A Co-Simulation Study to Assess the Impacts of Connected and Autonomous Vehicles on Traffic Flow Stability during Hurricane Evacuation

SAFETY RESEARCH USING SIMULATION

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16. Abstract
Hurricane evacuation has become a major problem to the coastal residents of the United States. Better traffic management strategies are needed to reduce crash risk and improve traffic stability. In this project, hurricane evacuation traffic was simulated using SUMO—a microscopic traffic simulation model. The effects of Connected and Autonomous Vehicles (CAVs) and Autonomous Vehicles (AVs) were evaluated using two approaches: (i) using the state-of-the-art car-following models and (ii) using separate vehicular ad-hoc network (VANET) simulation to find the effect of connectivity on evacuation traffic. Simulation experiments were performed by creating mixed traffic scenarios with 25, 50, 75, and 100 percentages of different vehicle technologies including CAVs or AVs and human-driven vehicles (HDV). A road network of I-75 in Florida was updated to represent real-world evacuation traffic observed in Hurricane Irma's evacuation periods. Simulation results suggest that the CACC car-following model, implemented in SUMO and commonly used in the literature to represent CAVs, produces highly unstable results. On the other hand, the ACC car following model, used to represent AVs, produces more stable results. With only 25% of market penetration rates of AVs, the number of potential collisions can be reduced by 65.9%. To assess the additional benefits of connectivity of CAVs, the effects of vehicle-to-vehicle communication was simulated by integrating a state-of-the-art communication simulator and SUMO. Results show that with introducing only 10% CAV in the traffic stream, the number of potential conflicts can be decreased by 75%. It is found that connectivity improves road safety as the information dissemination help vehicles decide to take proper maneuvers and stabilize the highly congested evacuation traffic.

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Abstract

Hurricane evacuation has become a major problem for the coastal residents of the United States. Devastating hurricanes have threatened the lives and infrastructure of coastal communities and caused billions of dollars in damage. There is a need for better traffic management strategies to improve the safety and mobility of evacuation traffic. In this project, hurricane evacuation traffic was simulated using SUMO—a microscopic traffic simulation model. The effects of Connected and Autonomous Vehicles (CAVs) and Autonomous Vehicles (AVs) were evaluated using two approaches: (i) using the state-of-the-art car-following models available in SUMO and (ii) using a separate vehicular ad-hoc network (VANET) simulation and integrating with SUMO to find the effect of connectivity on evacuation traffic. Simulation experiments were performed by creating mixed traffic scenarios with 25, 50, 75, and 100 percentages of different vehicle technologies including CAVs or AVs and human-driven vehicles (HDV). A road network of I-75 in Florida was updated to represent real-world evacuation traffic observed in Hurricane Irma's evacuation periods. Simulation results suggest that the CACC car-following model, implemented in SUMO and commonly used in the literature to represent CAVs, produces highly unstable results. On the other hand, the ACC car following model, used to represent AVs, produces more stable results. With only 25% of market penetration rates of AVs, the number of potential collisions can be reduced by 65.9%. To assess the additional benefits of connectivity of CAVs, the effects of vehicle-to-vehicle communication was simulated by integrating a state-of-the-art communication simulator and SUMO. Results show that with introducing only 10% CAV in the traffic stream, the number of potential conflicts can be decreased by 75%. It is found that connectivity improves road safety as the information dissemination help vehicles decide to take proper maneuvers and stabilize the highly congested evacuation traffic.

1 Introduction

Hurricanes have become more common in the coastal regions of the United States. Since 2017 we have seen several major hurricanes including Hurricane Harvey (2017), Hurricane Irma (2017), Hurricane Michael (2018), and Hurricane Ida (2021). Forecasting the path of a hurricane is challenging and may leave minimal time for residents to evacuate. After an evacuation order is issued, a large of volume of traffic tends to move from the evacuation zones towards safer zones. For example, during Hurricane Irma approximately 6.5 million people from the coastal regions of Florida were asked to evacuate. Since there were only two highways, a massive traffic congestion and a high number of crashes were observed in those highways during the evacuation period. A high influx of traffic results in unstable traffic flow and congestion~~s~~. Previous studies found that traffic flow significantly varies during evacuation with highly fluctuating speeds which may lead to rear end collisions [1] [2].

Although various traffic management measures such as contraflow and use of emergency shoulder helped accommodate high volumes of evacuation traffic, potential safety issues of evacuation traffic should be studied. For instance, Rahman et. al [3] found that for a high volume of traffic at an upstream location and a high variation of speed at a downstream location, the likelihood of a crash increases during evacuation. Stabilizing the traffic flow by reducing stop and go movements can help improve evacuation traffic safety. In our previous study [4], we found that by equipping 25% vehicles with Adaptive Cruise Control (ACC) technology, the number of potential conflicts can be reduced by 49.7%. Emerging vehicular technologies such as Connected and Autonomous Vehicles (CAVs) have shown further promises in stabilizing traffic. Field experiments have shown that a controller deployed in a single autonomous vehicle out of twenty vehicles in a circular track can stabilize traffic and reduce congestion [5].

In this project, we have assessed the effects of Connected and Autonomous Vehicles (CAV) using a microscopic traffic simulation model in a hurricane evacuation context.

Simulations can be used to evaluate more dynamic and complex traffic situations that may arise in extreme traffic events [6]. As smart vehicular technologies are increasingly adopted, it is imperative that these technologies are evaluated for real-world traffic scenarios that are more complex and have higher likelihood of crashes. Most previous literatures used simpler traffic networks (such as ring network or one single intersection) that are less likely to occur in the real world and/or assumed typical traffic conditions. However, real-world traffic dynamics ~~is~~ are highly variable, and evaluating these technologies over real-world scenarios ensures potential benefits providing important insights in managing more complex and extreme events.

1.1 Research Objective and Contributions

In this project, we evaluated the performance of Connected and Autonomous Vehicles (both AV and CAV) and human-driven vehicle (HDV) in a simulation environment that was calibrated to represent ~~an~~ evacuating traffic for Hurricane Irma in Florida. The safety impact of each technology was measured using different surrogate safety measures. We also collected the average flow rate and average travel times. Simulation experiments were designed to gain insights on how evacuation traffic safety and stability would change for different proportions of AV/CAV technology ~~to~~ co-existing in a network.

The report is organized as follows: first, we review previous works on which our simulation experiments are based upon and existing literature on connected and autonomous vehicles (CAVs) and surrogate safety measures to evaluate its performance. Then we discuss the methodology and the experimental setups used to evaluate the performance of CAVs and AVs. We evaluated the CAVs and AVs using two approaches: (i) using existing car-following models, representing CAVs and AVs, in a microscopic traffic simulation model; and (ii) using a separate vehicular ad-hoc network (VANET) simulation and integrating with a microscopic traffic simulation model to find the effect of connectivity on evacuation traffic. Finally, we present our results for different proportions of vehicle technology for each case and discuss our findings.

2 Literature Review

2.1 Review of the Car Following Models

In a simulation environment, different car following models are used to represent driving behavior. Some notable car following models are Gipps' model [7], the Krauss model [8], Intelligent Driver Model (IDM) [9], and Wiedemann car-following model [10]. These car following models have their own strengths and weaknesses, but we selected our car following model to represent each technology based on the objective, their expected behavior in the real world, and prior literatures.

