Date of publication xxxx 00, 0000, date of current version xxxx 00, 0000.

Digital Object Identifier 10.1109/ACCESS.2022.DOI

Leveraging Autonomous Vehicles to Tally Cooperative Driving Behavior

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ABSTRACT The number of Autonomous Vehicles (AVs) coexisting with conventional human-driven vehicles is expected to increase significantly in the coming years. It is foreseen that this coexistence will last decades before full AV adoption is achieved worldwide. However, the cautious nature of AVs and the aggressive behavior of some human drivers could create unprecedentedly challenging scenarios for AVs, such as being stuck on merge lanes and blocked by human-driven vehicles. On the other hand, the cooperative behavior of other human drivers could assist AVs in overcoming the challenging task of avoiding deadlock situations. As such, it is crucial to model the driving behavior of both AVs and human-driven vehicles interacting on the road and to propose solutions to the aforementioned challenges. In this paper, we propose to leverage AVs to tally the cooperative driving behavior of conventional vehicles in merge-lane scenarios. Before the adoption of AVs, such tallying was not feasible given the high infrastructural cost associated with installing specialized road equipment to monitor cooperation. In contrast, with the adoption of AVs, such tallying can be done using AVs' sensing technology at almost no extra cost. This can facilitate the construction of vehicular profiles that can be disseminated among AVs to guide their cooperative decisions toward human-driven vehicles in the future, with the objective of promoting cooperation across the population. To this end, we model cooperative driving behavior in a "highway merge" scenario, which tends to be challenging for AVs. We vary the level of human drivers' cooperation and estimate the percentage of AVs required to tally such cooperative acts. To maintain traffic safety, we rely on an unmodified Wiedemann's car following model to identify sufficient gaps to achieve the merging task. PTV Vissim, a multimodal traffic simulation software, is used to assess the impact of cooperation. Results show that cooperation leads to statistically significant findings with stop delay, number of stops, vehicle delay, and travel time reductions in the merge lane of up to 68%, 46%, 38%, and 5%, respectively, when fifty percent of the human drivers cooperate. Finally, we demonstrate that a 30% penetration of AVs is sufficient to tally up to 78% of cooperative behavior in highway scenarios.

INDEX TERMS Human-driven Vehicles (HVs), Cooperative Human-driven Vehicles (CHVs), Autonomous Vehicles (AVs), Highway merge, Modeling.

I. INTRODUCTION

THE full adoption of Autonomous Vehicles (AVs) is anticipated to take around 60 years [1]. Until then, AVs will coexist with conventional human-driven vehicles on public roads, resulting in deadlock scenarios never experienced before the adoption of AVs, such as getting stuck in a merge lane for a long period of time. These scenarios would occur mainly due to the difference between human drivers and AVs [2] in terms of maneuverability, reaction time, and the perception of the surrounding environment. While human drivers can effectively cooperate to avoid deadlock situations, AVs may easily experience these situations due to their cautious behavior and the lack of cooperation from the other vehicles. When human drivers are not given enough space to merge, they might force their way in, which is a challenging task for AVs.

The prediction and the study of these challenging scenarios are thus crucial before deploying AVs on public roads in order to propose appropriate solutions and induce cooperation from the human drivers side. A key factor to consider is safety, which should be a *North Star* for new models and technological advancements [3]. To integrate novel approaches into intelligent transportation systems [4] and to better understand the impact of AVs on both the road [5] and travel decisions [6], interdisciplinary research is required for behavioral modeling, autonomous vehicles' perception, and altruistic behavior, e.g., leveraging different notions recently adopted from psychology to robotics [7].

In this paper, we propose to leverage AVs' technology to tally cooperation from the human-driven vehicles' side—a challenging scenario for AVs as it requires intricate interactions [7]. Such tallying is not feasible without AVs given the high infrastructural cost associated with installing specialized road equipment to monitor cooperation. Fortunately, the adoption of AVs can facilitate the tallying process at almost no extra cost, leveraging their sensing technology.

We set out to estimate the percentage of AVs required to tally the majority of the cooperating vehicles as well as to comprehend the impact of cooperative behavior on a merge lane. This estimation would aid in the design of systems that react to the behavior of human-driven vehicles, such as awarding cooperative drivers a higher trustworthiness score. These scores could then be shared among AVs, so that they would behave accordingly, e.g., by cooperating with high-score vehicles in response to their prior cooperation with others.

To accomplish this goal, we model cooperative behavior and deploy it in a portion of the human-driven vehicles traveling a highway where AVs (and other human-driven vehicles) are attempting to merge. We then examine the influence of various cooperation levels on observability, delay/stops, and travel time. In contrast to existing approaches that propose modeling the behavior of AVs in the merge, we ensure traffic safety by relying on an unmodified Wiedemann's car following model to identify sufficient gaps for achieving the merging task.

In summary, the contribution of this paper is threefold:

- Estimating the percentage of AVs required to tally the majority of human-driven vehicles exhibiting cooperative behavior towards other vehicles when attempting to merge on a highway.
- Modeling cooperation in human-driven vehicles while maintaining traffic safety in achieving the merging task.
- Evaluating the proposed models in a highway layout with a merge under various levels of cooperation, AV penetration rates, and speed limits to demonstrate the impact of cooperation on delay, travel time, and observability.

This paper is organized as follows: Section II presents the background and related work. The cooperative driving and observation models in a highway merge are described in Section III. The simulation setup, performance metrics, the measure of effectiveness outcomes, statistical analyses, as well as observability results with various levels of cooperation, AV penetration rates, and speed limits are presented in Section IV. Finally, Section V concludes the study and outlines potential future directions.

II. BACKGROUND & RELATED WORK

Merging on a multi-lane highway occurs at an on-ramp (merge) segment when the traffic stream in the merge joins the highway traffic to form a single stream. When vehicles try to merge, two types of drivers on the highway can be distinguished: cooperative drivers who adjust their speed to allow the vehicles to merge, and non-cooperative drivers who continue their trip without adjusting their speed. Merging is challenging for AVs since they have to identify sufficient gaps to merge on the highway while assuring safety by accounting for human driving behaviors such as sudden deceleration/acceleration or sudden lane change, and they must complete the merging operation before the current lane ends [8].

