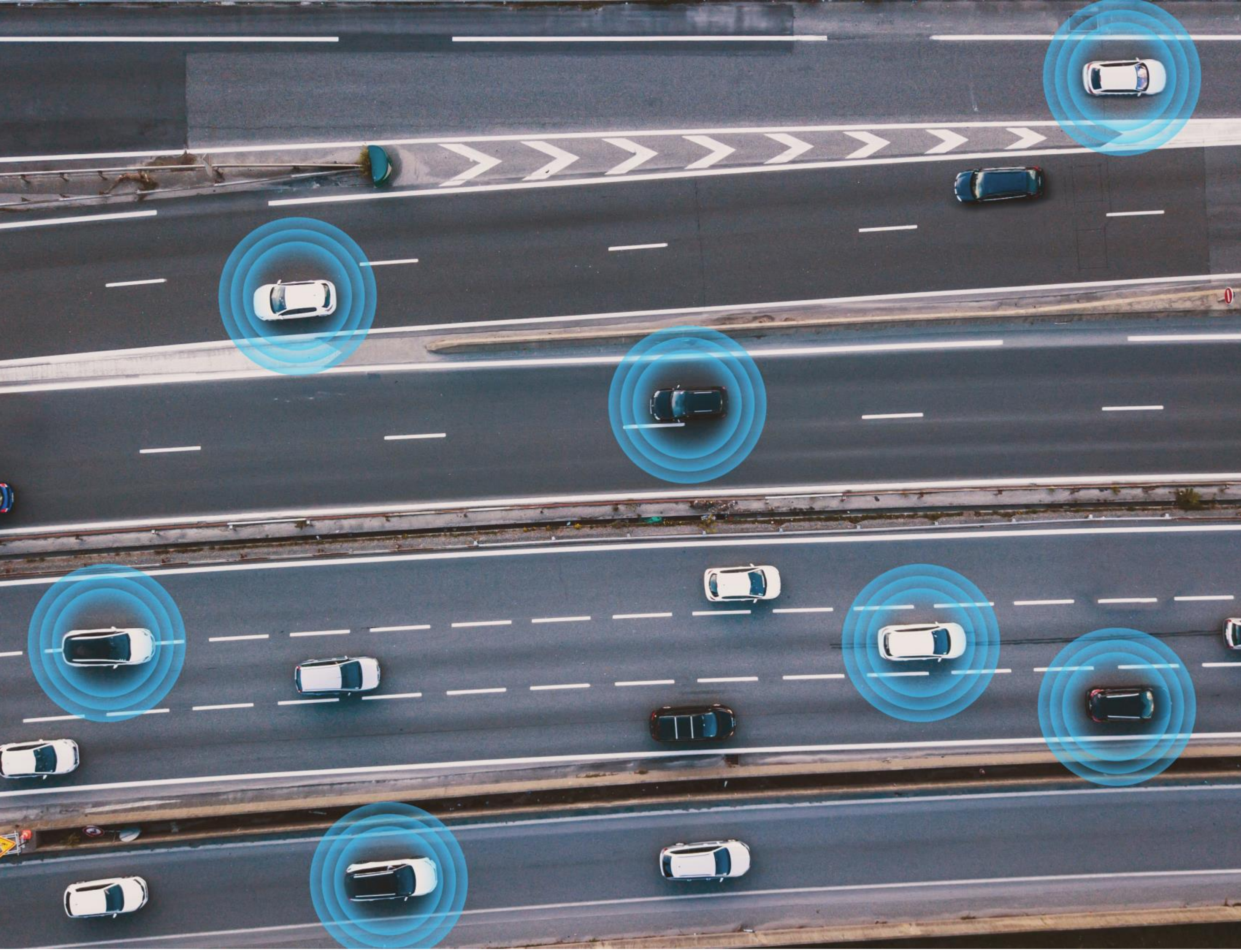

Smart Connected and Automated Vehicle Fleet Management: Developing Regional Dispatch Decision Support for Congestion Mitigation

Center of Excellence for Mobility and Congestion - Theme 2

NCDOT Research Project TCE2020-02

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16. Abstract

With the arrival of new technologies like connected and self-driving autonomous vehicles (AVs), the workload of regional dispatchers will increase. To this end, the CADS (Congestion Alerting Decision Support) tool was developed to support strategic transportation planning (on the order of weeks to months) and tactical transportation planning (on the order of hours to days). It allows dispatchers and other decision makers the ability to run what-if simulations to determine how and when to allocate future resources for different scenarios. Such a tool can be used operationally, like in the days before a hurricane to improve planning, but also in training to provide a host of practice scenarios for new planners, dispatchers and other emergency planning personnel. One current limitation of CADS is its inability to connect congestion metrics to predictions of safety, which could be very useful to dispatchers, especially as AVs increase in numbers. Research determined that when operating in mixed traffic as a following vehicle in a platooning scenario, AVs had longer response times, which could lead to an increase in the number and severity of conflicts, and thus problems with potential overall safety. If CADS could track metrics like AV platoon length, heterogeneity of platoon vehicles on a highway and braking response times, it is possible that CADS could highlight risk profiles for areas of congestion that involve AVs. However, additional research showed that incorporating commonly-used models likely do well in predicting where AVs will be at a given time, but struggle with predicting acceleration and deceleration, indicating more work is needed before such simulations can realistically be used for risk projections.

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Summary

With the arrival of enhanced vehicle and infrastructure connectivity, as well as new technologies like self-driving vehicles, the workload of regional dispatchers will increase for both routine and unusual congestion-management tasks. To this end, the CADS (Congestion Alerting Decision Support) tool was developed to support strategic transportation planning (on the order of weeks to months) and tactical transportation planning (on the order of hours to days). It allows transportation planners the ability to see the impact of congestion caused by various events including weather and rerouting apps on local communities (including hospitals, schools and first responders). It also provides the ability to determine when and where to communicate with both connected and conventional vehicles to minimize congestion impact both in advance of known traffic disruptions (like construction), but also for pending incidents like weather events. It also serves as a tool to explore how autonomous vehicles could impact local communities with potentially increased congestion.

One current limitation of CADS is its inability to connect congestion metrics to predictions of safety, which could be very useful to dispatchers, especially as AVs increase in numbers. For example, CADS currently depicts congestion as a function of vehicle throughput in a certain area, but it does not alert the dispatcher to possible increases in crash risk. It would be useful to have such predictions in the future, as this could then be a variable that factors in replanning recommendations.

Towards addressing this gap, this study determined that when operating in mixed traffic as a following vehicle in a platooning scenario, AVs had longer response times, and that as the platoon's length increases, so do instabilities in the system. This could lead to an increase in the number and severity of conflicts, and thus potential overall safety. If CADS could track metrics like AV platoon length, heterogeneity of platoon vehicles on a highway, and braking response times, it possible that CADS could highlight risk profiles for areas of congestion that involve AVs, and is an area of possible future work.

Additional work was conducted to determine whether underlying AV car models commonly used in such simulations (including CADS) adequately capture actual behaviors, with mixed results. When looking at three commonly-used AV car-following models (ACC, W99, IDM), none could predict the real-world AV acceleration without significant differences. The ACC model was the closest one to model the real-world acceleration profile, but W99 showed abrupt and unrealistic high acceleration and high deceleration results. In addition, the IDM model had the lowest acceleration noise due to its conservative driving algorithm. However, all the three car-following models predicted the AVs' positions in time with high accuracy.

These results indicate that if CADS, and other simulations like it, incorporate these models, they likely do well in predicting where vehicles will be at a given time. However, if such simulations are going to be adapted to predict high risk areas for collisions, current problems with predicting acceleration and deceleration likely indicate more work is needed before such simulations can realistically be used for risk projections.

Recommendations for next steps include determining how to operationalize CADS, the incorporation of non-linear car-following behavior of the following vehicle, improving underlying AV models in terms of acceleration and deceleration, and better calibration of existing models for more streamlined adaptation into a NCDOT preferred microsimulation platform.

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Introduction

The transportation industry is experiencing rapid change across multiple fronts with the growth of autonomous vehicles (AVs) and the promise of connected vehicles (CVs). Unfortunately, highway and pedestrian deaths continue to rise (1, 2) and prior to the pandemic, the average time Americans spend stuck in traffic was 87 hours per year at a cost of $87 billion a year for drivers and $74 billion for the freight industry (3).

Often proponents of connected and autonomous vehicles assert that these technologies will decrease congestion (4-6), but others assert just the opposite (7, 8). It is not at all clear which of these two views will prevail given the nascent nature of this technology, Moreover, there is also significant uncertainty around the nature of autonomous vehicle operations in general, including how to respond to AVs that break down and to what degree AV operations nay actually hinder, rather than improve congestion.

The need to better understand congestion potentially caused by AVs is illustrated by the number of "vehicle retrieval events" currently experienced by customers of Cruise® AVs. These vehicles freeze and block traffic to such a high degree that the City of San Francisco recently petitioned the National Highway Traffic Safety Administration (NHTSA) to not allow Cruise to operate its new multi-passenger shuttle called the Origin (9). It is possible that such acute congestion events could block first responders and thus could create a safety hazard.

All of these issues point to the need to develop a better understanding of if, where, how and when AVs contribute to congestion, the nature of any safety impacts, and what mitigations could be used to relieve this congestion. To this end, dispatchers in regional dispatch centers where state and/or local authorities monitor traditional vehicles (TVs) as well as AVs and CVs in the future need better tools both in planning and in real-time operations to better cope with emerging scenarios like those experienced by Cruise®. Much like trucking companies do today with their fleets, there will be a future need for independent oversight of the operations of AVs and CVs to provide an additional layer of safety and public accountability.

This report details a 2.5 year-long effort that studied various elements of emerging concerns surrounding connected and/or autonomous vehicles and their supervision.

Background

Understanding that it is likely CVs and AVs will come to public roadways in some fashion, it is not yet clear how jobs will change for regional dispatchers. Figure 1 illustrates the current tasks for regional dispatchers, along with three new possible tasks of 1) remote control of AVs, 2) passenger communications and 3) monitoring of platooning vehicles. These are discussed in detail elsewhere (10), but even if these tasks were added in the future, they would likely take up a small percentage of a dispatcher's workload.

The most likely impact of adding CVs and AVs to regional dispatcher's workload is increasing their current tasking for traditional tasks. Dispatchers spend the bulk of their time monitoring traffic, attending to highway messaging and coordinating with first responders, in addition to many administrative tasks as outlined in Fig. 1. In comparison to dispatchers of today, dispatchers of the future will likely have to monitor the real-time traffic flows of TVs, CVs, and AVs, and their possible interactions. The Cruise VREs mentioned previously have demonstrated that a failure of an AV navigation system can cause serious traffic jams that not only inconvenience a large number of people, but such jams also make it difficult for first responders to do their jobs.

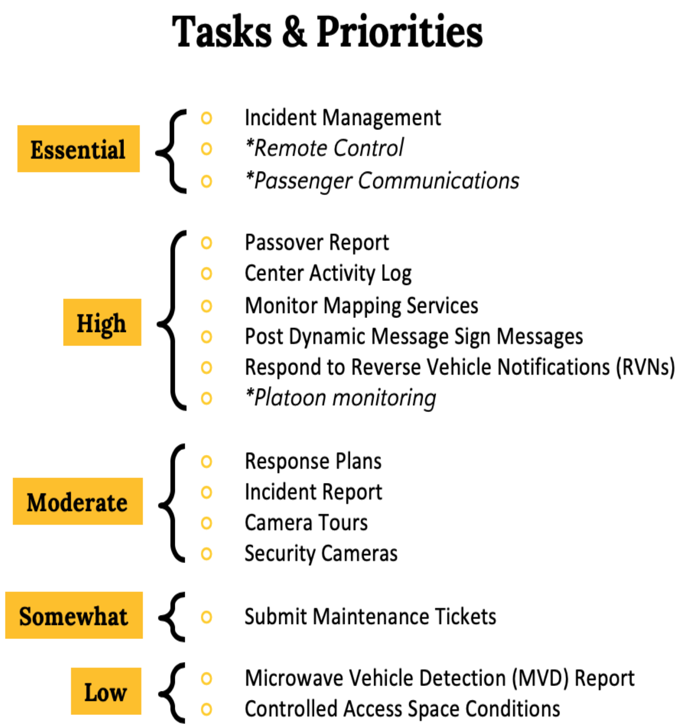


Figure 1: Regional Dispatcher Typical and Future Tasks

Once connectivity between vehicles (aka V-to-V) is more commonplace, dispatchers may be able to immediately communicate through a V-to-V network when problems emerge or congestion is high. They could redirect traffic of all types both to ease congestion but also to expedite emergency response, see for example. These remote dispatchers could affect change either through dynamic message signs, but they could work with mapping services like Waze® and Google Maps®.

However, interviews with the North Carolina Turnpike Authority highlighted the high workload that such interactions cause for regional dispatchers. Take, for example, the case of wild fires in Southern California. During one fire, many mobile navigation apps advised their users to follow roads that were closed due to the imminent fire hazards, because the crowdsourced apps identified them as having little traffic. Subsequently, the Los Angeles police needed to warn drivers against using mobile navigation in these areas to prevent people from driving directly into the fire (11), and it takes a significant amount of coordination to make this happen Closer to home, similar concerns were raised in 2018 during Hurricane Florence in North Carolina.

Thus, while the introduction of new technologies is often meant to make one user's workload easier (i.e., mapping helps drivers navigate more efficiently), they often shift workload to others (the dispatchers), who may not have the tools, training and staffing to handle a spike in workload. The brittleness of onboard automated systems that cannot account for context, like that of wildfires or hurricanes, means that regional dispatchers' workload could significantly increase and research and technologies are needed to help reduce this workload in future operations.

State of the Art, Science, and Practice

Despite the popularity of research into self-driving and automation-assisted cars, there is a dearth of research concerning how such operations could or should affect dispatchers of all types, including those in government (like regional dispatchers) and industry (like Walmart trucking dispatchers.) Most studies about autonomous vehicle dispatch focus on the resource allocation

problem, demonstrating that algorithms are better than people at such problems, i.e., (12, 13). Other than our previous work (10), there is no published research that looks at how the cognitive processes of dispatchers could or should be supported by technology. Even the previous works on resource allocation focus on human replacement as opposed to human augmentation.

To determine possible safety impacts of various concepts of operations, Surrogate Safety Measures (SSMs) are widely-used to estimate the likelihood of traffic conflicts using micro-simulation transportation models. SSMs assume that the closer vehicles are to each other in terms of temporal or spatial proximity metrics, the nearer they are to a potential collision (14). While commonly used in the transportation community, it is not clear how useful SSMs are in evaluating new technologies like connected and autonomous vehicles. Given that the AV field is quite nascent, it is also not clear if and how AVs influence SSM metrics. For example, one set of researchers determined that AVs would dramatically improve safety using one set of AV assumptions (15) but another set of researchers found that safety would not improve, and could actually worsen using several sets of published AV models (16). Our proposed research aims to help fill this gap.

Lastly, the paucity of real-world AV trajectory datasets has forced many researchers to rely heavily on simulation models to draw safety and operational inferences. In fact, the majority of the studies do not address any potential discrepancies between observed and car-following modeled AV data. Research is needed to examine the three widely-used ACC car following models (IDM, ACC and Wiedemann 99 (W99)) and determine if there is there a significant discrepancy between observed and car-following modeled AV data, and what factors, if any, contribute to these discrepancies.

Purpose and Scope

The purpose of this effort is to determine how to best support the cognitive tasks outlined in Fig. 1 for remote regional dispatchers, especially for operations that involved CVs and AVs. To this end, we explore what kinds of algorithms could be helpful in reducing workload, and an interface that helps dispatchers and planners understand how the arrival of CVs and AVs may change congestion management.

Because dispatchers are inherently attempting to maximize safety, it is critical to understand what kind of impact AV and CV fleets will likely have on crash numbers. Since AV and CV fleets are yet to generate reliable crash statistics, a second objective of this effort is to assess the role of SSMs in estimating conflict potential using real world vehicle platoons consisting of a mixture of traditional and autonomous vehicles under different leader follower arrangements. Such an analysis helps provide cost-benefit information in terms of not just congestion, but more critically, the impact on safety.

Because simulation is such a critical part of estimating the future impact of AVs and CVs for both dispatcher modeling and many other aspects of the transportation system, the study reports a detailed evaluation of three of the most widely used car following models for simulating autonomous vehicles, the ACC, IDM and Wiedemman99 models. Model predictions are compared against empirical following-vehicle trajectories and their advantages and limitations discussed.

This effort aims to significantly advance the State of North Carolina's capabilities in traffic planning and simulation, especially given the rapid advancement in AV and CV technology, Moreover, these results will advance NC DOT expertise in autonomous vehicle management and smart city transportation planning.

Research Approach

In order to develop policies and procedures that may need to be implemented at the regional Department of Transportation (DOT) level, traffic and safety models and a simulation capability is needed to mitigate any negative impacts of AV and CV growth. To that end, this effort takes a three-pronged approach:

1. Develop a simulation capability that allows DOTs the ability to ask what-if questions in terms of increasing levels of AVs and CVs and the effects on local traffic congestion, how should problems be represented to various stakeholders, and consider the impact of rerouting on local schools, hospitals and other first response resources.
2. Explore what the implications of increased AV and CV market saturation are for safety concerns through safety surrogate metrics.
3. Assess the utility of underlying simulations through the evaluation of widely-used car following models in simulations of autonomous vehicles;

Organization of the Report

The efforts for this work will be presented in three sections that look at: 1) tools and technologies to assist remote dispatchers responsible for regional oversight of traditional, connected and autonomous vehicles, 2) the role of safety surrogate metrics results that look at different levels of autonomous vehicle penetration in a platooning scenario; and lastly 3) an evaluation of widely-used car following models for autonomous vehicles.

Tools & Technologies to Assist Remote Dispatchers

Simulation Environment Selection

In order to develop prototype tools to aid regional dispatchers, we needed to develop a simulation environment that allowed us to leverage an underlying mapping functionality, but that also allowed us to insert different routing algorithms and agents, like connected and autonomous vehicles. The most common commercial traffic simulation model used across various research institutions to characterize AV operations is PTV VISSIM (17). One significant drawback to this tool is the difficulty in changing underlying parameters and models, and costs are another practical limitation.

To this end, we tested another option, the open-source simulation software package SUMO (Simulation for Urban Mobility). It is an open-source, highly portable, microscopic traffic simulation package created by the German Aerospace Centre DLR in 2001 (18). One important advantage of SUMO platforms (in addition to affordability) is flexibility in incorporating the latest algorithms for CV and AV operations and safety features as they become available in the public domain.

To that end, we conducted a study to directly compare the performance of VISSIM to SUMO to determine if there was a clear performance benefit to using VISSIM (19). As noted previously, SUMO provides significantly more flexibility for the purposes of our research, but we needed to determine if there was a measurable difference between the two simulations that would bring into question the results of SUMO.

Results showed the two simulators were generally equivalent in computational resource demand but produced delay estimates that were not consistent with one another, or internally. Another finding was that SUMO produced more variability than PTV Vissim, which is an advantage when representing human behavior uncertainty that is highly variable. Narrow confidence intervals are a known limitation in simulation studies (20), so SUMO's ability to represent larger confidence intervals raises our confidence that any resulting models would likely be more realistic. These results indicate that using SUMO for our simulation environment as opposed to PTV Vissim does not incur any performance decrement and provides larger bounds of uncertainty, so the development described for the remainder of this section occurred in SUMO.

Congestion Control Using Vehicular Adhoc Networks

In developing a decision support tool for dispatchers and traffic engineers, we first wanted to develop a highly efficient algorithm that could reroute multiple vehicles in a decentralized fashion, which would be the foundation to an interface for dispatchers to determine how to respond to congestion events. To this end, we explored the use of a Vehicular Adhoc NETworks (VANETs), which ideally reduce congestion on the roadway vehicle-to-vehicle communications. VANETs are similar to that of a Mobile Adhoc NETwork (MANETs), where nodes communicate via a peer-peer approach without having any centralized infrastructure. VANET's are a form of MANET where connected vehicles communicate with each other to form a network.

The Simulation for Urban Mobility (SUMO) environment provides larger bounds of uncertainty as compared to VISSIM, which may be preferable when modeling human behavior in driving settings.

In developing a decision support tool for dispatchers and traffic engineers, we first wanted to develop a highly efficient algorithm that could reroute multiple vehicles in a decentralized fashion, which would be the foundation to an interface for dispatchers to determine how to respond to congestion events. To this end, we explored the use of a Vehicular Adhoc NETworks (VANETs), which ideally reduce congestion on the roadway vehicle-to-vehicle communications. VANETs are similar to that of a Mobile Adhoc NETwork (MANETs), where nodes communicate via a peer-peer approach without having any centralized infrastructure. VANET's are a form of MANET where connected vehicles communicate with each other to form a network.

In a VANET, each vehicle broadcasts messages to other vehicles using a multi-hop approach. These messages include location and velocity. Sometimes, these messages also include the data of other vehicles. This type of congestion control mechanism, however, can be employed only at a local level of traffic. Most of the research conducted around VANETs is mostly confined to routing messages from the source to the destination. However, there has not been an attempt to use these protocols to reroute vehicles, which is more difficult since uncertainty can be much higher due to the kinematics and behaviors of other cars. Thus, we elected to explore whether this was both possible and advantageous.

Because the use of VANETs would require a network of vehicles dense enough to distribute messages, there are necessarily additional Infrastructure requirements in the case that the vehicle network is sparse (like traffic at 3am). Therefore, use of a technology like roadside units (RSU) along the highways and other urban and rural road networks would be required. The roadside unit gathers information about the traffic flow and broadcasts it to all the vehicles along that route or to its neighbor roadside units, and is considered to be a base requirement for any connected system (21).

VANETs come with challenges. While trying to avoid congestion at the traffic level, congestion could occur at the network layer. Redundant data transfer leads to significant overhead on the system and sometimes results in link breakage. Mobility and frequent topological changes could lead to packet loss and amplify negative impact (22). There are also security concerns with such networks (23).

In our effort, instead of sending control packets from vehicle to vehicle, we use routed messages from the source to a destination via any available resource, which provides both faster routes but also privacy. Vehicles communicated with other nearby vehicles, but with also any nearby RSUs. To determine the efficacy of such an approach we developed a simulation in SUMO to represent two different conditions: 1) the rerouting of vehicles in the native SUMO environment which leverages a traditional A* algorithm that finds the shortest path from a source to a goal, and 2) the Bee Jam A algorithm, which uses a decentralized VANET approach to rerouting (24). The A* approach is popular and can achieve optimality but it may not account for dynamic system changes (e.g., building congestion) (25), which would be a theoretical advantage of a VANET.

The use of Vehicular Adhoc NETworks (VANETs) for efficient route planning has significant limitations for application to small geographical regions.

To test these two approaches, we developed a visualization of a map area in SUMO seen in Fig. 2. There were three areas of interest, the smallest was an approximately 20 sq mi area, and then 4x larger and 9x larger. We wanted to look at increasing area sizes to determine whether the area of coverage would be a significant factor in the runtime. When we embedded the Bee Jam A algorithm in SUMO and tested it against native A* algorithm across all three maps with a lane closure for 20 minutes and 460/920/1380 cars entering at the designated points in Fig. 2, there was virtually no difference in the run time, 6.5s 2 for

Bee Jam A and 6.6s for the A* algorithm. The average delay per car was also very similar, 278s for Bee Jam A and 280s for the A* algorithm.

Further investigation of these results revealed that the VANET approach would not start to show any meaningful difference until the region of interest was nearly 1000 sq miles. Given that this research was designed to develop tools for regional state-level dispatchers whose areas covered at most a few hundred sq. miles it was clear that the VANET approach, along with the expensive need to layer in RSU infrastructure, would not provide any substantial benefits beyond traditional A* approaches.

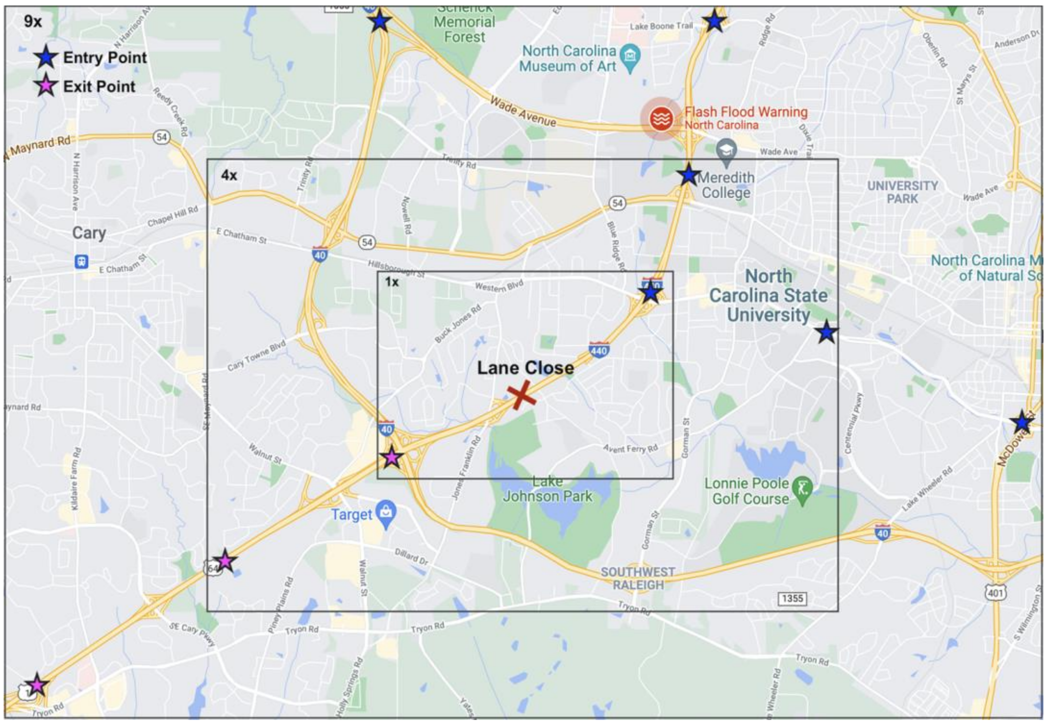


Figure 2: 1x, 4x and 9x Regional Maps of the Raleigh, NC Region

The Congestion Mitigation Tool

Realizing that popular and easy-to-implement A* algorithms provide valuable rerouting recommendations, we examined how and where they are currently used in transportation planning. For the most part, in transportation systems such tools are used by mapping companies like Waze® and Google Maps® to allow individual cars to determine the most optimal paths. One problem with these commercial implementations is that they generally do not account for areas where secondary congestion caused by rerouting could introduce additional problems.

