can be formulated as

$$\hat{t}_{\text{TTC}} = \Big[d_{\text{gap}} + \Delta\hat{d}_{\text{gap}}\Big] / \big[v_f + \Delta v_f - \big(v_p - \Delta v_p\big)\big], \quad \text{if } v_f + \Delta\hat{v}_f > v_p - \Delta\hat{v}_p \tag{4}$$

where v_f, and $\Delta\hat{v}_f$ are the current speed and the predicted speed change of the following vehicle, respectively; v_p and $\Delta\hat{v}_p$ are the current speed and the predicted speed change of the preceding vehicle, respectively; d_{gap} is the current intervehicle gap; $\Delta\hat{d}_{\text{gap}}$ is the predicted gap change.

In the "two CAVs" scenario, these predicted values in (4) are shared with each player because of the vehicle communication. For the "a CAV and a legacy vehicle" scenario, the predicted values of legacy vehicles can be assumed to be unchanged during a small-time interval Δt (0.02 s in the simulation), allowing CAV to estimate legacy vehicles' action. For example, in (4), if the following vehicle is a legacy vehicle, the predicted speed change $\Delta\hat{v}_f = 0$.

However, using only TTC is not enough to quantify the safety risk [31]. For example, if the preceding vehicle is faster than the following vehicle, TTC will be negative. Moreover, if the difference between the following vehicle and the preceding vehicle is small, it will generate a huge TTC indicating safety even though the intervehicle gap is small. By combining predicted TTC ($\hat{t}_{\text{TTC}}$) and predicted time headway of ego vehicle ($\hat{h}_{ev}$). The cost of rear-end collision risk (J^c_{risk}) for each action can be evaluated below as in (5)

$$J^c_{\text{risk}} = \begin{cases} \left(\begin{array}{l} \left[1 - \tanh\left(\hat{t}_{\text{TTC}}/H_{\min}\right)\right] \\ +\left[1 - \tanh\left(\hat{h}_{ev}/H_{\min}\right)\right] \end{array} \right)/2, & \hat{t}_{\text{TTC}} \geq 0 \\ \left[1 - \tanh\left(\hat{h}_{ev}/H_{\min}\right)\right]/2, & \hat{t}_{\text{TTC}} < 0 \end{cases} \tag{5}$$

$$\hat{h}_{ev} = \left[d_{\text{gap}} + \Delta\hat{d}_{\text{gap}}\right]/\left(v_f + \Delta\hat{v}_f\right) \tag{6}$$

where $H_{\min}$ is the minimum safe time headway based on the 3-second rule [32], $\hat{h}_{ev}$ is the predicted time headway of ego vehicle.

To consider the merging urgency of a ramp vehicle, the distance to the end of the merging area should be added to the risk value of the ramp vehicle, as shown in (7). The closer to the end of the merging area, the higher cost vehicles should pay. The risk of merging (J^m_{risk}) can be formulated as follows:

$$J^m_{\text{risk}} = \left[1 - \tanh\left(\hat{h}_{rv}/H_{\min}\right)\right]/2 \tag{7}$$

$$\hat{h}_{rv} = \left[d_r + \Delta\hat{d}_r\right]/\left(v_e + \Delta\hat{v}_e\right) \tag{8}$$

where $\hat{h}_{rv}$ is the predicted remaining time headway to the end of merging area for ramp vehicle; d_r is the remaining distance of merging area; $\Delta\hat{d}_r$ is the predicted remaining distance; and v_e and $\Delta\hat{v}_e$ are the current speed and predicted speed change of ego vehicle, respectively.

To summarize, the risk for mainline vehicles and ramp vehicles used in this study can be expressed in (9)

$$J_{\text{risk}} = \begin{cases} J^c_{\text{risk}}, & \text{Mainline vehicles} \\ \left(J^c_{\text{risk}} + J^m_{\text{risk}}\right)/2, & \text{Ramp vehicles.} \end{cases} \tag{9}$$

As aforementioned, saving travel time may be another target for players in the game. In addition, if we only consider safety in the cost function, players in the game will incline to more conservative behaviors (e.g., encouraged to be followers or to decelerate), resulting in unnecessary congestion along with the upstream. Therefore, adding a mobility term would help CAVs find the balance between safety and speed, and improve the traffic efficiency at the same time. Both mainline and ramp CAVs are encouraged to take actions with minimum speed drop, if the safety performance is not compromised. As shown in (10), the mobility cost function puts more penalties on deceleration maneuvers. The term $\tanh(\Delta\hat{v}_e/v_e)$ is more sensitive when the speed of ego vehicle is slow, as this algorithm cares more about mobility for low-speed driving, but safety for high-speed driving

$$J_{\text{mobility}} = 1 - \tanh\left(\Delta\hat{v}_e/v_e\right) \tag{10}$$

TABLE I
DECISION TABLE FOR NONCOOPERATIVE TWO-PERSON GAME

	Competitor		
	Role	Leader	Follower
Ego vehicle	Leader	∞	$\bar{J}_{lead}$
	Follower	$\bar{J}_{follow}$	∞

where $\Delta\hat{v}_e$ is the ego vehicle speed difference of either being a follower or a leader in the game, compared to the current speed.