In [5], the authors proposed a hybrid model to control the lane-changing decisions of AVs with the objective of optimizing the traffic flow. They showed that the actual discharge rate in weaving sections (merges closely followed by diverges) can be increased as the penetration rate of AVs increases. To achieve lane change in real-time, the authors in [9] proposed to use a recurrent neural network to model cooperation in dense traffic scenarios. The model assumes the same type of conventional human-driven vehicles nearby and predicts their interactive motions in response to the actions of AVs. In other words, this model does not allow for different types of drivers as it applies to all nearby vehicles. In addition, zero collisions are not guaranteed due to the absence of a safe area to merge into. Unlike [9], different cooperation intentions are considered in [10], where reinforcement learning is used such that AVs can interact with nearby drivers to merge into the traffic. However, and similar to [9], traffic safety is not guaranteed. Other reinforcement learning approaches for merge scenarios can be found in [11] and [12]. In [13], the authors proposed to model the interaction between an AV merging on a highway and the other driving vehicles based on a leader-follower game. Similar to [10] and unlike [9], different types of drivers are considered such that each nearby vehicle can choose whether or not to cooperate based on its driver type. The AV applies a control strategy that adapts to online estimated driving intents of the other vehicles to achieve the merging task while ensuring traffic safety, a major advantage over [9] and [10]. In comparison to [9, 10] and similar to [13], our model maintains traffic safety, and its advantage over [13] appears in the comprehensive consideration of vehicular interactions in the evaluation (the authors in [13] only consider a small number of actions in their representation of vehicular behavior).

The practice of cooperative driving is facilitated by sharing perception information [14] among vehicles, such that the shared information can be used in making timely decisions by the receiving vehicles. Exploiting information that is shared between AVs is discussed in [15], and a model is built for making navigation decisions based on a proposed policy for information utilization. At the vehicular network level, making decisions with the aid of information sharing can improve travel convenience and help in achieving better traffic management. Our proposed work differs from existing AVs' information-sharing proposals in its ultimate goal to transfer the utilization of shared information to the next level, in which AVs interact with human-driven vehicles based on their behavior history, thereby inducing cooperation toward AVs from the human drivers' side.

Current AVs behave conservatively to maintain traffic safety because human behavior is not always predictable [7]. However, it is shown that AVs are capable of inducing cooperative behavior and sympathizing with conventional vehicles. For example, in [2], the authors proposed to rely on experiential learning to train AVs as altruistic agents in a competitive driving environment. The quantification of the degree of an agent's altruism is known as the Social Value Orientation (SVO) [16], a social psychological notion that has been recently rethought to be part of the decision-making process of AVs, so that they can predict the behavior of human drivers and react accordingly [7]. In contrast, this work does not make behavioral predictions but rather relies on live vehicular interactions when AVs attempt to merge into the traffic. We focus on evaluating the impact of cooperative driving when AVs coexist with human-driven vehicles in challenging scenarios and estimating the required AVs penetration rate to tally cooperative decisions.

III. COOPERATIVE DRIVING AND OBSERVABILITY MODELS IN A HIGHWAY MERGE

Multi-lane highways that accommodate merging often experience additional turbulence in the traffic stream. The distinguishing characteristics to consider are lane changing caused by merging, more frequent changes in speed, the average speeds that are sometimes lower than the speeds on similar sections, and the need for greater driver vigilance [17]. As a result, highway merges are known to lead to capacity drops [18]. In fact, the distribution of lane changes in merging sections is one of the main drivers for such capacity drops [19]. Lane changes are made by the merging vehicle to align itself according to its desired movement, and by non-merging vehicles to avoid the turbulence caused by the merging maneuvers. While human drivers can find their way to merge on the highway, the task is challenging for AVs [7] who behave cautiously to avoid collisions and maintain safety.

In this section, we describe the proposed model for cooperative driving behavior in conventional human-driven vehicles, as well as the observation performed by AVs when both types of vehicles coexist in a highway merge, as depicted in Figure 1. The modeling design considerations are:

- Allowing both cooperative and non-cooperative driving behaviors in a challenging traffic scenario for AVs.
- Enabling realistic traffic scenarios with lane changing applied by the merging vehicles attempting to align themselves according to the desired movements, and non-merging vehicles trying to avoid the turbulence of the merging maneuvers.
- Allowing live cooperation and merging decisions based on traffic conditions.
- Maintaining traffic safety for all the vehicles on the highway and in the merge.

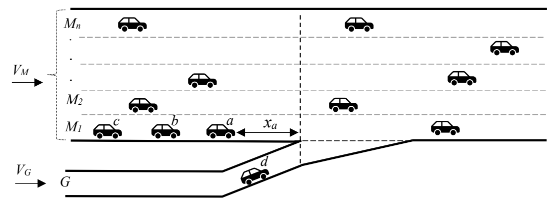


FIGURE 1: Highway layout.

To achieve the first design goal, we consider merging on a highway as a challenging scenario for AVs, where they share the road with two types of human-driven vehicles, cooperative and non-cooperative. As shown in Figure 1, the layout is composed of a multi-lane highway consisting of n lanes M_1 to M_n, and a merging lane G. A flow rate of V_M is distributed on the highway among three different types of vehicles as follows:

- Human-driven Vehicles (HVs) following Wiedemann's car following model with lane changing, without exhibiting cooperative behavior.
- Cooperative Human-driven Vehicles (CHVs) employing the developed cooperation model (Section III-A).
- Autonomous Vehicles (AVs) driving according to Wiedemann's car following model as described in [20], and tallying cooperation according to the proposed observation model (Section III-B).

The use of Wiedemann's car following model with lane changing aids the second design goal to ensure realistic traffic scenarios. On the merging lane, a flow rate of V_G is considered with two different types of vehicles, namely AVs and HVs. Although some of the vehicles in the merge could conceivably be driven by drivers who are willing to cooperate, our model does not consider them as cooperators, since the act of cooperation is only performed by vehicles on the main highway lanes.