For example, if a crash shuts down both sides of an interstate, most commercial mapping apps will reroute traffic off the interstate to the most direct path back to the interstate at a later junction, regardless of whether this traffic then creates significant congestion around areas of vulnerable populations like schools and hospitals. Moreover, such apps are often not able to respond to evolving emergencies like flooding. NC Turnpike Authority personnel cite numerous occurrences where despite interstate reversals for hurricane evacuations on the coast, the mapping companies will still send customers against the flow of traffic.

Given this background information, it was clear the what is needed is a decision support tool that helps transportation planners in strategic planning, but that also could help operational personnel like dispatchers develop more tactical plans. Figure 3 illustrates this need where strategic planning includes understanding regional traffic patterns, the need to accommodate construction projects, and also plan for traffic caused by major events, including state fairs. Tactical planning includes responding to urgent events like a pending hurricane, flooding of a road segment and major accidents.

Figure 3 illustrates that there are three ways to communicate with drivers to respond to both tactical and strategic planning, including permanent and mobile digital messaging signs, as well as in-vehicle telematics like apps and native navigation systems. There are three different kinds of drivers as noted in Fig. 3, including those of Traditional Vehicles (TVs), Connected Vehicles (CVs) and Connected Autonomous Vehicles (CAVs). These will be described in more detail in a later section.

Also noted in Fig. 3 are the different time scales of both the incidents and the ability to communicate information about them. For example, digital messaging signs can warn drivers days and weeks in advance of a potential road closure to help drivers plan for disruptions. Apps are better used for real-time traffic updates so are better communicators at the tactical level.

The Congestion Alerting Decision Support (CADS) tools allows users to explore what-if scenarios like "Will self-driving cars lead to more or less congestion?" or "When should dispatchers turn on dynamic message signs for rerouting recommendations?"

Thus, in order to develop a decision support tool for dispatchers that could support both strategic and tactical planning[1], we developed the Congestion Alerting Decision Support (CADS) tool (Fig. 4). CADS recognizes that rerouting can be communicated in one of two ways, either through individuals' use of smartphone or native mapping systems (a form of connectivity) but also through the use of either permanently-mounted or mobile dynamic message signs. Indeed, message sign management was also cited as a source of dispatcher workload and one that could benefit from additional technology assistance (Fig. 1).

[1] The tool is primarily meant for planning hours to months in advance because CADS uses predefined data models and not real-time traffic data, but could be adapted in the future to support decision making on the minutes time scale with the inclusion of this data.

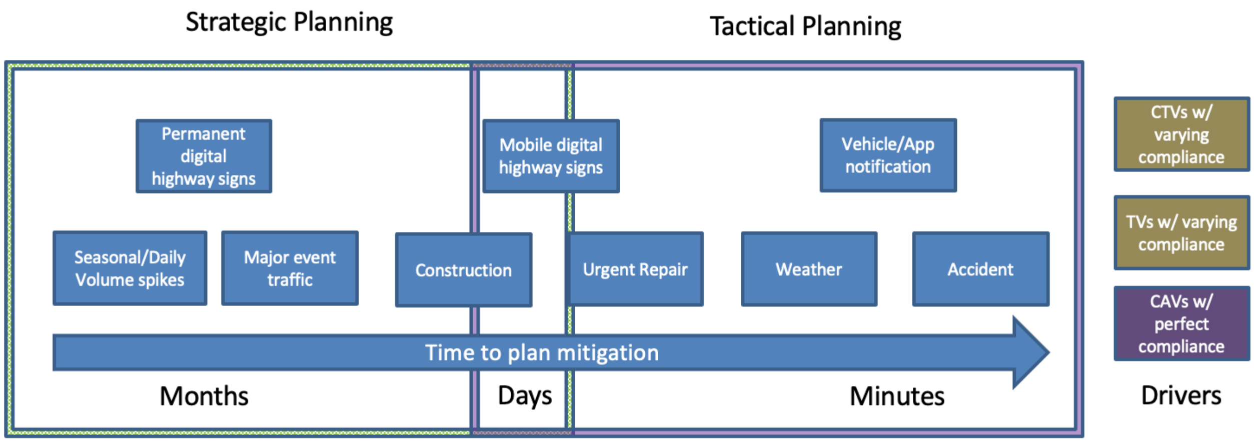


Figure 3: Strategic and Tactical Planning for Incident Management

CADS is designed as a what-if planning tool, i.e., if transportation planners want to investigate what the most efficient and safe rerouting plans would be for major interstate shutdowns, including the impact of new routes recommended by a third-party mapping service or through dynamic messages, CADS can show dispatchers and planners the likely outcomes of such plans. To this end, CADS can also assist planners and dispatchers in knowing where placement of mobile messaging signs could reduce congestion, or when and for how long rerouting recommendations should be made on currently-existing permanent dynamic message signs.

In addition, CADS can assist planners in investigating the possible impact of connected and /or autonomous vehicles in both nominal and off-nominal scenarios, i.e., if AV market saturation rises to 30% of all cars, would this new mix of vehicles help or hurt congestion? While there is significant debate in the transportation community as to whether AVs will improve congestion, regional and local planners need a set of tools to explore these questions for their unique geography, road design and usage patterns.

There are two primary modes of user interaction in CADS, which is built using SUMO: 1) The input mode (Fig. 4) and 2) the output mode (Fig. 5). Figure 4 primarily consists of a map, which depicts the region of interest. On the left side of the display, there are three clusters of actions the user can take. The first is adding a lane shutdown incident on one of the interstates[2]. Users can elect to shut down one or more lanes, for any specified length of time. Such a capability allows users to explore congestion caused by routine accidents that block one lane, but also more anomalous situations that shut down an entire interstate, when I-95 came to a halt due to snow storm in 2022.

The second functional cluster in Fig. 4 allows the user to explore a mix of different traffic flow rates and different vehicle types. In CADS, TV means traditional vehicle, which is a car that does have any connectivity in terms of an in-car navigation system, or a cell phone with a third-party mapping application. CTV means connected traditional vehicle, which is a car that includes path planning functions either through on-vehicle telematics or a cell phone. An AV is an autonomous vehicle that is assumed to use its onboard path planner plus any other external navigation aids to find the most efficient path.

[2] CADS is only designed to shut down major arterial roads at this time.

It is in this cluster where CADS includes unique capabilities to model the compliance of drivers, which can widely vary by developer, nationality, individual user and even whether there are other people in the car (26-28). Because these factors can significantly affect overall outcomes and can be difficult to model in other driving simulations, they are included in CADS through two different compliance variables: 1) CTV compliance rates and 2) TV modifications. As seen in Fig. 4, users can select what percentages of users will comply with their mapping rerouting recommendations, as well as which percentage of TVs will modify their original routes based on digital sign messaging.

Lastly in Fig. 4, users can input how many digital signs are under investigations, where they are located, and also how long it takes to get a message to display a sign. This time could be short, as in the case of a message that originates from a command center, but also long to represent the length of time it would take to deploy a mobile sign in the case of a major crash or other significant event.

Users can introduce an accident

Users can insert connected & autonomous vehicles, plus different traffic levels

Users can place & schedule digital messaging

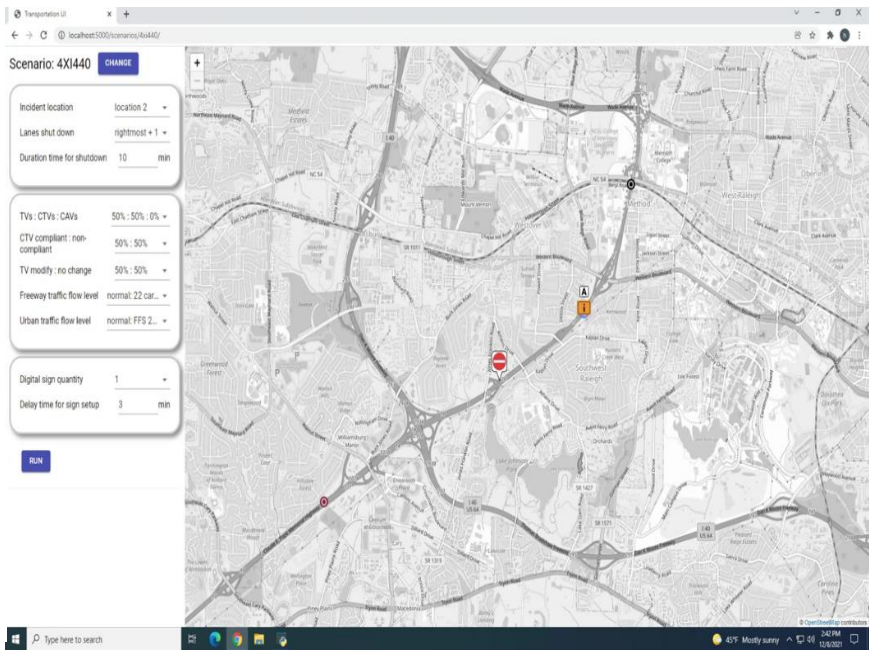


Figure 4: CADS Input Screen

Once all the data in entered in Fig. 4, users select run, which then generates a similar output to that in Fig. 5. The upper left block in Fig. 5 simply restates the input conditions. The middle upper block indicates how many cars of the various types made it through a run and the associated delays for the vehicle types. The graph on the far upper right indicates over the time of an event, how the delay times changed for the baseline case, i.e., no rerouting and no route modifications due to a digital message sign. This information is important to determine how delay times compared to those vehicles rerouted.

In keeping with the industry standard to offer up three possible alternate routes, CADS also shows three possible new alternate routes, along with the average delays experienced on each of these routes as well as the percentage of cars that took each route. The delays times over the course of the accident event are depicted as well so they can be compared to the baseline.

One of the most unique capabilities of CADS is its ability to show the impact of rerouting on vulnerable populations, explicitly on schools, hospitals and fire stations. As seen in Fig. 6, areas of high congestion will automatically be highlighted in CADS for any of the alternative routes within approximately 1000m of a school, hospital or fire station (both the type of vulnerable site and the distance can be modified within the code.)

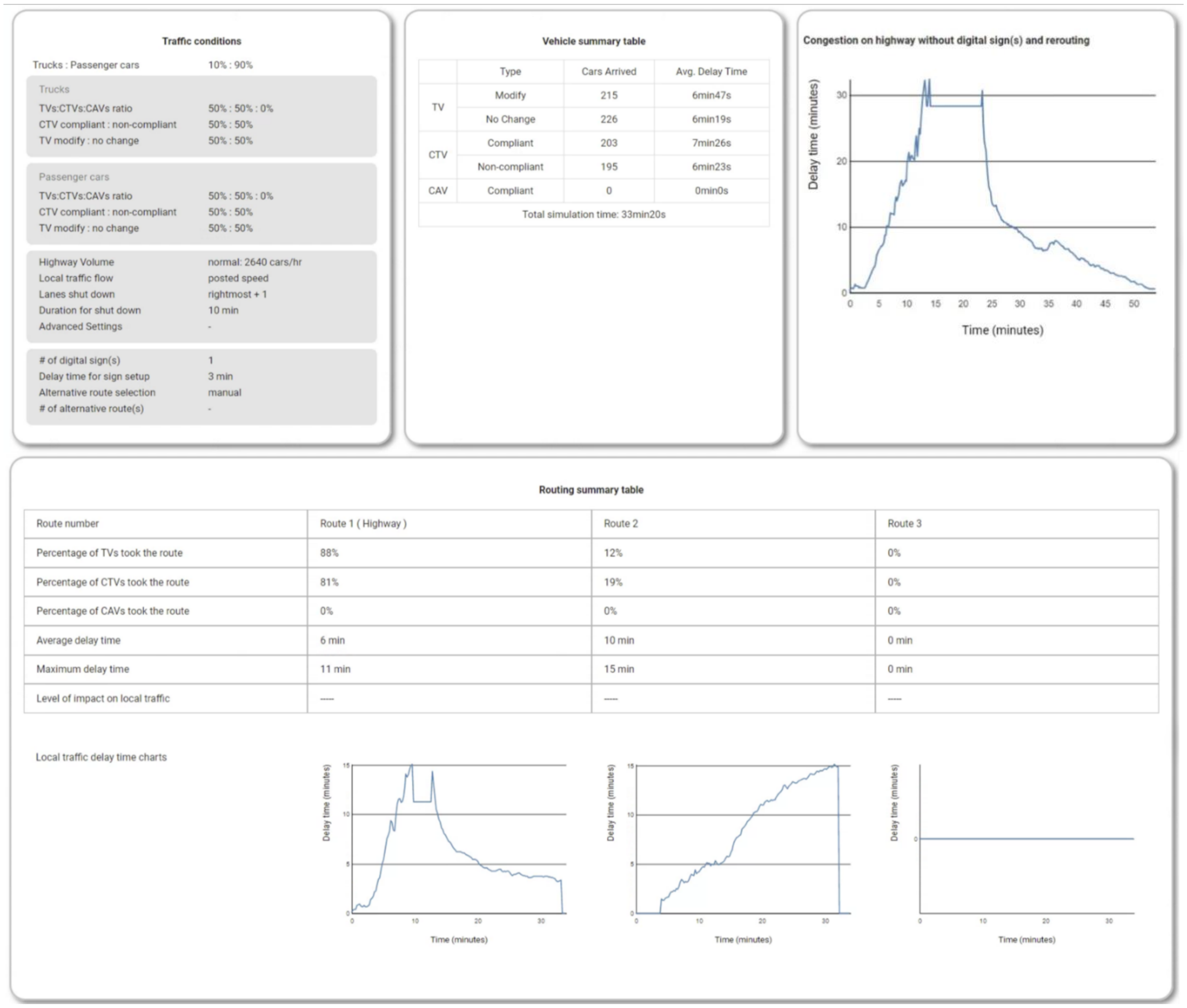


Figure 5: CADS Output Screen

This capability is critical because it would allow transportation planners the ability to see how either planned construction or areas with high accident rates affect local communities, particularly in the presence of large portions of the driving populations using some kind of path planning decision aids, including futuristic AVs. Such a tool would also allow planner to determine if and how the addition of digital messaging signs could help to alleviate such congestion (or even make it worse).

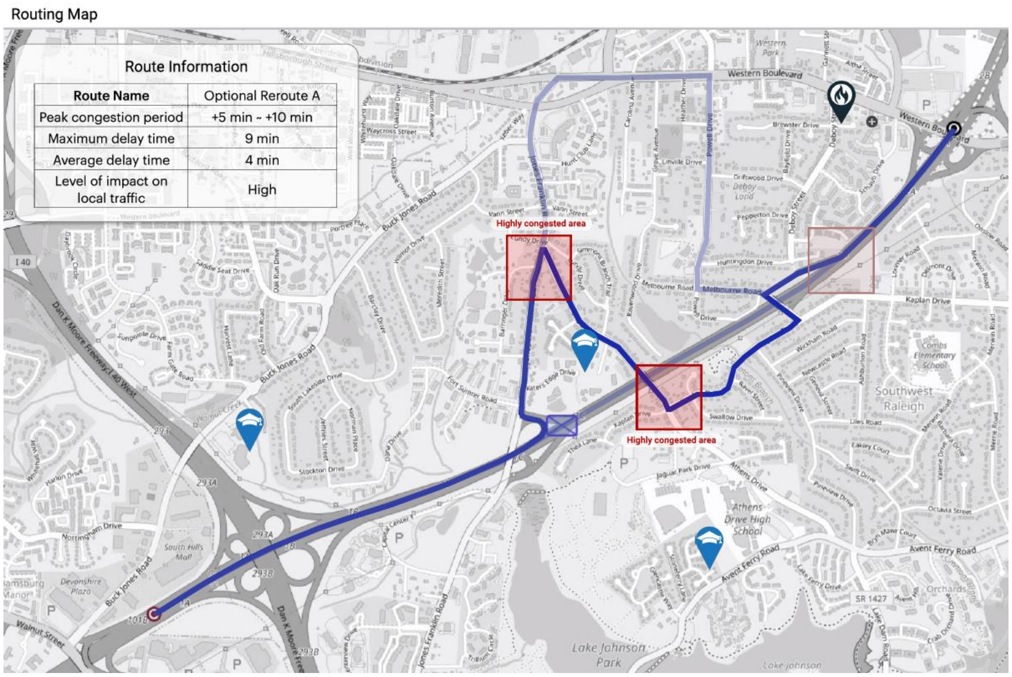


Figure 6: Highlighted areas of congestion in CADS

More details about how CADS works, the computations and assumptions underlying the simulation, and a tutorial that includes practice scenarios are included in Appendix A.

EXAMPLE RESULT

To demonstrate one possible application of CADS[3], take the case of a crash near the intersection of I-40 and I-440 heading east under the following conditions:

- Highway Volume: normal (4290 cars/hour)
- Three lanes are shut down due to an accident.
- The accident is cleared after 30 minutes
- 10% of traffic consists of trucks, and the for the remain 90%, half are TVs and the other half are CVs (base case).
- Connected TVs compliance with app recommendations for rerouting 50% of the time.
- A digital messaging sign is available 3 miles from the accident site, warning vehicles of a major accident, but it takes 10 minutes from the actual crash to the sign communicating the message
- 30 simulation runs were conducted for each experimental condition.

The first question we asked was how would autonomous vehicle market saturation affect delays times? As mentioned previously, researchers have asserted that the introduction of AVs could make delay times shorter as well as longer, so CADS simulations could provide useful predictions that account for the

[3] There are several other examples in the tutorial in Appendix B.

constraints of a specific environment. Figure 7 illustrates the average delay times for the different classes of vehicles, with the control case of 0% AV saturation, as well 25% and 50% saturation.

CADS predicts that indeed, the introduction of AVs could decrease the overall delays, but curiously, the traditional compliant and noncompliant vehicles, as well as the connected non-compliant vehicles had almost a minute less delay, on average. Moreover, the most dramatic reduction in delay times was with the introduction of 25% AVs, suggesting that there may be a plateau effect beyond that percentage, i.e., a larger AV market saturation beyond 25% may not have significant effect in reducing delay times due to crashes.

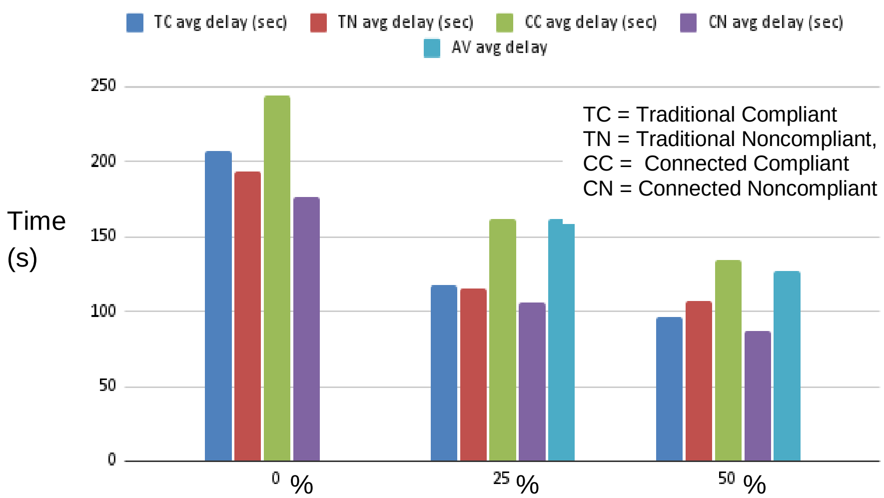


Figure 7: Delay Times per Level of Insertion of Autonomous Vehicles (AVs).

What this means is that in this specific case (a large accident that clears relatively quickly), the introduction of AVs assumed to be perfectly compliant to rerouting recommendations, created some delay by rerouting (in concert with those connected cars that also elected to reroute). Cars that did not reroute experienced, on average, about a 1-minute shorter delay than those that did. While this is just one example, it demonstrates that under some conditions, the use of AVs could be beneficial to reducing congestion times for everyone, but that traditional vehicles and connected vehicles who ignore recommendations for rerouting may stand to benefit the most.

USER STUDY

Dispatchers from the North Carolina Turnpike Authority (NCTA) were asked to use and provide feedback about CADS through a method called “cognitive walkthroughs (CW)”. In a CW, a moderator sits with a user (in the case of CADS, these were done virtually due to COVID19), and shows them how to use an interface and then gets feedback in real time as the user completes various tasks. For CADS, we executed both real time CWs but because of the shift nature of NCTA work, we also solicited asynchronous feedback from dispatchers. Figure 8 illustrates one set of asynchronous comments received from one of the dispatchers.

Overall, the feedback was positive, in that the dispatchers found the tool very usable and helpful in terms of planning. Several CADS changes were made as a result of the NCTA feedback including cosmetic changes, the insertion of trucks, updated car following and lane change models and the development of additional scenarios.

While feedback was overwhelmingly positive, the NCTA reviewers flagged the issue that the tool did not really support their current work flows and they were not sure how they could integrate it in the future. This is not unexpected feedback since the tool was really designed for strategic planning (on the order of months and weeks) and tactical planning on the scale of hours (Fig. 3). For example, CADS is meant to be used to plan possible alternate routes in advance of a strong storm that is forecasted to flood a road, either weeks or even hours before the arrival of a storm. Due to the inability of CADS to represent real-time traffic data, it would not accurately reflect the environment to be useful on the timescale of minutes, which represents the bulk of work for the current dispatcher population.

So, while the dispatchers see the utility of such a tool, they could not imagine when and how they would use it for planning (or even in training). We offered up the tool to NCDOT transportation planners, but were not able to generate any interest for cognitive walkthrough sessions. These issues will be further discussed in the Findings section.

- my questions:
  - - [x] traditional signs aren't easy to move around
  - - [x] digital signs would need to be implemented by navigation provider
  - - [x] explain about the simulation model underneath: micro? meso? macro?
    - - [x] how is O-D assignment handled? where are generated vehicle entering the sim?; using SUMO; specify start and end point when they are generate
    - - [x] are the traffic flow dynamics realistic? especially the jam density
    - - [x] the lane changing behavior? If the vehicles are trapped in the closed lane, won't this cause unrealistically large delays for some? Un-natural distribution of delays vs real-world traffic where motorists will mostly be able to merge over; how about zipper merge behavior? Can that be another model parameter?: Tianxin: assumed cooperative drivers
  - - [x] what is the local traffic flow?
  - - [ ] in visualization: suggestion: for the vehicle icons: better to choose icons that show the vehicle's direction
  - - [ ] the user has to hard code the alternate route. But might the alternate route also be variable depending on the conditions?
  - - [ ] p.22 the delay time series chart looks funny: no peak -- bat ears -- what happened?
  - - [ ] if the vehicles can see the jam ahead, won't TVs even reroute

Figure 8: Asynchronous Feedback from an NCTA Dispatcher

Traffic Conflict Analysis of Autonomous and Traditional Vehicle Platoons in Field Tests via Surrogate Safety Measures

Introduction

Highway safety is a critical concern for traffic systems around the globe. Although roadways are designed to minimize the number of crashes, the National Highway Traffic Safety Administration (NHSTA) reported that from January to September 2021, an estimated 31,720 individuals died in motor vehicle traffic crashes (1). In the coming decades, fully automated vehicles (AVs) are expected to become a reality (29). Litman predicts that by 2030, fifteen percent of the fleet on the road will be AVs with at least some lateral and longitudinal control automation (30), with the caveat that near hundred percent fleet of AVs in the streets is not likely to materialize before 2080. Thus, in the future, the vehicle fleet will likely be a mixture of autonomous and human-driven or traditional vehicles (TVs).

The majority of AV safety studies in mixed traffic are simulation-based (e.g., (31-33)) . Most of this simulation-based research is quite optimistic about the increased safety that AVs will bring to mixed traffic. Nevertheless, simulation-based studies work on some strict set of rules and algorithms, sometimes ignoring real-world stochasticity (34). Therefore, given the scarcity of AVs on highways, the safety enhancement by AVs is yet to be verified in real-world mixed traffic conditions.