To improve the driving comfort, hard braking and drastic acceleration are penalized with a cost as shown in (11)

$$J_{\text{comfort}} = \begin{cases} \hat{a}/\text{acc}_{\text{lim}}, & \hat{a} \geq 0 \\ \hat{a}/\text{dec}_{\text{lim}}, & \hat{a} < 0 \end{cases} \tag{11}$$

where $\hat{a}$ is the acceleration of ego vehicle in next time step, $\text{acc}_{\text{lim}} > 0$ is the acceleration limit, and $\text{dec}_{\text{lim}} < 0$ is the deceleration limit.

To summarize, the overall cost ($\bar{J}$) is

$$\bar{J} = \alpha_1 J_{\text{risk}} + \alpha_2 J_{\text{mobility}} + \alpha_3 J_{\text{comfort}} \tag{12}$$

where $\alpha_i \geq 0, i = 1, 2, 3$, is the weight for each term in the cost function, and $\sum_i \alpha_i = 1$. In this study, we choose $\alpha_1 = 0.4$, $\alpha_2 = 0.4$, and $\alpha_3 = 0.2$. A more detailed sensitivity analysis is presented in Section IV-B3.

3) Noncooperative Game and Cooperative Game: After estimating the cost of each player's action, the optimal result can be obtained from a decision table, which depends on the game type, either noncooperative or cooperative game.

In this study, a game can be only initiated by an equipped CAV. Once the CAV recognizes a potential conflict, it sends out a cooperation invitation and keeps waiting for a reply. If the CAV receives no response from the other party, a noncooperative two-player game will be formed. In this type of game, the CAV will adopt a selfish strategy, since it can only rely on the information from the radar system and optimize its own cost. The decision table of the noncooperative game is shown in Table I.

To avoid a collision, ego vehicle will not choose to play the same role with its competitor at the same time. Therefore, the costs for both players being the leaders or followers simultaneously are set to be infinity (or very large values). At each time step, ego vehicle will choose the option with the minimum expected cost, as described in (13)

$$\text{Action} = \min_{\text{actions}} \left\{\bar{J}_{\text{lead}}, \bar{J}_{\text{follow}}\right\}. \tag{13}$$

The game between two CAVs would be a cooperative one, where players can make decisions together. The decision table of the cooperative game between two CAVs is shown in Table II. Unlike a noncooperative algorithm which can provide the optimal solution only for ego vehicle regardless of system conditions, a cooperative game can optimize the total cost (based on the information shared via vehicle-to-vehicle communication) for both CAVs.

TABLE II
DECISION TABLE FOR COOPERATIVE TWO-PERSON GAME

	Partner		
	Role	Leader	Follower
Ego vehicle	Leader	∞	$\overline{J}_{lead}^{ego} + \overline{J}_{follow}^{p}$
	Follower	$\overline{J}_{follow}^{ego} + \overline{J}_{lead}^{p}$	∞

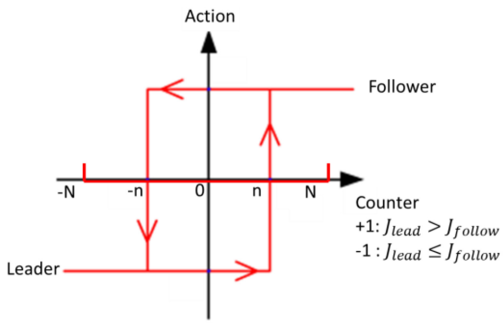

Fig. 3. Hysteresis controller for disturbance filtering.

As described in (14), both CAVs will take the action to achieve the system optimum

$$\text{Action} = \min_{\text{actions}} \left\{ \overline{J}_{\text{follow}}^{\text{ego}} + \overline{J}_{\text{lead}}^{p}, \overline{J}_{\text{lead}}^{\text{ego}} + \overline{J}_{\text{follow}}^{p} \right\} \quad (14)$$

where $\overline{J}_{\text{follow}}^{\text{ego}}$ and $\overline{J}_{\text{lead}}^{\text{ego}}$ are the costs of being a follower or a leader for ego vehicle, respectively; $\overline{J}_{\text{follow}}^{p}$ and $\overline{J}_{\text{lead}}^{p}$ are the costs of being a follower or a leader for its partner, respectively.

4) Disturbance Filtering: Although our system is designed to adapt to any environment dynamically, the game result should not be too sensitive to the small environmental disturbance. Hence, the hysteresis controller [28] is adopted to filter the game results and prevent unwanted rapid state switching as aforementioned. By taking recent system history into account, hysteresis can filter signals so that the output reacts less rapidly.

As shown in Fig. 3, the system history can be logged by a counter, ranging from $-N$ to N, which will increase when the cost of being the leader is greater than being the follower, which will increase/decrease when the cost of being the leader is greater/smaller than being the follower. Specifically, when the counter is greater than n, the output action is being the follower. It will not switch to being the leader immediately when the counter drops below n. Only when the counter decreases below $-n$, the output action will switch to being the leader.

