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Improving Truck Merging at Ramps in a Mixed Traffic Environment: A Multi-human-in-the-loop (MHuiL) Approach

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Abstract— **Freeway ramp merging is a challenging task for an individual vehicle (in particular a truck) and a critical aspect of traffic management that often leads to bottlenecks and accidents. While connected and automated vehicle (CAV) technology has yielded efficient merging strategies, most of them overlook the differentiation of vehicle types and assume uniform CAV presence. To address this gap, our study focuses on enhancing the merging efficiency of heavy-duty trucks in mixed traffic environments. We introduce a novel multi-human-in-the-loop (MHuiL) simulation framework, integrating the SUMO traffic simulator with two game engine-based driving simulators, enabling the investigation of interactions between human drivers in diverse traffic scenarios. Through a comprehensive case study analyzing eight scenarios, we assess the performance of a connectivity-based cooperative ramp merging system for heavy-duty trucks, considering safety, comfort, and fuel consumption. Our results demonstrate that guided trucks exhibit advantageous characteristics, including an enhanced safety margin with larger gaps by 23.2%, a decreased speed deviation by 30.4% facilitating smoother speed patterns, and a reduction in fuel consumption by 3.4%, when compared with non-guided trucks. This research offers valuable insights for the development of innovative approaches to improve truck merging efficiency, enhancing overall traffic flow and safety.**

I. Introduction

On-ramp merging and its associated research have attracted attention from both researchers and traffic operators, driven by the safety, mobility, and environmental considerations that arise from the chaotic nature of traffic within the merging zones. Frequent speed changes and weaving maneuvers can often provoke traffic congestion or shockwaves on both the mainline and on-ramps. These, in turn, can escalate energy consumption and mobile-source pollutant emissions.

A common strategy to manage on-ramp merging is ramp metering, which employs traffic signals at highway on-ramps to regulate the rate of traffic inflow onto the mainline, corresponding to the prevailing mainline traffic conditions [1]. Existing ramp metering research is typically divided into rule-based, control-based, and learning-based approaches [1]. However, such strategies can inadvertently create stop-and-go maneuvers for on-ramp vehicles, leading to an increase in both travel time and energy consumption. Furthermore, the coordination of merging maneuvers between on-ramp and mainline vehicles remains a challenge, potentially posing safety risks and disrupting the mainline traffic. In certain poorly designed locations, on-ramp vehicles, especially heavy-duty trucks, might struggle to achieve a safe and efficient merging speed due to insufficient acceleration lanes.

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Emerging technologies such as connected and automated vehicles (CAVs) have catalyzed the development of various algorithms addressing these ramp merging issues [3, 4]. Nevertheless, most of these algorithms only considered homogeneous traffic flow where all vehicles are light-duty CAVs, even differentiating in powertrain types [5]. Many studies also implemented a centralized optimal control of vehicle strings, assuming a pre-determined merging sequence and perfect compliance with the given guidance and planned trajectories. Such assumptions significantly deviate from real-world conditions, thereby curtailing the practicality and adaptability of these algorithms.

To bridge these research gaps, we develop a vehicle-to-everything (V2X) based cooperative ramp merging framework designed for a mixed and multimodal traffic environment, which encompasses both connected and non-connected vehicles (e.g., cars, trucks). This system is designed to enhance safety performance and enable smooth traffic flow at highway ramp merging areas. Our innovations are as follows:

- *Development of a Comprehensive Co-Simulation Platform*: We have developed an information exchange center, the *Edge Gateway*, that serves as a common interface for multiple driving simulators and a microscopic traffic simulator, thereby enabling multi-human-in-the-loop simulation and enhancing system scalability.
- *Analysis of Realistic Human-human Interaction*: Our developed platform facilitates the analysis, modeling, and simulation of multi-modal driving behaviors (including passenger cars and trucks), enabling a more accurate representation of interactions between human-operated vehicles in diverse traffic conditions.
- Truck-oriented Ramp Merging: To our best knowledge, no existing literature has examined truck-oriented ramp merging using dual driving simulators. Our study not only analyzes truck drivers' reactions to suggested speeds but also investigates realistic interactions between trucks and trucks/passenger vehicles (both with and without advisory information).

The remainder of this paper is arranged as follows: Section II elaborates on relevant background information. Section III presents the architecture of the connectivity-based cooperative ramp merging system and the development of a multi-human-in-the-loop (MHuiL) co-simulation framework. Section IV conducts a simulation study and analyzes the merging interaction between a truck and a car using the MHuiL framework, evaluating system performance in terms of merging safety, driver comfort, and environmental impacts.