We define a mixed traffic condition where the traffic stream contains a mixture of different vehicle types such as connected automated vehicles (CAVs), AVs, connected vehicles (CVs), and Traditional Vehicles (TVs). The fundamental difference among the vehicles mentioned above is presence of connectivity and autonomy. TVs are vehicles with no connectivity and autonomy. CVs have vehicle-to-vehicle (V2V) and/or vehicle to infrastructure (V2I) connectivity but lack autonomy. AVs lack connectivity but have autonomy, and CAVs have both connectivity and autonomy.

Regarding traffic safety assessment, historical crash counts have been traditionally used to assess roadway safety but such an approach is inefficient since (a) roadway crashes are random and rare events requiring a large sample size and (b) the approach is reactive and not anticipatory (35). Because of the paucity of AV exposure in the traffic stream in the near future, and due to the lack of sufficient observational crash data for those vehicles, researchers have shifted focus to using traffic conflict studies either in a simulation environment or with the limited open-source empirical datasets available.

A traffic conflict in this context is defined as an observable evasive action taken by a driver to avoid a collision with another vehicle (36, 37). Although a traffic conflict and a crash are not the same, it is theoretically possible to estimate crash frequency based on traffic conflict measurements (38, 39). To this effect, surrogate safety measures (SSMs) are widely used metrics that use pairwise velocity and spacing attributes derived from vehicular trajectories to flag or report a traffic interaction as a conflict (40). SSMs assume that the closer vehicles are to each other in terms of temporal or spatial proximity metrics, the nearer they are to a potential collision (14).

This study used real-world SAE level 2 AV trajectory data to conduct the traffic conflict study via SSMs. The AVs were adaptive cruise control (ACC) equipped and operated in mixed traffic, controlled experimental environments that included TVs. The ACC-equipped vehicles were classified as level 2 due to their ability to automatically maintain longitudinal and/or lateral control of the vehicle under the constant supervision of the driver (41-43). ACC control relies on sensor information from onboard sensors to automatically correct vehicle speed to maintain a safe distance from vehicles ahead (44). As the ACC system controls the longitudinal movement of the vehicles automatically, we used ACC-equipped vehicles to represent AVs' longitudinal behavior.

This study conducted the traffic conflict analysis first on three multi-vehicle platoons using the ACC-equipped SAE level 2 real-world mixed traffic trajectory database called OpenACC (41). Later, we conducted traffic conflict analysis on four two-vehicle platoons to get more information about the impact of different car-following scenarios on mixed traffic safety. This study addresses the following two research questions

1. Do AV-exclusive platoons experience fewer longitudinal traffic conflicts compared to TV-exclusive platoons and mixed AV-TV platoons?
2. Does the introduction of AVs decrease longitudinal traffic conflicts in two-vehicle platoons comprising AV and TV mixed leaders and followers?

The section of the report is organized in the following manner. Following this introductory section, we provide a review of the relevant literature, followed by the methodology section. Results and related discussions are then presented.

Previous work

This section provides an overview of the SSMs used in AV studies.

SSMs Used in Mixed Traffic Assessment: The primary assumption underlying the use of SSMs is that if one can detect high-risk, safety-critical situations that occur considerably more frequently than crashes, then it would be possible to detect unsafe traffic conditions without the need for waiting for historical crash data (40). Therefore, the main idea is to establish several potential conflict types arising from temporal or spatial proximity under the assumption that the closer vehicles are to each other, the nearer they are to a collision (45). SSMs used for mixed traffic conflict assessment fall into three categories:

1. Temporal proximity SSMs: Temporal proximity SSMs are the most used SSMs for mixed traffic safety assessments. These SSMs reflect the time remaining to an imminent collision. They assume that the interacting vehicles will continue their current speed and path within the considered time interval (45). Thus, temporal proximity SSMs cannot report conflicts where a collision course between vehicle pairs does not exist (46).
2. Spatial proximity SSMs: The distance available to avoid a collision is the main element for conflict reporting in this category. The distance covered by the vehicles depends on their initial speed and the response time (RT) of the following driver. The ability of a driver to maneuver according to the RT and stop or decelerate within the available distance determines whether a potential crash will happen or not (31). Among spatial proximity SSMs, time integral difference between space distance and stopping distance (TIDSS) and Difference between space distance and stopping distance (DSS) are used for mixed traffic safety assessments comprising AVs.
3. Combined SSMs: SSMs that cannot categorize into any of the previous classes and combinations of multiple classes (45) or uses different domain knowledge to report traffic conflict are labeled as combined SSMs. Driving Volatility (DV) is the most used SSM for mixed traffic safety assessments comprising AVs under this category. Most researchers use the standard deviation of speed (47), speed coefficient of variation (31) and the number of jerks (33) to represent DV.

SAFETY ASSESSMENT OF AVS IN MIXED TRAFFIC

Many studies on AV safety imply that a high market penetration rate (MPR) of AVs will reduce traffic conflicts. For example, Deluka Tibljaš, Giuffrè, Surdonja and Trubia (48) found that at 100% AV MPR, lane-changing conflicts disappear and rear-end conflicts decrease by 60% for a simulated roundabout in VISSIM using the Surrogate Safety Assessment Metric. Similarly, Morando, Tian, Truong and Vu (49) found that a 100 percent AV MPR reduced the number of conflicts by 65%, where the base condition was 100 percent TVs for a signalized intersection and a roundabout, both of which had varying AV MPRs.

In a similar vein, Mousavi, Osman, Lord, Dixon and Dadashova (33) used VISSIM to simulate mixed traffic consisting of AVs and TVs at an unsignalized intersection under different levels of traffic densities and AV MPR. The authors used TTC and DV to assess mixed traffic safety. They found that at all density values, increasing the AV MPR up to 100% yielded a reduction in the number of rear-end conflicts and lane-changing conflicts by 84% to 100% and 42% to 100%, respectively. The authors also found that higher AV MPR significantly reduced the DV measures.

Tu*, et al.* (50) Qin, He and Ran (51) and Yao, Hu, Jiang and Xu (47) investigated the safety implications of CAVs losing V2V connectivity with nearby CAVs when the preceding vehicle is a TV, resulting in AVs. The three studies found that when the CAVs degenerate into AVs due to communication failure, the safety risk of mixed traffic increases significantly. The instability of AVs operating in the platoon significantly contributed to the increased safety risk. Tu*, et al.* (50) further found that CAV degradation to AV had a considerable negative impact on the longitudinal safety of mixed traffic during decelerating driving conditions.

The impacts of low AV MPR on mixed traffic safety are inconsistent in the literature. For example, Arvin, Khattak, Kamrani and Rio-Torres (31) applied the micro-simulation platform SUMO at a four-legged intersection. The authors used a Time-to-Collision (TTC) threshold of 0.5 s and DV of two standard deviations from the mean speed and found that until AV MPR reaches 40%, the introduction of AVs caused an increase in DV and traffic conflicts. On the other hand, Richter et al. (52) concluded that traffic conflicts are not likely to increase at low AV MPR (about 10%), irrespective of traffic demands. Their research simulated a mixed traffic scenario comprising CVs, AVs, and TVs for a two-lane directional freeway segment using SUMO.

Mahdinia et al., (53) studied the impacts of AVs and CAVs using real-world data collected by Park et al. (54) in two platooning scenarios: (a) CAV followed by four AVs (hybrid platoon) and (b) a five CAV platoon. The results showed that the exclusive CAV platoon reduced volatility by 13.6% to 29% compared with the hybrid platoon. Furthermore, they found that the hybrid platoon exhibited a higher crash propensity compared to the CAV platoon. The authors further concluded that the absence of V2V communication among AVs increased the speed difference between the two following vehicles and, as a result, increased traffic conflicts.

Most studies evaluating AVs' safety impact on mixed traffic were simulation-based due to a lack of real-world data. All AVs are typically defined with similar vehicular characteristics in the simulation. For example, Tu et al. (50) simulated AVs using a ACC car-following model based on only Nissan vehicles (55). Therefore, the calibrated ACC car-following parameters was unrealistic as it ignored the heterogeneity in vehicular characteristics due to different manufacturers. The OpenACC dataset used in this study uses commercially available ACC-equipped vehicles of different manufacturers. Therefore, this study considers the heterogeneity in vehicular characteristics due to different manufacturers that resemble real-world conditions.

Among many studies investigating AV safety, Mahdinia et al. (53) employed field data via the CARMA dataset (54), which provides data for platooning experiments involving ACC and cooperative adaptive cruise control (CACC) vehicles. However, the study did not include any TVs in its experiments, which ignores the likely mix of AVs and TVs, especially in the near future This study aims at filling that gap using real-world mixed traffic trajectories comprising AVs and TVs. In addition to multi-vehicle platoons, this study also tests the impact of AVs at the car-following level by testing two-vehicle platoons with mixed leaders and followers.

Study methodology

The methodology carried out in this paper includes:

- Definitions of the selected SSMs used for the longitudinal traffic conflict analysis
- Description of the dataset extracted from the openACC platform and experiments aimed at addressing the two posited research questions, and
- Description of the method used for hypothesis testing.

SELECTED SURROGATE SAFETY MEASURES (SSMS)

Each SSM has its own definition and measurement methodology. Therefore, the use of a single SSM represents only a portion of traffic events. As a result, traffic conflicts reported by a single SSM may not accurately reflect the overall safety of the investigated locations, resulting in a biased traffic conflict evaluation (56). In addition to conflict frequency reporting, it is also necessary to record the severity of the traffic conflicts. Consequently, to get the complete safety condition, the authors selected multiple SSMs from temporal, spatial and combined SSM classes to report the extent and severity of traffic conflicts. SSMs within the scope of this analysis are shown in Fig. 9. See Appendix B1 for definitions and equations.

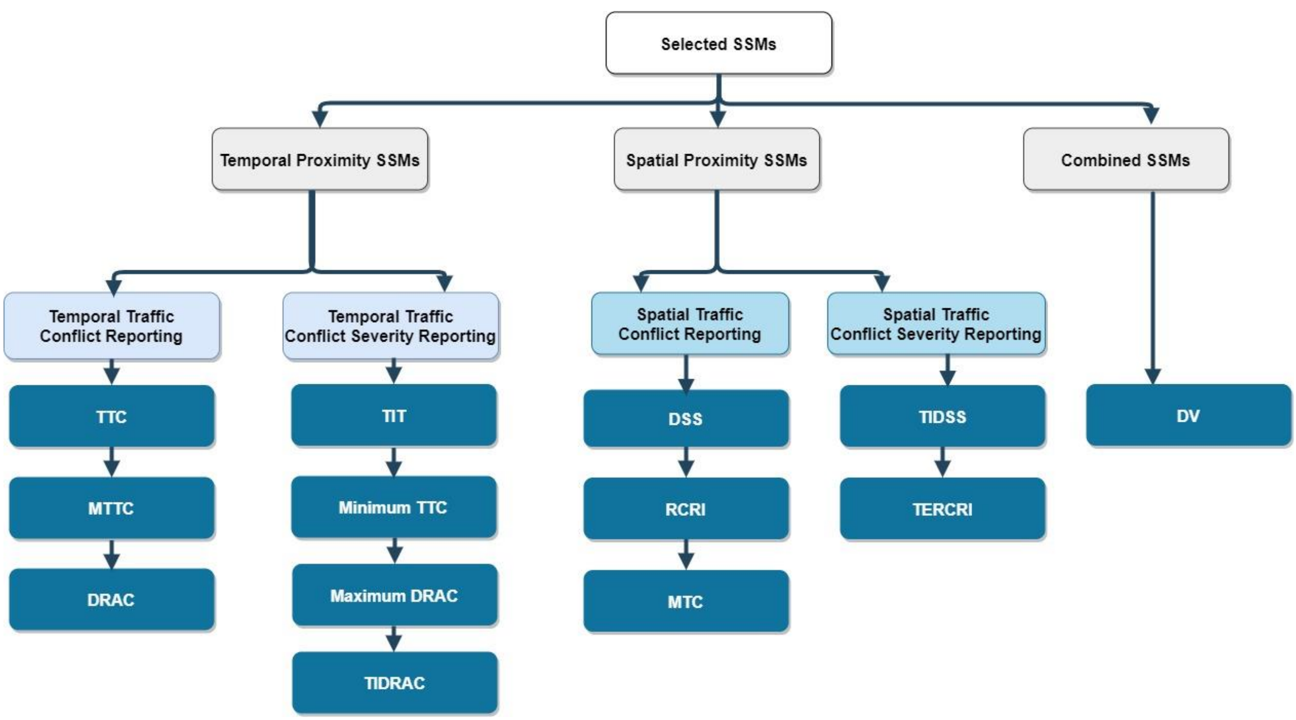


Figure 9: Selected surrogate safety measures for this study. See Appendix B1 for definitions.

DESCRIPTION OF THE DATASET

We used the OpenACC dataset, which includes a set of experimental car-following campaigns using test tracks and real-world highways (41). ACC-equipped vehicles are seen as a proxy for future AVs (57-59) and SAE level 2 car-following characteristics are considered the baseline for SAE level 5 AV car-following characteristics (41, 60, 61). SAE level 5 cars are those that can drive themselves with no requirement for human oversight (43). Therefore, we used ACC-equipped vehicles to mimic the longitudinal behavior of AVs.

Among several test sites available in OpenACC, this study used a dataset collected at Ispra-Vicolungo, Italy. This campaign occurred in the first quarter of 2019. It involved three days of car-following testing from Ispra (VA) to Vicolungo (NO) and back in Northern Italy. The testing was performed with TVs and ACC-equipped vehicles of different makes and models driving in platoon formation. Tests were scheduled for non-peak hours to minimize the disturbances from other road users. The platoon leader was instructed to perform occasional random decelerations and accelerations over the desired speed in a realistic manner (42). While driving in ACC mode, the followers used the shortest time gap setting to avoid cut-in situations from other users. Besides, no-overtaking was performed. There are twelve tests in the Ispra-Vicolungo dataset, each with a different time length. Among them, six tests were chosen for this study based on the availability of the requisite data and the similarity of the speed profile of the lead vehicles.

The six tests comprise one hour and three minutes of driving, covering a length of 80.61 km. We have provided a detailed description of the vehicles involved, and test sites in Appendix B2. For more information about the data collection procedure, see (41).

We chose three multi-vehicle platoons for this study:

1. Exclusive TV Platoon, a four-vehicle TV platoon
2. Exclusive AV platoon: a four-vehicle AV platoon
3. Mixed platoon: a mixed platoon with three AVs and two TVs

The exclusive TV platoon was considered as the base scenario. To determine the impact of different car-following scenarios on mixed traffic safety, four two-vehicle platoons were chosen:

1. 1. A TV following a TV (TV-TV)
2. 2. An AV following a TV (TV-AV)
3. 3. A TV following an AV (AV-TV)
4. 4. An AV following an AV (AV-AV).

The following vehicular properties were extracted: (a) speed profile, (b) time gap distribution with other vehicles, (c) acceleration profile, (d) relative speed vs. lead vehicle, (e) relative distance vs. lead vehicle, and (f) inter-vehicular spacing. All data were reported at a resolution of 10 Hz. Figure 10 shows the experimental setup.

DATA SCREENING

To be confident that the three multi-vehicle platoons depicted in Fig. 11a and four two-vehicle platoons depicted in Fig. 11b can be compared in terms selected SSMs, the following vehicle(s) should be subjected to the same level of speed and acceleration variation generated by the lead vehicle.

First, we compared the speed of the lead vehicle across all platoons. The speed profile (first 374.6 s of the experiments) of the three platoon leaders is shown in Fig. 12a. Figure 12b shows a box and whisker plot of the platoon leader speed distribution. The leader mean speeds were 29.79, 30.19 and 28.63 m/s for the exclusive TV, exclusive AV and mixed platoon, respectively. The corresponding speed standard deviations were 4.31, 3.43 and 4.47 m/s, respectively.

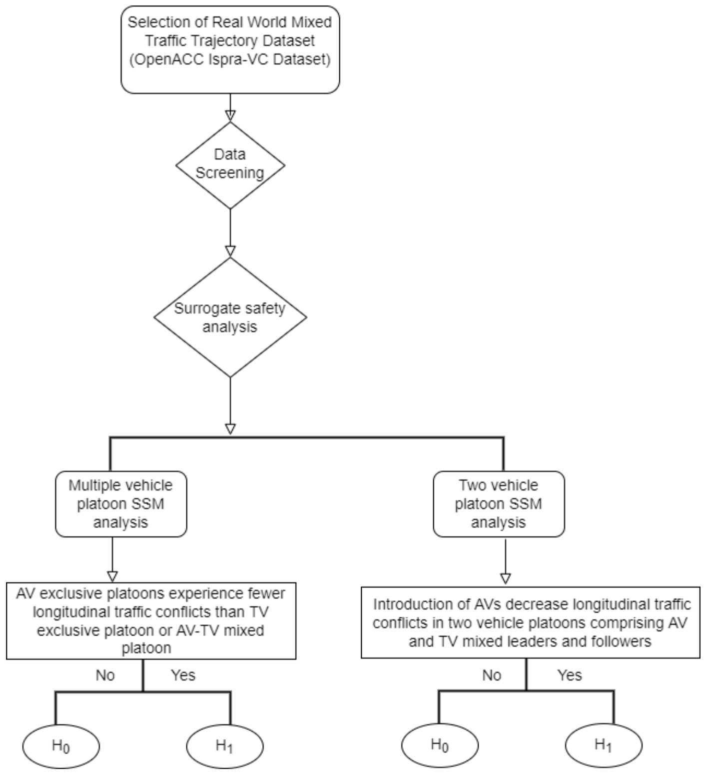
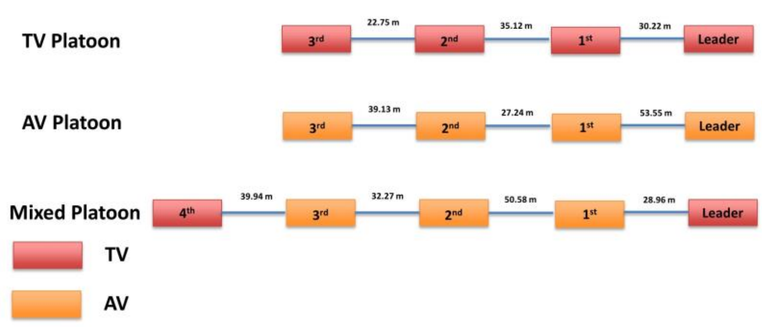
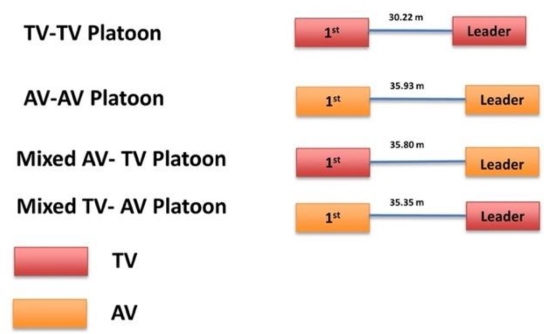


Figure 10: Experimental Setup



(a): Inter vehicular spacings at the start of experiment for multi-vehicle platoons

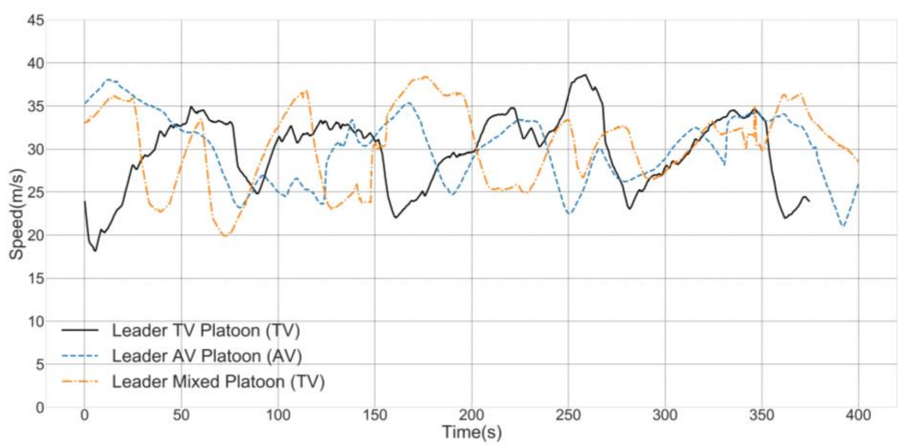


(b): Inter-vehicular spacings at the start of experiment for two-vehicle platoons

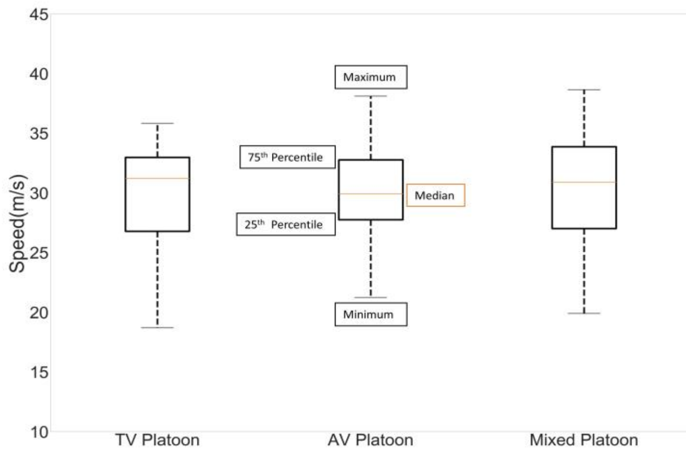
Figure 11: Initial inter-vehicular spacings (IVSs) in Test Platoons

Three K-S two-sample tests showed that the null hypothesis that all three platoon leaders had similar speed distributions could not be rejected at the 95% confidence level. The results of K-S tests for both multi-vehicle and two vehicle platoons are given in Appendix B3. Furthermore, the acceleration noises (62) of the leading vehicle for three-multi vehicle platoons are 0.53 m/s^2, 0.53 m/s^2 and 0.56 m/s^2 respectively. The acceleration noise and speed variations confirm that the following vehicles were under same level of acceleration and speed variations.

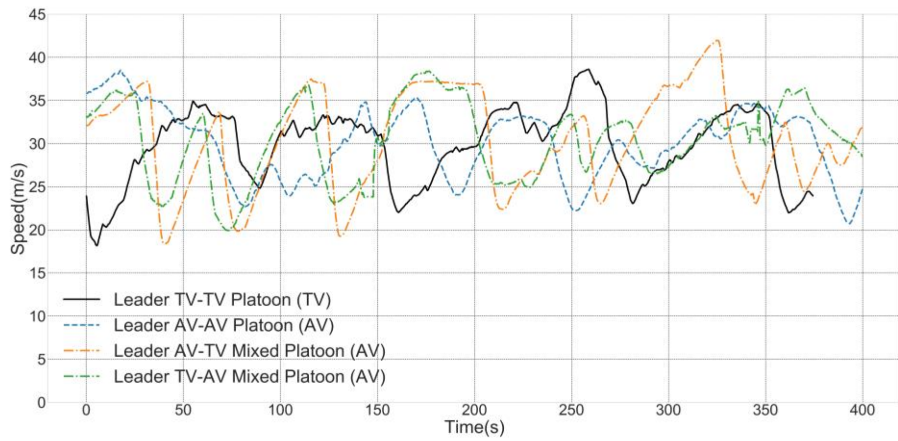
In addition, the initial inter-vehicular spacing (IVS) in the platoons was evaluated to ensure the similarity of initial conditions. Figure 11a shows the IVS of the vehicles in the multi-vehicle platoon at the start of the experiments. They indicate some spatial variations across platoons, with the initial mean spacing between vehicles estimated at 29.47, 39.97 and 37.93 meters for the exclusive TV, exclusive AV, and mixed platoons, respectively.



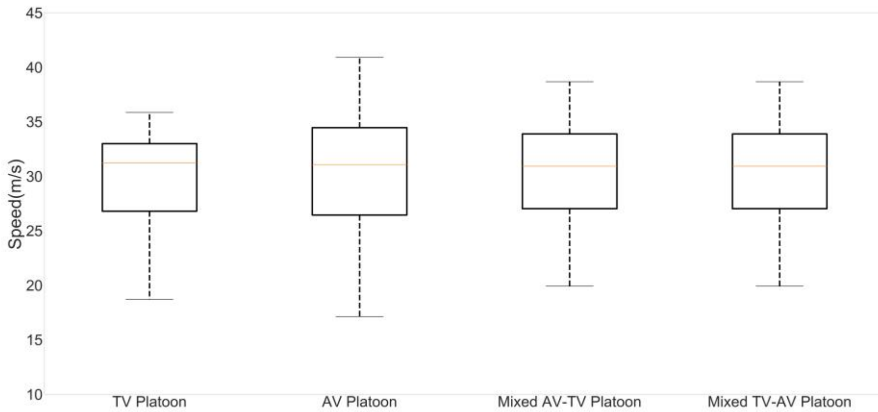
(a) Speed profiles of multi-vehicle platoon leaders



(b) Box and Whisker plot of the multi-vehicle platoon leaders speed distribution



(c) Speed profiles of two-vehicle platoon leaders



(d) Box and Whisker plot of the two-vehicle platoon leaders' speed distribution

Figure 12: Speed Characteristics of Platoon Leaders

Similar to multi-vehicle platoons, the first test compares the lead vehicle speed across platoons for two-vehicle platoons. The speed profile (first 374.6 s of the experiments) of the three platoon leaders is portrayed in Fig. 12a. Figure 12b shows a box and whisker plot of the platoon leader speed distribution. The leader mean speeds were 30.48, 30.55, 30.57 and 29.79 m/s for the TV-AV, AV-AV, AV-TV, and TV-TV platoons. The corresponding speed standard deviations were 4.24, 5.17, 5.39 and 4.11 m/s.