IV. CASE STUDY AND RESULTS EVALUATION

On the customized Unity-SUMO integrated platform, a traffic flow-level simulation is carried out under different CAV penetration rates and congestion levels. The simulation results are analyzed in terms of mobility and fuel efficiency.

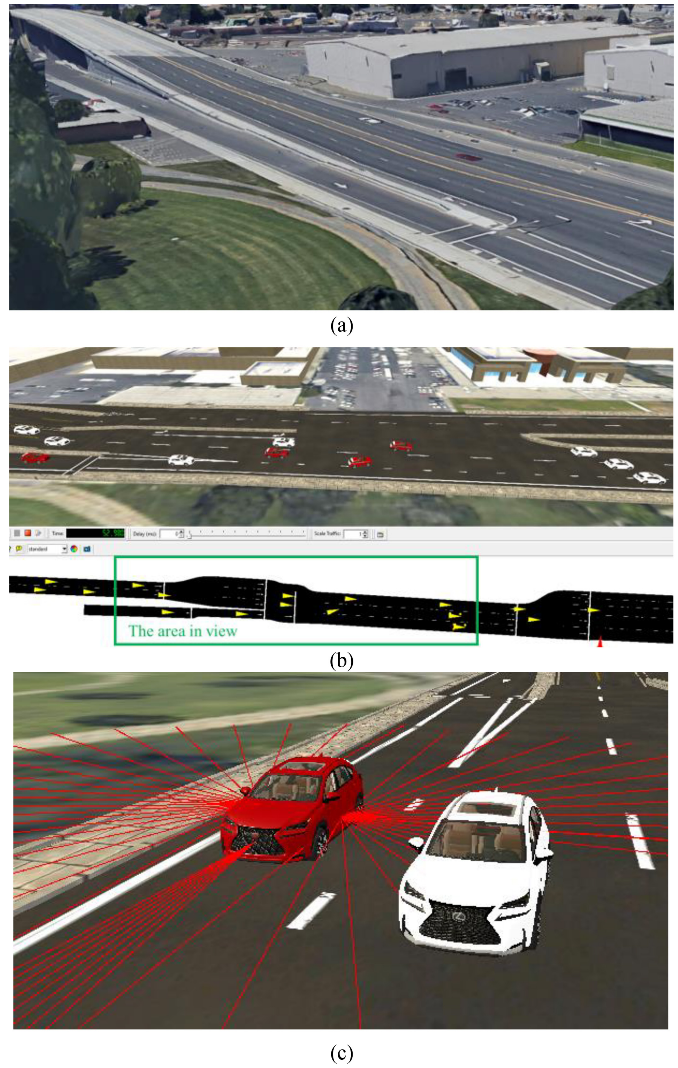

Fig. 4. Unity-SUMO integrated simulation based on a real-world ramp merging area in Riverside, CA: (a) View from Google Maps at the real-world ramp; (b) user interface of the Unity-SUMO co-simulation platform; (c) CAV (in red) with radar system and a legacy vehicle (in white).

A. Unity-SUMO Co-Simulation

A real-world traffic network is coded in the simulation, spanning from the intersection of Chicago Avenue to the intersection of Iowa Avenue along Columbia Avenue in Riverside, California. It consists of a single-lane on-ramp and a segment of multilane mainline (Google Maps view is shown in Fig. 4(a). The integrated simulation environment is shown in Fig. 4(b), where the upper part with terrain details is the Unity environment, and the lower part is the corresponding SUMO network. Two-way communication via UDP Socket connects and synchronizes these two simulation platforms in real time, allowing SUMO to control legacy vehicles while Unity controls CAVs with the proposed algorithm. CAVs are color coded in red, while legacy vehicles are in white. As shown in Fig. 4(c), the red rays spread from the CAV indicate the detection range of its onboard radar system, where the long-range radar in the front has a 150-m detection range and 18° field of view, while short-range radars on the side have a 25-m detection range and 70° field of view. The characteristics

TABLE III
SIMULATION SETUP PARAMETERS

Vehicular Parameters		
Vehicle type	CAVs	Legacy vehicles
Control platform	Unity	SUMO
Initial speed (adaptive to traffic)	ramp: 15 m/s; mainline: 20 m/s	
Minimum inter-vehicle gap	5 m	
Acceleration range	-5 ~ 3 m/s^2	
Desired speed (speed limit)	20 m/s	
Desired minimum time headway	1 s	
Initial distance to merging point	ramp: 250 m; mainline: 280 m	
Emergency braking	-9 m/s^2	
Simulation Environment Parameters		
Penetration rate of CAVs	0%, 30%,70%,100%	
Congestion level (v/c ratio)	0.35, 0.60, 0.85	
Traffic demand (veh/hr)	1400, 2400, 3400	
Merging zone length	89 m	
Speed limit	20 m/s	
Simulation time step	0.02 s	

and performance parameters of this onboard radar system are selected based on off-the-shelf radar sensors [33].