A. COOPERATION MODEL

The proposed cooperation model is presented below, which extends Wiedemann's car following model to achieve cooperative behavior in human-driven vehicles, as part of the third design goal. The model defines an Area Of Interest (AOI) in M_1 starting from a predetermined distance upstream of the merging point. For a vehicle b of type CHV in the AOI as shown in Figure 1, the time $T_{b_{M_1}}$ to reach the merging point is described in Equation (1), where $x_{b_{M_1}}$ is the distance to the merging point, and $v_{b_{M_1}}$ is the speed of vehicle b at time t.

$$T_{b_{M_1}}(t) = \frac{x_{b_{M_1}}(t)}{v_{b_{M_1}}(t)} \tag{1}$$

Similarly, the time T_{d_G} for any vehicle d (which can be either an AV or HV) driving on lane G to reach the merging point is described in Equation (2), where x_{d_G} is the distance to the merging point, and v_{d_G} is the speed of vehicle d at time t.

$$T_{d_G}(t) = \frac{x_{d_G}(t)}{v_{d_G}(t)} \tag{2}$$

If vehicle b decides to cooperate (i.e., allow the vehicle d in the merging lane to join the highway in front of it), it attempts to create a time gap ($\bar{T}_{mrg}$) so that vehicle d can safely merge, which can be formulated as per Equation (3). In other words, if vehicle b decides to cooperate, it should arrive at the merge point at least $\bar{T}_{mrg}$ time units later than vehicle d.

$$T_{b_{M_1}}(t) \geq T_{d_G}(t) + \bar{T}_{mrg} \tag{3}$$

Equation (4) represents the upper bound of the recommended speed for vehicle b, which fulfills the inequality in Equation (3) to create a time gap $\bar{T}_{mrg}$ that allows vehicle d to safely merge. The upper bound speed limit is employed to avoid unnecessary speed reductions.

$$v^*_{b_{M_1}}(t) = \frac{x_{b_{M_1}}(t).v_{d_G}(t)}{\bar{T}_{mrg}.v_{d_G}(t) + x_{d_G}(t)} \tag{4}$$

In addition to $\bar{T}_{mrg}$, there should be a longitudinal time gap of T_{lg} between two consecutive vehicles on M_1 for the vehicle d to merge safely. In other words, vehicle b should be at least T_{lg} time units behind its downstream vehicle a, implying that there is enough room for the merging vehicle to merge on the highway. Equation (5) determines the recommended speed for b to create the longitudinal time gap T_{lg}, where $v_{a_{M_1}}$ is the speed of vehicle a , and $x_{a_{M_1}}$ is the distance to the merging point at time t.

$$v^{**}_{b_{M_1}}(t) = v_{a_{M_1}}(t) - \frac{x_{b_{M_1}}(t) - x_{a_{M_1}}(t)}{T_{lg}} \tag{5}$$

The ultimate recommended speed for vehicle b is the minimum speed of $v^*_{b_{M_1}}(t)$ and $v^{**}_{b_{M_1}}(t)$ to assure that the vehicle in the merge lane has a sufficient time gap to merge safely. The associated deceleration with the recommended speed is determined by Wiedemann's car following model. This recommended cooperative vehicle speed assures the necessary time gap for the merging vehicle to merge, provided traffic conditions remain constant (i.e., both the cooperative and merging vehicles maintain their speed) and the cooperative vehicle can decelerate instantaneously, which is not realistic. In reality, vehicle deceleration is constrained by complex vehicle dynamics and kinematics. In addition, while the cooperating vehicle decelerates, the merging vehicle accelerates, resulting in a substantially higher new recommended speed for the cooperating vehicle. In other words, there is no obligation in most scenarios to reach the initial recommended speed since it will fluctuate over time.

Furthermore, in order for the vehicle b to cooperate, the value of $[(T_{b_{M_1}}(t) - T_{d_G}(t)]$ must be less than or equal to a specified predetermined value $\bar{T}_{CHV}$, which is defined as the time difference between vehicle b and vehicle d to reach the merge point. This mimics the cooperative vehicle trailing the merging vehicle, and both will arrive at the merging point within $\bar{T}_{CHV}$ time units, where the merging decision is influenced by the cooperative vehicle's behavior.

Moreover, safety is maintained on the highway by avoiding speeds below the minimum defined highway speed. This is achieved by employing the recommended cooperative vehicle's desired speed as long as it is greater than the minimum highway speed ($v_{M_{min}}$). Additionally, a time gap $T_{up_{b_{M_1}}}(t)$ (Equation (6)) must be greater than a predefined time ($\bar{T}_{up}$). This time gap corresponds to the time headway between the cooperative vehicle b and its upstream vehicle c, where $x_{c_{M_1}}$ is the distance between the current location of vehicle c and the merging point, and $v_{c_{M_1}}$ is the speed of vehicle c at time t. This emulates the human driver's behavior when looking at the rear-view mirror before slowing down when intending to cooperate.

$$T_{up_{b_{M_1}}}(t) = \frac{x_{c_{M_1}}(t) - x_{b_{M_1}}(t)}{v_{c_{M_1}}(t)} \tag{6}$$

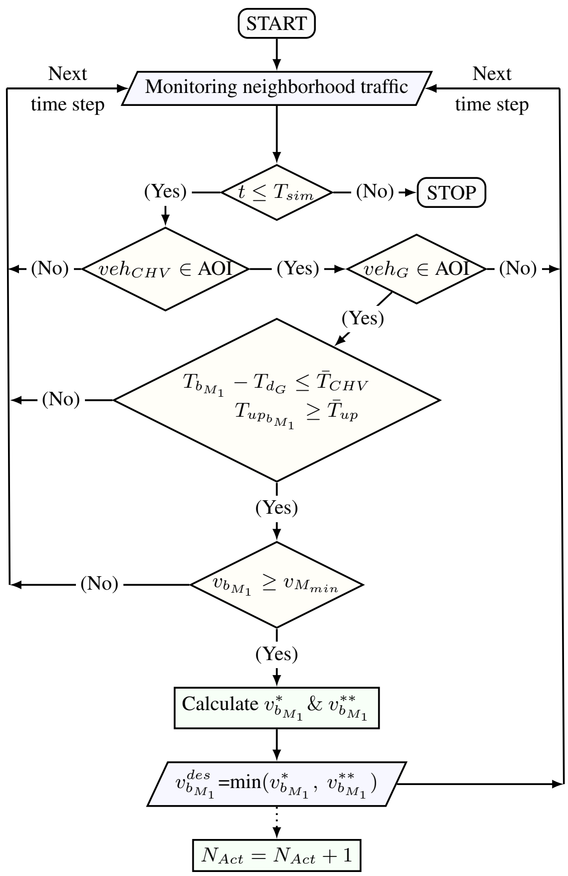


FIGURE 2: Cooperative driving model.