We chose the Krauss model to represent human-driven vehicles (HDVs) since it represents naturalistic driving behavior of humans and has been found to be consistent with the real-world traffic patterns found from detector data [4]. The Krauss model follows the speed change of the leader vehicle and have less errors in speed predictions for unsteady traffic condition than other car following models like IDM [11]. We used the ACC car-following model to represent autonomous vehicles (AV) and the CACC car following model to represent Connected Autonomous Vehicles (CAV). These two car-following models were developed to represent vehicles equipped with adaptive cruise controller (ACC) and cooperative adaptive cruise controller (CACC). Due to the similarity in the underlying technology and therefore similar driving behavior of ACC to the AVs and CACC to the CAVs, past studies used these car-following models in simulations.

2.2 Adaptive Cruise Control (ACC)

The adaptive cruise controller (ACC) has been increasingly available in new cars and proved to increase traffic throughput and safety. ACCs are state-of-the-art driving assistance systems which maintain a constant headway between subject and leader vehicle by adjusting the subject vehicle's speed and acceleration. However, ACC depends only on onboard sensors. Many previous studies used the ACC car following model to represent autonomous vehicles (AVs).

2.3 Co-operative Adaptive Cruise Control (CACC)

The Cooperative Adaptive Cruise Controller (CACC) is an emerging technology that incorporates vehicle to vehicle communications (V2V) or vehicle to infrastructure (V2X) communications in addition to ACC sensors to make a subject vehicle's ~~speed~~ speed-change decisions. These technologies are the fundamental technologies behind CAVs. CACC uses the same maneuvers as ACC but additionally enjoys the benefits of data available through vehicular communication.

2.4 Modeling ACC and CACC in Traffic Simulations

Milanes et al. 2014 [12] modelled the ACC and CACC car following models based on the data collected from the response of real ACC and CACC equipped vehicles in field tests. The car following models are based on mathematical derivations to reflect the car following characteristics of the ACC and CACC equipped vehicles. The model was further improved by Xiao et al., 2017 [13] and Liu & H., 2018 [14]. Both the ACC and CACC car following models have three modes of operation: (i) the speed control mode, (ii) the gap control mode, and (iii) the gap closing control mode.

Speed control mode: it is activated when there is no leader vehicle at least 120 m in front of the subject vehicle. The mode keeps the vehicle at the desired speed by adjusting the vehicle acceleration. The characteristic equation for this mode is given by Equation 1

$$\alpha_{i,k+1} = k_1(v_d - v_{i,k}),\ \ k_1 > 0 \quad \textbf{(1)}$$

where $\alpha_{i,k+1}$ is the acceleration of the ith car (subject vehicle) and $k+1$ is the next time step. The v_d is the desired speed and $v_{i,k}$ is the speed of the ith vehicle at time step k. The k_1 is the control gain parameter of the subject vehicle which controls the rate of the change of speed deviation. Since connectivity has no effect on the free flow speed of the vehicle, both ACC and CACC models can be represented using the same equation (equation 1).

Gap control mode: it is used to control the subject vehicle when following a leader vehicle. The leader vehicle is defined as the vehicle immediately in front of the subject vehicle within ~~its~~ 120m. This mode of operation is modeled using a second order transfer function as shown in Equation 2 and a first order transfer function as shown in Equation 4 for ACC and CACC car following models, respectively

ACC control mode:

$$\alpha_{i,k+1} = k_2 e_{i,k} + k_3(v_{i-1,k} - v_{i,k}),\ \ k_2, k_3 > 0 \quad \textbf{(2)}$$

$$e_{i,k} = x_{i-1,k} - x_{i,k} - t_d v_{i,k} \quad \textbf{(3)}$$

CACC control mode:

$$v_{i,k+1} = v_{i,k} + k_5 e_{i,k} + k_6 \dot{e}_{i,k},\ \ k_5, k_6 > 0 \quad \textbf{(4)}$$

$$\dot{e}_{i,k} = v_{i-1,k} - v_{i,k} - t_d \alpha_{i,k} \quad \textbf{(5)}$$

All the control gain noted as k_1, k_2, k_3, k_5, and k_6 are empirically calculated using data collected from real-world ACC and CACC equipped vehicles. The index i represents the subject vehicle and $(i-1)$ represents the leader vehicle. The index k refers to the time step. α , v and $e_{i,k}$ are the acceleration, the velocity, and the gap derivative of i^{th} consecutive vehicle at the current time step k, respectively.

Gap closing control mode: it is a transitory mode such that when the subject vehicle detects a leader vehicle, the subject vehicle smoothly transitions to gap control mode. To make this transition smooth, the third mode of operation was introduced which is characterized using the same model as gap control but with different gain values.

If an ACC equipped vehicle is allowed to drive itself according to the model with a set number of driving parameters such as desired speed and headway, we can assume that the vehicle is autonomously driving with the help of onboard sensors and call it an AV. Similarly, a CACC equipped vehicle can be considered as a CAV.

2.5 A Review of the Past Micro-simulation Studies

Previously, many studies run simulation models to assess the effects of connected autonomous vehicle (CAVs) and autonomous vehicles (AVs) for different traffic network and conditions. The results of a simulation experiment highly depend on the assumptions made during experiment setups. The results obtained from one experiment for a given model may not be valid for a more complicated traffic network that we simulated in this project. Thus, we reviewed different literatures that use similar vehicle technology and traffic context.

Rahman et al. [4] used real-world evacuation data available from the periods of Hurricane Irma's evacuation to calibrate a SUMO simulation model and a traffic network to assess the safety impacts of Adaptive Cruise Control (ACC) technology for evacuation. The study developed a 9.5-mile-long traffic network of the interstate I-75 and calibrated the network using real-world traffic data collected from detectors. The traffic data were collected during the evacuation period of Hurricane Irma from September 6th to September

10th, 2017. A two-hour window on September 8, 2017, between 1:30 pm and 3:30 pm was simulated as it was the time when most crash occurred. The study then ran a comparative analysis of ACC car following model with Krauss car following model which represents normal human driven vehicle~~s~~ characteristics. This study found that with a 25% market penetration rate the 49.7% of the potential traffic conflicts can be reduced. The ACC car following model also proves to increase flow and decrease travel time.

Arvin et. al. [15] assessed CAVs for different mixture of traffic at an intersection. They evaluated the ACC and CACC car-following models at an intersection using two surrogate safety measures: time to collision (TTC) and speed volatility. The TTC measures the time taken for a subject vehicle to crash into the leader vehicle provided both their speed and direction are maintained. They have considered a TTC value less than 0.5s as a potential conflict. The speed volatility is the number of vehicles that exceeded a threshold speed within a given period. Their study shows that with 25% of ACC equipped vehicles the safety marginally increases, but a better impact is seen when the proportion of ACC equipped vehicles increases to at least 40%. With CACC they were able to show some additional improvements. However, in this study the vehicle parameters such as the desired speed and headway of ACC/CACC vehicles used were not well defined and the network is limited to one intersection.

Guériau & Dusparic [16] quantified the impact of CAV on traffic safety and efficiency for various mixed proportion of autonomy using 3 different road networks: urban, national, and motorway. Their study shows that although CAV improves the efficiency of traffic, it is highly dependent on the traffic network and level of congestion. The study used CACC car following model to represent level 2 autonomy and IDM to represent a fully autonomous vehicle. IDM is not a good representation of autonomous vehicles as it is primarily modeled to represent the collision-free human driving behavior and incorporates a naturalistic behavior that may not be applicable to CAVs. The main assumption behind using IDM is that autonomous vehicles drive perfectly with set parameters and 100% of sensors actively working. To identify potential conflicts, the study used different threshold levels of TTC. For instance, for CAVs a potential conflict is defined as ~~when~~ TTC is less than 0.75s and for an HDV ~~normal~~ vehicle the threshold is 1.5s. This is because CAVs have faster reaction times than normal drivers and require less time to avoid a potential conflict. They found that, for a market penetration of 30 % of CAV, there was an increase in potential traffic conflict, followed by a gradual decrease in potential traffic conflict as the proportion of CAV increases.