B. Simulation Design

Default car-following and lane-changing models of SUMO are used to generate the legacy traffic flow as the baseline. Then, the proposed algorithm is evaluated in a mixed traffic simulation under different penetration rates.

To generate a more realistic mixed traffic environment and carry out a fair evaluation, the parameters are carefully selected as shown in Table III. And, more details are discussed below.

1) Car-Following Model: For legacy vehicles controlled by SUMO, the Krauss car-following model [34] is adopted for the longitudinal control, due to its simplicity and its high execution speed [35]. Proven within a set of car-following model comparisons using a real-world dataset, the Krauss model shows valid results in terms of headways and speed [36]. To be specific, both the desired time headway and reaction time is set to be 1 s, based on the Krauss parameters calibration [37] and real-world data fitting [38]. To generate the traffic flow as close to the real-world situations as possible in SUMO, Bjärkvik *et al.* [39] well tuned the parameters of the Krauss car-following model, such as the minimum desired time headway (*tau*), acceleration, deceleration, and the result was verified with collected traffic data in the real world. In this study, the speed limit of 20 m/s is chosen based on the speed limit of the specific road segment of the testbed. To avoid homogeneous driving behaviors, the imperfection parameter is set to be 0.5. In addition, the speed deviation is set to be 10%, resulting in a speed distribution where 95% of the vehicles would travel at a speed ranging from 90% to 110% of the legal speed limit. As a result, parameter distributions of the car-following model in our simulation are well aligned with the suggested values in Bjärkvik *et al.*'s work. Moreover, the car-following model of CAV comes from the one in our previous study, as shown in (3).

2) Lane-Changing Model: The default collision-free lane change model in SUMO developed by Erdmann [40] controls the lateral maneuver of legacy vehicles, and the default parameters for passenger vehicles are adopted in our simulation.

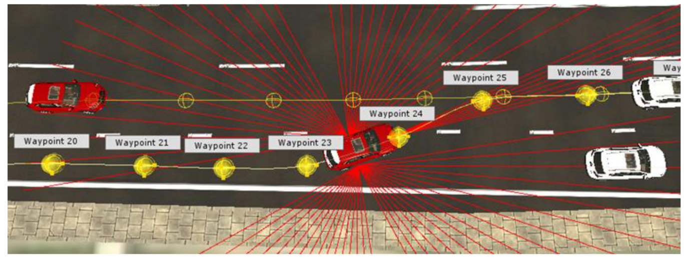

Fig. 5. Bezier curve generator for CAV lane change maneuver.

Although our algorithm focuses on longitudinal control, we need to guide the vehicles to change lanes in Unity. Lane change maneuvers for CAVs are governed by Unity's built-in Bezier curve generator. In the simulation, each lane has its reference path consisting of waypoints for every CAV to track. If gaps are determined to be safe, then CAVs can start their lane changes which can be triggered by moving the future waypoints from one lane to another. As shown in Fig. 5, the CAV just passes *Waypoint 23* and is ready to perform a lane change. Based on its current speed, it first selects the finishing waypoint (*Waypoint 25*) of lane change on its left (target) lane. Next, the Bezier Curve generator creates *Waypoint 24* between *Waypoint 23* and *Waypoint 25*, and connects those waypoints with a smoothed path.

As shown in Fig. 4(b), vehicles are running on a two-lane mainline segment and a ramp, so mainline vehicles on the right lane can avoid the conflict with ramp vehicles by changing to the left lane. As Table III shows, the proposed algorithm is evaluated in three congested levels, including light traffic with the volume-to-capacity (V/C) ratio of 0.35, moderate traffic with a ratio of 0.6, and congested traffic with the ratio of 0.85, where traffic demands are 1400, 2400, and 3400 vehicles per hour, respectively. The ratio of ramp demand to mainline demand is 1 : 2. In addition, to assess the system performance of the proposed algorithm in various mixed traffic scenarios, four levels of CAV penetration rate (i.e., 0%, 30%, 70%, and 100%) are evaluated in the simulation. Moreover, to statistically analyze the simulation results, 3 random seeds are selected for each of 12 scenarios (i.e., three congestion levels and four penetration rates). Therefore, a total of 36 simulation runs are carried out in this study. Based on these preset traffic demands, a traffic stream generator schedules the itinerary for each vehicle, which is modeled as a Poisson process. Therefore, vehicles' departure times follow an exponential distribution. The simulation only terminates when the last vehicle leaves the network to guarantee fair comparison across different strategies.

C. Simulation Result Analysis

To evaluate the performance of the proposed algorithm, we analyze the processes for two types of games, and their influence on the traffic flow. For the traffic flow-level evaluation, mobility, energy efficiency, and driving volatility are analyzed in each traffic scenario for mainline and ramp vehicles, respectively.