Section V concludes the paper and proposes future research directions.

II. Background

In this section, we will review the state-of-the-art studies on both ramp merging algorithms based on vehicle-to-everything (V2X) communications and emerging simulators that enable connected and automated vehicle (CAV) research.

A. V2X-Based Ramp Merging Algorithms

Recent studies have proposed various ramp merging strategies that leverage CAV technology to improve road safety and efficiency in a fully connected environment [6]. For example, Zhou et al. [7] formulated cooperative ramp merging as two optimal trajectory planning problems for a pair of ramp and mainline vehicles, and Rios-Torres et al. [8] presented an optimization framework for online coordination of CAVs at ramp merging zones. However, most of these studies assume a 100% CAV penetration rate and do not consider the impact of mixed traffic or truck involvement in ramp merging. To address these issues, Huang and Sun [11] proposed a dynamic programming-based approach for mixed traffic ramp merging, and Liao et al. [12] developed a game theory-based strategy for CAVs in mixed traffic. Studies on truck-involved scenarios have also become popular, with research focusing on the impacts of truck platooning on merging areas [13,14] and developing solutions for efficient and safe merging coordination between trucks and cars [15,16]. This study uses an algorithm to coordinate both passenger cars and trucks for smoother and safer merging at ramps.

B. Advanced Simulators for CAV Research

Advanced simulators have been developed in recent years to evaluate advanced driving assistance systems (ADAS) and cooperative automated driving systems (CADS). These simulators can be divided into two types: microscopic traffic simulators, such as SUMO [17], Aimsun [18], and VISSIM [19], which are capable of generating realistic traffic flows and simulating their behaviors with well-calibrated car-following and lane-changing models; and vehicle-level simulators such as SVL [20], CARLA [21], Gazebo [22], Carsim [23], and PreScan [24], which can model realistic vehicle dynamics and complex sensor characteristics. Some recent research has integrated multiple simulators, such as VISSIM with driving simulators to assess the influence of adverse weather on traffic flow characteristics [25], and SUMO with CommonRoad [26], a software framework that provides a benchmark for motion planning of automated vehicles, to evaluate motion planners under realistic traffic scenarios [27]. Additionally, other studies have integrated SUMO with Matlab/Simulink [28], Unity and SUMO [30], and CARLA and SUMO [31]. These integrated simulators are capable of assessing ADAS effects and efficiency, but they do not consider more realistic driving behavior via the human-in-the-loop (HuiL) approach. By taking advantage of 3D vehicle-level simulators, researchers can analyze human behaviors under CAV application environments using the HuiL approach, which is a prototype platform for quickly exploring novel in-the-loop applications that can enhance the interactions between human beings and the physical world [32]. This approach has been used in different research topics related to human interaction with control systems, such as rollover prevention for sport utility vehicles [33], and solving safety-critical interaction problems in SAE Level 3 automated vehicles [34]. To understand human behaviors in response to ADAS applications and the effects on traffic safety and environmental sustainability, many integrated simulators are not only capable of assessing ADAS effects and efficiency but also taking human factors into account. Hussein et al. proposed a 3D simulator for cooperative ADAS, and AVs called 3DCoAutoSim which is composed of SUMO, ROS, and Unity [35]. Gao et al. proposed a co-simulation by integrating ROS and Aimsun, which allows a user to drive an ego vehicle in the traffic flow to investigate driving behavior [36]. The integrated traffic-driving-networking simulator (ITDNS) exploited PARAMICS, NS-2, and driving simulator to create a virtual environment, allowing a human driver to control a vehicle while communicating with other vehicles and infrastructure [37]. Zhao et al. developed a co-simulation platform incorporating SUMO, Unity, and AWS to collect driving data via HuiL and provide personalized data analysis and data storage [38]. Some multi-driver simulation systems have been developed for investigating the dynamic interaction between human-driven vehicles and the interrelationship between individual drivers behavior [39,40,41]. However, none of them take advantage of microscopic traffic simulators for realistic traffic environment generation or consider potential problems caused by heavy-duty vehicles involved in transportation.

III. Methodology

The methodology employed in this study leverages the nascent V2X technology for connected vehicles, encompassing both human-driven and automated vehicles. It considers vehicle types (e.g., passenger cars, heavy-duty trucks), their respective dynamics (e.g., maximum acceleration rate, braking distance), and the inherent imperfections of human behavior when formulating driving guidance or control strategies.