Two other studies [17] [18] have used simulation to assess CAVs and found that CAVs have a positive impact on traffic flow and help reduce potential traffic conflicts. However, their network design portrays normal traffic and does not include highly congested traffic in freeways as typically seen during hurricane evacuation.

Table 1: Summary of studies using different car-following models

Study Reference	Simulation Software Used	Car-following model CACC	Car-following model ACC	Car-following model for HDV	Thresholds chosen for surrogate safety measures (SSMs)
Trans-Aid deliverables [17]	SUMO	CACC	ACC	Krauss	TTC < 3s
2021_Ramin Arvin [15]	SUMO	CACC	ACC	Wiedemann	TTC < 0.5s, Speed Volatility
2020_Maxime Gu´eriau [16]	SUMO	IDM	ACC	Krauss	For CAV, TTC < 0.75s, For HDV, TTC < 1.5s PET 0.75s
2018_M.M. Morando [18]	SUMO	CACC	ACC	Wiedemann 99 car-following	For AV, TTC < 0.75s, For HDV, TTC < 1.5s PET <5s

3 Experimental Setup for Microscopic Simulation of Evacuation Traffic

In this project, we simulated a portion of a freeway network used for hurricane evacuation after calibrating a simulation model so that it represents the traffic condition observed during evacuation. We used a microscopic traffic simulator called Simulation of Urban Mobility (SUMO) version 1.10.0. For simulation, we adopted the traffic network used in Rahman et al., 2021 [4]. However, we made a few modifications in that network to make it more realistic.

3.1 Network Design

The simulated traffic network consists of a 9.5-miles long road segment in I-75 between Ocala and Gainesville, Florida with two entry and two exit ramps as shown in Figure 1 and Figure 2. The traffic data used in this study were obtained from the Regional Integrated Transportation Information System (RITIS) platform [19] for the selected road segments. The main modifications were made in the ramp merging sections. Intuitively, vehicles tend to change lanes as soon as they merge into the freeway rather than waiting for the end. So, a suggested approach is to elongate the speeding section in simulations such that vehicles have more time to change the lanes and prevent any unlikely queue formation at the ~~merging~~ merge point. Earlier, in our simulation, we observed that when vehicles were merging from a ramp to the freeway or from the freeway to an exit ramp, some vehicles on the freeway had to wait for others to change the lane which in turn started to form queues. Furthermore, we defined the junction between the end of ramp lane and free way as “zipper node”. A zipper node is a junction type where vehicles in the freeway get priority over vehicles ~~at~~ in merging lanes and similar to real life the incoming vehicles wait till the freeway lane is clear. This modification made the simulation consistent with real-world freeway traffic and we noticed a better traffic flow than previous configurations. For the exit ramps, we also increased the length of the exit lane so that vehicles have more time to change lanes and avoid last minute lane changes. In

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simulation, each segment of the road is called an edge and a junction or node connects two edges. To replicate free flow of traffic in freeways we made sure that the full network is continuous, and each junction is defined so that vehicles do not slow down or stop ~~from~~ going from one edge to another.

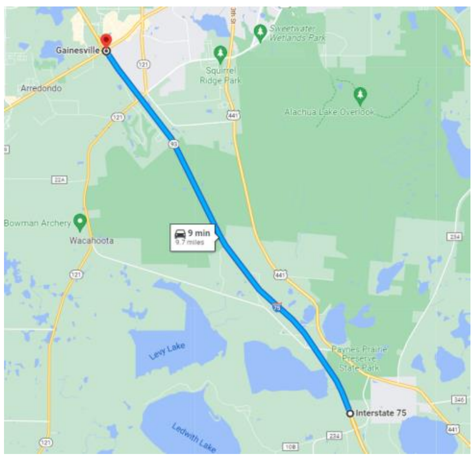

Figure 1: Road segments in I-75 used for simulation

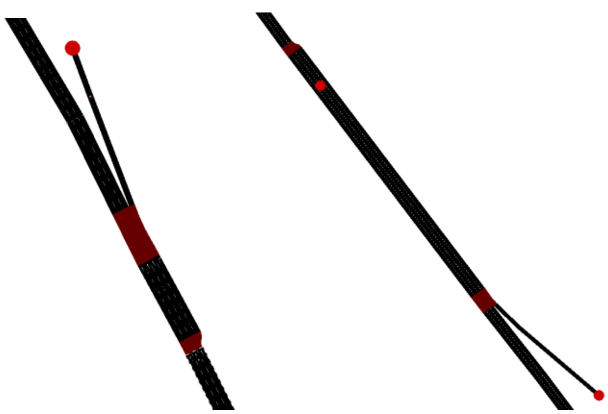

Figure 2: Exit ramp (left) and entry ramp (right)

3.2 Measures of Traffic and Potential Conflicts

In this project, we assessed the traffic safety aspect during hurricane evacuation, along with average traffic flow and travel time for the selected road segments. Average traffic flow and travel time calculations are straightforward; however, conflicts are harder to measure. To identify whether a vehicle is in a conflict ~~when~~ and an intervention is required, a surrogate safety measure (SSM) is used. SSMs have become more popular in road safety-related research [20]. SSMs define traffic events that are deemed as possibly hazardous to participating road users. These unsafe traffic events, also called potential traffic conflicts, include road users coming in close spatial or temporal proximity to each other, where if no evasive action is applied, collision is bound to happen. Therefore, it can be argued that observing and analyzing these potential traffic conflicts, can be an indicator for possible collisions between road-users.

For this purpose, Time-to-collision (TTC) was chosen as an SSM in this research. Time-to-collision (TTC) is the primary conflict severity indicator, where a lower TTC value indicates a higher severity of a crash [20]. TTC is defined as the expected time for two vehicles to collide, provided they both continue with their present speed and trajectory. [21] . TTC values are calculated by extrapolating vehicles trajectories, assuming constant velocity and unchanged course of collision [22].

When calculating TTC a threshold has to be selected. Any event where the TTC value is less than the threshold value the event is considered as a potential conflict. Previously, TTC was used with 1.5s threshold value for human-driven vehicles. In this experiment, we used a 0.5s threshold value for AV/CAVs and 1.5s for normal human-driven vehicles according to previous literature~~s~~ [4],[15], [16]. Since AV/CAVs have better reaction times, they should have a lower TTC threshold value [18].

3.3 Parameters of the Car Following Models

To simulate human-driven vehicles (HDVs), we used the same model calibrated in Rahman et al. (2021) [4] with same flow rate to replicate hurricane evacuation traffic. The traffic parameters are shown in Table 2.

Table 2: Traffic parameters for HDVs

Vehicle Type	Car Following Model	Max Speed (mph)	Speed Factor norm (mean, deviation, min, max)	Min Gap (m)	Max Accel. (m/s^2)	Max Decel. (m/s^2)	Desired Headway (s)
HDV	Krauss	70	normc(0.96,0.3,0.2,1)	2	4.5	6.5	1.2

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The maximum speed is set at 70 mph which is the speed limit ~~found~~ in the interstate segment simulated. The speed factor sets individual vehicle speeds using a normal distribution. In this case 96% of vehicle will travel at mean speed with a standard deviation of 0.3. The min (0.2) and max (1) are the cut off values, indicating that the speed distribution will be always between 2% and 100% of the speed limit.