Furthermore, at the 95 percent confidence level, six K-S two-sample tests reveals that the null hypothesis that all four platoon leaders had similar speed distributions cannot be rejected. Furthermore, the acceleration noises for four-two vehicle platoons are 0.59 m/s^2, 0.52 m/s^2, 0.54 m/s^2 and 0.57 m/s^2 respectively. The acceleration noise and speed variations confirm that the following vehicles were under same level of acceleration and speed variations. In addition, the initial inter-vehicular spacing (IVS) in the platoons was evaluated to ensure the similarity of initial conditions. Figure 11b shows the IVS of the vehicles in the two-vehicle platoon at the start of the experiments.

Results and Discussion

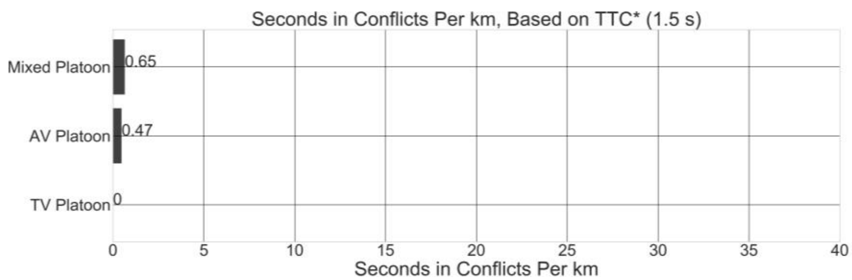
The results section covers two sub-sections. The first section evaluates the hypothesis that the introduction of AVs decreases longitudinal traffic conflicts in multi-vehicle platoons (whether present in an AV-exclusive or mixed AV-TV platoon). The next section addressed the second research question, namely whether the introduction of AVs decreases longitudinal traffic conflicts in *two-vehicle platoons* comprising AV and TV mixed leaders and followers.

MULTI-VEHICLE PLATOON SSM FINDINGS

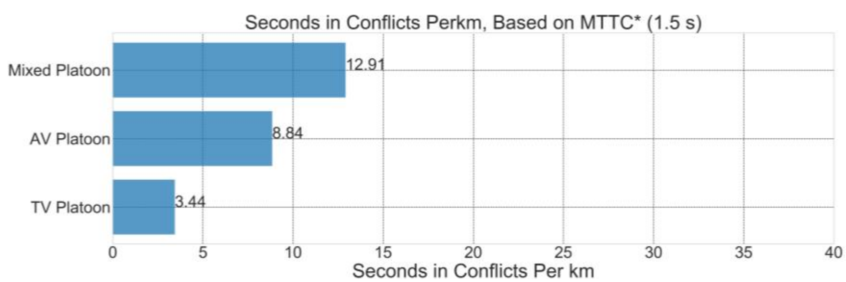
Figure 13 depicts the duration in traffic conflict per km as reported by the selected temporal and spatial SSMs for the different multi vehicle platoons. For example, Fig. 13b shows that the duration in conflict per km of travel for a mixed platoon using Modified Time to Collision (MTTC) is 12.91 s, based on an MTTC threshold of 1.5s. Figure 13 shows that the exclusive TV platoon reports the smallest, where's, the mixed platoon reports the highest duration in longitudinal conflicts per km, whether temporal (TTC, Deceleration Rate to Avoid Collision (DRAC) and MTTC) or spatial (Rear End Crash Index (RCRI), DSS and MTC) SSMs are employed. In addition, the duration per km in longitudinal traffic conflicts for the exclusive AV platoon are consistently higher than those reported for the exclusive TV platoon.

In summary, the multi-vehicle platoon analysis shows that the introduction of AVs in mixed traffic platoons with TVs does not appear to reduce the number of longitudinal traffic conflicts. The other and somewhat concerning observation in Fig. 13 is the obvious large disparity in conflict rate reporting across all SSMs. Using the mixed platoon example, the choice of SSM will generate a wide range of conflict rates. This varied from a low value of 0.65 sec/km using TTC* of 1.5 s all the way to over 38.48 sec/km should one select RCRI as the SSM.

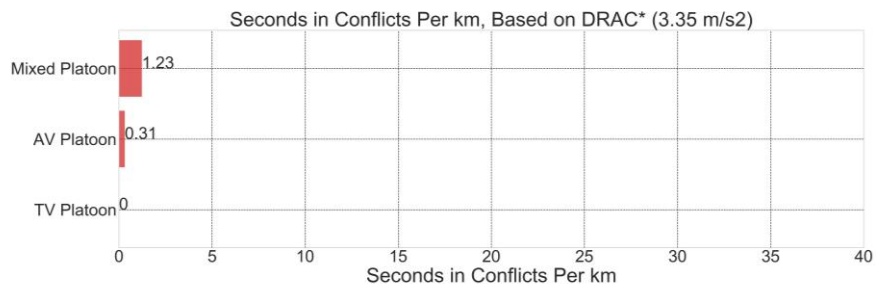
What Fig. 13 does not show is how much, if any, overlap exists between those time periods where a conflict is reported by several SSMs. An analyst has higher confidence in those conflict periods where multiple SSMs simultaneously exceed their threshold values.



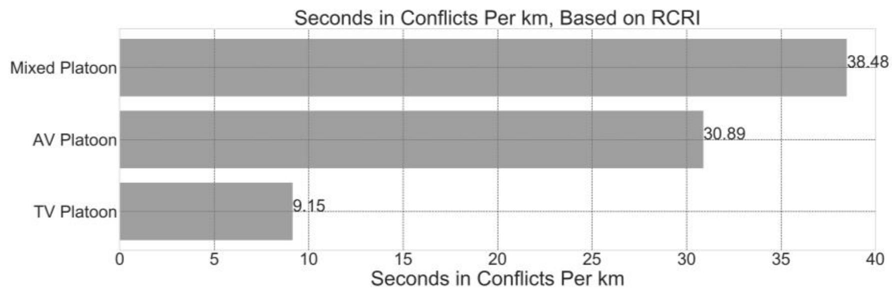
(a)Traffic conflict reporting based on TTC



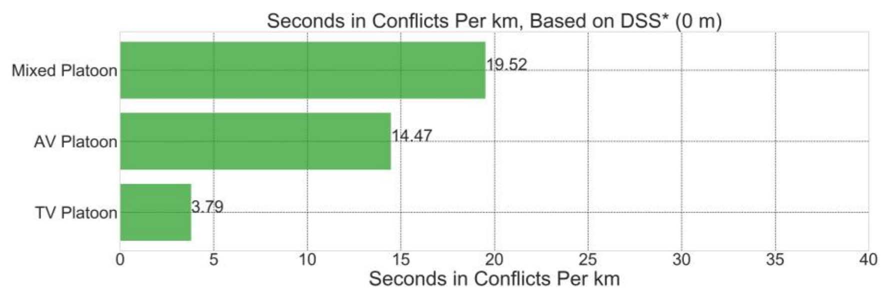
(b) Traffic conflict reporting based on MTTC



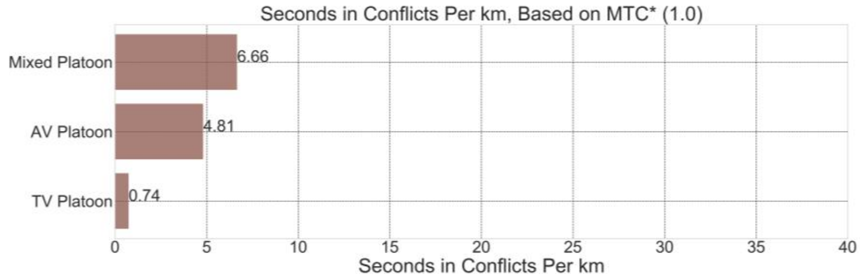
(c) Traffic conflict reporting based on DRAC



(d) Traffic conflict reporting based on RCRI



(e) Traffic conflict reporting based on DSS



(f) Traffic conflict reporting based on MTC

Figure 13: Longitudinal traffic conflict rate reports by SSM and multi-vehicle platoon type

Next, we evaluated traffic conflict severity measures such as TIT (Time integrated time to collision.). Since low TTC values indicate greater traffic conflict severity, the larger the TIT value, the higher the severity of the traffic conflicts. In addition, other conflict severity measures such as TIDRAC (Time integrated DRAC) TIDSS (Time integrated DSS) and TERCRI (Time Exposed Rear End Crash Index) are also explored. Table 1 shows the conflict severity analysis. First, it is evident that the TV platoon has the highest TTC_{min} (3.34 s) and lowest $DRAC_{max}$ (0.618 m/s^2) among the three multi-vehicle platoons. Conversely, the mixed platoon has the lowest TTC_{min} (0.51 s) and highest $DRAC_{max}$ value (6.931 m/s^2). This pattern is further confirmed across all other temporal and spatial SSM measures shown in Table 1. Therefore, the results indicate that the exclusive TV platoon has the lowest and mixed platoon has the highest traffic conflict severity.

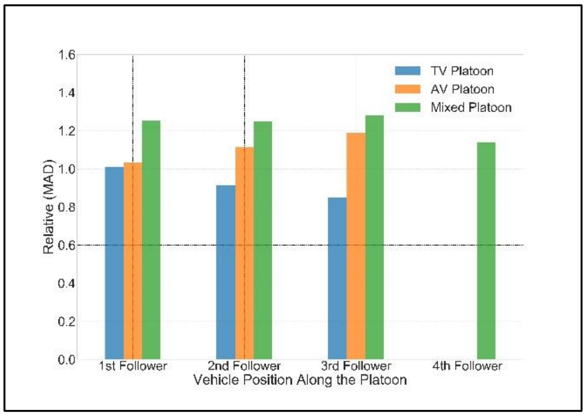
Table 1: Longitudinal traffic conflict severity analysis of the selected multi-vehicle platoons

SSM	TV Platoon	AV Platoon	Mixed Platoon
TIT/Km (s2/km)	0.00	0.01	0.18
TTCmin (s)	3.34	1.31	0.51
DRACmax (m/s2)	0.62	3.55	6.93
TIDRAC/Km (m/s/km)	0.00	0.06	0.17
TERCRI/Km (s/km)	0.93	3.09	3.85
TIDSS/Km (m-s/km)	2.75	4.81	29.20

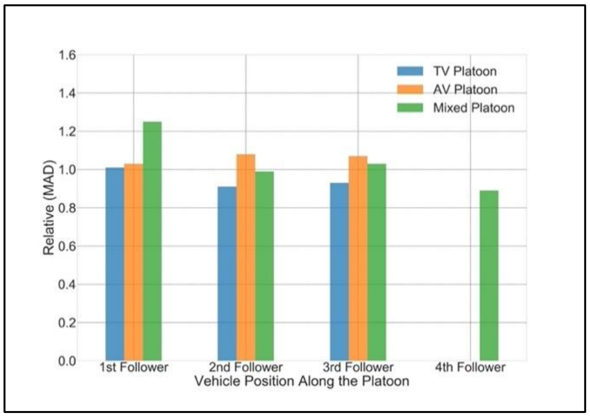
TTC*=1.5 s; DRAC*=3.40 m/s^2; DSS*=0 m

To further confirm the trends shown in Table 1, we analyzed the relative MAD trends across platoons. Note that a relative MAD value above 1 indicates that speed variations are amplified further upstream by following vehicles. Conversely, a value below 1.0 indicates that speed variations are successfully dampened within the platoon.

Figure 14a shows that the relative MAD of the TV platoon is either stable or decreasing for all three following vehicles compared to their platoon leader. The same trend is evident when the relative MAD is based on the immediate leader, according to Fig. 14b. Figure 14a shows that the relative MAD values exceed 1.0 for both the exclusive AV and mixed platoon compared to the platoon leader. MAD values of the mixed platoon mostly exceed a value of 1.2, meaning that the leader speed variations are amplified by about 20% by most following vehicles. The only exception is the last vehicle in the mixed platoon, which happens to be a TV. The same trends are evident when tracked against the immediate leader. Figure 14b shows that the higher MADs associate with the following AV. Therefore, the introduction of AVs in mixed traffic platoons increases speed volatility. The speed volatility increases with the increment in the following position of AVs. The increase in speed volatility also indicates AVs string instability, resulting in a higher likelihood of rear-end traffic conflicts.



(a): Relative MAD corresponding to platoon leader



(b): Relative MAD versus immediate leader

Figure 14: Multi-vehicle platoon speed volatility measures

TWO-VEHICLE PLATOONS SSM FINDINGS

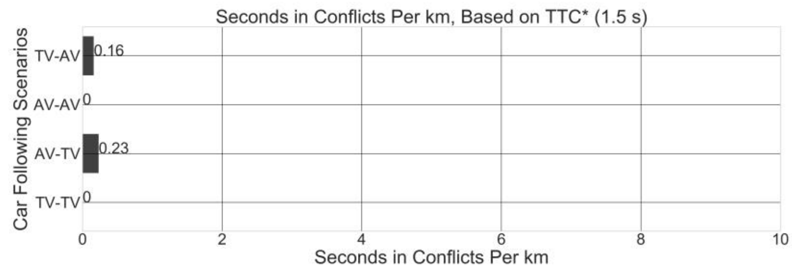
This section addresses the second research question, namely whether the introduction of AVs decreases longitudinal traffic conflicts in *two-vehicle platoons* comprising AV and TV mixed leaders and followers. The TV-TV car-following scenario was taken as the base scenario. Figure 15 shows the temporal and spatial traffic conflict reporting using selected SSMs for different car-following scenarios. Figure 15 (a-c) shows that as per TTC and DRAC in an AV-AV scenario or a TV-TV scenario, the duration in longitudinal traffic conflicts per km is less than the duration in longitudinal traffic conflicts per km for mixed AV-TV or TV -AV scenario.

However, as per MTTC, both AV following (AV-AV and TV-AV) scenarios show a higher duration in longitudinal traffic conflicts per km than AV-TV or TV-TV scenarios. Similar to TTC and DRAC analysis, MTTC shows that the TV-TV scenario reports the lowest number of traffic conflicts per km. From Fig. 15 (d-f), we see that in terms of spatial SSMs, the TV-TV and AV-AV scenario reports fewer seconds in longitudinal traffic conflicts per km than the seconds in longitudinal traffic conflicts per km reported for mixed AV-TV or TV-AV scenarios.

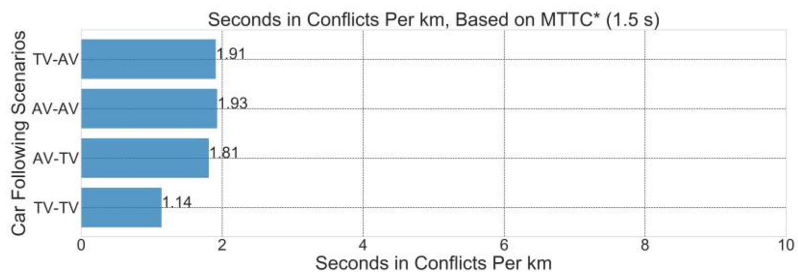
Table 2 shows the findings of the temporal and spatial traffic conflict severity analysis using selected SSMs for different car-following scenarios. The TV-AV shows the highest longitudinal conflict severity in terms of both temporal (TIT and TIDRAC) and spatial (TERCRI and TIDSS) conflict severity measures. In addition, a relatively lower TTC_{min} (0.3 s and 0.16 s for AV-TV and TV-AV scenario, respectively) and higher $DRAC_{max}$(3.44 m/s^2 and 4.88 m/s^2 for AV-TV and TV-AV scenario, respectively) indicates that both

AV-TV and TV-AV scenarios have high longitudinal traffic conflict severity compared to homogenous platoons (AV-AV, and TV-TV).

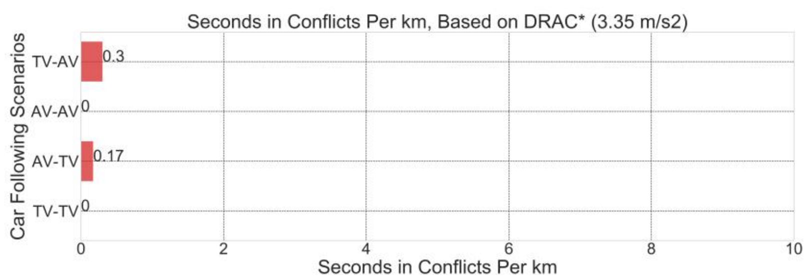
This low traffic conflict severity results for AV-AV and TV-TV scenario also gets boosted by low TIT, TERCRI, TIDRAC and TIDSS values (Table 2). Thus far, the SSM analysis of different car-following shows that the introduction of AVs in mixed traffic in the presence of TVs increases the number and severity of longitudinal traffic conflicts.



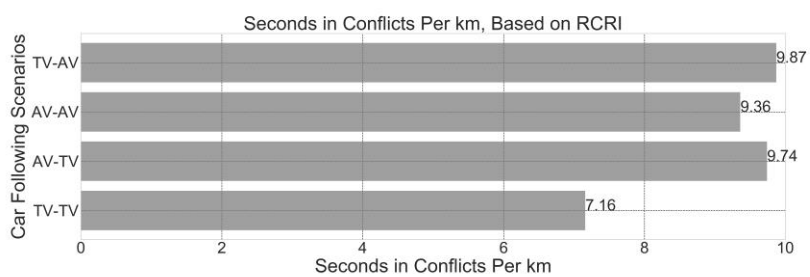
(a) Traffic conflict reporting based on TTC



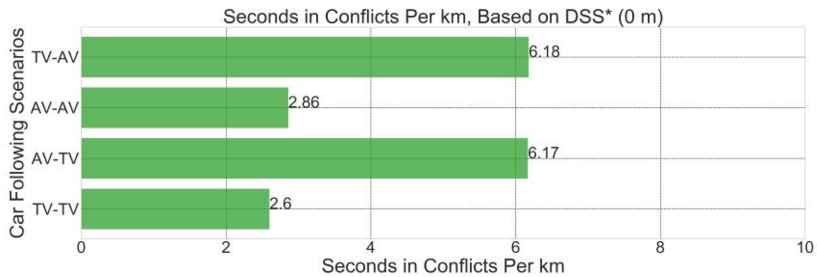
(b) Traffic conflict reporting based on MTTC



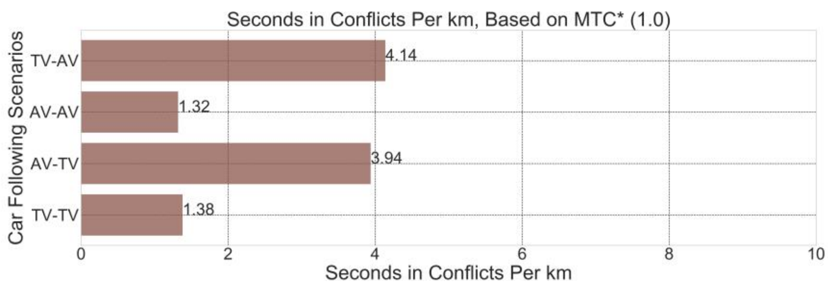
(c) Traffic conflict reporting based on DRAC



(d) Traffic conflict reporting based on RCRI



(e) Traffic conflict reporting based on DSS



(f) Traffic conflict reporting based on MTC

Figure 15: Longitudinal traffic conflict rate reports by SSM and two-vehicle platoon type

Table 2: Longitudinal traffic conflict severity analysis of the selected two-vehicle platoons

SSM	TV-TV	AV-AV	AV-TV	TV-AV
TIT/Km (s^2/km)	0	0	0.27	0.22
TTC_{min} (s)	3.55	3.56	0.30	0.16
$DRAC_{max}$ (m/s^2)	0.4	1.14	3.44	4.88
TIDRAC/km (m/s/km)	0	0	0.11	0.21
TERCRI/km (s/km)	1.15	1.51	1.57	1.59
TIDSS/Km (m-s/km)	11.16	77.15	114.09	123.86

TTC*=1.5 s; DRAC*=3.40 m/s^2; DSS*=0 m

Based on DRAC, the TV-AV scenario yields more seconds in conflict than the AV-TV scenario. In addition, as per MTTC we find AV-AV and TV-AV having greater number of traffic conflicts than AV-TV and TV-TV. Moreover, we find a relative speed volatility value of 1.06 and 1.17 for AV-AV and TV-AV scenario respectively (Fig. 16), indicating an increase in speed volatility while AV is the follower. The time gap and acceleration profile deviation can also explain the increased relative volatility. For example, TV-AV scenario, the standard deviation in the time gap is 1.95 s, with a minimum time gap of 0.024 s and a maximum time gap of 6.73 s. In the TV-TV scenario, the standard deviation in the time gap is 0.40 s, with a minimum time gap of 0.22 s and a maximum time gap of 1.97 s.

Similarly, for the TV-AV scenario, the standard deviation in acceleration (0.66 m/s^2) is greater than in acceleration (0.56 m/s^2) for TV-TV. The less deviation in time gap and acceleration profile indicates that the TV-TV scenario had smoother traffic flow than TV-AV, resulting into a smaller number of traffic conflicts and severity. The increased traffic conflicts and traffic conflict severity for the TV-AV scenario are consistent with earlier multi-vehicle platoon analyses.

TV as a follower while following an AV (0.89) or following a TV (0.96) shows no increase of speed volatility. To find the reason behind that we have plotted a magnified speed vs. time plot for the selected car-following scenarios (Fig. 17). It shows that an AV has a greater time lag than a TV while following an AV or TV. To further confirm the hypothesis that AVs have a greater response time, we have estimated the response time of TV and AV for the four different car-following scenarios.