A. Problem formulation

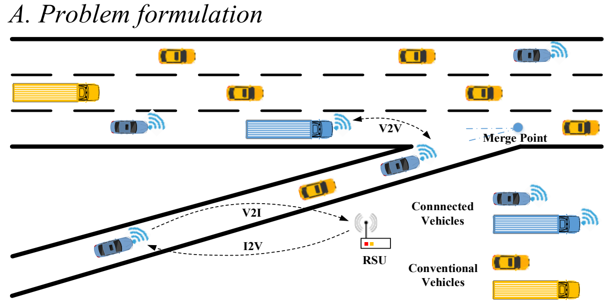

Figure 1. Connectivity-based Cooperative Ramp Merging System

The proposed system leverages V2X communications to coordinate the merging sequence, time, and speed in a mixed-traffic environment. We use decentralized sequencing and speed guidance algorithms that account for the heterogeneous characteristics of different vehicles. The problem is formulated as either a cooperative or non-cooperative game, contingent on the vehicles' connectivity and sensor availability, as depicted in Fig 1. We apply Game Theory to determine the leader and follower roles, or the necessity of lane changes, to ensure safe and efficient merging. A decentralized multi-agent system (MAS) approach, such as a consensus-based algorithm [42], is developed for driving guidance or vehicle control. The decentralized algorithm we propose is more apt for multimodal and mixed traffic scenarios and more adaptable for handling disturbances like lane changes. The next section will delve into more detail about this algorithm.

B. Connectivity-based cooperative ramp merging

Our strategy is based on a decentralized agent-based model, empowering vehicles to operate autonomously. The strategy's workflow, as shown in Fig 2, incorporates six modules: Conflict Prediction, Conflict Avoidance, Role Identification, Game Formation, Merging Sequence Determination, and Acceleration Control. The Conflict Prediction Module uses radar data and information from other CAVs to anticipate potential vehicle conflicts, considering speed and distance parameters. The Conflict Avoidance Module prioritizes lane change actions to evade conflicts, utilizing time-to-collision and inter-vehicle gap metrics as inputs. The Role Identification Module differentiates each vehicle as either a CAV or a legacy vehicle, thereby determining the game type for the Game Formation Module. Subsequently, the Game Formation Module organizes individual games between each conflicting vehicle, computing the anticipated acceleration and costs for each participant. The Merging Sequence Determination Module then outlines the merging sequence. The Acceleration Control Module ensures the vehicle maintains the desired speed, tracks the lane, and safely executes lane changes. The consensus control algorithm from previous research calculates acceleration and maintains an inter-vehicle gap and speed with the target vehicle. This algorithm's string stability is guaranteed in a purely CAV environment, ensuring error signals are not amplified upstream along the platoon.

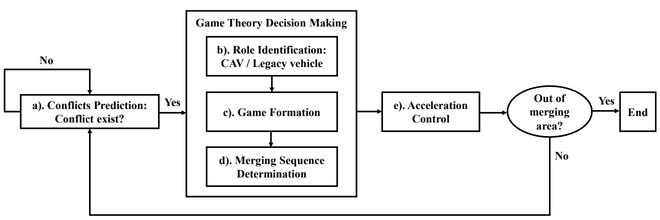

Figure 2. System Workflow of the Mixed Traffic Ramp Merging Strategy for CAVs

C. Development of multi-human-in-the-loop (MHuiL) co-simulation framework

In this study, we strive to develop a multi-driver simulation framework that can assess the interactions between heavy-duty trucks and passenger vehicles within mixed-traffic scenarios via a MHuiL simulation framework. Fig 3 graphically presents the overall system architecture of this framework. For the software part, we chose Unity, a high-performance game engine, to model and visualize the ego vehicle's surroundings and provide high-resolution sensor information. Additionally, we employed SUMO, a microscopic simulator, to generate realistic traffic flow across varying degrees of congestion and differing penetration rates of connected and automated vehicles. On the hardware end, we outfitted the framework with a steering wheel, brake, and throttle, functioning as human-machine interfaces to gather human driving behavior data.