The cooperative driving model flowchart is shown in Figure 2. As the figure shows, CHVs check if they are within the AOI at each time step throughout the simulation/operation period (T_{sim}). If veh_{CHV} is in the AOI, it then checks if there is a vehicle (veh_G) driving in link G within the AOI. The recommended speeds in Equations (4) and (5) are calculated if the time between veh_{CHV} and veh_G (the first vehicle on the merge link) is less than or equal to a predefined time ($\bar{T}_{CHV}$), the time between the cooperative vehicle and the upstream vehicle ($T_{up_{b_{M_1}}}$) is greater than or equal to a predefined time ($\bar{T}_{up}$), and the cooperating vehicle's speed is at least as high as the minimum freeway speed. The ultimate cooperative vehicle's desired speed ($v^{des}_{b_{M_1}}$) is the minimum of the two recommended speeds. The number of cooperating vehicles (N_{Act}) is updated once per vehicle whenever a cooperative vehicle cooperates.

B. OBSERVABILITY MODEL

To tally cooperation, we propose leveraging AVs due to their technological capabilities and the anticipated near-future adoption. This could actually induce cooperation and improve travel convenience at no additional cost. The AV observability model is presented in Figure 3.

As illustrated in the figure, an AV reports whether or not cooperation occurs when the following scenario is observed: a vehicle is driving in the merging lane and its distance to the merging point is smaller than that of the vehicle on the freeway; both vehicles are within the AV's sensing range (SR) and within the AOI. Moreover, the number of vehicles between the cooperating and the observing AV (N_b) should be less than or equal to a predetermined value ($\bar{N}_b$), which provides a simplified assumption of AVs' sensing capability when obstacles exist. The observing vehicle may observe from any lane as long as the observing conditions are fulfilled. In the evaluation, we set $\bar{N}_b$ to 1, meaning that an AV can observe cooperation if there is at most one vehicle between the AV and the cooperating vehicle.

Furthermore, to be tallied as a cooperating vehicle, the human-driven vehicle should exhibit cooperative behavior, by slowing down to allow a merging gap for the vehicle attempting to merge. At each time step, the number of observed cooperative vehicles (N_{Obs}) is updated.

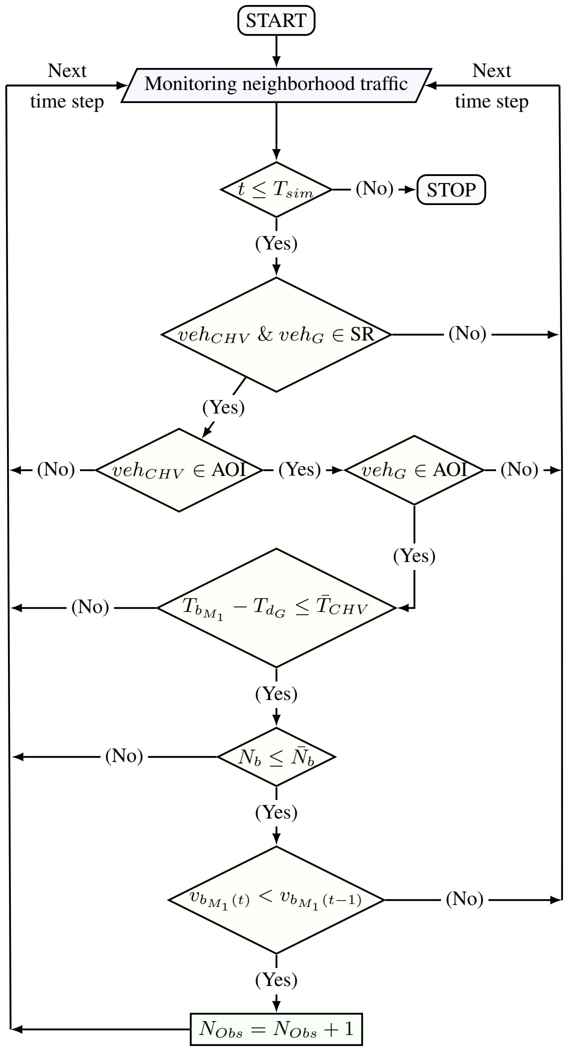


FIGURE 3: AV observation model.

IV. EVALUATION

The evaluation aims to achieve two main objectives: First, to demonstrate the impact of collaboration on vehicle delay, stop delay, number of stops, and travel time. Second, to provide an estimate of the percentage of AVs required to tally most of the cooperative cases under different levels of co-operation. The models are implemented in PTV Vissim [20] simulation environment to be evaluated on a highway with a merging lane. In this section, we discuss the simulation setup as well as the evaluation scenarios (Section IV-A), performance metrics (Section IV-B), and simulation results (Section IV-C).

A. SIMULATION SETUP

The highway layout considered in this evaluation is one kilometer long, with two straight lanes and one 513-meter-long on-ramp that mimics a real-world highway segment. Three types of vehicles are defined according to the model (AVs, HVs, and CHVs). AVs follow the definition of autonomous vehicles in PTV Vissim, which is based on Wiedemann's car following model [20], and HVs follow the same model according to the definition of conventional vehicles in PTV Vissim. On the other hand, CHVs are defined to utilize the developed cooperation model that is implemented on top of the driving models of PTV Vissim. Figure 4 provides a screenshot of a running simulation, where the red vehicles represent AVs, the black vehicles represent HVs, and the green vehicles represent CHVs. The route is empty at the beginning of the simulation, and the simulation time (T_{sim}) is set to one hour, with a 5-minute warm-up period and a 15-minute extra to evacuate the network.

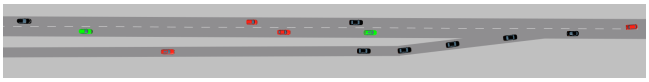


FIGURE 4: Vissim snapshot, with red vehicles representing AVs, green vehicles representing CHVs, and black vehicles representing HVs.