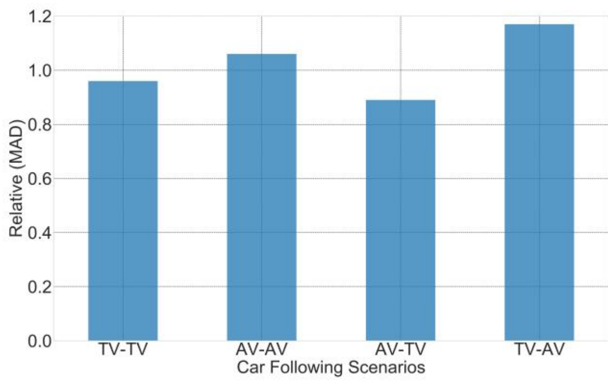
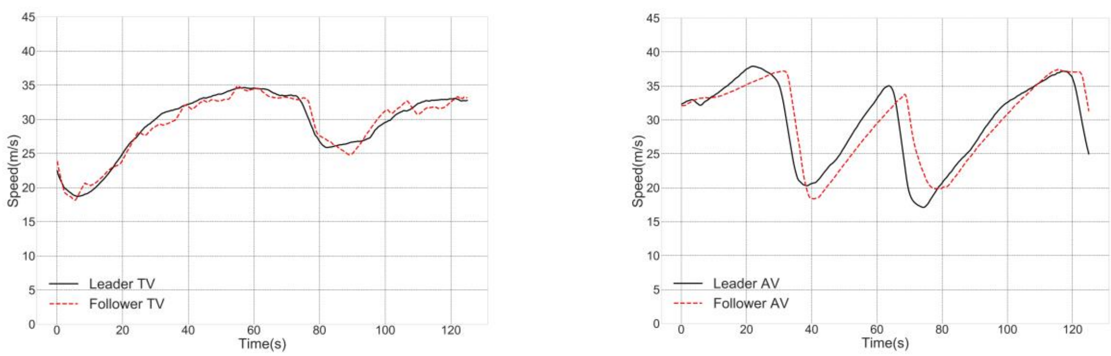
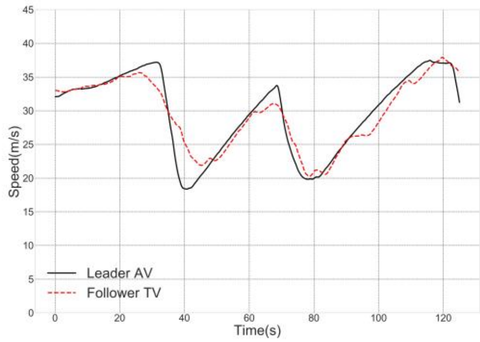


Figure 16: Two-Vehicle Platoon Speed Volatility Measures

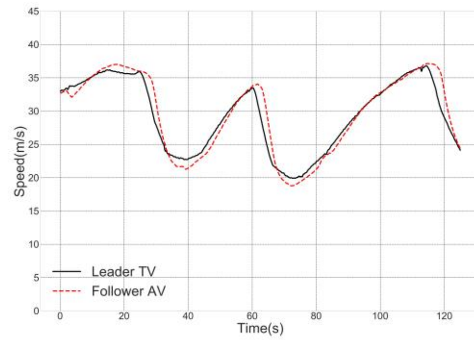


(a) Time Lag of TV Following a TV

(b) Time Lag of AV Following an AV



(c) Time Lag of TV Following an AV

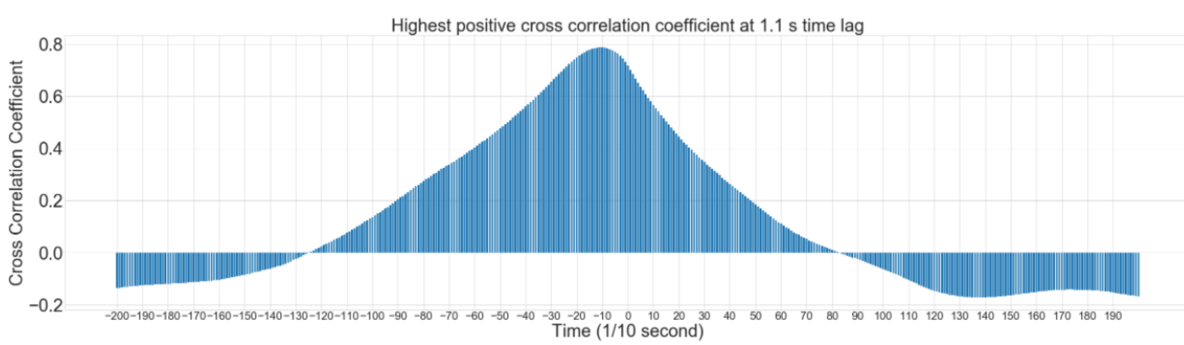


(d) Time Lag of AV Following a TV

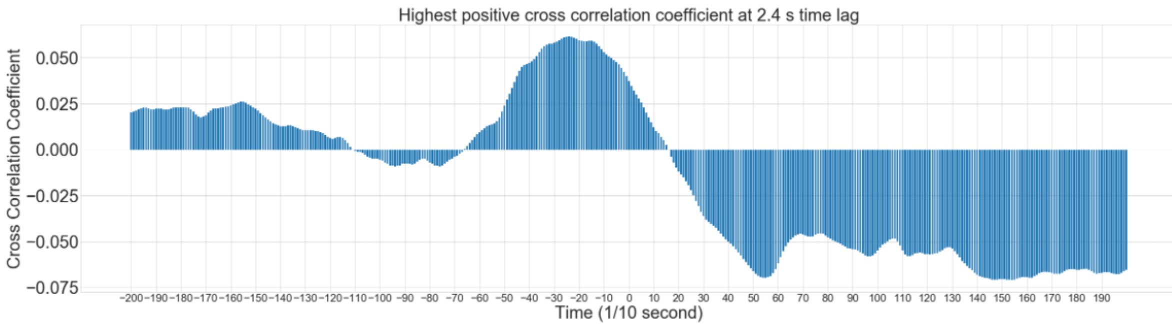
Figure 17: Leader Path and Follower Time Lag

Response time lag of the following vehicle

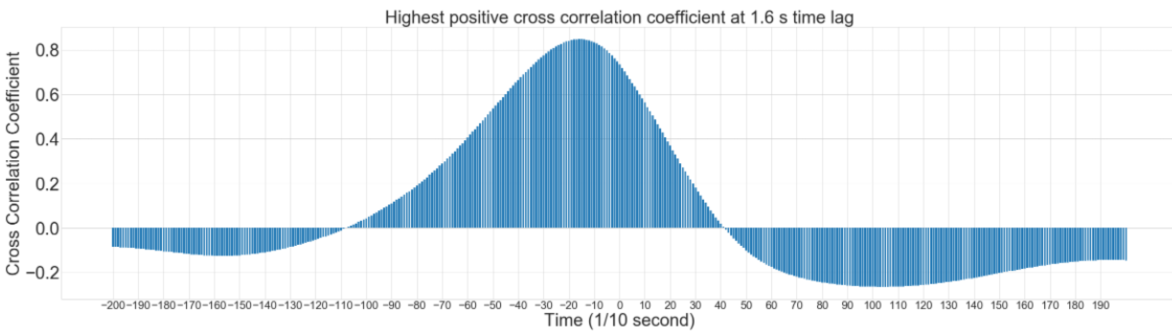
Figure 18 shows the cross-correlogram of the follower's RT in the different car-following scenarios. The cross-correlation coefficient is positive when the two time series depictions (response and stimulus) are in phase (i.e., peaks aligned with peaks). The lag value with the highest correlation coefficient represents the best fit between the two time series depictions. From Fig. 18a, it is evident that in the TV-TV car-following case, the response of the following vehicle best fit with the stimulus at 1.1 second time lag. Similarly, we have estimated the following vehicles' RT for all other scenarios. TVs show similar RT (1.1 s and 1.2 s) while following a TV and AV, respectively. However, AVs had a larger RT while following an AV (1.6 s) or a TV (2.4 s). Our findings are consistent with (41), who found that AVs have a longer time lag in response.



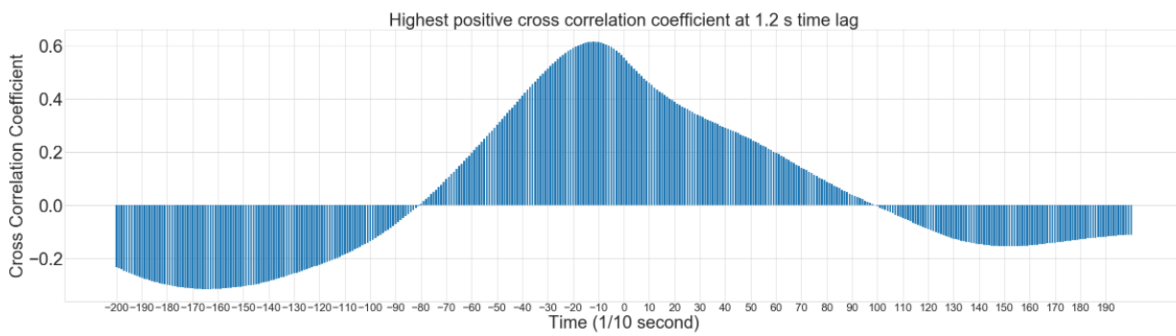
(a) TV-TV



(b) TV-AV



(c) AV-AV



(d) AV-TV

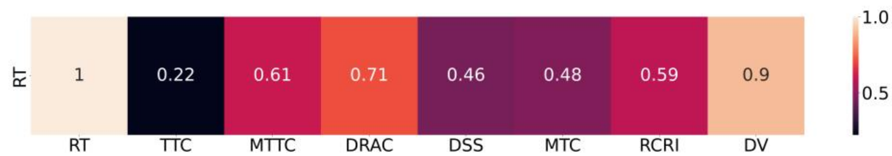
Figure 18: Cross-correlogram of Follower's Response Time

The analysis shows that TV drivers appear to anticipate the leading vehicle's maneuvers earlier, therefore, reacting fast and reducing the speed volatility. However, SAE level 2 AVs sense the front vehicle's maneuver with a larger delayed response than TVs resulting in greater traffic conflicts and increased speed volatility. To further confirm the hypothesis that AVs longer RT contributes to higher traffic conflicts and severity, we checked the correlation of RT with traffic conflict reporting and severity.

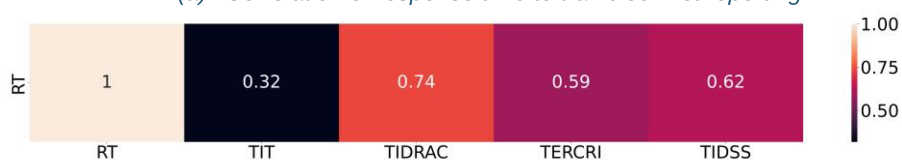
Impacts of response time lag on traffic conflict reporting and traffic conflict severity

Figure 19a shows that RT has a positive correlation with the duration of traffic conflicts per km when analyzed by different SSMs. Similarly, RT shows positive correlation with the traffic conflict severity analyzed by different SSMs (Fig. 19b). That means an increase in RT (of a following vehicle) increases the number of seconds per km in longitudinal traffic conflicts and traffic conflict severity. This positive correlation can be explained by our analysis where we have seen AVs having the longest RT while following a TV. As a result, the TV-AV scenario has the highest number of traffic conflicts according to MTC, RCRI, DSS and DRAC. In the same way, TV-AV scenario is showing the highest traffic conflict severity according to TTC_{min}, $DRAC_{max}$, TIDRAC, TERCRI and TIDSS.

The increased RT also affects the string stability. Though not checked in this study, Milanés and Shladover (55) found that when ACC-equipped vehicles drive in a string, the delay introduced by onboard sensors and the undershoot identified in the last braking maneuver are amplified. Therefore, the authors concluded that ACC-equipped AVs are string unstable. Furthermore, Ahmed et al. (63) showed that string instability significantly increases the risk of longitudinal crashes. Our findings indicate that SAE level 2 AVs have higher RT, primarily while operating in mixed traffic settings, indicating string instability. Therefore, the longitudinal traffic conflicts are intensified by string instability, supported by our analysis.



(a) Correlation of response time to traffic conflict reporting



(b) Correlation of response time to traffic conflict severity

Figure 19: Correlation of Response Time to Traffic Conflict Reporting and Severity

Additionally, we have conducted a sensitivity test to assess the impact of SSM threshold selection on the overall study findings. We did the sensitivity analysis of traffic conflict reporting based on three TTC and MTTC thresholds (1.0s, 1.5s and 2.0 s) and two DRAC thresholds (3.40 m/s^2 and 3.35 m/s^2). From the TTC or MTTC threshold definition, we can expect that the increase in the threshold will eventually lead to a rise in traffic conflict reporting. We found that for every 0.5 s increase in the threshold value, the approximate increase of seconds in conflicts per kilometer as per TTC and TIT/Km (s^2/km) is between 18 and 36 percent and 37 to 56 percent, respectively. Due to a 0.5 s rise in the threshold value, the seconds in conflicts per kilometer measured by MTTC increase by around 25 percent to 36 percent.

The sensitivity analysis of the TTC and MTTC threshold reveals that threshold selection does not affect the study's overall findings. For example, exclusive platoons and pairs of vehicles exhibit fewer longitudinal conflicts than mixed platoons and pairs in terms of different TTC and MTTC thresholds.

Similarly, from the definition of the DRAC threshold, it is expected that the decrease in the DRAC threshold will increase the number of traffic conflict reporting. As expected, we found the percent increase in seconds in conflicts per km as per DRAC and TIDRAC/km (m/s/km) due to change in DRAC threshold from 3.40 m/s^2 to 3.35 m/s^2 ranges from 3 percent to 17 percent. Similarly, the DRAC threshold sensitivity analysis does not alter the overall findings of the study, where the exclusive platoons and pairs of vehicles still exhibit fewer longitudinal traffic conflicts.

Conclusion

The introduction of AVs on the road comes with the expectation that they will enhance traffic safety. Most of the studies that have assessed the impacts of AVs on traffic safety have done this primarily either in simulation or analytical modeling environments. However, a verdict regarding the level of safety improvement by introducing AVs based on real-world data and field experiments of mixed AVs and traditional vehicles (TVs) is lacking. Moreover, the absence of real-world exposure of AVs in the traffic stream over extended periods precludes the use of crash data currently. Therefore, there is a need for additional empirical evidence concerning the impacts of AVs on traffic safety prior to broad-scale deployment. By applying SSMs to a real-world AV trajectory database, this study addresses this research gap.

The analysis is enabled via an open-source, large-scale experiments with vehicle trajectories obtained through field testing (OpenACC). In addition, this study also considers the manufactural heterogeneity mostly ignored in previous field research. Our analysis finds that an exclusive AV platoon does not generate greater longitudinal conflicts than a TV-exclusive platoon using a Time to collision (TTC) threshold of 1.5 s and a Deceleration Rate to Avoid Collision (DRAC) threshold of 3.35 m/s^2. We conclude that an exclusive AV platoon performs well in terms of longitudinal traffic conflicts. However, AVs operating in a mixed platoon show an increase in longitudinal conflicts. In mixed platoons when an AV follows a TV, we note a greater number of longitudinal conflicts than when a TV follows an AV scenario under near-identical initial following conditions. In general, platoons and pairs of vehicles exclusive to one or the other vehicle class generally exhibit fewer longitudinal conflicts than platoons or vehicle pairs having a mixture of AVs and TVs.

This study also finds that when operating in mixed traffic as a following vehicle, AVs had a longer response time, which could lead to string instability. The relative MAD study confirms that as the platoon's length increases, so does the magnitude of this instability. This has a major impact on the amount of traffic conflicts and the severity of those conflicts. There are a few limitations of the study that must be acknowledged. The study was restricted to SAE level 2 ACC-equipped vehicles that had no lane changing information. Thus, traffic conflicts introduced by improper lane changes were not investigated. Furthermore, the results were limited to a restricted set of settings (e.g., short time gap settings for AVs) and field tests (e.g., no disturbance from surrounding vehicles such as cut in, tests were scheduled for non-peak hours) in particular scenarios. Finally, the response time analysis was also limited to the linear Gasiz-Herman-Rothery (GHR) traffic model.

A Real-World Assessment of Key Autonomous Vehicle Based Car Following Models

Introduction

As discussed in the previous section, Adaptive Cruise Control (ACC) car-following is routinely used to predict the impact of autonomous vehicles (AVs) on traffic mobility and safety (61). Despite the extent of this research, the functional design of ACC car-following used by different manufacturers is still unclear to the research community, as industrial intellectual property laws protect it, and few attempts have been made to reverse engineer it (34).

The dearth of experimental efforts focused on ACC-AVs makes it challenging to comprehend the level of connection in the execution logic used by different manufacturers or existing in different vehicle models. However, few small-scale car-following experiments offer a path for understanding ACC in-vehicle technologies and longitudinal response of ACC-AVs. For example, Gunter et al. (64) conducted a car-following experiment with eight ACC-AVs operating in a platoon to observe their response characteristics. This data is publicly available.

Another publicly available dataset is OpenACC collected by the European Commission Joint Research Centre. This database aggregates vehicular data of different car-following experiments involving 28 vehicles, 22 of which were equipped with commercial ACC systems (41). The main objective of that experiment was to engage the whole scientific community towards a better understanding of the properties of ACC-AVs to anticipate their possible impacts on traffic flow and prevent potential problems in their widespread introduction. Experiments were carried out in the framework of four test campaigns (two highways and two testbeds), designed to study ACC vehicle dynamics in real-world conditions.

As part of the California Path project, Milanes and Shladover (55) conducted experimental tests employing up to four ACC-equipped Nissan vehicles. Their objective was to compare the performance of three different car-following; 1) ACC car-following, 2) IDM car-following, and 3) Cooperative-ACC (CACC) car-following. The experiment was conducted in a controlled environment with two vehicles in a car-following mode. Their resulting model was later modified by Xiao et al. (65), but dataset from their work is not publicly available.

Knoop et al. experimented with seven platooning SAE level-2 ACC-AVs on public roads in the Netherlands but again, this dataset is not publicly available (66). In addition, a few small-scale ACC-equipped vehicle experiments have taken place (67, 68) but have not released their dataset. With the exception of the work by Milanes and Shladover (55), none of these other efforts resulted in ACC models.

Background

The operational and safety impacts of commercial ACC-AVs have been mainly addressed through simulation studies. However, simulation-based results are often influenced by factors such as assumptions of the model built, models' layout, precision measurement techniques, calibration and validation process, data used for calibration and validation and so forth. Widely-used intelligent driving models (IDMs) for modelling ACC-equipped AVs include Kesting et al. (69), Milanés and Shladover (55) and Wiedemann 99 (70).

The Intelligent Driving Model (IDM) is a time-continuous single regime car-following model that balances two different objectives: the necessity to keep safe separation from the vehicle in front and the desire to achieve free-flow speed. Likewise, in any car-following model, the idea within the IDM is that users can control their vehicles in order to react to the stimulus from leading vehicles. Researchers often chose to use the IDM to simulate AVs because all IDM parameters are interpretable and empirically measurable (69). Another IDM variant was created by Manolis et al., (71), who then used that modified model to simulate ACC-AVs mixed with TVs.

As mentioned earlier, another commonly-used ACC model was developed by Milans and Shladover (55) and Xiao, et. al. (65). It uses four regimes, including (a) a speed control mode when the distance between vehicle pairs does not impact their desired speed, (b) a gap control mode when the following vehicles' maneuvers are governed by the leading vehicle motion and the following vehicle tries to maintain a constant gap with leading vehicle (c) a gap closing mode when the gap between moving leading and following vehicle decreases and (d) an approaching mode when the following vehicle is approaching a stopped or slowing leading vehicle.

In addition to IDM and ACC models, another commonly-used model is the Wiedemann 99 and Wiedemann 74 models (72-74). However, neither model was initially developed to characterize the response of ACC-AVs. In PTV VISSIM 11, connected vehicles (CVs) were added because the driving behavior models of CVs were calibrated and validated using real-world CV data in the CoEXist project, which is a European Union’s Horizon 2020 funded project (75). Though the CoExist project did not use AVs to calibrate and validate the Wiedemann models, the project proposed a list of parameter values for AVs that can be used to model AV car-following. Beyond the IDM, ACC and Wiedemann, researchers have developed customized but publicly inaccessible models, to simulate the behavior of ACC-equipped vehicles (76-78).

Traffic micro-simulation platforms have used the above-mentioned car-following models to simulate real-world AV operations. For example, VISSIM uses Wiedemann 99 and Wiedemann 74 for simulating AVs (79). Another popular micro-simulation platform, SUMO, allows the users to pick either ACC, IDM or Wiedemann 99 models to simulate AVs (17).

Research Objectives

As mentioned earlier, the paucity of real-world AV trajectory datasets has forced many researchers to rely heavily on simulation models to draw safety and operational inferences. In fact, the majority of the studies mentioned in the previous section do not address any potential discrepancies between observed and car-following modeled AV data. This research therefore addresses two major research questions to fill that gap, using the three widely-used ACC car following models namely IDM, ACC and Wiedemann 99 (W99):

1. Is there a significant discrepancy between observed and car-following modeled AV data?
2. What factors, if any, contribute to these discrepancies?

Following this section, we describe the study methodology. Results and related discussions are presented before concluding with key findings.

Methodology

In this study, we modeled the follower trajectory of an ACC-AV based on a lead human-driven traditional vehicle (TV) trajectory using three widely used car-following models (IDM, ACC, and W99). We then compared the modeled trajectories with the corresponding field-observed AV trajectories from the OpenACC database (41) to evaluate to what extent each model matches the car-following track of the real-world AVs. Details of the dataset are given in the next section. The workflow used for this study is depicted in Fig. 20. It begins with the selection of real-world TV-AV pairs.

The first TV-AV platoon comprised a lead Mitsubishi Space Start vehicle driven manually, followed by a Ford S-Max driven in ACC mode. The second TV-AV platoon comprised a Fiat (Model: 500 X) driving manually while Ford (Model: S-Max) driving with ACC turned on. A python script was created to implement the car-following models. Finally, we compared the modeled follower trajectories with real-world AV trajectories in terms of speed profile, vehicle position over time and acceleration profiles.

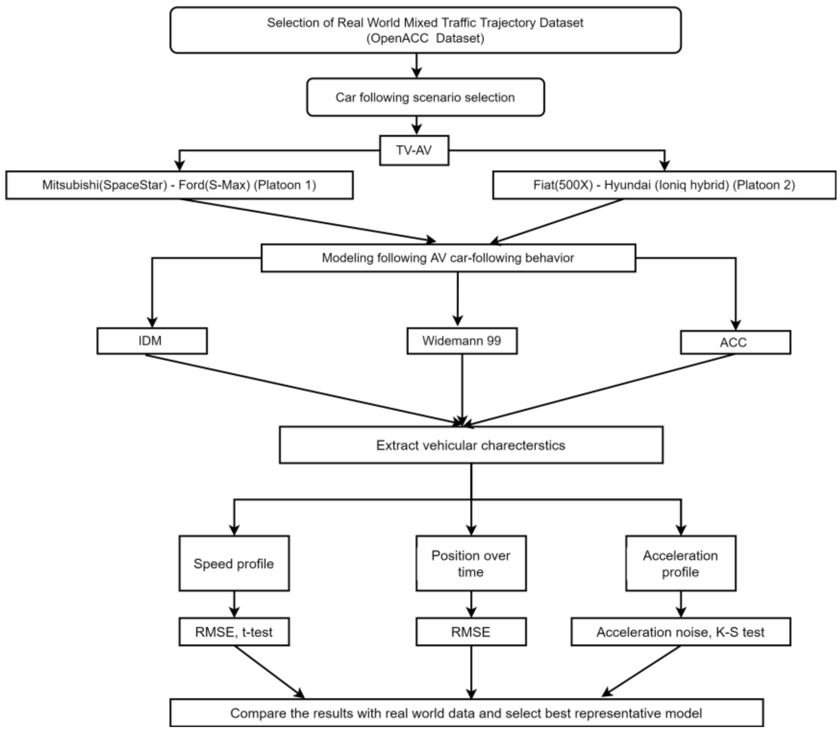


Figure 20: Study workflow

DATA DESCRIPTION

This study uses the OpenACC dataset, also used in the previous section. It includes a set of experimental car-following experiments using test tracks and real-world highways providing an overview of commercial ACC-AVs' longitudinal performance under different driving conditions (41) Among several test sites available in OpenACC, this study used two datasets collected at the Vicolungo and Cherasco, Italy.

The two tests comprise around 22 minutes of driving, covering a combined 44.51 km. The AVs drove with the minimum distance setting indicating that AVs followed the TVs with the minimum inter-vehicular spacing possible. Testing was performed with a mix of one TVs and one ACC-AVs of different makes and models driving in a two-vehicle platoon formation. The driver of the TV (platoon leader's driver) was instructed to perform occasional random decelerations and accelerations over the desired speed in a realistic manner. We selected ACC-AVs of different makes to assess whether the results may be impacted by the OEM settings. For more information about the data collection procedure, see (41).

PERFORMANCE METRICS FOR MODEL ASSESSMENT

Our study's objective was to investigate the capability of the three widely-used ACC car following models (IDM, ACC and Wiedemann 99 (W99), detailed in Appendix C) in representing the movement of AVs from a longitudinal control perspective. To characterize the differences between observations and models, we used four metrics:

1. Normalized Root Mean Square Error (NRMSE)
2. Mann-Whitney U (MHU) test
3. Normalized acceleration noise
4. Kolmogorov–Smirnov (K-S) test

RMSE measures the difference between observed and modeled values, whereas NRMSE calculates the difference between observed and modeled values while considering different data ranges. We calculated NRMSE by dividing the RMSE by the standard deviation of the observed data. The difference in observed and predicted speed and location over time was calculated using NRMSE. Furthermore, we used NRMSE to test whether the selected car-following models can predict transition periods or not.

We define transition periods when a vehicle exerts high acceleration just after high deceleration or high deceleration to high acceleration. If the NRMSE value is less than 0.3, then we can say that the model predicts the observed values well (80). The nonparametric equivalent of the two-sample t-test is the Mann-Whitney U test (81). While the t-test assumes population distribution, the Mann-Whitney U Test does not. We used the Mann-Whitney U test to determine whether the discrepancies between observed and modeled AVs' speed and location over time were significant or not. Normalized acceleration noise was also checked, as in the Safety Surrogate Section, to find whether the acceleration profiles of observed and modeled AVs were similar or not.

Results and Discussion

In this section, we present the three car-following modeled AVs' speed, acceleration profile, and complete trajectory. We then compare those with their OpenACC counterparts to assess the ability of the tested models to represent actual AV car-following response.

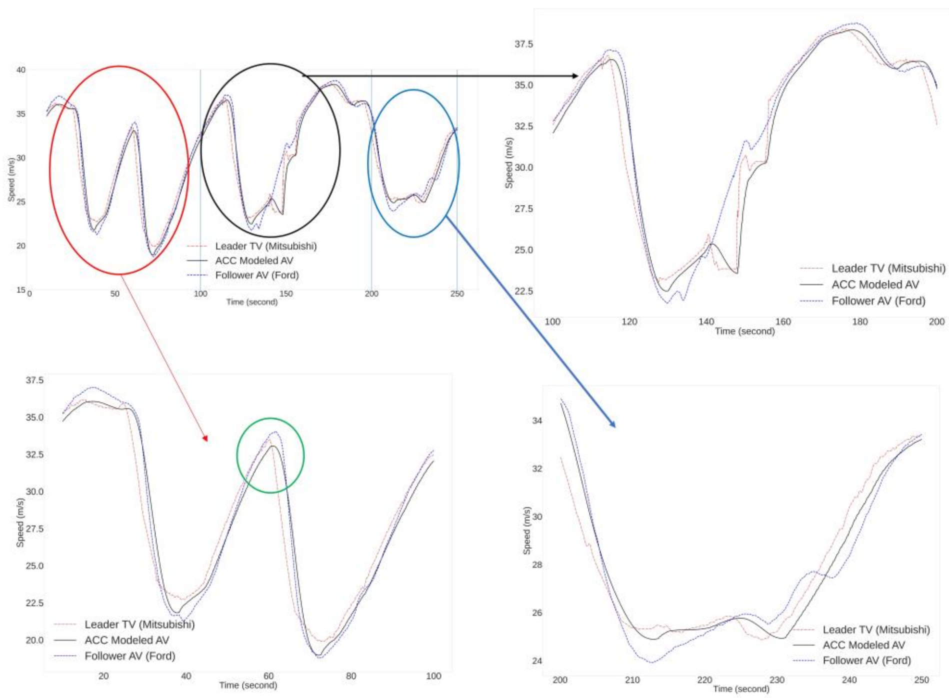
SPEED PROFILES OBSERVATION FOR SELECTED CAR-FOLLOWING MODELS

Figures 21-23 show the ACC, IDM and W99 modeled and real-world AV speed profiles along with their TV leader for platoon one and two, respectively. For each of the figures, the top left quadrant shows the full trip set of trajectories; other quadrants highlight speed details in the sub-trip portions. The red and blue dotted lines represent the speed profiles of the real-world TV and AV, respectively, while the solid black line represents the speed profile of the modeled (ACC, IDM and W99) AV.