The total simulation run time is 7200 seconds (2 hours) where the first 1800 seconds (30 minutes) and the last 1800 seconds data are considered as warm up and cool down periods, respectively and all results are collected from the middle 3600 seconds (1 hour). This time in real life corresponds the traffic of September 8, 2017, between 2 pm and 3 pm. Previously 8 MVDS (Microwave Vehicle Detection System) detector data along the road segment were used to calibrate the network. The raw data, reported in every 20-30 seconds, were aggregated into 5-minute~~s~~ intervals. The simulation network also contains loop detectors located near the same positions where the MVDS detectors were in the highway. We calculate the mean flow from these 8 loop detectors. Rahman et al. (2021) [4] used the Geoggrey E. Heaver statistics and chi-square statistics to compare the field volume with the simulated volume as part of the calibration process to find the evacuation traffic demand which were also used in this study.

When running the simulation experiments, we used a step length of 0.1s and changed the default lane changing model parameters. With a step length of 0.1s the simulation makes 10 times more calculations compared to a simulation performed with the default 1s step length. Our previous study [4] used a step length of 1s; however, using a 0.1s step length yielded a higher number of potential conflicts in the unmodified network. We also observed that near the freeway ramps, due to heavy traffic, the number of potential conflicts increased, and queues were formed. A plausible explanation of these queues would be the lane changing behavior of the vehicles near ramps; this may also increase the number of potential conflicts. Thus, we explored different lane changing parameters in the simulation. In our experiments, we used the lane changing model LC2013 implemented in SUMO after modifying two default lane changing parameters, listed in Table 3.

Table 3: Lane changing parameters used in the simulation

Lane Changing Parameters	Description	HDV	AV/CAV
Strategic	The eagerness for performing strategic lane changing. Higher values result in earlier lane changing.	10	100
Cooperative	The willingness for performing cooperative lane changing. Lower values result in reduced cooperation	0.8	1

Commented [A3]: Do these values have units or a scale?

Human-driven vehicles (HDVs) may not always strategically change lanes ~~beforehand~~ when approaching a merge point which may result in more last-minute changes, especially when taking an exit. On the other hand, autonomous vehicles (AV/CAVs) with a set route are more likely to be strategic when changing lanes. Thus, we changed the “Strategic” parameter for AV and CAV to 100, as suggested in previous literature [16]. This means AV and CAV will be able to anticipate lane changes 10 times earlier than HDV. In addition, an HDV is less likely to fully cooperate when changing lanes, thus we reduced the value of the lane changing parameter known as “Cooperative” from the default value of 1 to 0.8.

3.4 Simulating the effects of CAVs and AVs

To simulate the effects of CAVs, previous studies adopted the CACC car following model in SUMO. Through different experiments they found that CAVs can achieve higher traffic flow with better stability leading to improved traffic safety. However, we wanted to assess the feasibility and potential safety impacts of CAVs in our setting (evacuation traffic). We used different percentage of CAVs along with HDVs. Initially, we used the same traffic parameters as defined for the ACC parameters in Rahman et. al. [4] so that our results are comparable to previous literature~~s and~~ in our base case. We have changed only the desired headway of CAVs to 1.3s since AV/CAVs are likely to maintain a longer safe distance than human-driven vehicles.

To simulate the effects of AVs, we selected the ACC car following model available in SUMO and used the parameters reported in our previous study [4] which evaluated the effects of ACC equipped vehicles on evacuation safety. We ran the ACC car following model using the same traffic parameters (e.g., max speed, min gap, desired headway) used in CACC simulation. The traffic parameters for AVs and CAVs are given in Table 4.

Table 4: Traffic parameters for AVs and CAVs

Vehicle Types	Car Following Model	Max Speed (mph)	Speed Factor norm (mean, deviation, min, max)	Min Gap (m)	Max Accel. (m/s^2)	Max Decel. (m/s^2)	Desired Headway (s)
CAV	CACC	70	normc(0.96,0.3,0.2,1)	2	4.5	6.5	1.3
AV	ACC	70	normc(0.96,0.3,0.2,1)	2	4.5	6.5	1.3

The car-following models are empirically calibrated using real-world data by changing the values of the gain parameters ($\boldsymbol{k}$). As discussed in Section 2.4, there are three gain parameters: k_1, k_5, k_6; the main difference from one operational mode of CAV to another depends on the value of these gain parameters. However, it is more challenging to set the gain parameters of CACC vehicles as we found a few discrepancies among the values previously used. Since we have no CACC data to calibrate the model, we rely on previous literature~~s~~ and ran a sensitivity analysis on three sets of values of the gain parameters, summarized in **Table 5**. The literature parameters consist of the values used by previous studies [12] [23] and the SUMO ~~default parameters were the~~ parameters set as default in the SUMO software. ACC vehicles rely only on on-board sensors to maintain a constant headway and do~~es~~ not have any vehicle-to-vehicle communication. Since ACC and CACC are inherently similar except for ~~the~~ connectivity ~~part~~, we set the corresponding ACC gain parameters to find the effects of those parameters on simulation results.

Table 5: CACC gain parameters used in the simulation

Gain Parameters	Parameters equivalent to ACC model	Literature parameters	SUMO defaults
speedControlGain, k_1	-0.4	-0.4	-0.4
gapClosingControlGainSpeed, k_6	0.8	1.6	0.05
gapClosingControlGainSpace, k_5	0.04	0.01	0.005
gapControlGainSpeed, k_6	0.07	0.25	0.45
gapControlGainSpace, k_5	0.23	0.45	0.0125
collisionAvoidanceGainSpace k_6	0.8	0.8	0.45
collisionAvoidanceGainSpeed, k_5	0.23	0.23	0.05

4 Simulation Results

4.1 Base Case Results

We first ran the simulation for our base case scenario that is 100% HDVs with Krauss car following model. We used only the parameters reported in the previous literature [4]. To reduce the effect of randomness, we ran the simulations 10 times. We recorded the mean potential conflicts as the number of events that have a TTC value less than 1.5s, the standard deviation of the TTC count, the average travel time, and the average traffic flow. Since this scenario consists of only HDVs the total TTC count is equal to the TTC count for HDV vehicles only.

After simulating the base case with parameters equivalent to the previous study [4], we modified the lane changing parameters (given in Table 3). All the simulation results from the base case are given in Table 6. Increasing the “strategic” parameter from the default value of 1 to 10 decreased the number of potential conflicts from 250 to 158. Also, we see a decrease in average travel time and a decrease in average traffic flow. Since both the potential number of conflicts and the average travel time decrease, it indicates a more stable traffic and the potential impacts of lane changing parameter on simulation results. Next, we modified the “cooperative” lane change parameter to 0.8 to see its effects simulation results. The number of potential conflicts increased from 250 to 789. This sharp increase may have resulted from the decreased cooperation among vehicles when changing lanes, making traffic more unstable, but increasing traffic flow rate. We chose 0.8 as the cooperative lane change parameter as there is no data to support the percentage of cooperation. This also indicates the likely impacts of lane change parameters on simulation results.

Table 6: Simulation results of the base case

Experiment Name	Strategic parameter	Co-operative parameter	Scenario	HDV TTC count	std for TTC-HDV	Average travel time (minutes)	Average traffic flow (vehicle per hour)
Literature parameters	1	1	Krauss-100	249.9	96.34	10.01	4597.55
Strategic parameter change	10	1	Krauss-100	158.2	25.39	9.999	4480.69
Cooperative parameter change	1	0.8	Krauss-100	789	144.86	10.22	6856.97

4.2 Simulation Results of the Effects of CAVs

For each set of CACC model gain parameters, as given in Table 5, we ran the simulation 10 times and compiled the results in Table 7 and Table 8. In the table the scenario column represents the percentage of type of vehicle present in each scenario, i.e., CACC-25 means that 25% of the vehicles are CACC equipped vehicles (equivalent to CAVs).