There are two approaches to constructing the simulation environment in both Unity and SUMO:

1. Vehicle Modeling

To create a realistic mixed traffic flow and design cooperative Advanced Driver Assistance Systems (ADAS) using the MHuiL simulation framework, we define three primary vehicle types involved in the simulation: legacy vehicles, CAVs, and HCVs. At the simulation level, these vehicles are divided into two categories based on the controlling engine - either Unity or SUMO. For the control of CAVs and HCVs, we rely on the Unity engine, whereas SUMO regulates the rest of the vehicles.

Legacy vehicles on this framework are entirely SUMO-controlled using car-following and lane-changing models, with their deployment and removal hinging on a predefined route file. CAVs are controlled by user-defined algorithms encoded in Unity, with our study employing a game theory-based algorithm for their control. These vehicles also feature onboard sensors like cameras, radar, LiDAR, and GPS, delivering realistic data as point clouds and images.

In the MHuiL simulation, we construct two HCV models in Unity: the human-controlled truck (HCT) model and the human-controlled passenger vehicle (HCPV) model, both depicted in Fig 3. The HCPV is a standard four-wheel vehicle, whereas the HCT is a heavy-duty truck with a truck head and trailer linked by a hinge. Notably, for the HCT, we employ a diesel engine with a 'flat-curve' torque design. This design ensures the engine generates the maximum torque at the 'lower-to-middle-end' of its engine speed, i.e., in the range between 900 and 1300 rpm (revolutions per minute) [43]. Both HCV models incorporate two side mirrors and one rearview mirror for an immersive driving experience, as shown in Fig 3, and ADAS suggestions are displayed on the HCV models' windshield.

2. Hardware Setup

As shown in Fig. 3, the multi-driver co-simulation framework supports two human-machine interface setups: HCPV simulator and HCT simulator. Each simulator has one cockpit and three screens (including two side mirrors), extending the driver's field of view about surrounding vehicles. Besides, it is necessary to have brake and throttle pedals allowing longitudinal control and a steering wheel allowing latitudinal control. Specifically, the HCPV simulator is composed of a Logitech gaming steering wheel and pedal set which is supported by a Unity joystick input interface. On the other hand, HCT hardware is connected to a USB4 encoder and outputs can be decoded into voltage values which can be conveniently converted to control signals of HCT.

3. Simulation Environment Construction

Using the game engine, we construct a high-quality simulation environment in Unity based on a real-world map, including the network, infrastructure, and buildings. We also create a set of waypoints for each lane in the network to facilitate the lateral and longitudinal control of CAVs.

- NETCONVERT tool can convert an OpenStreetMap (OSM) file into a 2D SUMO network file, which can then be used to build the 3D map in Unity*.

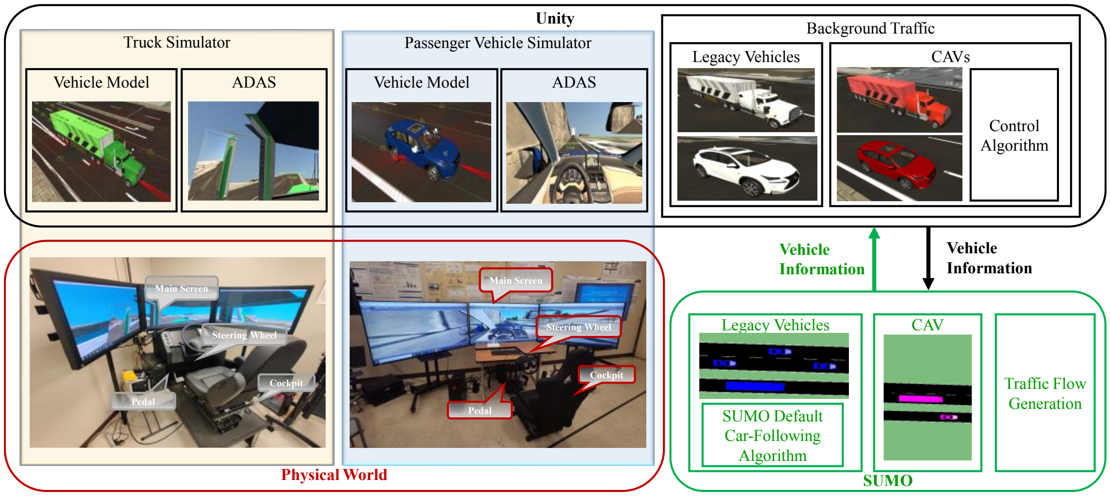

Figure 3. Overall Architecture of the Multi-driver Co-simulation Framework

- A 3D network in Unity can be used to create the same 2D map in SUMO, ensuring that both maps have the same reference point for position synchronization between the two simulators.