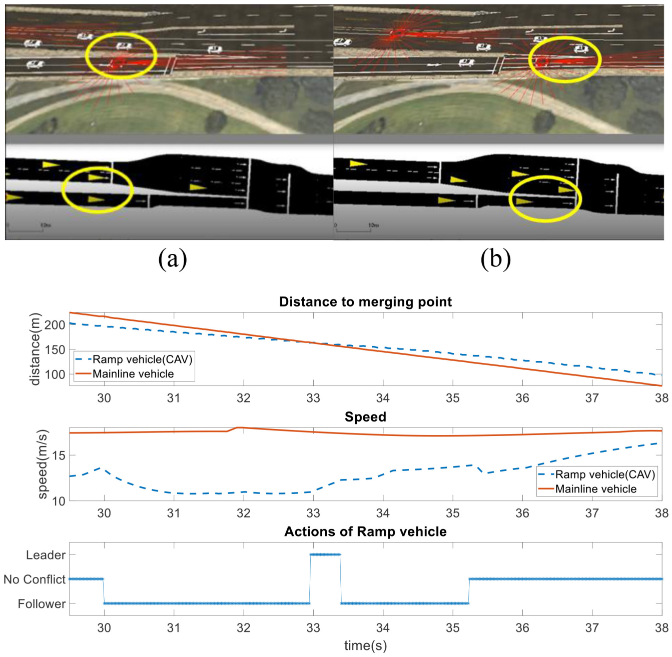

Fig. 6. Game process of a noncooperative game. (a) On-ramp CAV and a mainline legacy vehicle compete for merging. (b) Merging order is determined. (c) Whole process of the game.

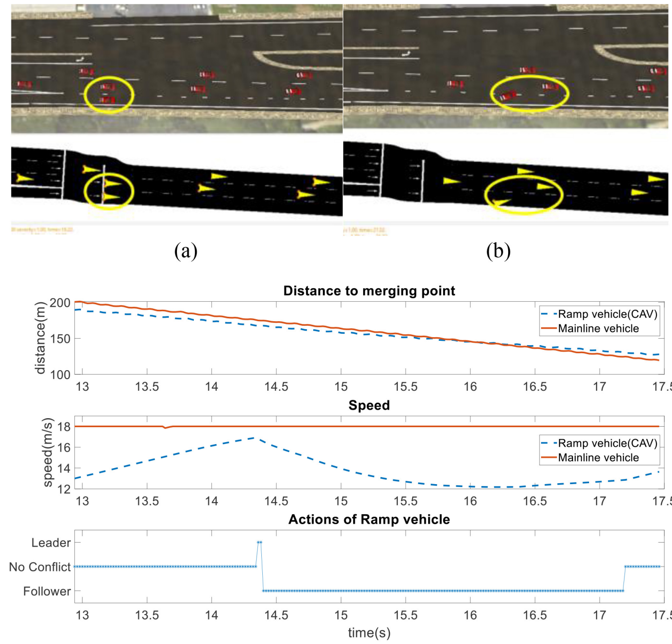

Fig. 7. Game process of a cooperative game. (a) Two CAVs compete for merging. (b) Merging order is determined. (c) Whole process of the game.

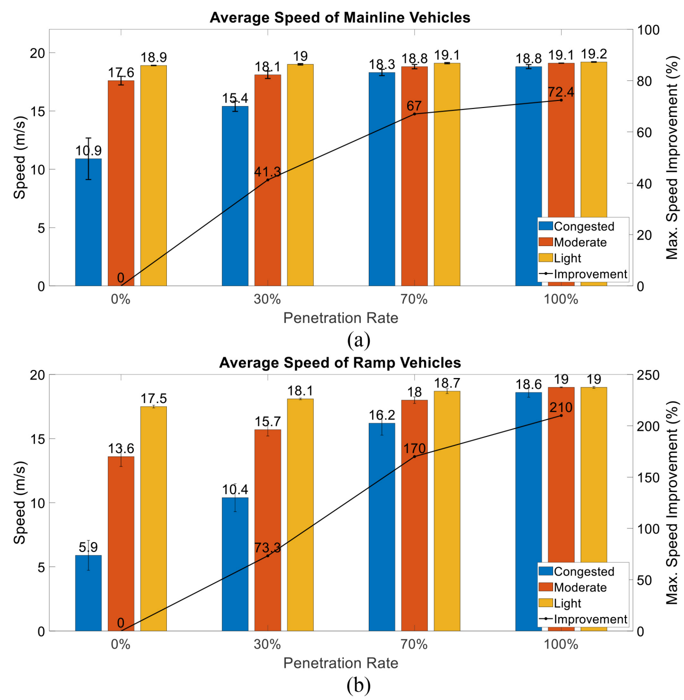

Fig. 8. Speed of traffic flows. (a) Average speed of mainline vehicles. (b) Average speed of on-ramp vehicles.

1) Game Process: Two merging conflicts are selected from the simulation for illustrating how the game evolves. Fig. 6 shows an example of a noncooperative game between a CAV and a legacy vehicle. In Fig. 6(a), as circled in yellow, an on-ramp CAV (in red) encounters a mainline legacy vehicle (in white), and a noncooperative game is formed. In Fig. 6(b), the game is settled with the merging order determined, and the CAV finds a slot with ensured safe longitudinal merging gap. Fig. 6(c) presents the whole process of the game, starting from 29.98 s, and ending at 35.24 s. The CAV first decides to be the follower when the conflict emerges. At 32.96 s, two vehicles drive in parallel, and when the legacy vehicle slows down, CAV decides to be the leader. However, legacy vehicle does not mean to yield and keeps running at a high speed. Therefore, CAV's decision flips back to being a follower.