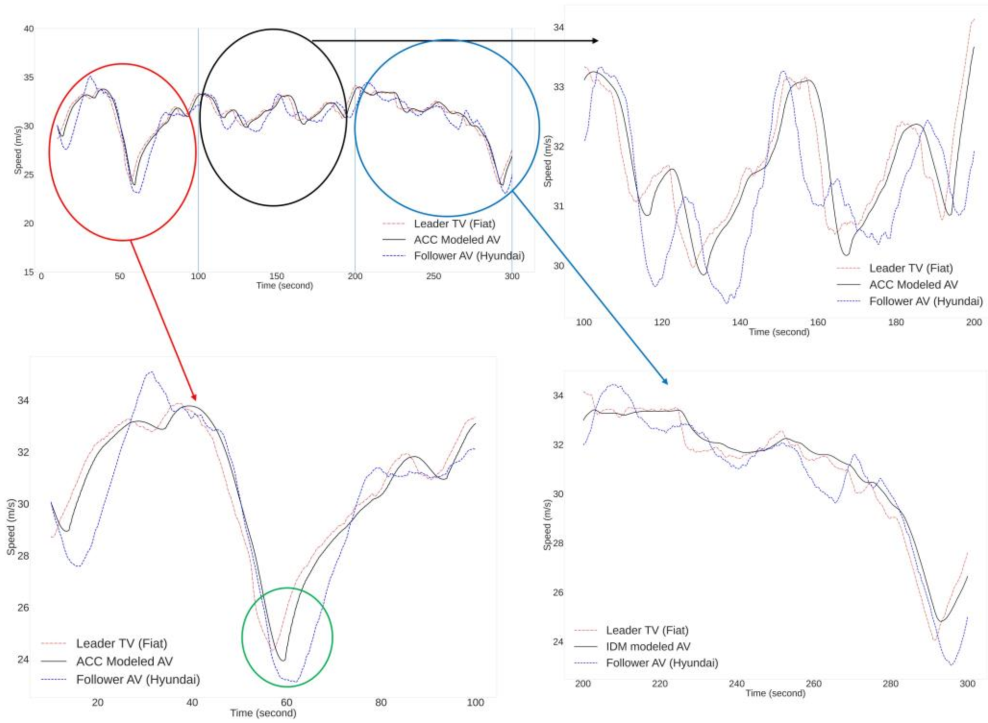
SPEED PROFILES PREDICTED BY SELECTED CAR-FOLLOWING MODELS

In **Fig. 21a**, we observed that in time step around the 20s, the actual AV (Ford) decelerated beyond what the ACC model predicted. A relatively high acceleration within time follows the observed high deceleration rate in steps 21s to 40s. We further observed that the ACC model did not capture the AVs' transition periods time steps (55 s to 65 s in Fig. 21a and 58 s to 61s in Fig. 21b). From Fig. 21a, we observed that the actual AV decelerated after acceleration for time steps 55s to 65s (marked by the green circle), indicating a transition period. The NRMSE (time step 55s to 65 s) was 0.99 m/s, whereas the NRMSE (for the entire trip) was 0.18 m/s, indicating that the ACC model predicted the observed AVs' transition period poorly.

Similarly, Fig. 21b shows that the actual AV decelerated after acceleration for time steps 58 s to 61 s (marked by the green circle), indicating a transition period. The NRMSE (time step 58 s to 61 s) was 0.99 m/s, whereas the NRMSE (for the entire trip) was 0.46 m/s; therefore, the ACC model predicted the observed AVs' transition period poorly. The fundamental cause for the ACC model's inability to depict the transition time might be a failure to account for AV sensor latency. Because real-world AVs use sensors to detect the leading vehicle, sensor latency must be included while simulating real-world AVs.



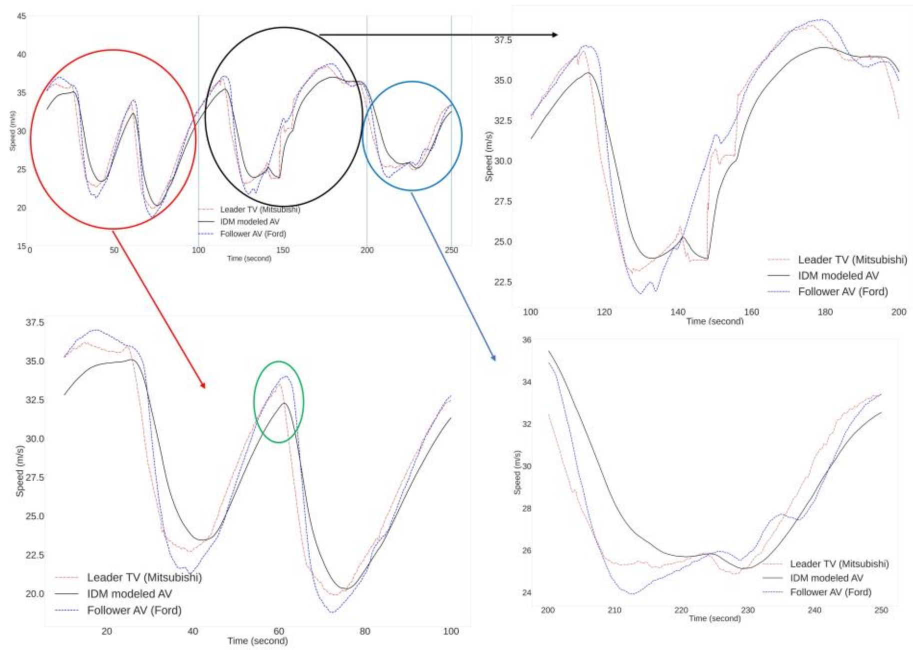
(a) Platoon 1: ACC model



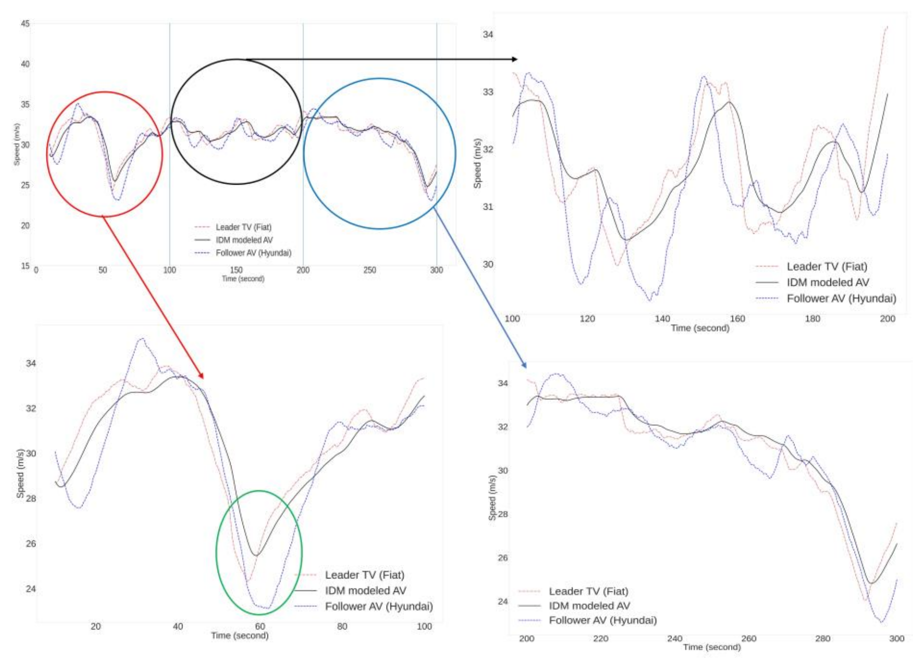
(b) Platoon 2: ACC model

Figure 21: Speed profiles predicted by ACC car-following model

Similar to the ACC model, the IDM and W99 model could not accurately predict the transition periods (Table 3, Figs. 22-23). We also observed that all three car-following models have lower NRMSE value for platoon 1 than platoon 2 (Table 3). The results indicate that platoon 1 was relatively well predicted by all three car-following models.

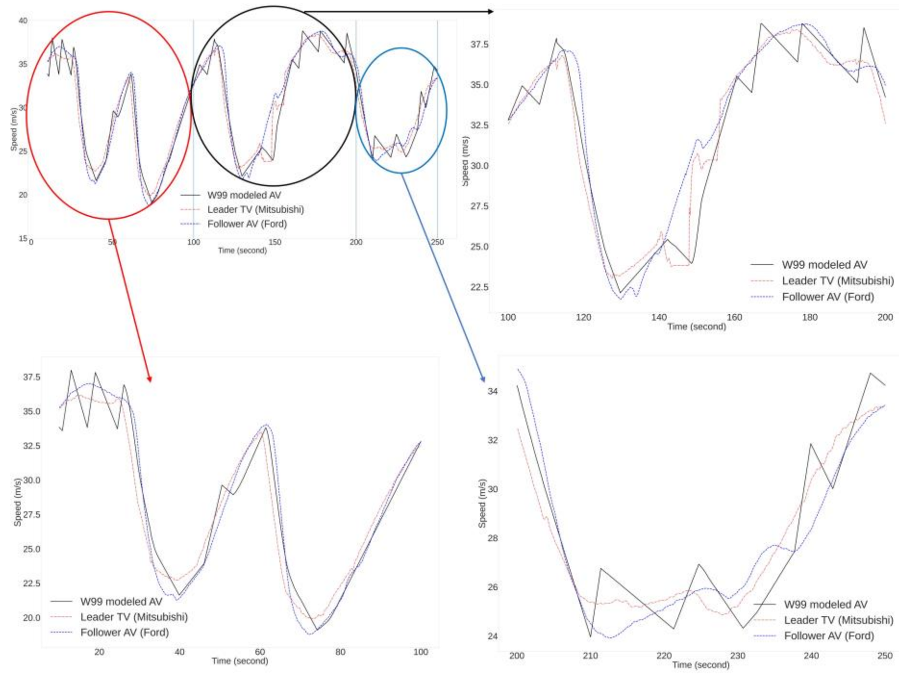


(a) Platoon 1: IDM model

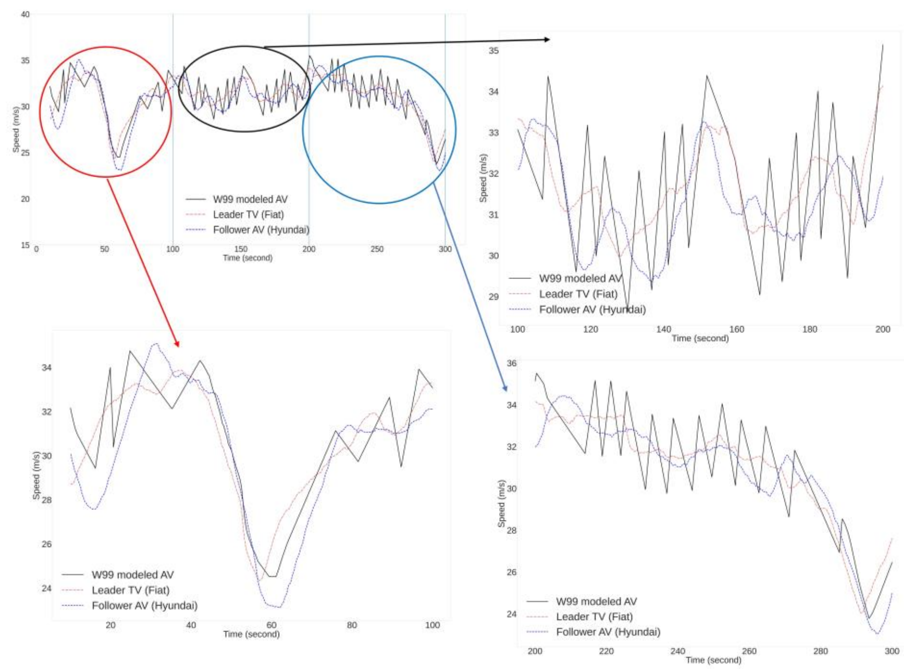


(b) Platoon 2: IDM model

Figure 22: Speed profiles predicted by the IDM car-following model



(a) Platoon 1: W99 model



(b) Platoon 2: W99 model

Figure 23:Speed profiles predicted by the Wiedemann 99 car-following models

Among the three car-following models the ACC model predicted the observed platoon one's speed more accurately than the other two models. Furthermore, the NRMSE value of platoon two for all three car-following models were >0.3 m/s indicating a poor prediction. To further verify our assumption about the goodness of fit of the car-following models we used MHU test. The results of MHU test are described in the next section.

Car- following model	Transition period NRMSE of speed profile (m/s) (Platoon 1)	Overall NRMSE of speed profile (m/s) (Platoon 1)	Transition period NRMSE of speed profile (m/s) (Platoon 2)	Overall NRMSE of speed profile (m/s) (Platoon 2)
ACC	0.99	0.18	2.85	0.41
IDM	1.18	0.30	2.17	0.42
W99	1.05	0.25	1.97	0.53

Table 3: NRMSE of the speed profile for the selected car-following model

SUMMARY EVALUATION OF THE MODELED SPEED PROFILES

The discrepancy between the modeled car-following in ACC, IDM, and W99 and observed AV speed profiles for platoon 1 appears not be significant (p value >0.05), as shown in Table 4. Consequently, we can say that all three models well predicted the platoon first's speed profile. However, the discrepancy between the modeled (ACC, IDM, and W99) and observed AV speed profiles was significant (p value <0.05) for platoon 2, as shown in Table 5. As a result, none of the three models could accurately model platoon two's observed AV speed profile. Consequently, we found that the heterogeneity of the manufacturer has a significant impact on AV longitudinal movement. Unfortunately, none of the tested models can take manufacturer heterogeneity into account.

Table 4: MHU test results of modeled and observed AV speed profiles for platoon 1

<table>
<tr><th colspan="3">Sample 1</th><th colspan="3">Sample 2</th><th rowspan="2">Null Hypothesis</th><th rowspan="2">p Value</th><th rowspan="2">Result</th></tr>
<tr><th></th><th>Mean (m/s)</th><th>Std. Dev. (m/s)</th><th></th><th>Mean (m/s)</th><th>Std. Dev. (m/s)</th></tr>
<tr><td>ACC modeled speed profile</td><td>29.71</td><td>5.49</td><td>Observed speed profile</td><td>29.93</td><td>5.74</td><td>ACC modeled speed profile and observed speed profile are not significantly different at 95 % confidence interval</td><td>>0.05</td><td>Null hypothesis cannot be rejected</td></tr>
<tr><td>IDM modeled speed profile</td><td>29.67</td><td>5.00</td><td>Observed speed profile</td><td>29.93</td><td>5.74</td><td>IDM modeled speed profile and observed speed profile are not significantly different at 95 % confidence interval</td><td>>0.05</td><td>Null hypothesis cannot be rejected</td></tr>
</table>

W99 modeled speed profile	29.69	5.45	Observed speed profile	29.93	5.74	W99 modeled speed profile and observed speed profile are not significantly different at 95 % confidence interval	>0.05	Null hypothesis cannot be rejected

Table 5: MHU test results of modeled and observed AV speed profiles for platoon 2

Sample 1			Sample 2			Null Hypothesis	p value	Result
ACC modeled speed profile	Mean (m/s)	Std. Dev. (m/s)	Observed speed profile	Mean (m/s)	Std. Dev. (m/s)	ACC modeled speed profile and observed speed profile are not significantly different at 95 % confidence interval	<0.05	Null hypothesis rejected
	31.09	2.21		30.69	2.55			
IDM modeled speed profile	31.08	2.06	Observed speed profile	30.69	2.55	IDM modeled speed profile and Real-world speed profile are not significantly different at 95 % confidence interval	<0.05	Null hypothesis rejected
W99 modeled speed profile	31.12	2.37	Observed speed profile	30.69	2.55	W99 modeled speed profile and Real-world speed profile are not significantly different at 95 % confidence interval	<0.05	Null hypothesis rejected

TESTING OF MODELED ACCELERATION PROFILES

Figure 24 depicts the modeled (ACC, IDM, and W99) and real-world acceleration profiles. Figure 25 illustrates the normalized acceleration noise for both modeled and observed AVs. From visual inspection, we observe that W99 model shows some abrupt acceleration and deceleration. Figure 25a shows that for platoon 2, other than IDM all the modeled and observed normalized acceleration noise had a value greater than one. The result indicates that only IDM model, while predicting the observed acceleration, could dampen the disturbance exerted by leader TV. However, for real-world AV, it is evident that the follower is unable to damp the oscillation exerted by the leader. Even for platoon 1 the IDM had the lowest normalized acceleration noise indicating damping the leader disturbance better than other two models.

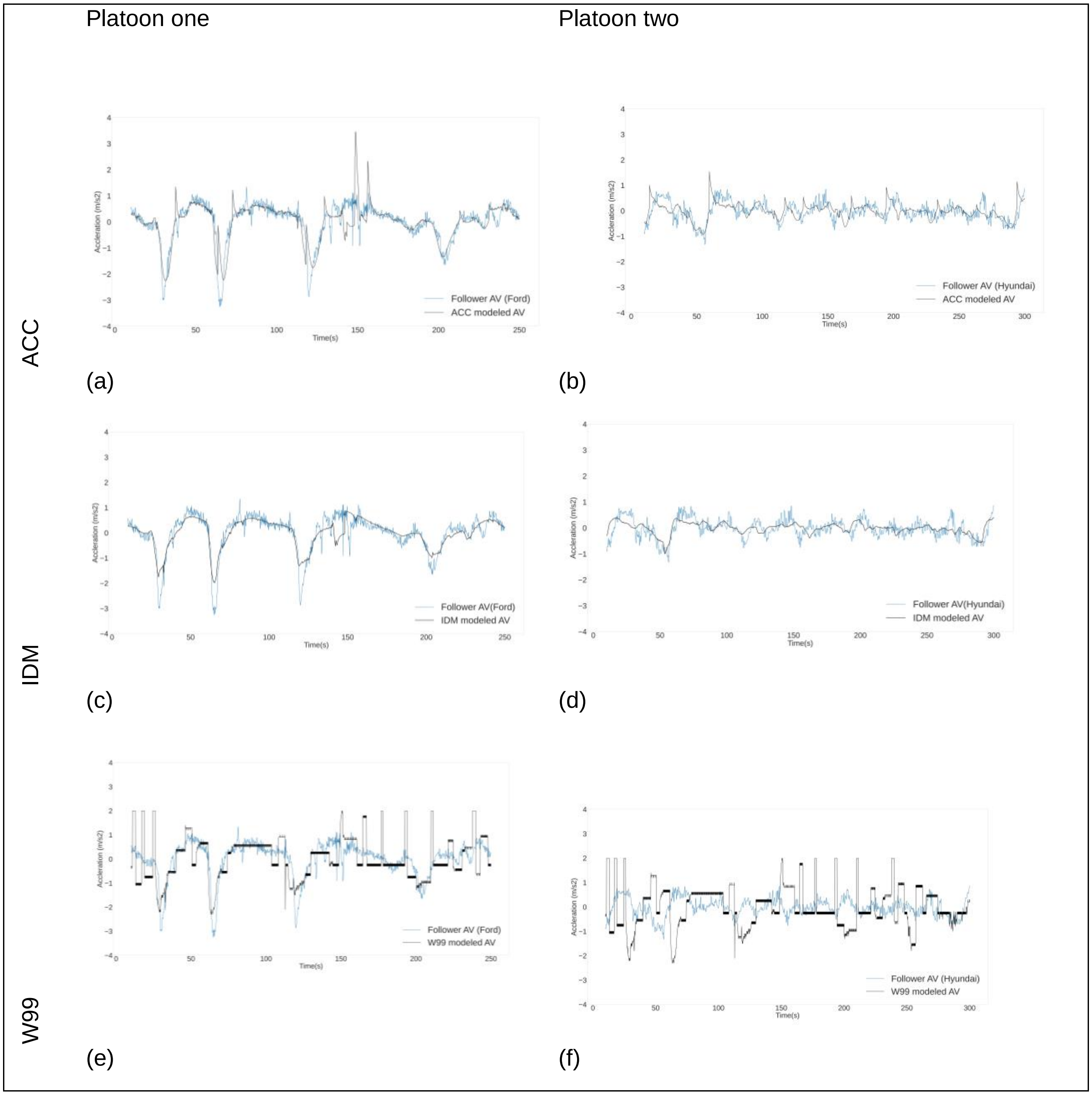
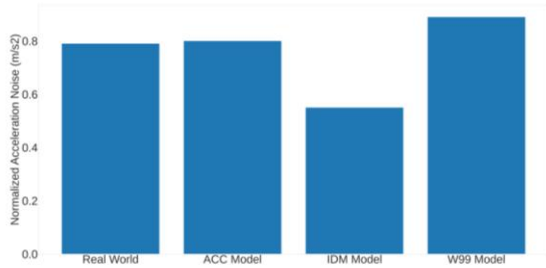
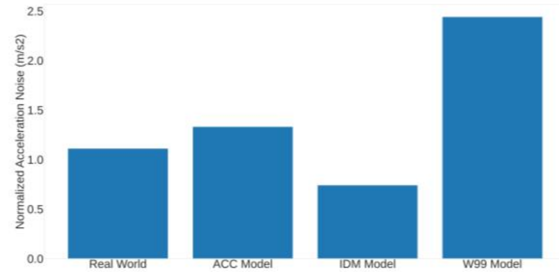


Figure 24: Acceleration profile for modeled and real-world AVs



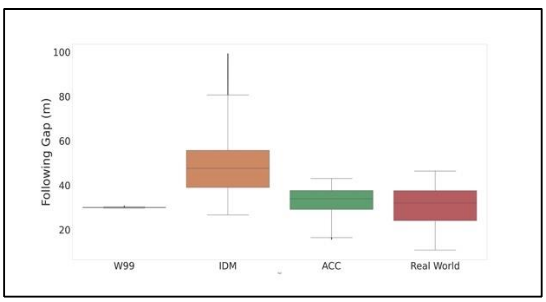
(a): Platoon 1



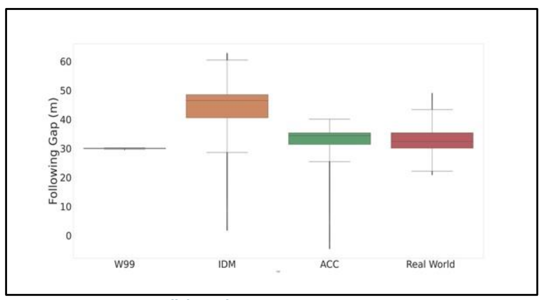
(b): Platoon 2

Figure 25: Acceleration noise for modeled and real-world AVs

The fundamental reason behind IDM's ability to damp the oscillation was its conservative driving algorithm. Figure 26 shows that the IDM model behaves more conservatively than the other two car-following models. The following median gap for IDM modeled AV was higher for both platoons than for the other two car-following models. We also observed that the ACC modeled AV had a similar following gap to real-world AV for both platoons. Figure 25b further shows that the W99 had the highest normalized acceleration noise for platoon 2, indicating high, abrupt acceleration and deceleration, which we already observed in Fig. 23b. This abrupt acceleration and deceleration may be due to W99's algorithm that keeps almost constant following gap by exerting high acceleration or deceleration with little standard deviation (Fig. 26).



(a): Platoon 1



(b): Platoon 2

Figure 26: Following gap maintained by observed and modeled AVs

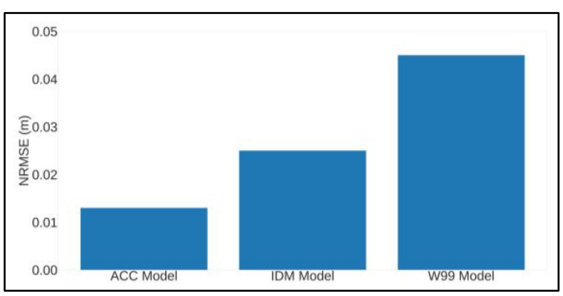
Table 6 displays the results of the two sample K-S tests of the modeled and field-observed acceleration profiles. The K-S test was used to determine whether the modeled acceleration profile deviated significantly from the field-observed acceleration profile. Table 6 further shows that none of the selected car-following models was able to model the real-world acceleration profile without significant difference. In terms of normalized acceleration noise, the ACC model predicted the acceleration of the real-world AVs' better than other two models. It was further observed that the IDM model had less standard deviation in acceleration indicating smooth acceleration or deceleration, where's W99 had highest standard deviation in acceleration indicating abrupt unrealistic acceleration or deceleration.