The standard deviation (std) of each measure is recorded in a separate column to understand the deviation of measured value across 10 simulation runs. If we investigate the standard deviation values, we see very high values indicating high fluctuations in the results. This also indicates the failure of the CACC car following model to produce stable results to simulate the effects of CAVs. As such, the simulation results from the CACC scenarios should be cautiously taken.

For a given set of gain parameters, we see a general decrease in potential conflicts with increasing percentage of CAVs. A 100% CAV scenario (CACC-100) gives the least number of potential conflicts. The best results were found using the literature parameters with the lowest number of potential conflicts and lowest standard deviations in CACC-75 and CACC-100 in comparison to other corresponding parameter sets. The average flow rate gradually decreases with percentage increase in CAVs for literature parameters set (see Table 8). Although the traffic measures for the literature parameter report a higher travel time and lower traffic flow in most scenarios, it appears that traffic is more stable for the literature parameter set. Simulation runs with SUMO defaults have lower TTC count and standard deviation than the simulation runs with literature parameter, but it performs poorly in CACC-75 and 100. Thus, we used literature parameter gain as CACC parameters.

Table 7: Number of potential conflicts for all three sets of CACC model gain parameters

Parameter sets	Scenario	HDV TTC count	std of TTC-HDV	CACC TTC count	std of TTC-CACC	Total TTC count	std of total TTC count
Literature parameters	CACC-25	554.2	446.83	18.4	16.69	572.6	463.06
	CACC-50	463.5	207.19	27	13.57	490.5	217.86
	CACC-75	227.8	48.99	22.3	11.80	250.1	49.95
	CACC-100	0	0	0	0	0	0
Parameters equivalent to ACC model	CACC-25	595.8	394.87	21.5	14.68	617.3	408.48
	CACC-50	531.2	339.43	38.8	21.05	570	356.03
	CACC-75	269.4	139.61	55.4	34.49	324.8	173.49
	CACC-100	0	0	1.89	1.30	1.8	1.303
SUMO defaults	CACC-25	486.8	219.41	13.6	4.51	500.4	222.05
	CACC-50	311.4	140.77	28.4	6.3	339.8	145.63
	CACC-75	289	114.30	85.6	44.09	374.6	155.65
	CACC-100	0	0	4.6	1.82	4.6	1.82

std: standard deviation

Table 8: Traffic measures for all three set of CACC model gain parameters

Parameter Sets	Scenario	Average travel time (minutes)	Average traffic flow (vehicle per hour)
Literature parameters	CACC-25	11.20	4532.10
	CACC-50	11.97	4470.14
	CACC-75	15.32	4340.86
	CACC-100	13.88	4331.29
Parameters equivalent to ACC model	CACC-25	10.96	4562.46
	CACC-50	12.23	4443.87
	CACC-75	14.72	4335.64
	CACC-100	10.60	4350.49
SUMO defaults	CACC-25	10.94	4484.77
	CACC-50	11.18	4437.18
	CACC-75	15.36	4271.34
	CACC-100	9.755	4405.01

We also investigated the effect of speed deviation of CACC. The speed deviation parameter in the simulation works along with the speed factor which defines the distribution of speed for each vehicle type. We changed the speed deviation parameter from 0.1 to 0.05 since CAVs are likely to have less speed deviation than normal vehicles. We found there is significant decrease of about 15% in total TTC count from literature parameter gain set (Table 8) at CACC-25 scenario, but other scenarios have little to no impact. The results are summarized in Table 9.

Table 9: Number of potential conflicts for CACC with speed deviation set at 0.05

Scenario	HDV TTC count	std of TTC-HDV	CACC TTC count	std of TTC-CACC	Total TTC count	std of total TTC count
CACC-25	468.4	232.2505	17.2	12.61745	485.6	243.498
CACC-50	457.2	181.936	37	20.18663	494.2	196.5062
CACC-75	255	101.3336	39	17.81853	294	112.5766
CACC-100	0	0	3	1.224745	3	1.224745

*std: standard deviation

4.3 Simulation Results of the Effects of AVs

To simulate the effects of AVs, we ran 10 simulations for different market penetration of ACC equipped vehicles (equivalent to AVs). The results of 10 simulation runs are given in Table 10 and **Error! Reference source not found.**~~Table 11~~. Unlike the CACC scenarios, we do not observe high standard deviation values in different scenarios, indicating the stability of the simulation results.

Most of the potential conflicts in each scenario are occurring among HDVs. At ACC-25 we see that there is a 29% decrease in the total number of potential conflicts compared to the base case of 100% HDV with lane changing behavior unchanged. This confirms that our results are consistent with the previous study by Rahman et. al. (2021) [4]. With an increase in the percentage of ACC we see a significant decrease in the number of potential conflicts although travel times remain same. However, from **Error! Reference source not found.**~~Table 11~~ we see an uneven increase in flow rate. At ACC-50 scenario, we see there is a slight increase in average traffic flow from the ACC-25 scenario. At ACC-

75, the flow rate is slightly higher than flow rate in ACC-50 and is almost equal to the flow rate at ACC-25. At ACC-100 we see the highest flow rate among all the scenarios.

Table 10: Number of potential conflicts for ACC vehicles

Scenario	HDV TTC count	std for TTC-HDV	ACC TTC count	std for TTC-ACC	Total TTC count	std deviation
ACC-25	174.9	30.573	0.5	0.707	175.4	30.652
ACC-50	65.3	22.370	0.7	0.948	66	22.325
ACC-75	26.3	10.625	0.5	0.707	26.8	10.580
ACC-100	0	0	0.3	0.483	0.3	0.483

*std: standard deviation

Table 11: Traffic measures for ACC vehicles

Scenario	Average travel time (minutes)	Average traffic flow (vehicle per hour)
ACC-25	10.05	4594.35
ACC-50	10.03	4605.81
ACC-75	10.01	4594.09
ACC-100	10.02	4637.37

5 Comparative Traffic Safety Assessment between CACC and ACC Technologies

In summary, we calibrated the Krauss model (base case) with modified lane change parameters, the ACC model, and CACC model with proper gain and lane changing parameters. Lists of the ~~experimented~~ experimental and selected parameters are given in Table 12. All the scenarios were run with these parameters along with the traffic parameters given in Table 2 and Table 4. After finalizing all the parameters, we ran each scenario ten times and tabulated the results summary in Table 13 and Table 14.