Fig. 7 shows how two CAVs solve a similar conflict with a cooperative game. The actions of two CAVs are exclusive, with one being the follower and the other one being the leader. In Fig. 7(c), before the conflict starts, the on-ramp CAV accelerates to reach the mainline speed. At the instant of two CAVs encountering each other, the merging sequence is decided. In case of any unexpected emergency braking of one CAV due to preceding legacy vehicles, however, the game still exists until the CAV solves its conflicts or leaves the merging area. Compared with the noncooperative game, the decision of two CAVs is stable, and the mainline vehicle does not need to change its speed. Moreover, the cooperative game takes only 2.86 s to solve the conflict, which is much faster than 5.26 s in noncooperative game.

2) Mobility: Fig. 8(a) and (b) present the average speeds (i.e., the ratio between vehicle-meter-traveled and vehicle-second-traveled) of mainline vehicles and ramp vehicles, respectively. The error bars (one standard deviation) indicate the result variability. As shown in the figures, the variance is reduced when the penetration rate grows, or the congestion level decreases. It can be observed that the proposed algorithm improves not only the average speed of mainline vehicles, but also the one of ramp vehicles.

In Fig. 8, the solid line indicates the most significant improvement made by the proposed algorithm, compared with

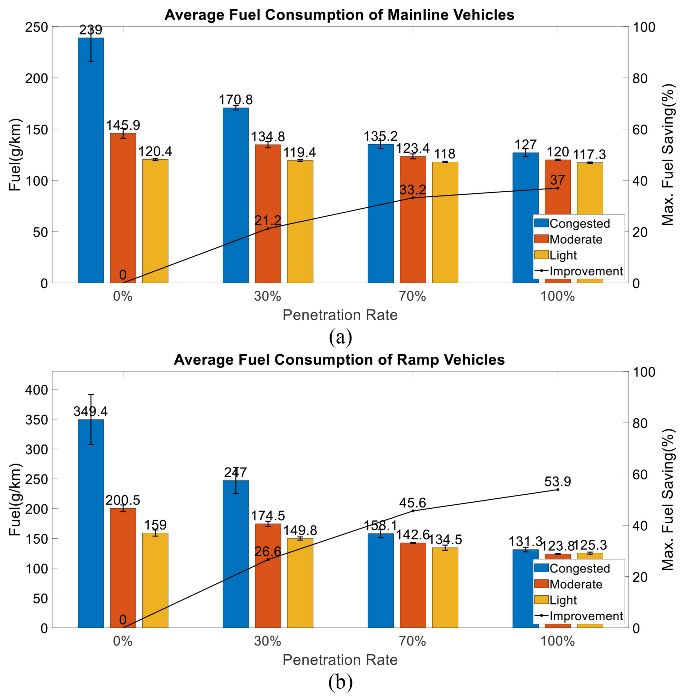

Fig. 9. Average fuel consumption. (a) Fuel consumption of mainline vehicles. (b) Fuel consumption of on-ramp vehicles.

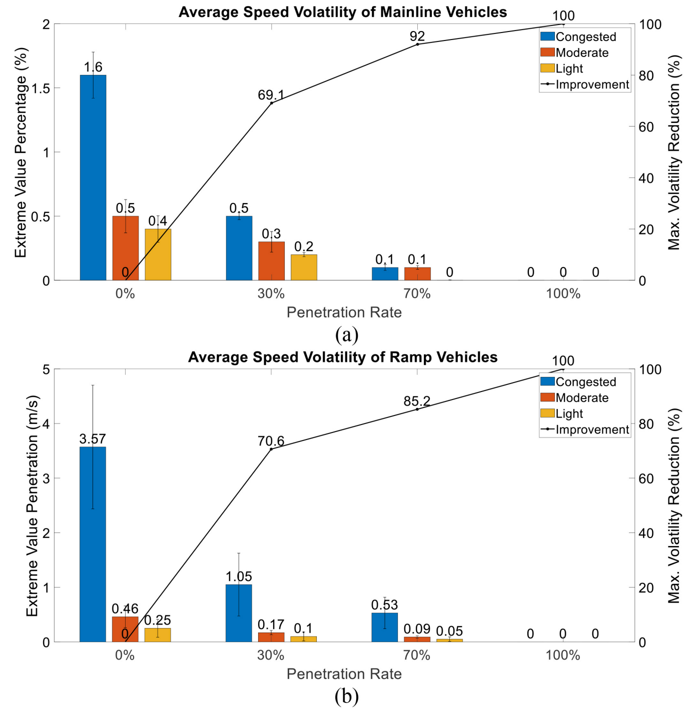

Fig. 10. Average driving volatility. (a) Speed volatility of mainline vehicles. (b) Speed volatility of on-ramp vehicles.

the baseline (i.e., 0% penetration rate). The largest improvement of average speed is gained in the congested traffic, i.e., 210% for ramp vehicles and 72.4% for mainline vehicles, compared with the baseline. When the penetration rate grows, the average speed increases significantly because the proposed algorithm for each CAV can coordinate the merging maneuvers (including the sequence) implicitly, which helps mitigate the congestion. It is noted that in scenarios with 100% penetration rate of CAVs, average speeds for both mainline vehicles and ramp vehicles are close to the free flow speed (20 m/s), regardless of congestion levels. This means that the proposed algorithm can effectively regulate the traffic under different traffic demands when the penetration rate of CAVs is high.