Table 6: K-S test of modeled and real-world AV acceleration profile

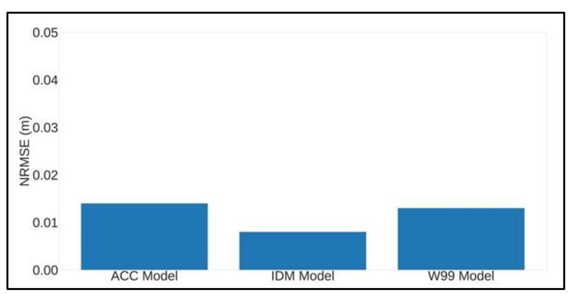
Platoon 1				
Sample 1	**Sample 2**	**K-S Stat**	**p value**	**Result**
ACC modeled acceleration profile	Real-world acceleration profile	0.1635	<0.005	Null hypothesis rejected
IDM modeled acceleration profile	Real-world acceleration profile	0.119	<0.005	Null hypothesis rejected
W99 modeled acceleration profile	Real-world acceleration profile	0.2501	<0.005	Null hypothesis rejected
Platoon 2				
Sample 1	**Sample 2**	**K-S Stat**	**p value**	**Result**
ACC modeled acceleration profile	Real-world acceleration profile	0.2735	<0.005	Null hypothesis rejected
IDM modeled acceleration profile	Real-world acceleration profile	0.3119	<0.005	Null hypothesis rejected
W99 modeled acceleration profile	Real-world acceleration profile	0.3801	<0.005	Null hypothesis rejected

FOLLOWER VEHICLE POSITION

In a car-following model, it is expected that the modeled vehicles follow the same trajectories as the real-world vehicles. That is, they follow the same pattern of the lead vehicle's time-space plots. We checked to see if there was a difference in the time and space values between the observed and modeled AVs. We took the location difference at the same points in time for the observed and modeled data and calculated the NRMSE (Fig. 27), which shows that all the three car-following models predicted the AVs' position in time with low NRMSE and high accuracy. The three car-following models' high accuracy in predicting AV position is further confirmed by t-test where we found that the differences between the trajectories of the modeled AVs and observed AVs are insignificant at 95% confidence interval. Therefore, all the three models were following the same trajectories as the real-world AV's without statistically significant difference.



(a) Platoon 1



(b) Platoon 2

Figure 27: NRMSE of follower vehicle position over time of modeled AVs

Conclusion

AVs are expected to impact the traffic network, creating a dire and immediate need for the investigation of these affects. Due to the paucity of AV exposure on roadways, most AV studies are simulation based and rely highly on car-following models employed by different simulation platforms. As such, a foundational step towards investigation of the effect of these vehicles necessitate exploration of the discrepancies between the real-world and car-following modeled AVs. Consequently, the objectives of our research were to a) find whether there exists a significant discrepancy between real-world and car-following modeled AVs, and b) unravel the cause of such discrepancies, if any.

We compared the real world and car-following modeled AV data using speed profile, acceleration profile and vehicle position in time. We used two real-world TV-AV platoons' trajectories collected as part of the OpenACC. While selecting the TV-AV platoons, we also considered manufactural heterogeneity. We modeled the longitudinal characteristics of AVs using ACC, IDM and W99 car-following models. Regarding speed profile, we found that the ACC model outperformed both IDM and W99 model with the lowest NRMSE value for both platoons. However, while modeling the transition periods, all the car-following models showed high NRMSE even more than one for both platoons. Therefore, none of the car-following models could predict the transition period well. In other words, the sudden high acceleration or deceleration after high deceleration or acceleration, could not predicted by existing car-following models. In addition, we also found that the manufacturer's heterogeneity significantly impacts AV longitudinal movement. None of the available car-following models can account for manufacturer heterogeneity.

Regarding the acceleration profile, none of the selected car-following models could predict the real-world AV acceleration without significant difference. Again, the ACC model was the closest one to model the real-world acceleration profile. On the other hand, W99 was showing abrupt and unrealistic high acceleration and high deceleration. In addition, the IDM model had the lowest acceleration noise due to its conservative driving algorithm. Lastly, all the three car-following models predicted the AVs' position in time with low NRMSE and high accuracy.

We recognize that this study was limited in scope. We dealt only with the longitudinal behavior of AVs. However, we did find differences, especially insofar as the speed and accelerations are concerned; and we believe we have set a precedent for how such comparisons can be conducted in the future. Furthermore, the results were obtained from analyzing a limited set of scenarios and field tests in specific circumstances. Therefore, the results are limited to the discussed scenarios and might not be generalizable to other conditions. More data can be collected by expanding the scenarios examined in different mixed traffic environments and conditions to obtain more generalizable results.

Findings and Conclusions

With the arrival of enhanced vehicle and infrastructure connectivity, as well as potentially new technologies like self-driving vehicles, the workload of regional dispatchers will increase for both routine and unusual congestion-management tasks. In-vehicle technologies like GPS-enabled navigation software applications theoretically aid drivers in reducing the impact of congestion on their travel times, but resulting emergent behavior can cause new areas of congestion that cause safety problems at the regional level. Moreover, not all drivers use such alerting tools so it is not clear how and when to push communications to traditional vehicles in order to mitigate negative congestion consequences.

To this end, the CADS (Congestion Alerting Decision Support) tool was developed to support strategic transportation planning (on the order of weeks to months) and tactical transportation planning (on the order of hours to days). It allows transportation planners the ability to see the impact of congestion caused by various events including weather and rerouting apps on local communities (including hospitals, schools, and first responders). It also provides the ability to determine when and where to communicate with both connected and conventional vehicles to minimize congestion impact both in advance of known traffic disruptions (like construction), but also for pending incidents like weather events. It also serves as a tool to explore how autonomous vehicles could impact local communities with potentially increased congestion.

This prototype tool demonstrates how dispatchers and any other NCDOT decision makers can run what-if simulations to determine how to respond to different conditions, and determine how and when to allocate future resource needs. Such a tool can be used operationally, like in the days before a hurricane to improve planning, but also in training to provide a host of scenarios for new planners, dispatcher and other emergency planning personnel to practice solving complex scenarios. CADS as currently designed is an offline planning tool and does not support real-time traffic planning but could be adapted in the future to include this capability.

One current limitation of CADS is it inability to connect congestion metrics to predictions of safety, which could be very useful to dispatchers, especially as AVs increase in numbers. For example, CADS currently depicts congestion as a function of vehicle throughput in a certain area, but it does not alert the dispatcher to possible increases in crash risk. It would be useful to have such predictions in the future, as this could then be a variable that factors in replanning suggestions.

Towards addressing this gap, one study in this effort determined that when operating in mixed traffic as a following vehicle in a platooning scenario, AVs had longer response times, which could lead to string instability. The accompanying relative MAD study suggested that as the platoon's length increases, so does the magnitude of this instability. This has a major impact on the amount of traffic conflicts and the severity of those conflicts, and thus potential overall safety. Such findings have a direct impact of simulations like CADS, as they suggest that CADS could track metrics like AV platoon length, heterogeneity of platoon vehicles on a highway, and braking response times to develop risk profiles for areas of congestion that involve AVs.

There are limitations to these results about this traffic conflict prediction. The study was restricted to SAE level 2 ACC-equipped vehicles that had no lane changing information. The results were limited to a restricted set of settings (e.g., short time gap settings for AVs) and field tests (e.g., no disturbance from surrounding vehicles such as cut ins). Finally, the response time analysis was also limited to the linear Gasiz-Herman-Rothery (GHR) traffic model.

While these results are encouraging, the final investigation of this study focused on overall model quality, which is at the core of a simulation like CADS. The current offline aspect of a planning tool like CADS means that models can be carefully checked to ensure they reflect reality to an acceptable degree. However, if such a tool were to be used for near real-time planning, like in emergency scenarios, the veracity of the underlying models would need to reflect dynamic environments. In addition, since self-driving cars are not yet operationalized, it is not clear how effective either tactical or strategic models for planning would be in predicting correct vehicle and fleet behaviors.

Towards achieving this goal, additional work assessed whether the underlying AV car models adequate capture actual behaviors, and results were mixed. When looking at three commonly-used AV car-following models (ACC, W99, IDM), none could predict the real-world AV acceleration without significant differences. The ACC model was the closest one to model the real-world acceleration profile, but W99 showed abrupt and unrealistic high acceleration and high declaration results. In addition, the IDM model had the lowest acceleration noise due to its conservative driving algorithm. However, all the three car-following models predicted the AVs' positions in time with low NRMSE and high accuracy.

These results indicate that CADS, and other simulations like it, that incorporate these models likely do well in predicting where vehicles will be at a given time. However, if such simulations are going to be adapted to predict high-risk areas for collisions, current problems with predicting acceleration and deceleration likely indicate more work is needed before such simulations can realistically be used for risk projections.

Recommendations

Given the results of this effort, the following recommendations are provided:

- Develop a team to determine which divisions in NCDOT would be best supported by CADS, both operationally and in training, and any additional agency requirements.
- Determine how CADS could move from prototype to a functional NCDOT tool, including internal development or contracting to an external party.
- Determine how surrogate safety measures could be incorporated into CADS for risk predictions for increased crash risk.
- For simulations that include individual car estimates, incorporating non-linear car following behavior of the following vehicle to estimate response time could likely improve results.
- The effect of connectivity and autonomy in mixed traffic safety under real-world settings needs further exploration. Likewise, the effect of AVs and CAVs on emissions should also be assessed in real-world settings.
- Variability in human driving behavior can potentially lead to models that underperform. To what extent this relates to AV systems and the most significant challenges that come with the mass implementation of AVs needs additional research.
- There is still work to be done on the relationship between the physical meaning of car-following parameters in traffic microsimulation modeling and empirically observed values. Establishing a link between the two can be extremely beneficial for practitioners and researchers.
- Recalibrate the ACC and IDM models using the platoon data available to the research team. Such an effort would determine whether multiple regimes are required to improve the models' fit. The final model could then be implemented into the NCDOT preferred microsimulation platform.

Implementation and Technology Transfer Plan

The first research product from this effort is CADS and the associate training material is detailed in Appendix A. It is a deliverable software package that is built on top of SUMO. Currently it is housed on a Duke virtual server with remote access ability (Appendix A). It is available to be freely transferred to NCDOT or for external third-party licensing in conjunction with the Duke University, who partially funded this effort.

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Appendices

Appendix A

A1. CADS DESIGN, UNDERLYING MODELS AND ASSUMPTIONS

Congestion Alerting Decision Support (CADS) is a software tool designed for dispatchers to help plan for congestion mitigation through simulation. In addition to understanding possible areas of congestion for traditional and connected vehicles, CADS can help better understand where and when to place digital signs to reduce congestion with what-if analysis. It works by simulating different traffic conditions and placing digital signs in different locations to generate results and then compare. This tool also assists in planning for the impact of connected and/or autonomous vehicles with choices of different traffic mixes.

SUMO functions as the back end and utilizes the A* rerouting algorithm native to SUMO to model the connected and autonomous vehicles. A user-friendly interface sits on top of SUMO. Dispatchers can directly select all inputs in a clear manner and obtain all data analysis without extra efforts.

This document details the process of designing and implementing CADS, and explains the models, assumptions, and performance metrics used in the tool.

Acronyms

Abbreviation	Explanation
CADS	Congestion Alerting Decision Support
TVs	Traditional Vehicles
CTVs	Connected Traditional Vehicles
CAVs	Connected Autonomous Vehicles
LOS	Level of Service
SUMO	Simulation of Urban Mobility
TRACI	Traffic Control Interface

CADS Design

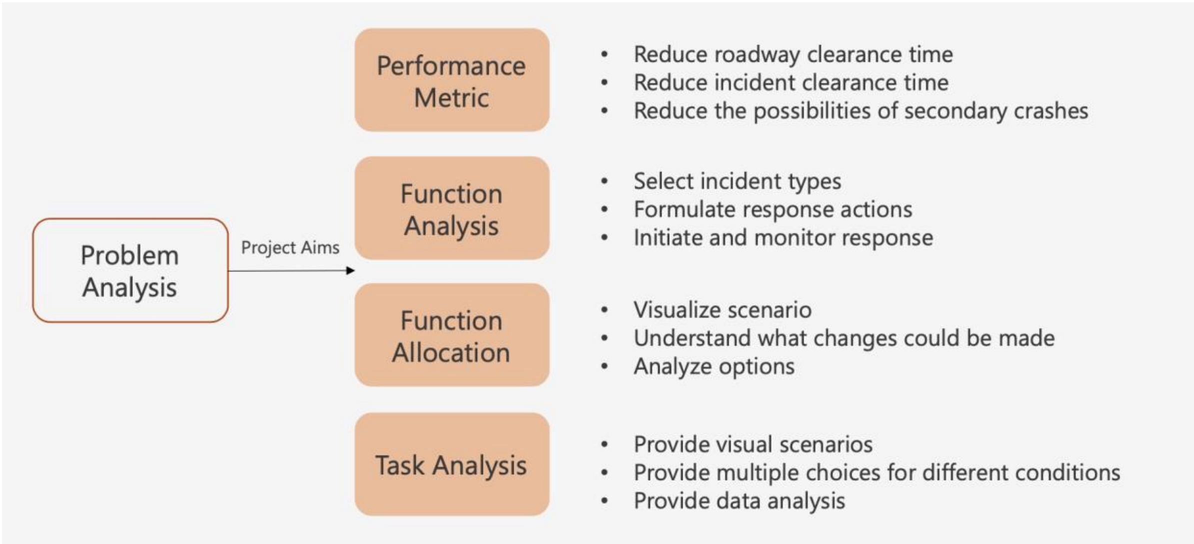
With the arrival of enhanced vehicle and infrastructure connectivity, as well as potentially new technologies like self-driving vehicles, the workload of regional dispatchers will increase for both routine and unusual congestion-management tasks. In-vehicle technologies like GPS-enabled navigation applications theoretically aid drivers in reducing the impact of congestion on their travel times, but resulting emergent behavior can cause new areas of congestion and safety problems.

Moreover, not all drivers use such alerting tools so it is not clear how and when to push communications to traditional vehicles in order to mitigate negative congestion consequences. To this end, CADS (Congestion Alerting Decision Support) tool was designed to allow transportation planners to see the impact of congestion-caused rerouting apps on local communities.

It also provides the ability to determine when and where to communicate with both connected and conventional vehicles to minimize congestion impact.

Information Requirements

The process for the development of the decision support tool is divided into three phases: planning, analysis, and design. The Hybrid Cognitive Task Analysis (hCTA) method was used for the analysis phase, which included four steps: Performance metric analysis, function analysis, function allocation, and task analysis to obtain the detailed information requirements. The summary for each step is shown below.



The table below lists the information requirements for a typical scenario of “Accident at an exit”. It’s divided into inputs, outputs and visual representation for the convenience of algorithm development, where inputs are selected or inserted by the users, outputs are significant information from simulation results, and the visual representation contains other objective information needs to be shown on the map.

	Group	Information Requirement
1	Inputs	C(AV)s, CVs, and TVs ratio
2		traffic flow level / congestion level
3		incident impact lanes number
4		incident location
5		Duration time for shut down
6		Number and location of roadside unit
7		minimize congestion of routes around school/hospital or not
8	Outputs	Any unauthorised roads in the alternative routes
9		Best performance alternative route
10		Accident area traffic back to normal conditions time
11		Alternative routes congestion level
12		Delay time caused by alternate routes
13		Delay time caused by congestion
14		Overall CVs delay time chart (CV's percentage vs delay time Histogram)
15		rerouting end time vs. Average delay time chart
16	Visual representation	Nearest hospital/police station/fire station location
17		Alternative routes
18		Alternative routes traffic flow level
19		location of roadside unit
20		incident location
21		Road around schools & hospitals
22		traffic flow level / congestion level

Interface and Interaction Design

The interfaces for CMDA consists of three main views:

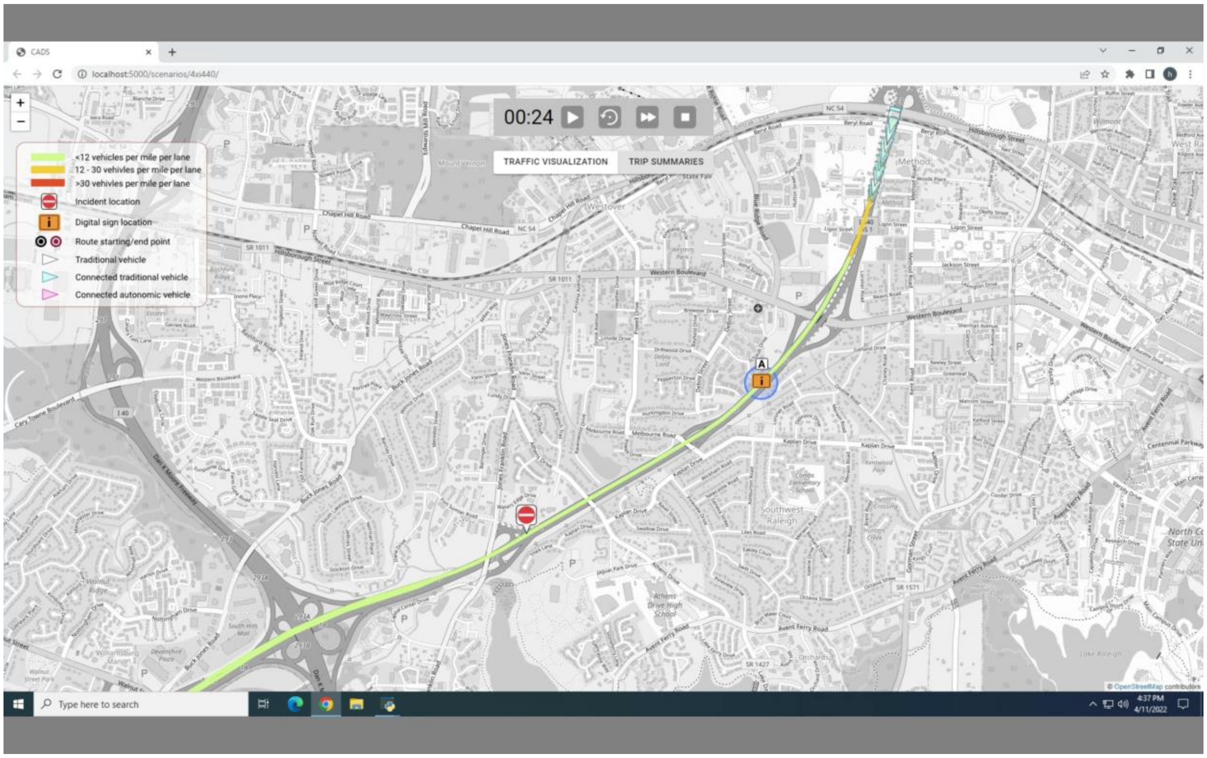
1. Setup view;
2. Traffic visualization view; and
3. Simulation results summary view.

The components and functionality for each view are listed below.

Setup View

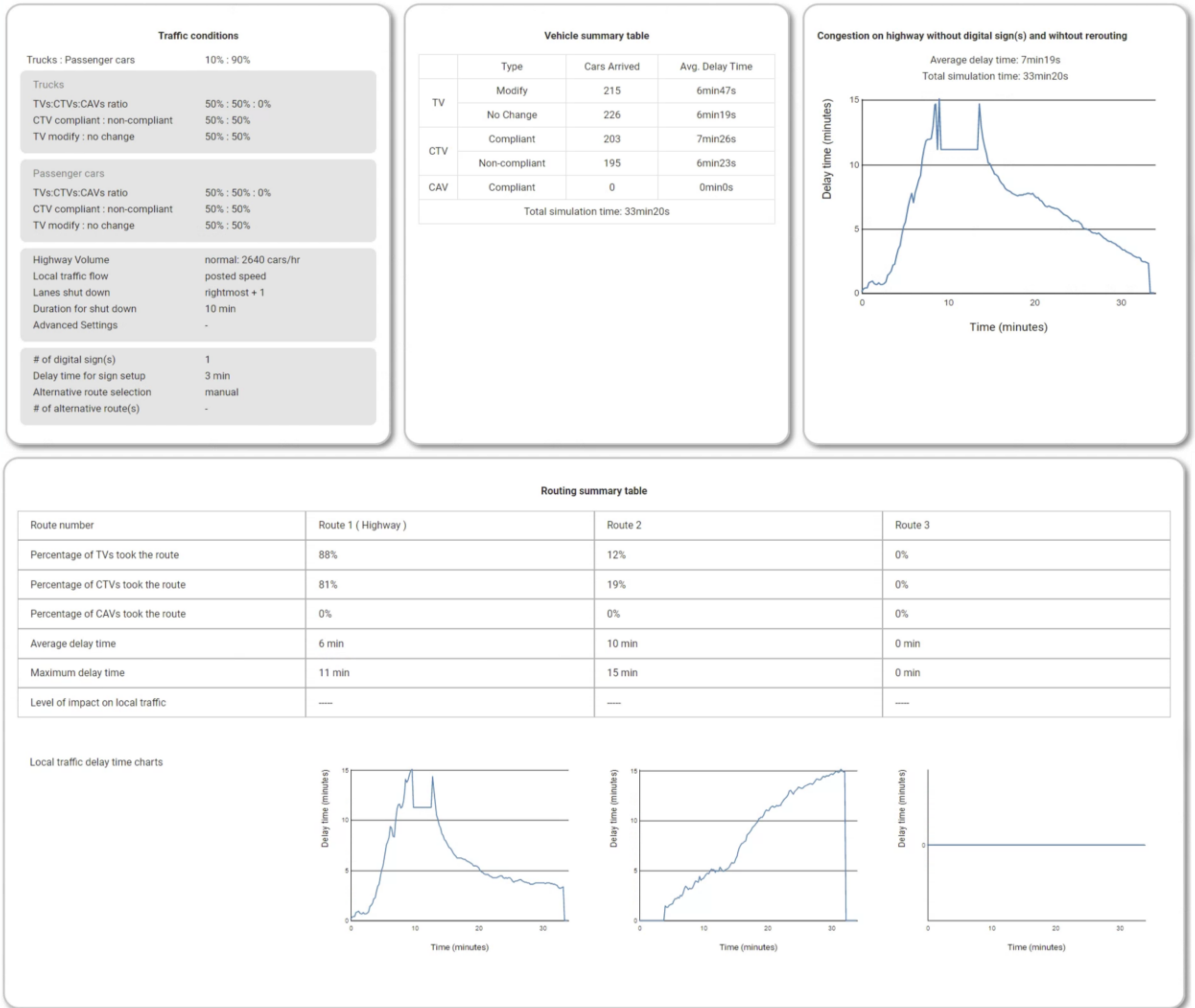
1. Input box on the left: Contains all input information and parameters, grouped into four boxes. The user can select from provided choices.
2. Map: Local map of the example incident region, the user can place incident location and digital sign location arbitrarily on the map. The user can also select alternative route manually on the map.

TrafFIc visualization view



1. Vehicle routes and real-time traffic congestion shown in color. Allow dispatchers to supervise the entire process from the shutdown of lanes to the entire traffic area returns back to normal condition.
2. Symbolized vehicles, including passenger cars and trucks.
3. Labels, play buttons: Show meanings for visual elements; Control animation.

Simulation results summary view



1. Traffic conditions summary table
2. Vehicle summary table
3. Congestion on highway without digital signs and without rerouting
4. Routing summary table
5. Other info regarding regulation/risk

Tutorial

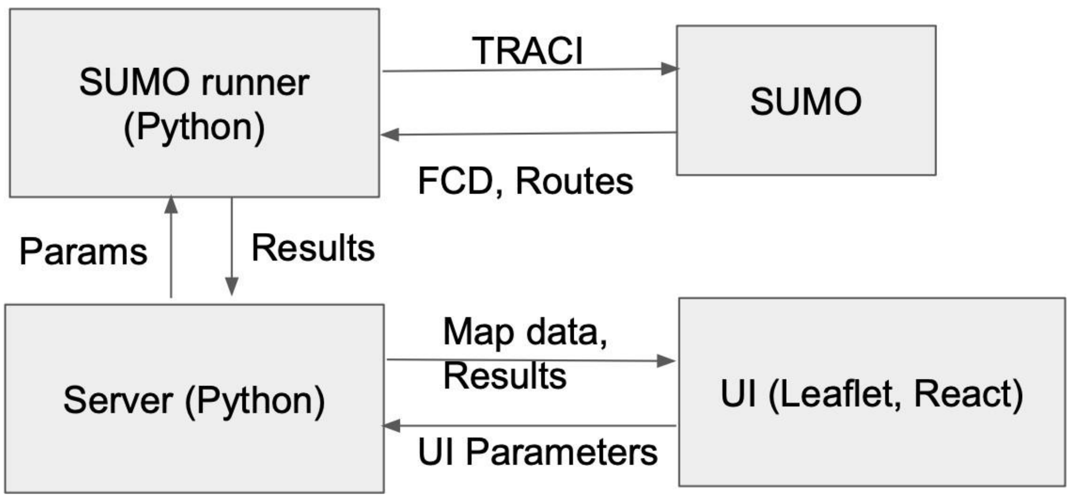
In order to conduct user tests, a remote server was set up to host a tutorial on both how to access the remote server and how to fully use the functions embedded in CADS. The walk-through tutorial contains an introduction section, a scenario example problems section, and a practice problems section. CADS is introduced, some background information is provided about vehicles and scenarios, and then users practice with CADS (Appendix A2).