The simulation scenarios are conducted with modeling parameter values selected based on realistic traffic safety assumptions [21] and AVs' technology [22] that allow a long sensing range of around 250 meters with high precision and accuracy [23]. The following are the set of parameters used in the simulations along with their values:

$$\begin{array}{lll} \text{AOI} = 150\text{ m}, & \bar{T}_{CHV} = 5\text{ sec}, & \bar{T}_{mrg} = 2\text{ sec} \\ v_{M_{min}} = 60\text{ km/h}, & T_{lg} = 4\text{ sec}, & \bar{T}_{up} = 1\text{ sec} \\ \text{SR} = 250\text{ m}, & \bar{N}_b = 1 & \end{array}$$

The main road demand is set to 1800 (veh/h), and the on-ramp demand is set to 600 (veh/h). These demands represent relatively uncongested traffic conditions appropriate for evaluating cooperative driving, since cooperation might be rarely required in low-traffic scenarios, and would not help in high-congestion conditions. We designed 30 simulation scenarios (S1 to S30) as shown in Table 1. The percentage of CHVs varies from 10% to 50%, with a 10% increment on the main highway road. The percentage of AVs varies from 5% to 50% on the main and the on-ramp roads. These 30 scenarios are evaluated under three different speed values 80, 100, and 120 km/h. These deterministic desired speed values remain unchanged throughout the simulation unless updated by the cooperative model, allowing for an accurate evaluation of the impact of the developed cooperative model and for a fair comparison of the findings across various scenarios. For comparative evaluation, we consider a base case scenario for each speed value, where the simulation runs without cooperative behavior in the scene.

B. PERFORMANCE METRICS

To assess the impact of cooperation, several measures of effectiveness (MOEs) are reported, including vehicle delay, stop delay, the number of stops, and travel time, all of which are defined below.

- Delay: the average vehicle delay time of all vehicles is calculated in seconds by subtracting theoretical travel time from actual travel time. The theoretical travel time is calculated in free-flow conditions, in the absence of other vehicles or other reasons to stop.
- Stop delay: the average stopped time in seconds across all simulated vehicles.
- Number of stops: the average number of vehicle stops per vehicle, calculated by dividing the total number of stops by the total number of simulated vehicles.
- Travel time: the average travel time in seconds for vehicles traversing the network.

The MOE percentage reduction is calculated and formulated as shown in Equation (7) to demonstrate the improvement achieved by each of the 30 cooperative scenarios in terms of a given MOE [MOE($CHVs$)], and in comparison to the base case, when no cooperation is present.

$$\text{MOE Red. } (\%) = \frac{\text{MOE(Base)} - \text{MOE}(CHVs)}{\text{MOE(Base)}} \times 100 \tag{7}$$

AVs Observability is another performance metric that is calculated using Equation (8).

$$\text{Observability } (\%) = \frac{\text{Observed Cooperation } (N_{Obs})}{\text{Actual Cooperation } (N_{Act})} \times 100 \tag{8}$$

TABLE 1: Simulation scenarios

Link \ Scenario	Vehs	S1	S2	S3	S4	S5	S6
Main	CHVs	0.5	0.5	0.5	0.5	0.5	0.5
	AVs	0.05	0.1	0.2	0.3	0.4	0.5
	HVs	0.45	0.4	0.3	0.2	0.1	0.0
Merge	AVs	0.05	0.1	0.2	0.3	0.4	0.5
	HVs	0.95	0.9	0.8	0.7	0.6	0.5
	Vehs	S7	S8	S9	S10	S11	S12
Main	CHVs	0.4	0.4	0.4	0.4	0.4	0.4
	AVs	0.05	0.1	0.2	0.3	0.4	0.5
	HVs	0.55	0.5	0.4	0.3	0.2	0.1
Merge	AVs	0.05	0.1	0.2	0.3	0.4	0.5
	HVs	0.95	0.9	0.8	0.7	0.6	0.5
	Vehs	S13	S14	S15	S16	S17	S18
Main	CHVs	0.3	0.3	0.3	0.3	0.3	0.3
	AVs	0.05	0.1	0.2	0.3	0.4	0.5
	HVs	0.65	0.6	0.5	0.4	0.3	0.2
Merge	AVs	0.05	0.1	0.2	0.3	0.4	0.5
	HVs	0.95	0.9	0.8	0.7	0.6	0.5
	Vehs	S19	S20	S21	S22	S23	S24
Main	CHVs	0.2	0.2	0.2	0.2	0.2	0.2
	AVs	0.05	0.1	0.2	0.3	0.4	0.5
	HVs	0.75	0.7	0.6	0.5	0.4	0.3
Merge	AVs	0.05	0.1	0.2	0.3	0.4	0.5
	HVs	0.95	0.9	0.8	0.7	0.6	0.5
	Vehs	S25	S26	S27	S28	S29	S30
Main	CHVs	0.1	0.1	0.1	0.1	0.1	0.1
	AVs	0.05	0.1	0.2	0.3	0.4	0.5
	HVs	0.85	0.8	0.7	0.6	0.5	0.4
Merge	AVs	0.05	0.1	0.2	0.3	0.4	0.5
	HVs	0.95	0.9	0.8	0.7	0.6	0.5

C. SIMULATION RESULTS

This section describes the outcomes of simulating the scenarios illustrated in Table 1 at various speed limits (80, 100, and 120 km/h). Each scenario is conducted ten times with different random seeds, and the average of these runs is presented for each scenario. First, the impact of cooperation on the merge lane and the network is discussed in section IV-C1. The statistical significance of the findings is then discussed in Section IV-C2. Finally, in Section IV-C3, the observability results are presented and discussed.

1) Impact of Cooperation

This section summarizes the impact of cooperation on the merge lane and the network (the highway and the merge) at three different speed limits (80, 100, and 120 km/h) in terms of the various MOEs.