The first approach is generally easier, but the quality of the OSM model may not always accurately reflect real-world network geometry and situations. As such, we chose the second approach for this study, using a real road network in Riverside, California, and creating the virtual environment from scratch. The network covers the stretch from the intersection of Chicago Avenue to the intersection of Iowa Avenue along Columbia Avenue.

(a) (b)

Figure 4. The 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 framework.

IV. SIMULATION STUDY AND RESULTS

In this project, we aim to study the merging interaction between the truck driver and the car driver. Using the MHuiL framework, we are able to provide immersive driving with mixed traffic environments and replay the merging scenario for a fair comparison, where the driving operations and vehicle states of both truck and car drivers can be captured every time step.

A. Simulation Network Environment

As previously described, a real-world traffic network is coded in the simulation, spanning from Chicago Avenue to Iowa Avenue along Columbia Avenue in Riverside, California. It consists of a single-lane on-ramp and a segment of multi-lane 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.

TABLE 1. VEHICULAR PARAMETERS AND SIMULATION SETUP

Vehicle type	Car	Truck
Initial speed (adaptive to traffic)	ramp: 15 m/s; mainline: 20 m/s	
Minimum inter-vehicle gap	2.5 m	5 m
Acceleration range	$-5 \sim 3\ m/s^2$	$-4 \sim 1.3\ m/s^2$
Maximum RPM	6000	1900
Desired speed (speed limit)	10 m/s	
Desired minimum time headway	1 s	1.5s
Vehicle length	5 m	12 m
Initial distance to the merging point	ramp: 250 m; mainline: 440 m	
Congestion level (v/c ratio)	0.60	
Traffic demand (veh/hr)	2400	
Fuel Type	Gasoline	Diesel

To generate a more realistic mixed traffic environment and carry out a fair evaluation, the parameters are carefully selected as shown in Table 1.

B. Study Scenarios

We invite 7 subjects with real-world driving experience to participate in this MhuiL simulation framework. All participants involved in the study have received the necessary ethical approvals. To have a fair comparison, we assign the same person to drive the truck simulator for all runs, while the subjects only drive the car simulator. All subjects have the chance to drive both the mainline car scenarios and the ramp car scenarios, and for each role, they will experience non-guided and speed-guided cases. For each scenario, every subject takes two runs.

For the speed-guided case, the drivers are suggested to try their best to follow the speed guidance during the simulation, so that the ego vehicle can perform the cooperative merging maneuvers more smoothly compared to the scenario when no speed guidance is provided. The interface of speed guidance is shown Fig. 5.

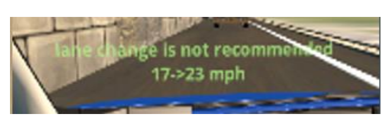

Figure 5. The interface of speed guidance.

In the non-guided case, to make sure the truck and car encounter each other for creating merging conflicts, preceding vehicles are set for both drivers, and the car following behavior will take the two drivers to the merging area nearly at a close time.

At the very beginning, to make the user familiar with the driving simulator, each subject drives the vehicle on the simulator for two trial runs of non-guided and speed-guided cases, respectively. Note that the subject is randomly asked to drive either the ramp vehicle or the mainline vehicle. Additionally, only one subject at a time is allowed to enter the room of the simulator. Therefore, the subject will not have any prior knowledge regarding the traffic scenario.

In this study, we explore different vehicle interactions of scenario combinations and conditions, considering the vehicle types, road types, and with/without speed guidance. As a result, each subject performs eight runs, as shown in Table 2.

C. Results and Analyses

To evaluate the capability of the MHuiL framework and to quantify the algorithm performance, we perform a cross-comparison between trips with or without guidance on trucks and with or without guidance on cars, regarding merging safety, driver comfort, and environmental effects. Specifically, safety is evaluated by the average of minimum time-to-collision to its preceding vehicle during the merging action,

$$TTC_{min}(s) = \frac{\sum_{i=0}^{N_s} \min(TTC_i)}{N_s} \quad (1)$$

where s represents the investigated scenario, N_s is the number of trips of the scenario, TTC_i is the time-to-collision of a vehicle during the merging action.

While the driver comfort is evaluated by the average of speed standard variance, during the merging process,

$$V_{std}(s) = \frac{\sum_{i=0}^{N_s} \min(V_{std_i})}{N_s} \quad (2)$$

where, V_{std} is the standard deviation of speed during the merging process.