Table 12: Summary of the parameters selected from experiments

Type of Parameter	Parameter	Experimental values used	Selected value
Lane changing parameter	Strategic lane change	HDV= [1, 10] AV/CAV= [1, 100]	HDV=10 AV/CAV=100
	Co-operative lane change	HDV = [1, 0.8]	HDV=0.8
Model Parameter	CACC gain parameter sets	[Literature parameter, Parameter equivalent to ACC, SUMO defaults]	Literature parameters
Traffic Parameters	Speed deviation	CACC= [0.1, 0.05]	0.05

Table 13: Number of potential conflicts for all scenarios using the final parameters

Scenario	HDV TTC count	std for TTC-HDV	CACC TTC count	std for TTC-CACC	Total TTC count	std deviation	Percentage change from base case
Krauss-100 (Base case)	184.4	28.342	0	0	184.4	28.342	0
ACC-25	62.8	24.066	0	0	62.8	24.066	**-65.94**
ACC-50	21.2	7.190	0	0	21.4	7.503	-88.39
ACC-75	8.8	5.069	0	0	8.8	5.069	-95.23
ACC-100	0	0	0	0	0	0	-100
CACC-25	328.6	259.741	15	14.089	343.6	273.569	86.33
CACC-50	342.6	224.976	24.8	20.315	367.4	244.966	99.24
CACC-75	161.6	49.883	11.4	1.516	173	49.904	-6.18
CACC-100	0	0	0.2	0.447	0.2	0.447	-99.89

Table 14: Traffic measures for all scenarios using the final parameters

Scenario	Average travel time (minutes)	Average traffic flow (vehicle per hour)
Krauss-100	10.154	4495.469
ACC-25	9.995	4503.757
ACC-50	9.991	4504.678
ACC-75	9.981	4522.059
ACC-100	9.972	4556.027
CACC-25	10.706	4491.89
CACC-50	12.800	4467.727
CACC-75	12.306	4469.815
CACC-100	12.862	4391.387

The number of potential conflicts for each scenario is plotted in Figure 3~~Figure 3~~, and we can visualize the change in potential conflict for all the scenarios. Each color represents the market penetration rates for a given technology. Since there are almost zero potential conflicts for scenarios with 100% AVs and 100% CAVs, the bars for these two scenarios are not visible. Our results show a 65.9% drop in potential conflicts with 25% AV or ACC vehicles which is a 16.2% improvement from the previously reported result [4]. This improvement in safety is mainly due to the modification of lane ~~changing~~ change parameters. The ACC car following model has outperformed the CACC car following model ~~at~~ in every corresponding scenario with a lower number of potential conflicts, less average travel time, and higher average traffic flow. The standard deviation values are also significantly less, meaning that the ACC car following model produces more stable and consistent results in simulating the effects of AVs.

The results are highly fluctuating for CACC scenarios with very high standard deviation values at each scenario. This indicates that the CACC car-following model, implemented in the SUMO simulation model, is unstable in simulating the effects of CAVs for the chosen hurricane evacuation scenario. In addition to the unstable behavior of the CACC simulation results, we find that the number of potential conflicts in CACC-25 and CACC-50 scenarios are higher than the base case scenario. Then in the CACC-75 scenario, it significantly drops to a total 173 potential conflicts, a modest 5.9% drop from the base case scenario (Krauss-100).

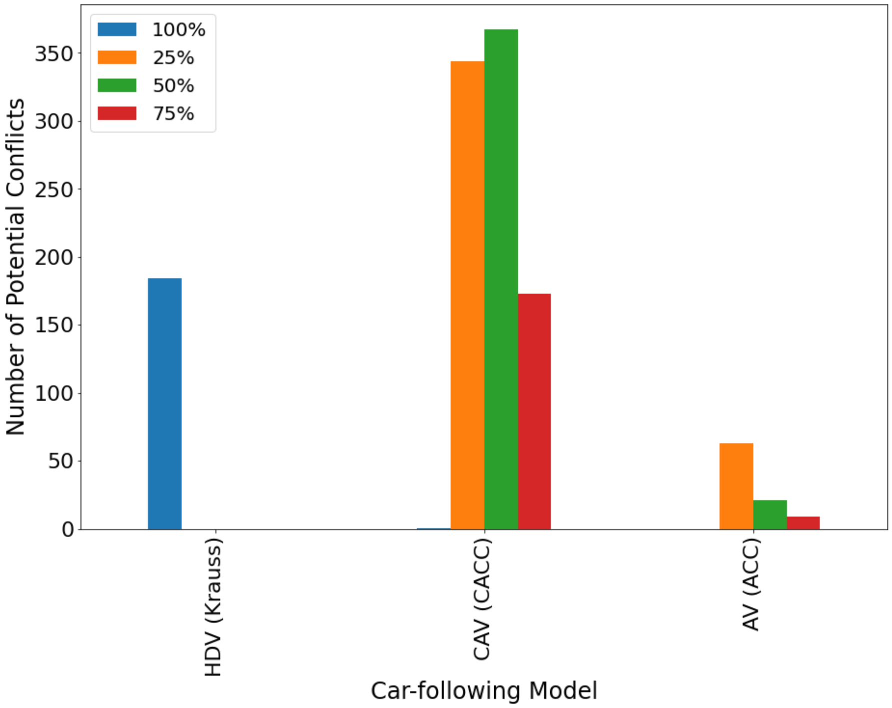


Figure 3: Number of potential conflicts across different vehicle technologies (the car following models used to simulate those technologies)

6 Integration of Vehicular Ad hoc Networks

One of the key components of the CAV technology is the Vehicular Ad-hoc Networks (VANETs), which allow the exchange of information between vehicles on the road; this is in the form of both vehicle to vehicle and vehicle to infrastructure communication. This is possible through communication technology specifically developed for this purpose known as Dedicated Short-Range Communication (DSRC). VANETs can be used for a wide range of applications based on the sharing of information between vehicles such as safety, efficient traffic, driver assistance, infotainment, and sensing [24]. Cooperative Awareness

Applications is one of the safety-related approaches that utilizes VANETs. Their main goal is the periodic dissemination of vehicle dynamics information for the enhancement of the overall road safety [25], [26]. Hence, VANETs, thereby in extension CAV, can provide a promising solution for the hurricane evacuation traffic safety problem.

Instead of assessing CAVs using a car following model, we alternately chose to assess VANET during a hurricane evacuation event. In this study, a co-simulation framework was built using both a microscopic traffic simulation model (SUMO) and a discrete event-based vehicular communication network simulation platform (OMNeT++). The framework uses outputs from each simulation tool as an input to the other for feedback. Therefore, it closely simulates both traffic and communication network-related parameters, without the need to add any assumptions in either. Different market penetration rates for CAVs were studied and compared. Both traffic-safety related indicators as well as communication-related indicators were presented.

6.1 Framework development

For the implementation of this approach, multiple tools were used as seen in (Figure 4). SUMO is an open-source traffic simulator, which provides various tools and packages for every step of traffic network simulation. It comes with ready to use and adjustable car-following model which allows for a flexible calibration and validation process. On the other hand, VEINs is a tool that interfaces with SUMO with the communication network simulator OMNeT++, to allow for the coupling of traffic and communication simulation to be running in synchronization. In this framework, SUMO simulates different traffic-related parameters such as vehicle positions, speed, and acceleration, then sends this information to OMNeT++ through VEINs, which then simulates these vehicles as communicating mobile nodes.

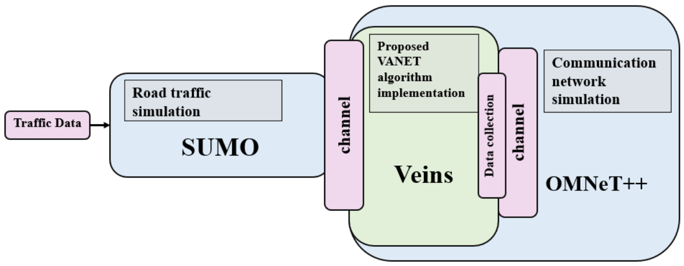


Figure 4: Implemented co-simulation framework

6.2 VANET Protocol for Safety Improvement

In this experiment, the objective is to study the impact of vehicular communication on the improvement of safety in a hurricane evacuation scenario. It is assumed that each vehicle can acquire distance information to its leading vehicle as well as it being equipped with a communication module that enables bidirectional communication; where it is able to send and receive data with the surrounding vehicles.

In general, a follower vehicle is tasked with always maintaining an appropriate headway to its leader vehicle by regularly actuating its acceleration [27]. The calculated acceleration is based on the follower vehicle's velocity, the leader's relative velocity, and the spacing between both vehicles [28]. Vehicular communication can be utilized as a convenient method in conveying such information among the vehicles.