The average percentage reduction of the MOEs on the merging lane is shown in Figure 5. As illustrated in Figure 5(a), increasing the percentage of CHVs to 50% reduces the stop delay in the merge lane by 66.20%, compared to a 6.61% reduction when only 10% of the vehicles are CHVs. Similarly, when half of the vehicles are CHVs, the number of stops and vehicle delays are reduced by 44.37% and 38.28%, respectively, compared to reductions of 3.98% and 3.20% when only 10% of the vehicles are CHVs. Travel time is reduced by 4.96% when half of the vehicles cooperate. In general, the MOE reduction increases as the percentage of CHVs increases.

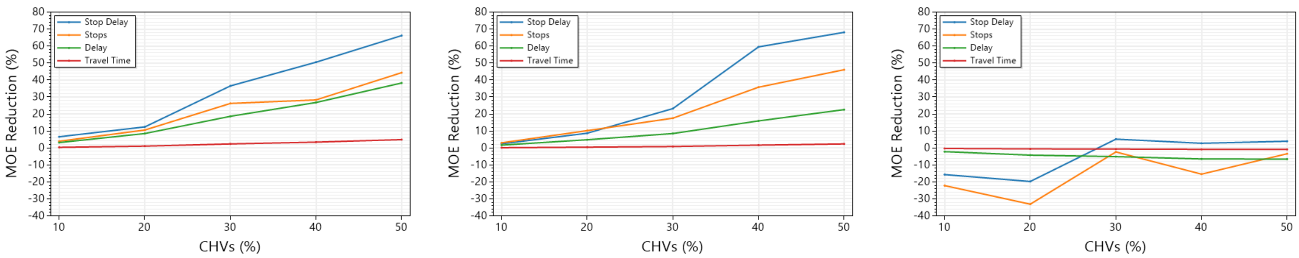
Reductions in the MOEs are also observed when the freeway desired speeds are 100 km/h, as shown in Figure 5(b). For example, with 50% CHVs, the merge stop delay is reduced by 68.14%, the number of stops is reduced by 46.09%, and the vehicle delay is reduced by 22.60%. However, aside from slight stop delay reductions, no reductions can be observed when the speed limit is increased to 120 km/h, as shown in Figure 5(c). The reason for this is that, at this high speed, the decelerations of cooperating vehicles are insufficient to create merging gaps for vehicles in the merging lane. They would rather result in lower speeds for highway vehicles and longer delays for merging vehicles.

At the network level (Figure 6), the findings show that at the speed of 80 km/h, increasing the percentage of CHVs on the highway to 50% reduces the stop delay by 66.39%, compared to a reduction of 6.04% when CHVs represent 10% of the vehicles, as shown in Figure 6(a). The reduction varies from 3.35% to 44.12% in terms of the average number of stops, and from 2.88% to 32.00% in terms of the vehicle delay when the percentage of CHVs increases from 10% to 50%. Increasing the speed to 100 km/h resulted in a reduction of up to 68.4% in terms of stop delay, 46.25% in the average number of stops, and up to 18.0% in the vehicle delay with 50% CHVs, as shown in Figure 6(b). Predictably, no benefits are observed at the network level when the speed is increased to 120 km/h, as shown in Figure 6(c). As aforementioned, the cooperation did not result in MOE reductions for the merging lane at that speed, resulting in a similar impact on the network level.

In an attempt to achieve a positive impact for cooperation at the speed of 120 km/h, a longer area of interest is introduced to allow cooperating vehicles to decelerate earlier, and higher values of T_{CHV}, $\bar{T}_{mrg}$, and T_{lg} are introduced to promote merging, as follows:

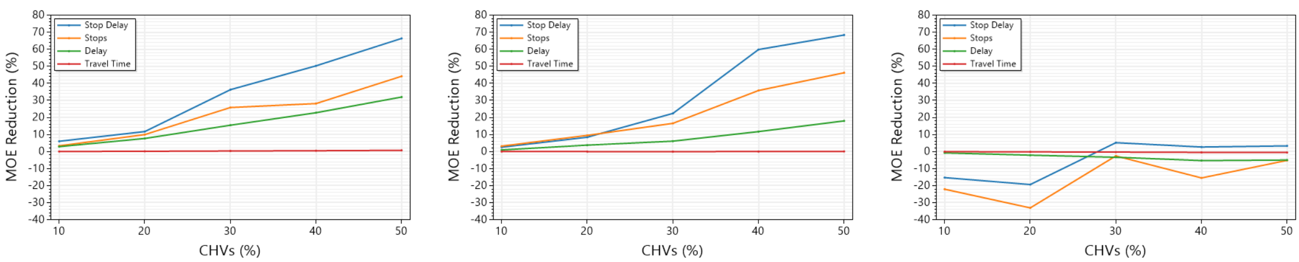
$$\text{AOI} = 200\text{ m}, \quad \bar{T}_{CHV} = 6\text{ sec}$$
$$\bar{T}_{mrg} = 4\text{ sec}, \quad T_{lg} = 6\text{ sec}$$

Figure 7 depicts the findings, while no impact can be ob-



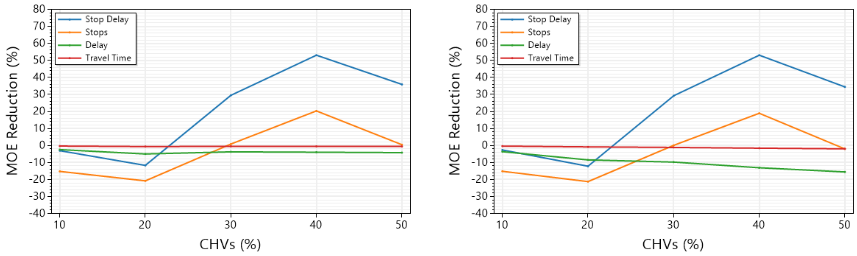
(a) 80 km/h (b) 100 km/h (c) 120 km/h

FIGURE 5: Merge lane MOEs reductions at 80,100,120 km/h.



(a) 80 km/h (b) 100 km/h (c) 120 km/h

FIGURE 6: Network MOEs reductions at 80,100,120 km/h.



(a) Merge lane (b) Network

FIGURE 7: MOEs reductions at 120 km/h after accommodating the simulation parameters.