3) Energy Efficiency: We also analyze the energy efficiency of the proposed strategy with the open-source MOVESTAR fuel and emission model [41]. Fig. 9(a) and (b) present the fuel consumption of mainline vehicles and ramp vehicles, respectively, under the assumption that all vehicles in the simulation are passenger cars powered by gasoline. The variance of energy results shows the same pattern as the speed results. As expected, the results show that the proposed algorithm can considerably reduce the fuel consumption for both mainline and ramp vehicles, where the most significant reduction of fuel consumption happens in the congested traffic scenario for ramp vehicles. As the improvement in Fig. 9 shows, up to 53.9% of fuel consumption can be saved since vehicles can merge in a coordinated manner and minimize speed changes that might generate shock waves.

4) Driving Volatility: The driving volatility is defined as the deviation from the norm, reflecting the stability of the vehicle's movement. As the higher driving volatility is associated with higher risk [42], it can also be used as one of the surrogate measures for safety. In this study, we adopt the "percent of extreme values" method to evaluate the speed volatility which can quantify the driving risk and comfort. This performance index captures driving volatility by counting the number of observations beyond a defined threshold band, where any hard brake or drastic acceleration will increase the volatility.

The speed volatility ($V\%$) can be defined in (15)

$$V\% = \frac{1}{t}\sum_{i=0}^{t-1} I\left\{x(i) > T_{\text{upper}}, x(i) < T_{\text{lower}}\right\} \tag{15}$$

where $I\{\cdot\}$ denotes the indicator function, which equals 1 if the mathematical expression "statement" is true, and equals 0 otherwise; $x(i)$ is the observed value at time step i; and t is the total time steps of the observations. The upper and lower thresholds, T_{upper} and T_{lower}, can be defined in (16)

$$\begin{cases} T_{\text{upper}} = \bar{x} + 2 \times S_{\text{dev}} \\ T_{\text{lower}} = \bar{x} - 2 \times S_{\text{dev}} \end{cases} \tag{16}$$

where $\bar{x}$ is the mean of observations and S_{dev} is the standard deviation.

Fig. 10(a) and (b) show the speed volatility of mainline and ramp vehicles, respectively. As the CAV penetration rate increases, the speed volatility decreases significantly. The most remarkable improvement is obtained in 100% CAV penetration rate scenarios, where the outliers or extreme values (due to hard brake or drastic acceleration) are completely eliminated.

D. Sensitivity Analysis on Weights

In cost functions (13), the weights α_1, α_2, and α_3 represent how much the algorithm would value safety, mobility, and driving comfort, respectively. Tuning these weights can

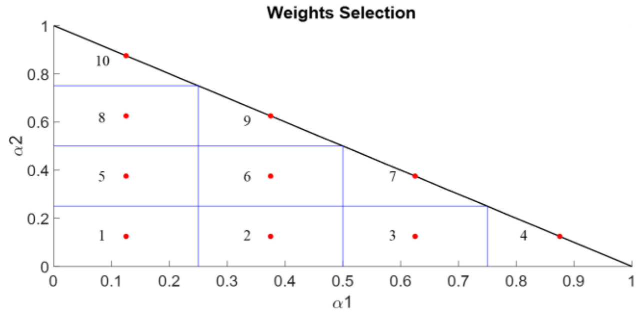

Fig. 11. Weight selection for sensitivity analysis.

TABLE IV
SENSITIVITY ANALYSIS FOR CAV PERFORMANCE MEASUREMENT

α_1	α_2	α_3	Avg. Fuel (g/km)	Avg. Speed (m/s)	Speed Volatility (%)	Acc. Volatility (%)
0.125	0.125	0.75	130.22	18.71	0	4.5
0.375	0.125	0.5	**124.31**	18.69	0.02	**4.44**
0.625	0.125	0.25	127.37	18.67	0.02	4.84
0.875	0.125	0	127.03	18.69	0.07	5.06
0.125	0.375	0.5	129.84	18.59	0.06	**4.46**
0.375	0.375	0.25	**125.18**	**18.91**	0.03	**4.49**
0.625	0.375	0	126.98	18.76	0	4.84
0.125	0.625	0.25	126.05	**18.83**	0	4.55
0.375	0.625	0	**125.12**	**18.83**	0.03	4.71
0.125	0.875	0	125.34	**18.88**	0.05	4.85

generate different driving behaviors for CAVs, thus affecting the traffic flow in different ways. To better understand the impacts of these weights, we carry out simulations for ten different combinations (see Fig. 11), and analyze the results of mobility, energy efficiency, and driving volatility, respectively. Because $\sum_i \alpha_i = 1$ and $\alpha_i \geq 0$, we set $\alpha_3 = 1 - \alpha_1 - \alpha_2$, and select α_1 and α_2 in the domain of $\alpha_1 + \alpha_2 - 1 \leq 0$. As shown in Fig. 10 and 11, ten red dots representing ten different weight combinations are evenly distributed within the domain.