We used a communication protocol that allows the dissemination of vehicle-related information such as speed and acceleration. The proposed application layer protocol is defined such that each vehicle broadcasts its speed and acceleration information at certain intervals. On receiving this information, coupled with information about the vehicle's leader, a vehicle can calculate conflict indicators such as time-to-collision. If the time-to-collision value is below a certain threshold, then it implies that the vehicle is in a hazardous situation. It then adjusts its speed in such a way to avoid collision.

The task of each follower vehicle is to maintain a certain "desired minimum gap", which is defined by the below equation:

$$s(v_\alpha, \Delta v_\alpha) = s_0 + vT + \frac{v\Delta v}{2\sqrt{ab}} \quad (6)$$

where s_0 is the jam distance, reasonable ranges are from $1m - 5m$ so a value of $2m$ is used in our approach.

Equation (6) is the desired minimum gap between two vehicles according to the Intelligent Driver Model (IDM) [28]. The term vT plays a key role in non-stationary scenarios, as it ensures a constant time gap regardless of the speed. It is also noticed that the desired minimum gap is directly proportional to the speed of the vehicles, which means that it increases with the increase of the speed. If maintained, this formulation of the desired gap guarantees collision-free behavior.

$$\dot{\mathrm{V}}_\alpha(s_\alpha, v_\alpha, \Delta v_\alpha) = a\left(1 - \left(\frac{v_\alpha}{v_0}\right)^\delta - \left(\frac{s(v_\alpha, \Delta v_\alpha)}{s_\alpha}\right)^2\right) \quad (7)$$

Where:

v_α: velocity of follower vehicle

Δv_α: velocity difference between leader and follower vehicles

a: maximum acceleration (value of $1.4\mathrm{m}/s^2$ is used)

v_0: desired velocity

T: Safety time gap (value of $1.5s$ is used)

b: Desired deceleration (value of $2.0\mathrm{m}/s^2$ is used)

Building further on this concept, equation (7) defines the IDM acceleration function which takes advantage of the safety properties of the desired minimum gap equation (6). Each follower vehicle utilizes the equation (7) to calculate the appropriate acceleration to be applied to always maintain an appropriate inter-vehicle headway of $1.5s$.

In our proposed approach, we adopt a vehicular communication algorithm based on the work by [27]. Their approach focuses on minimizing the inter-vehicle gaps in platoons for better road utilization, while our approach aims at always maintaining safe time gap between vehicles.

For every update cycle, vehicles broadcast their position and speed to their direct neighbors. It is assumed that each vehicle can calculate the distance to its leader, so if a vehicle is detected as a leader vehicle, the follower vehicle sends its position and speed information to it. Each follower vehicle maintains a record about its leader by constantly listening to beacons from the leader that contains position and speed information. Both leader and follower vehicles update records according to vehicles entering and leaving the traffic stream through periodic beacons. Vehicles can be both a leader and a follower based on its position in the traffic stream.

The pseudo-code for leader and follower vehicles is explained in Algorithm (1) and Algorithm (2) consecutively.

Algorithm 1: Vehicle information updating algorithm: Leader

```
for all vehicles do
    Broadcast x_leader and v_leader;
    if receives message from follower then
        store follower information;
    end
end
```

Algorithm 2: Vehicle information updating algorithm: Follower

1 **for** *all vehicles* **do**
2   **if** *receives message* **then**
3   calculate s_{leader} to leader vehicle;
4   **if** $(s_{leader}/v_{follower}) < 4s$ **then**
5   declare vehicle as leader;
6   send $x_{follower}$ and $v_{follower}$ to leader;
7   calculate new acceleration to be applied next time-step;
8   **end**
9   **end**
10 **end**

Initially, a vehicle is unaware whether it has the role of a leader or a follower or both. Therefore, all vehicles start by broadcasting their position and speed information. The following chain of events decides the role of the vehicle. If it detects another vehicle preceding it, then it is a follower. If it receives messages that encapsulate its own ID in addition to speed and position information, then it is assumed that this information was sent by a follower, and it is assigned the role of a leader.

Algorithm ~~(~~1~~)~~ defines the behavior of a vehicle with the leader role. The vehicle starts by broadcasting its position (x_{leader}) and speed (v_{leader}). Lines 3-5 indicate that the vehicle has received a message from its follower and stores the corresponding information. On the other hand, algorithm ~~(~~2~~)~~ explains the behavior of the vehicle if it is assigned the follower role. Lines 2-3 indicate that the follower vehicle has received a message, which contains speed and position information. The distance to the vehicle (s_{leader}) is calculated based on this information. If it is decided that the received information was from the preceding vehicle, then this vehicle is defined as the current leader. Then, the time headway to the preceding vehicle is calculated in lines 4-8 and if it is below a threshold of $4s$, then the follower calculates the appropriate acceleration to be applied according to equation (**Error! Reference source not found.**~~2~~)

6.3 Traffic Safety Analysis Results

Since the aim of this study is to understand the impact of vehicular communication on safety, traffic-related indicators as well as communication-related indicators were collected and compared.

To study traffic safety-related indicators and how the communication protocol improved safety and overall traffic state, the scenario was run with different CAV penetrations rates where a comparison between them was conducted for each communication range. The simulation duration was 2 hours, where the first 30 minutes were used as a warm-up period and the last 30 minutes were used as a cool-down period. Table 15~~Table 15~~ the parameters used in the co-simulation framework.

Table 15: Simulation parameters for the co-simulation framework

Simulation Aspect	Parameters	Value
Communication Simulation	Transmission Power	$15mW$
	Sensitivity	$-70dBm$
	Bitrate	$6Mbps$
	CAV Penetration Rates	$10\%, 50\%, 75\%, 100\%$
Traffic Simulation	Simulation Duration	$7200s$
	Maximum Acceleration	$4.0m/s^2$
	Tau	$1.5s$
	Sigma	0.3
	Car Following Model	Krauss
	Simulation step length	1sec

Several safety indicators were calculated including the number of registered conflicts, percentage change in conflict numbers and an analysis of time-to-collision values. As seen in ~~(~~Table 16~~)~~, the registered number of potential conflicts for different market penetration rate for CAVs were calculated and compared for the average of 8 simulation runs. It is noted that the number of registered conflicts is based on the lowest time-to-collision value registered throughout a certain interaction. The threshold for registering a conflict is ~~(~~$TTC \leq 1.5s$~~)~~. Furthermore, we see that the number of conflicts decreases with the increase in percentage of CAVs introduced in the traffic stream. Using 100% CAV in the traffic stream, the number of conflicts is decreased by 95%.