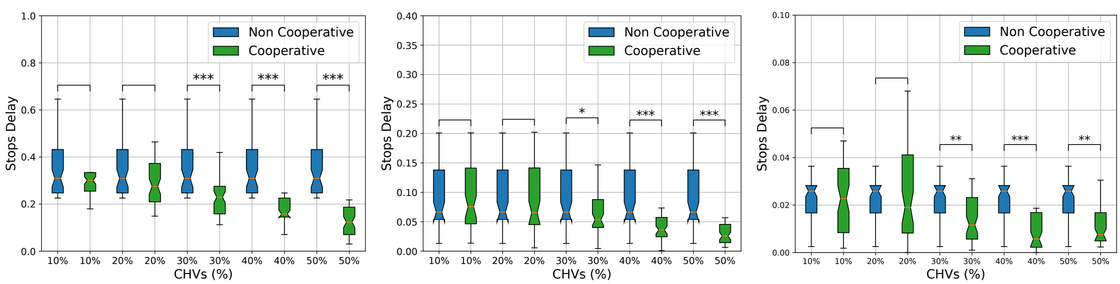
served in terms of delay and travel time, stop delay and the number of stops at the merge lane are reduced by up to 53.10%, and by 20.36%, respectively, as shown in Figure 7(a). At the network level, stop delay can be reduced by a maximum of 53.09%, and the average number of stops by up to 18.96%, as shown in Figure 7(b). The network level stop delay and the number of stop improvements are relatively close to those at the merge level, implying that the network level improvement is mostly attributable to merging improvements that did not have a detrimental impact on the main highway.

The number of stops and the stop delay were reduced as a result of modifying these parameters. Merging vehicles do not come to a complete stop because CHVs cooperate on the highway for a longer period of time and begin to decelerate earlier, reducing the stop delay. These reductions deteriorate as the percentage of CHVs increases, as more vehicles reduce their speed and the time gap between them shrinks (unsteady conditions), i.e., the merging vehicle cannot find an appropriate gap. This is not the case at lower speed limits, where there are no significant differences between free flow speed and minimum highway speed. In contrast, the delay in the merge lane changes slightly, while the network delay increases noticeably. This is because the vehicles on the highway were traveling at higher speeds prior to the accommodating parameters being applied. A larger-scale evaluation would be part of our future work to gain better insights into the benefits of human-driven vehicle cooperation at higher speeds. Overall, the findings in this section show that cooperation improves traffic performance.

2) Statistical Analysis

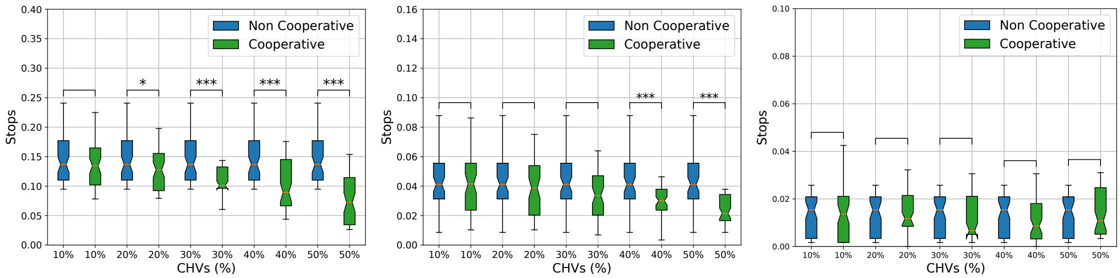
To investigate the statistical significance of the previous section's findings, the $p\text{-}value$ is used to validate a hypothesis against observed data. The stronger the statistical significance of the observed difference, the lower the $p\text{-}value$. A $p\text{-}value$ of 0.05 or less is considered statistically significant. In the results shown in Figures 8, 9, 10, and 11, the absence of stars indicates that the result is not statistically significant. On the other hand, the presence of stars indicates a statistically significant result, where * indicates that $p\text{-}value < 0.05$, ** indicates that $p\text{-}value < 0.005$, and *** denotes that $p\text{-}value < 0.0005$.

The statistical significance of the findings for each of the 30 scenarios at each of the considered speeds (80, 100, and 120 km/h) in terms of stop delay is shown in Figure 8. According to the figure, the stop delay results are statistically significant when the percentage of CHVs ranges from 30% to 50%. The statistical significance for the same scenarios at each of the considered speeds is shown in terms of the number of stops in Figure 9. The results are statistically significant when CHVs represent at least 20% of the vehicles at the speed of 80 km/h (Figure 9(a)), and at least 40% of the vehicles at the speed of 100 km/h (Figure 9(b)). On the other hand, the number of stops at the speed of 120 km/h is not statistically significant as shown in Figure 9(c). In



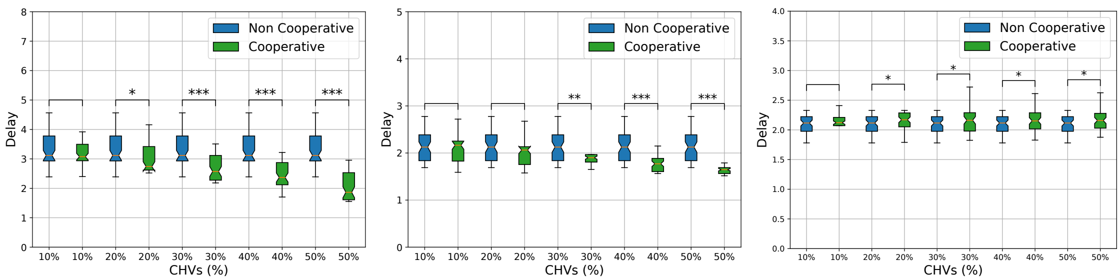
(a) 80 km/h (b) 100 km/h (c) 120 km/h

FIGURE 8: Statistical significance of merge lane *stop delay* results at 80,100,120 km/h.