Different from Section IV-B2, we analyze the direct influence of weight tuning only for CAVs rather than the whole traffic flow, because the weights determine the behavior of the CAV, and the influence of the weight on a legacy vehicle is indirect. Simulation results of sensitivity analysis are shown in Table IV and Fig. 12. The fuel consumption varies from 125.83 to 131.64 g/mi. The top three lowest values are located in area 2, 6, and 9 (see Fig. 11), with the weight combinations of (0.375, 0.125, 0.5), (0.375, 0.375, 0.25), and (0.375, 0.625, 0), respectively. According to the results in Fig. 12(a), the average fuel consumption shows a decreasing trend as α_1 and α_2 grow, and at $\alpha_1 = 0.375$, it reaches a local minimum.

As Fig. 12(b) shows, the average speed increases as α_2 increases since α_2 is the weight for mobility. The speed volatility ranges only from 0 to 0.07%, which is trivial. Thus, the acceleration volatility is further considered. As Fig. 12(c) shows, in the area where both α_1 and α_2 are small, the value of acceleration volatility is small, since the cost function emphasizes more on the comfort term. As $\alpha_3 = 1-\alpha_1-\alpha_2$ decreases, the acceleration volatility increases.

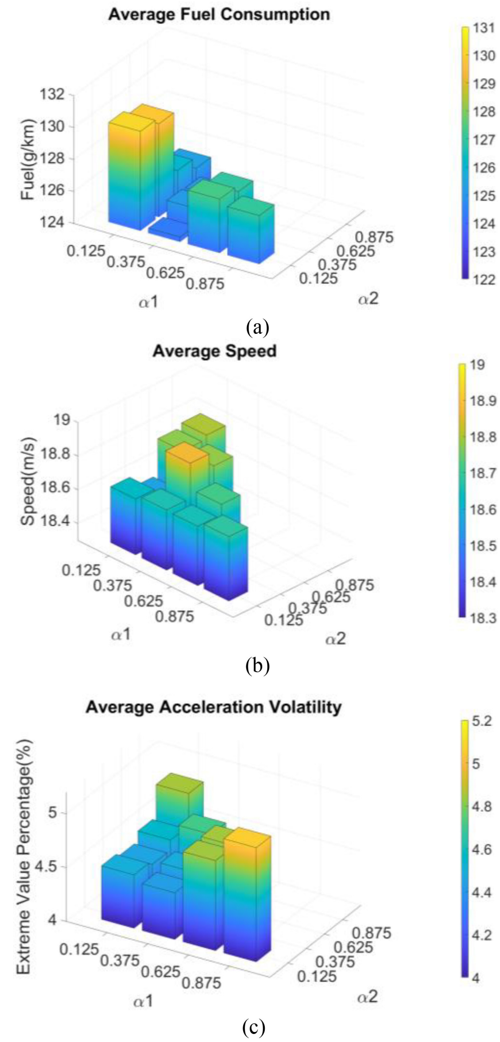

Fig. 12. Sensitivity analysis for CAV performance measurement. (a) Average fuel consumption. (b) Average speed. (c) Average acceleration volatility.

V. CONCLUSION AND FUTURE WORK

In this study, a game theory-based ramp merging strategy has been proposed for CAVs in the mixed traffic environment. The system has been developed, implemented, and evaluated in a customized co-simulation platform, which fuses a game engine-based simulator (Unity) and a microscopic traffic simulator (SUMO). Compared with the baseline merging algorithm of SUMO, the proposed algorithm can significantly improve system mobility (by up to 210%) and reduce fuel consumption (by up to 53.9%) under different traffic demands and CAV penetration rates.

As one of the few ramp merging algorithms developed for mixed traffic, some challenges need to be addressed along its future development pathway: 1) human–machine interaction in the game theory-based algorithm needs further investigation, since the modeling of human behaviors is still challenging; 2) with the development of Unity-SUMO co-simulation platform, human-in-the-loop (HuiL) simulation tests can be carried out to obtain valuable data for more in-depth human behavior research; and 3) in addition to safety, mobility and driving comfort, environment-related factors can be considered in the design of game functions to build an eco-friendly ramp merging system.

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The contents of this article only reflect the views of the authors, who are responsible for the facts and the accuracy of the data presented herein. The contents do not necessarily reflect the official views of Toyota Motor North America.

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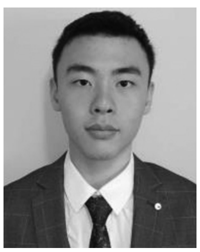

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