Regarding the environmental effect, we calculate the average fuel consumption factor using MOVESTAR, which is an open-source vehicle fuel and emission model based on USEPA MOVES [44]. $Fuel$ represents the fuel consumption factor in the following equation:

$$Fuel(s) = \frac{\sum_{i=0}^{N_s} \min(Fuel_i)}{N_s} \quad (3)$$

TABLE 2. EXPERIMENT SCENARIOS

Scenario	Mainline Vehicle	Guidance	Ramp Vehicle	Guidance
1a	Truck*	No	Car	No
1b	Truck	Yes	Car	Yes
1c	Truck	No	Car	Yes
1d	Truck	Yes	Car	No
2a	Car	No	Truck	No
2b	Car	Yes	Truck	Yes
2c	Car	No	Truck	Yes
2d	Car	Yes	Truck	No

* Truck simulator is always driven by the same person, and car simulator is handling by other 7 subjects in turn.

Table 3 illustrates the significant influence of truck guidance on various parameters. One noteworthy observation relates to fuel consumption. When the truck is operating on the mainline, the guided truck exhibits marginally lower fuel consumption values than its non-guided counterpart, with differences standing at -0.7% and -0.1% for the car with and without guidance respectively. When the truck maneuvers on the ramp, the guided variant exhibits a more pronounced reduction in fuel consumption, registering -3.4% and -2% respectively.

TABLE 3. THE IMPACT OF TRUCK GUIDANCE ON THE TRUCK

Performance Metrics	Guided Truck	Non-Guided Truck	Difference
Fuel Consumption Factor (g/mile)	1b: 118.6	1c: 119.4	-0.7%
	1d: 121.3	1a: 121.4	-0.1%
	2b: 115.5	2d: 119.6	-3.4%
	2c: 122.5	2a: 125.0	-2%
Minimum Time-to-Collision (s)	1b: 3.78	1c: 3.22	17.4%
	1d: 3.74	1a: 3.26	14.7%
	2b: 3.61	2d: 2.93	23.2%
	2c: 3.58	2a: 2.99	19.7%
Speed Standard Deviation (m/s)	1b: 0.58	1c: 0.79	-26.6%
	1d: 0.73	1a: 0.96	-24%
	2b: 0.64	2d: 0.92	-30.4%
	2c: 0.93	2a: 1.27	-26.8%

Concerning safety performance, guided trucks maintain a larger TTC in all scenarios compared to non-guided trucks. The differences in TTC are 17.4% and 14.7% for scenarios 1b/1c and 1d/1a, while for scenarios 2b/2d and 2c/2a, the gaps increase to 23.2% and 19.7% respectively. This underscores the ability of guided truck drivers to sustain larger safety gaps, thus mitigating potential collisions. The introduction of speed guidance helps mainline cars create sufficient space for ramp trucks, curtailing dangerous cut-ins.

Examining speed variability, the non-guided truck displays higher speed standard deviation values across all scenarios, suggesting less consistent behavior compared to guided trucks. This indicates that non-guided trucks deviate much more significantly from the average speed, potentially resulting in more safety and mobility concerns.

In summary, guided trucks outperform non-guided ones by allowing more time for the drivers to react before potential collisions, maintaining uniform speed profiles, and achieving better fuel efficiency. These results underline the crucial role of the guidance system in ensuring safer and more efficient truck operations.

V. CONCLUSIONS AND FUTURE WORK

In this paper, we presented a connectivity-based truck ramp merging system in mixed traffic and evaluated its performance. We developed a MHuiL simulation framework that integrates SUMO traffic simulator with two game engine-based driving simulators (in Unity) to study interaction between truck drivers and car drivers. We recruited 7 subjects in the experiment with 8 different scenarios, considering the vehicle type (i.e., truck vs. car), road type (i.e., mainline vs. on-ramp), and with/without speed guidance. The results of our study indicate that the use of cooperative ramp merging algorithm has the potential to improve safety, comfort, and fuel efficiency for the target trucks.

As a future step, we will extend the scope by collecting and analyzing more data samples under different traffic conditions and vehicle mixes (e.g., autonomous vehicles). We will also further evaluate the impacts of the proposed ramp merging system on the conflicting car and other surrounding traffic, and even investigate the personalized driving behaviors or interactions from the truck driver's perspective.

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