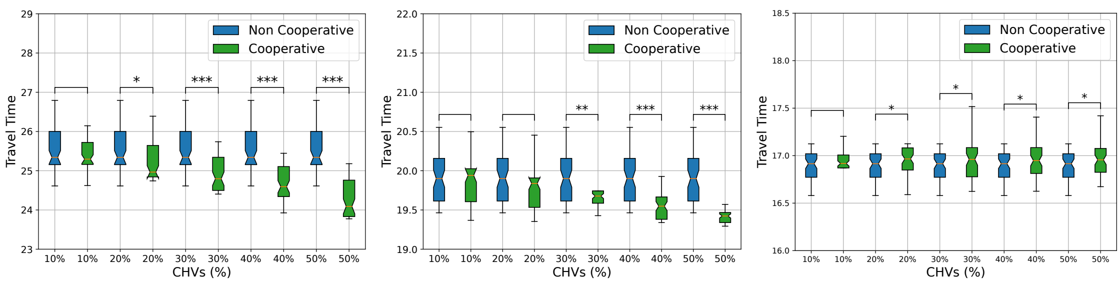
(a) 80 km/h (b) 100 km/h (c) 120 km/h

FIGURE 9: Statistical significance of merge lane *number of stops* results at 80,100,120 km/h.



(a) 80 km/h (b) 100 km/h (c) 120 km/h

FIGURE 10: Statistical significance of merge lane *delay per vehicle* results at 80,100,120 km/h.



(a) 80 km/h (b) 100 km/h (c) 120 km/h

FIGURE 11: Statistical significance of merge lane *travel time* results at 80,100,120 km/h.

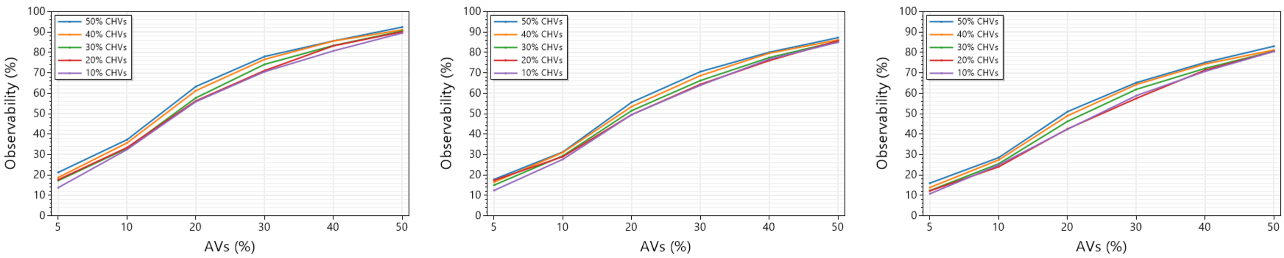
terms of delay, the results are statistically significant at every speed limit, when at least 20% or 30% of the vehicles are cooperating, as illustrated in Figure 10. Figure 11 depicts a similar significance in terms of travel time. In general, the statistical significance increases as the percentage of cooperative vehicles increases.

3) Observability

This section presents the percentage of cooperative behavior observed by AVs when it occurs within their sensing range. Figure 12 presents the observability (%) as a function of the AVs penetration rate for different cooperation levels (i.e., percentage of CHVs). Figure 12(a) demonstrates that at a speed of 80 km/h, increasing the penetration rate of AVs from 5% to 50% improves observability from 13.84% to 89.55% when 10% of the vehicles cooperate. This percentage improves to a slightly higher range (21.30% to 92.44%) when the level of cooperation increases to 50%.

Analyzing the individual lines in Figures 12(a), 12(b), and 12(c) reveals that increasing the percentage of AVs increases observability for a given percentage of CHVs significantly. Moreover, increasing the percentage of CHVs at a specific percentage of AVs increases the ability to observe cooperative occurrences as shown in the figure. This increase is marginal, and it can be concluded that the percentage of AVs has a greater impact on observability than the percentage of CHVs. This can be explained by the fact that observability is determined not by cooperative occurrences but by the percentage of AVs present to observe them.

Results at the speed of 100 km/h are shown in Figure 12(b),



(a) 80 km/h (b) 100 km/h (c) 120 km/h

FIGURE 12: AVs observability at 80,100,120 km/h.

which demonstrates that raising the percentage of AVs from 5% to 50% improves observability from 12.47% to 85.04% at 10% CHVs, and from 17.86% to 87.28% at 50% CHVs. Here, we observe lower observability percentages in comparison to the results obtained at 80 km/h. Increasing the speed to 120 km/h shows even lower observability as demonstrated in Figure 12(c) (from 10.82% to 80.52% at 10% CHVs and from 16.04% to 83.05% at 50% CHVs).

According to the cooperative model's set of conditions, cooperative behavior decreases as speed increases, with high-speed vehicles exiting the AOI quickly and having a lower chance of exhibiting cooperative behavior. Besides, as speed increases, the CHV on the main highway travels faster than the vehicles in the merge lane, arriving at the merge point faster, i.e., the relative speed difference and corresponding time increase, violating the cooperation condition associated with ($\bar{T}_{CHV}$). Moreover, as speed increases, the likelihood of observing a cooperative maneuver decreases as vehicles exit the sensing range of AVs faster. Nevertheless, at a given speed, more cooperating vehicles can marginally improve observability, which significantly, and intuitively improves when the percentage of AVs increases.

V. CONCLUSION

A cooperative driving model is proposed in this paper to replicate vehicular cooperation in a highway merge while maintaining traffic safety. The results demonstrate that cooperation improves traffic performance by reducing travel time, delay, stop delay, and the number of stops on the merge lane as well as the entire network. For example, in the merge lane, the stop delay was reduced by up to 68%, and the number of stops was reduced by up to 46%. The statistical analysis reveals that these findings are statistically significant.

To observe cooperation, we leverage the sensing technology of AVs. The ultimate goal is to tally cooperation, so AVs can later behave accordingly towards human-driven vehicles. The evaluation results on a simulated highway segment with an on-ramp show that 20% of autonomous vehicles can report up to 64% of cooperating vehicles and up to 92% of them when AVs represent half of the vehicles on the road. We emphasized that at higher speeds, AVs can observe less since vehicles leave the sensing range of AVs faster. In addition, cooperation at higher speeds may not be necessary to improve traffic performance.

In future work, we plan to extend the proposed models for application and evaluation in a city-scale scenario at various speeds and densities. Such evaluation would inspire the design of rewarding schemes, where cooperating vehicles are rewarded to further induce cooperation and enhance traffic performance.

ACKNOWLEDGMENT

M. Menendez acknowledges the support of the NYUAD Center for Interacting Urban Networks (CITIES), funded by Tamkeen under the NYUAD Research Institute Award CG001.

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