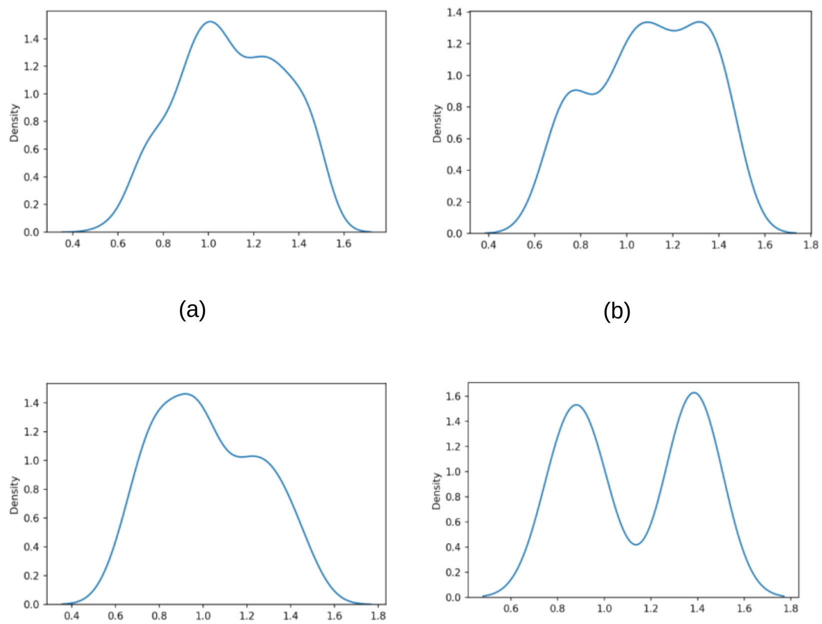
Table 16: Number of potential conflicts at different market penetration rates

Communication range	CAV Market Penetration	Potential Conflicts ($TTC \leq 1.5s$)	std of conflicts	% Change
	0% (base condition)	161.25	24.08	0
50m	10%	38.75	15.3	-75.9%
	50%	20.2	6.08	-87.4%
	75%	14.25	8.4	-91.16%
	100%	8	0	-95.03%

Looking further into the TTC values calculated from the CAV vehicle's perceptive, (Table 17) shows the mean values of TTC for each scenario. For the base scenario, the average recorded TTC values was 1.2s. Starting with the lowest CAV market penetration rate at 10%, a mean TTC of 1.11s is recorded

Table 17: Number of conflicts at different market penetration rates

Communication Range	CAV Market Penetration	Mean TTC Values (s)	Standard Deviation
	0%	1.2	0.05
50m	10%	1.11	0.05
	50%	1.08	0.08
	75%	0.99	0.089
	100%	1.13	0.01



(a) (b)

(c) (d)

Figure 5~~6~~: Distribution of time-to-collision at different market penetration rates (a) 10% (b) 50% (c) 75% (d) 100%

6.4 Communication Network Analysis Results

To understand the efficiency of the proposed communication protocol, the number of total packets lost during the simulation for each communication range and CAV market penetration ratio were collected. Multiple factors contribute to this value; namely, the number of participating vehicles, the communication range as well as the frequency by which messages are sent.

The values in ~~(~~Table 18~~)~~ represent the mean ~~of~~ packet loss in each scenario as well as the standard deviation. As the number of participating connected vehicles increases, packet loss also increases. This can also be observed in the overall packet loss distribution in ~~(~~Figure 6~~Figure 7~~~~)~~.

Table 18: Mean packet loss values across different CAV market penetration

Communication Range	CAV Market Penetration	Mean of Packet Loss	Standard Deviation
50m	10%	0.096	0.43
	50%	2.07	2.6
	75%	4.7	4.7
	100%	8.4	7.5

6.5 Summary

In this study, a communication algorithm for the online adjustment of individual vehicle acceleration was implemented. The main purpose of this algorithm was to observe the impact vehicle-to-vehicle communication can have on safety enhancement in a hurricane evacuation scenario. The framework used consists of a traffic micro-simulator (SUMO), a communication network simulator (OMNET++) and an application that allowed for the integration and co-simulation between the two platforms (VEINs). A highway scenario was simulated, and the extracted vehicle trajectories were used to test the proposed communication algorithm.

The results of this study showed that introducing connected autonomous vehicles can in fact improve ~~the safety of the~~ overall traffic safety. It shows around 75% decrease in the number of conflicts with introducing only 10% CAV in the traffic stream. This is especially useful in the case study presented, where hurricane evacuation is a special scenario that is characterized by high vehicle volume as well as a high number of conflicts.

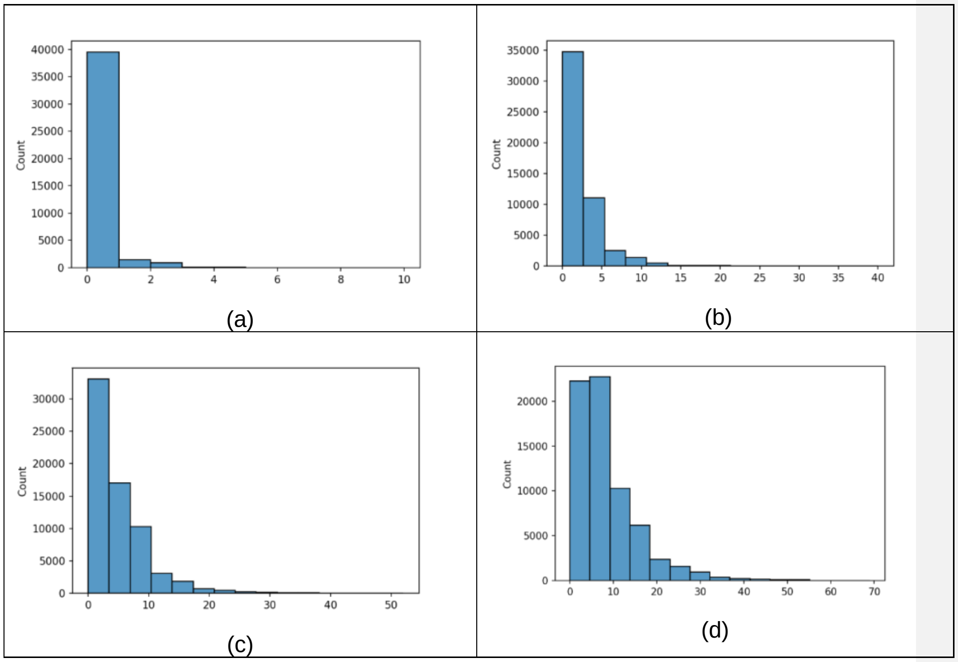


Figure 6~~7~~: Distribution of packet loss across different CAV Market Penetration Rates: (a) 10% (b) 50% (c) 75% (d) 100%

7 Conclusion

Overall, the simulation experiments conducted in this project provide~~s~~ insights on improving the simulation-based approaches to assess different vehicle technology in a hurricane evacuation scenario. Despite many positive results found in the literature for the CACC car-following models representing CAVs, our results suggest that the CACC car-following model produces very unstable results reflected by high standard deviations in reported results. From the unstable nature of the result and lack of real-world CAV data it is unclear whether the CACC car-following model should be used to model CAVs. Our results suggest that the CACC car following model is not appropriate to simulate the effects of CAVs, at least, in a hurricane evacuation context. However, we confirmed and enhanced the previously found results that ACC equipped vehicles (equivalent to AVs), even with a 25 % market penetration rate, can significantly reduce the number of conflicts. With the modified lane changing parameters we showed that, with only a 25% market penetration rate, AVs can decrease the number of potential conflicts by 65.9% (vs. 49.7% found in our previous study). Our results also suggest that the ACC car following model is more stable and performing better than the CACC car following model in terms of traffic safety and traffic flow. Thus, we may continue to simulate the effects AVs with ACC car following model.

Moreover, to see the effects of connectivity among vehicles, we used a separate state-of-the-art communication simulator integrated with SUMO in a co-simulation framework that incorporates a car-following model with an ability to communicate with other vehicles. We incorporated V2X communication on Krauss car following model, since we want to assess the effect of connectivity and Krauss is used in our base case study. We experimented for different penetration rates of CAVs. Results show that with introducing only 10% CAVs in the traffic stream, the number of potential conflicts decreases by 75%. From our study of a vehicular ad-hoc network, we found that connectivity increases road safety as the information dissemination help vehicles decide to take proper maneuvers and stabilize the traffic.

8 Acknowledgement

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9 References

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