Users are provided two example problems to walk them through the actions and steps needed to use CADS to solve the problems. By using mainly figures and demonstration videos, all information is explained. The correct solutions are given, and users can compare the results with what they have generated.

A2. SYSTEM DESIGN & ASSUMPTIONS

CADS architecture

The architecture for CADS is consisted of four parts: SUMO, SUMO runner, Server, and UI. SUMO is an open source microscopic traffic simulation software, and it can be used and modified according to a user's needs. Data of the simulation in SUMO can be accessed through TRACI, stand for "Traffic Control Interface". The figure below shows how different parts work together.



1. Server reads the scenario files and sends the UI the location of the map and default data
2. UI shows the map with default incident location, digital signs and etc.
3. User changes the input as needed and start the simulation
4. Server receives the input, prepares the input files(routing and config), and run the SUMO using TRACI
5. After SUMO finishes the simulation, parses the output files (fcd and routes) and calculates the delay times
6. Server reads the result and send back to UI for showing the result and simulation

Models and Assumptions of CADS

Passenger Cars

All passenger cars regardless of the vehicles category utilize the default passenger vehicle type parameters of SUMO. The car following model we use is Krauss and all parameters are listed in 4.1.2 below.

Other parameters not included in the table is default value of SUMO. Detailed SUMO docu- mentation of vehicles parameters and default value is on this page:

https://sumo.dlr. de/docs/Definition_of_Vehicles%2C_Vehicle_Types%2C_and_Routes.html.

Trucks

Trucks are different from passenger cars in length, acceleration, deceleration, etc. We referred to the vehicle parameter defaults of trunk vehicle class defined by SUMO:

https://sumo.dlr.de/docs/Vehicle_Type_Parameter_Defaults.html

The actual parameters used are listed below and other vehicles parameters like depart lane all are default values. The ratio of trunks and passenger cars can be selected in the input box of "Trucks : Passenger cars."

class	length	minGap	accel	decel	decel	maxSpeed	speedDev
car	5m	2.5m	2.6m/s2	4.5m/s2		9m/s2	200km/h 0.1
truck	16.5m	2.5m	1.1m/s2	4m/s2		7m/s2	130km/h 0.05

Traditional Vehicles (TVs)

Traditional Vehicles (TVs) represent the vehicles which have no access to real-time traffic information and drivers' drive them according to their experience or map. In SUMO, TV are defined as the basic vehicles without rerouting device and will only respond to digital signs when they reach the range of digital signs are visible. The car following model for TVs is default passenger car model. The lane changing model is mostly default except we change "lcStrategic" and "lcCooperative" to be 0.5 instead of 1, in order to resemble average drivers' behaviors.

Additionally, the "modify TV" and "no-change TV" means the behavior of traditional vehicles when they see the digital signs. For "modify TVs", they will believe in the digital sign's content of incident ahead and reroute to the alternative routes whether automatic generated by the fasted route algorithm (A* algorithm) in SUMO or manually selected by dispatchers. For "no-change TVs", drivers will ignore the digital sign's content, thus they will continue on their original highway route. This ratio of "TV modify : no change" can be selected in the input parameters.

Connected Traditional Vehicles (CTVs)

Connected Traditional Vehicles (CTVs) represent the vehicles have access to real-time traffic information, like traffic mobile applications (google map, Waze, etc.) or traffic radios which broadcast real-time incidents. In SUMO, CTVs have the rerouting device and they could also respond to digital signs when visible. The car following model for CTVs is the default passenger car model in SUMO. The lane changing model is the same with TVs, with "lcStrategic" and "lcCooperative" to be 0.5 instead of 1, in order to resemble average drivers' behaviors.

The routing approach in SUMO works by giving some or all vehicles the capability to re-compute their route periodically. This routing takes into account the current and recent state of traffic in the network and thus adapts to jams and other changes in the network. The SUMO documentation related to this topic can be accessed with this link:

https://sumo.dlr.de/docs/Demand/Automatic_Routing.html.

The device rerouting parameters are contained in the additional files in SUMO and are set as:

$$device.rerouting.periodvalue = 60 \qquad (1)$$

$$device.rerouting.adaptation - intervalvalue = 1 \qquad (2)$$

$$device.rerouting.adaptation - stepsvalue = 60 \qquad (3)$$

Additionally, the "compliant CTV" and "non-compliant CTV" reflect the behavior of connected traditional vehicles when they see the digital signs. For "compliant CTVs", they will reroute to the alternative routes whether automatically generated by the fasted route algorithm (A* algorithm) in SUMO or manually selected by dispatchers. Non-compliant CTVs will continue on their original highway route. This ratio of "compliant : non-compliant" can be selected in the input parameters.

Connected Automatic Vehicles (CAVs)

Connected Automatic Vehicles (CAVs) always follow the routing decisions generated by a rerouting algorithm, assumed to be onboard the vehicle, but could be augmented by information received through its connection to external information networks. I n SUMO, the rerouting parameters for CAVs are listed as follows.

$$device.rerouting.periodvalue = 60 \qquad (4)$$

$$device.rerouting.adaptation - intervalvalue = 1 \qquad (5)$$

$$device.rerouting.adaptation - stepsvalue = 60 \qquad (6)$$

CAVs will reroute every 1 minute, the interval for updating the edge weights is 1s, and the number of adaptation steps for averaging is 60. For more information regarding automatic rerouting in SUMO, please refer to this page:

https://sumo.dlr.de/docs/Demand/Automatic_Routing.html.

The car following model for CAVs uses the default passenger car model parameters, and the lane changing model is default with perfect strategic and cooperative behavior.

Flow Density

Traffic flows are well defined with the reference of Level of Service (LOS) definitions for both highway and urban arterial. CADs provides the ability to set custom values for both highway traffic volumes and local traffic flows.

Highway Volume

The Highway Volume choices are generated by averaging the number defined by each level of service referred to Highway Engineering by Findley and Schroeder[4]. We convert the density in cars/mi per lane to car number per hour due to the flow input requirements in SUMO.

TABLE 1 LOS Criteria for Urban Arterial (1, Exhibit 15-2)

	Average Travel Speed by Class			
	I	II	III	IV
Range of free-flow speeds (FFS)	55–45 mph	45–35 mph	35–30 mph	35–25 mph
Typical FFS	50 mph	40 mph	35 mph	30 mph
LOS				
A	>42	>35	>30	>25
B	>34–42	>28–35	>24–30	>19–25
C	>27–34	>22–28	>18–24	>13–19
D	>21–27	>17–22	>14–18	>9–13
E	>16–21	>13–17	>10–14	>7–9
F	≤16	≤13	≤10	≤7

Local Traffic Flow

The Local Traffic Flow choices are generated per the Highway Capacity Manual[5]. Since urban arterials have complex conditions regarding road size, location, speed limit, etc., instead of setting a specific number for each level, three categories are provided: Posted speed; 65% posted speed; 40% posted speed.

Digital Sign Model

Digital messaging signs in CADS are assumed to be permanent overhead signs or mobile signs that are commonly setup when there is temporary road work or construction. In CADS, the length of time to set up such a sign is provided, which can be short (on the order of minutes for a permanent sign) or long (like hours for a mobile sign.)

Drivers are assumed to have seen the sign at the distances prescribed in this article: Road Sign Detection Distance and Reading Distance at an Uncontrolled Intersection. CADS sets this distance as a circle effect area with a radius of average sign reading distance of 50 meters.

When the TVs and CTVs enter the effective range of a digital sign (illustrated by a blue circle around the digital sign), the compliant vehicles will perform a fastest route check and calculation and reroute if the alternative route costs less time. The non-compliant vehicles and CAVs will not be affected by the digital sign.

[4] Bastian J. Schroeder, Part 5 - Traffic Operations, Highway Engineering, Butterworth-Heinemann, 2016, Pages 255-432, ISBN 9780128012482.

[5] Highway Capacity Manual. TRB, National Research Council, Washington, D.C., 2000.

Alternative route model

By default, the route with the least travel time is chosen. The travel time depends on the current routing mode (configurable via traci.vehicle.setRoutingMode) or via the explicit routingMode argument to traci.simulation.findRoute.

The routing algorithm we use is the A* routing algorithm. It uses a metric for bounding travel time to direct the search and is often faster than Dijkstra's algorithm. Here, the metric Euclidean distance / maximum Vehicle Speed) is used. More information can be found in this link: *https://sumo.dlr.de/docs/Demand/Automatic_Routing.html*

Performance Metrics of CADS

Average Delay Time

The average delay time is calculated by this formula:

$$t_{avg} = (t_{total} - t_{free})/n_{vehicle} \tag{7}$$

where t_{avg} is the average delay time for selected vehicles, t_{total} is the total travel time of the vehicles with the incident, t_{free} is the free flow travel time of the vehicles when there is no incident, and $n_{vehicle}$ is the total number of vehicles arrived. In short, it's the difference between the total sum of travel time and the free flow travel time divided by the total number of vehicles.

Maximum Delay Time

The maximum delay time is simply the maximum number of the delay time among all vehicles.

$$t_{max} = max(t_{delay}[all]) \tag{8}$$

where t_{max} is the maximum delay time, and t_{delay} is the delay time array for all arrived vehicles.

Level of Impact

The Level of Impact appeared in the routing summary table indicated the congestion level around that area and it is defined as:

- Low: local traffic flow increase < 10%
- Medium: local traffic flow increase > 10% and < 30%
- High: local traffic flow increase > 30%

The local traffic flow increase is measured by the average traffic speed in the entire simulation run compared to the posted speed.

A3. CADS TUTORIAL

What is CADS?

- Congestion Alerting Decision Support (CADS) is a software tool designed for dispatchers to help plan for congestions mitigation through simulation.
- In addition to understanding possible areas of congestion for traditional and connected vehicles, CADS can help to better understand wher and when to place digital signs to reduce congestion.
- It works by simulating different traffic conditions and placing digital signs in different locations to generate results and compare with each other. In addition, it includes three types of vehicles: Traditional, connected, and autonomous.

What is this Tutorial for?

- This tutorial demonstrates how to use CADS and explains the detailed functions and user interface with an example scenario.
- It also provides two case studies to illustrate how to use it.
- After going through this demo, you should understand what CADS is used for, how to use it and what results you can get.

Vehicle Types and Compliance

- **Traditional Vehicles (TVs):** Vehicles with drivers using in-car navigation systems or apps like Google Maps, Waze, etc., and have access to real-time traffic information and alerts.
- **Connected Autonomous Vehicles (CAVs):** Vehicles without drivers (but potentially with passengers) and fully controlled by a central navigation system, follow real-time rerouting commands.

Each type of vehicle can be set with different speed variance in the advanced settings of deviation.

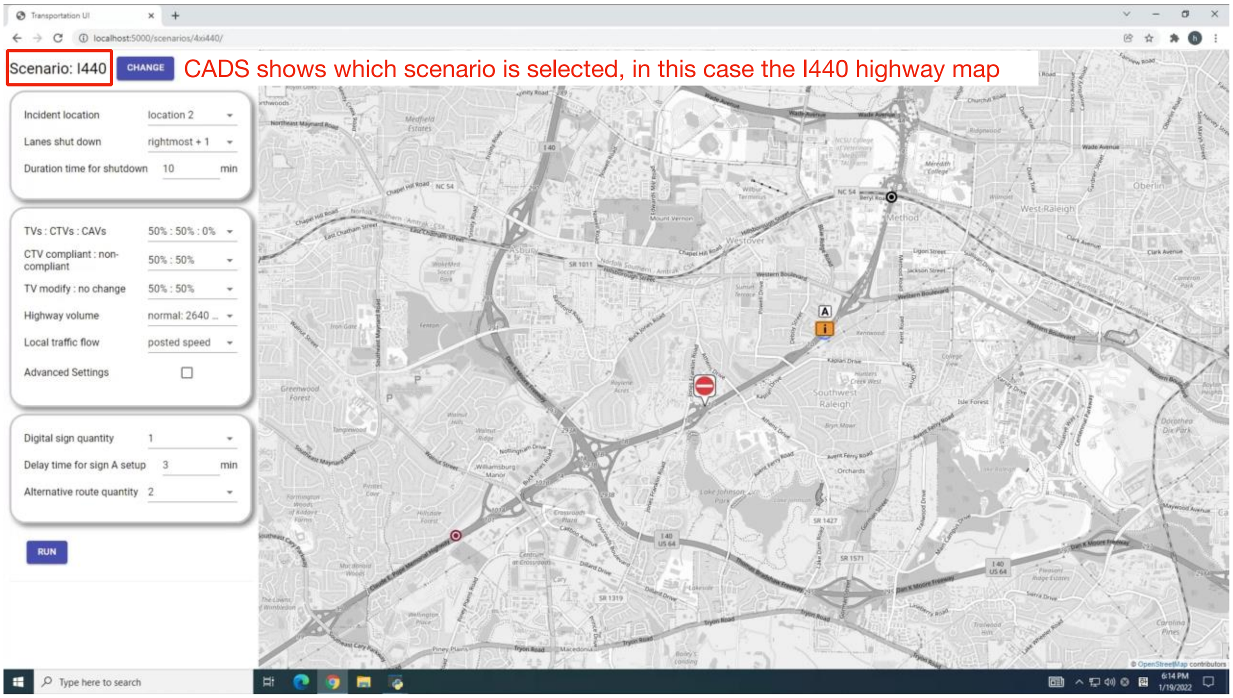
TVs w/ varying compliance	CTVs w/ varying compliance	CAVs w/ perfect compliance

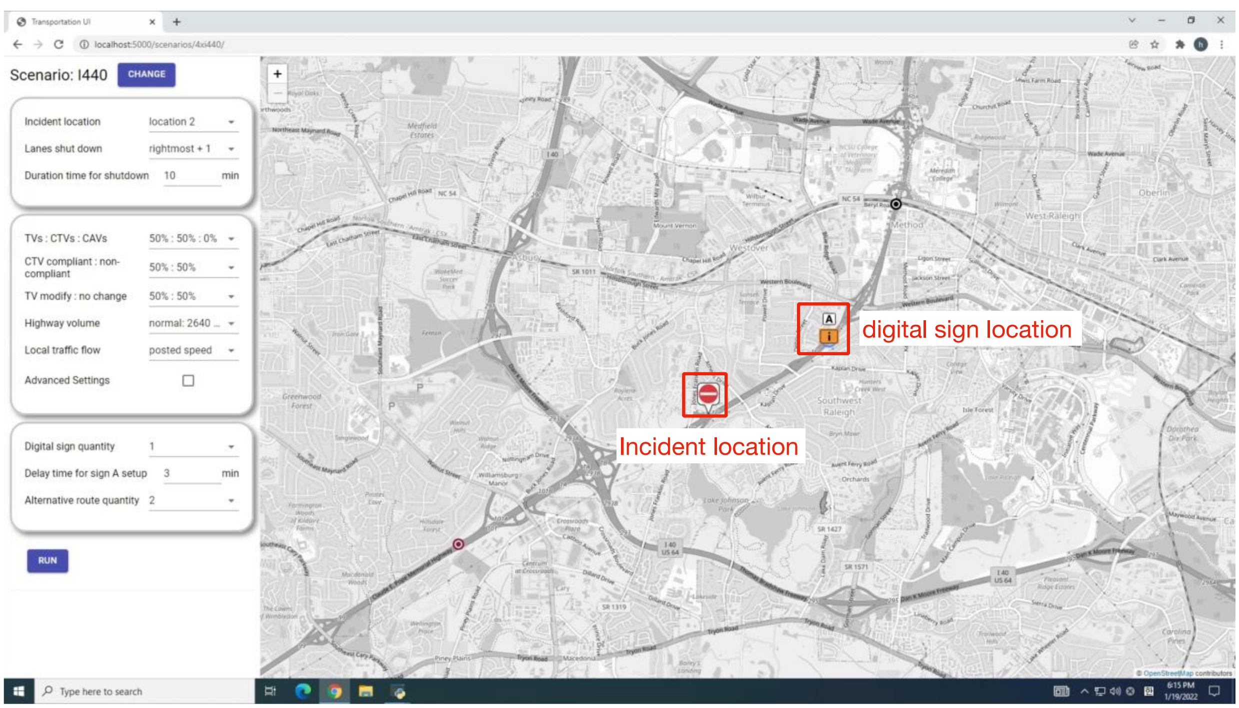
- **Compliance:** Refers to whether vehicles will reroute according to a digital sign's or navigation app's recommendations.
- A compliant TV will reroute once the driver sees the digital sign while non-compliant TV drivers will ignore the sign and continue on their original path.
- A compliant CTV will reroute according to a navigation app suggestion while a non-compliant CTV will ignore the reroute suggestion and continue on its original path.

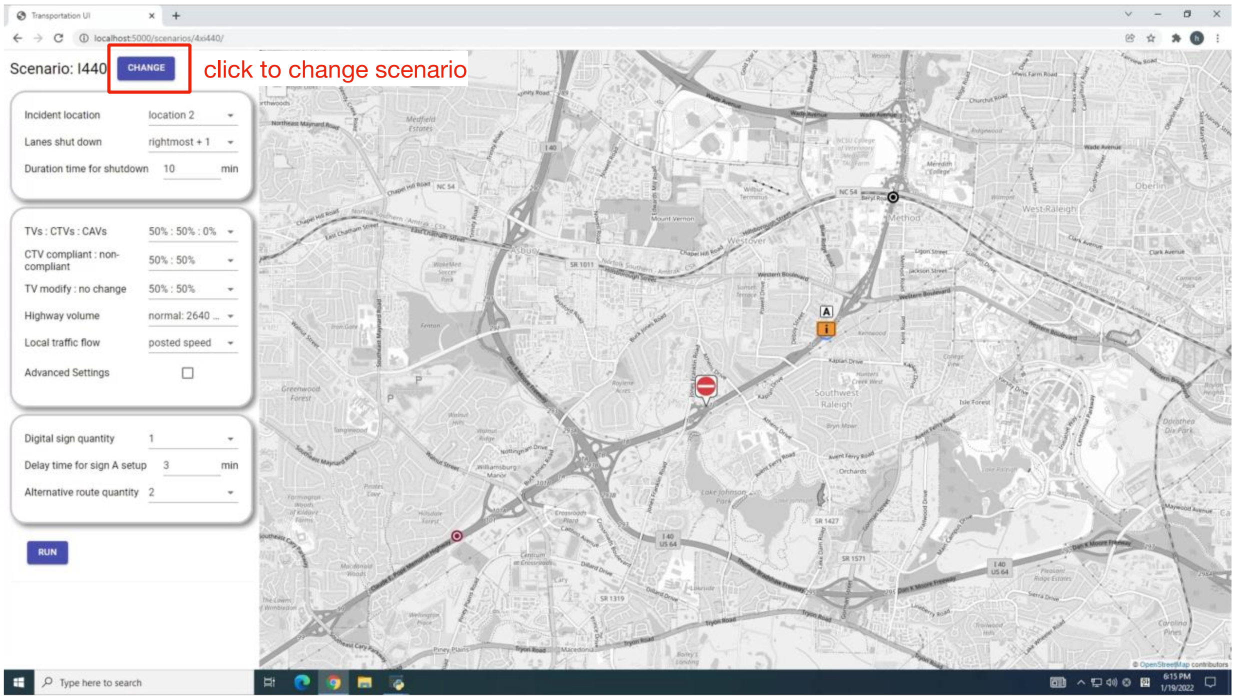
Example Problem

- You notice that there are accidents happening on I440 frequently, and this cause serious traffic delays.
- You want to use CADS to see if placing a digital sign at a certain location will help redistribute traffic ans reduce dealy time.

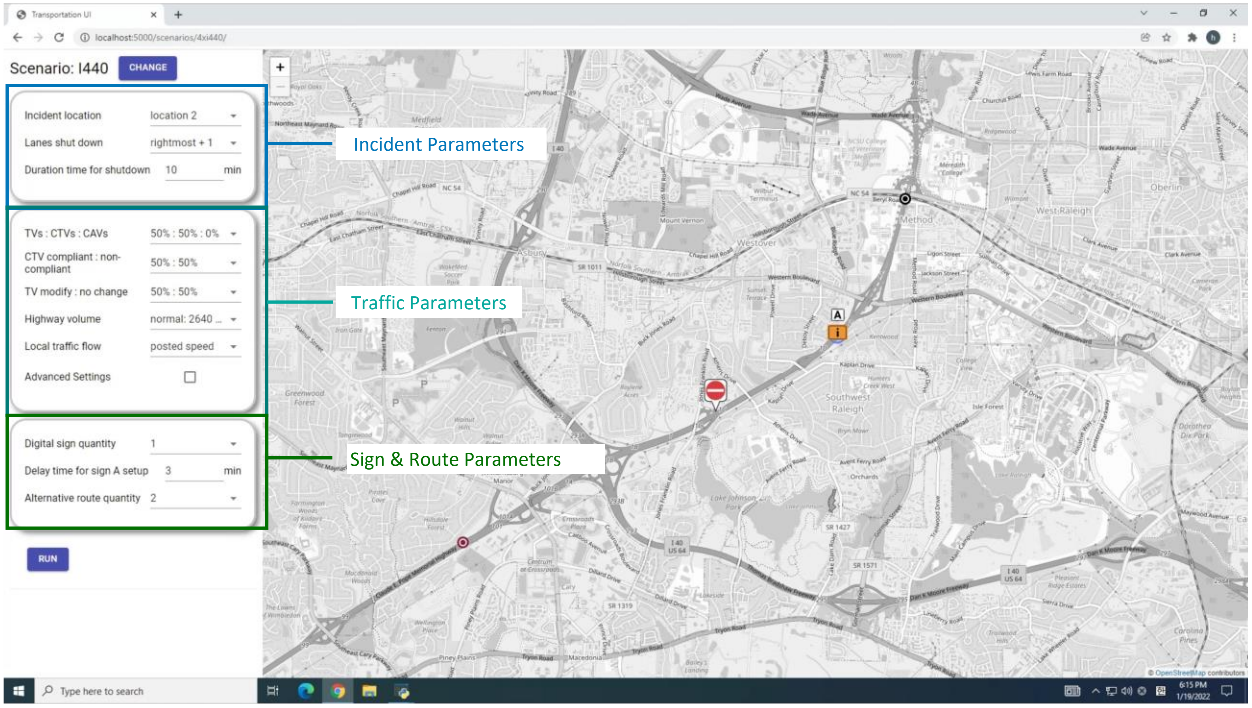
- The following slides show how you can solve this problem with CADS.

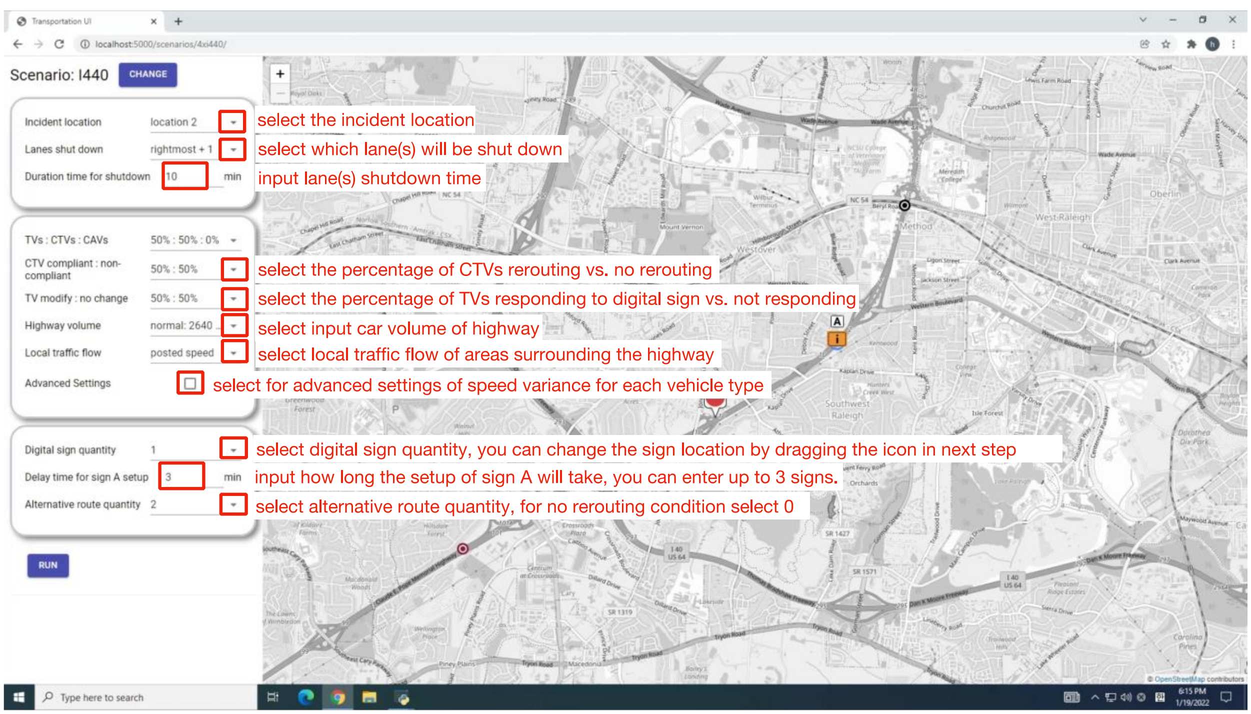


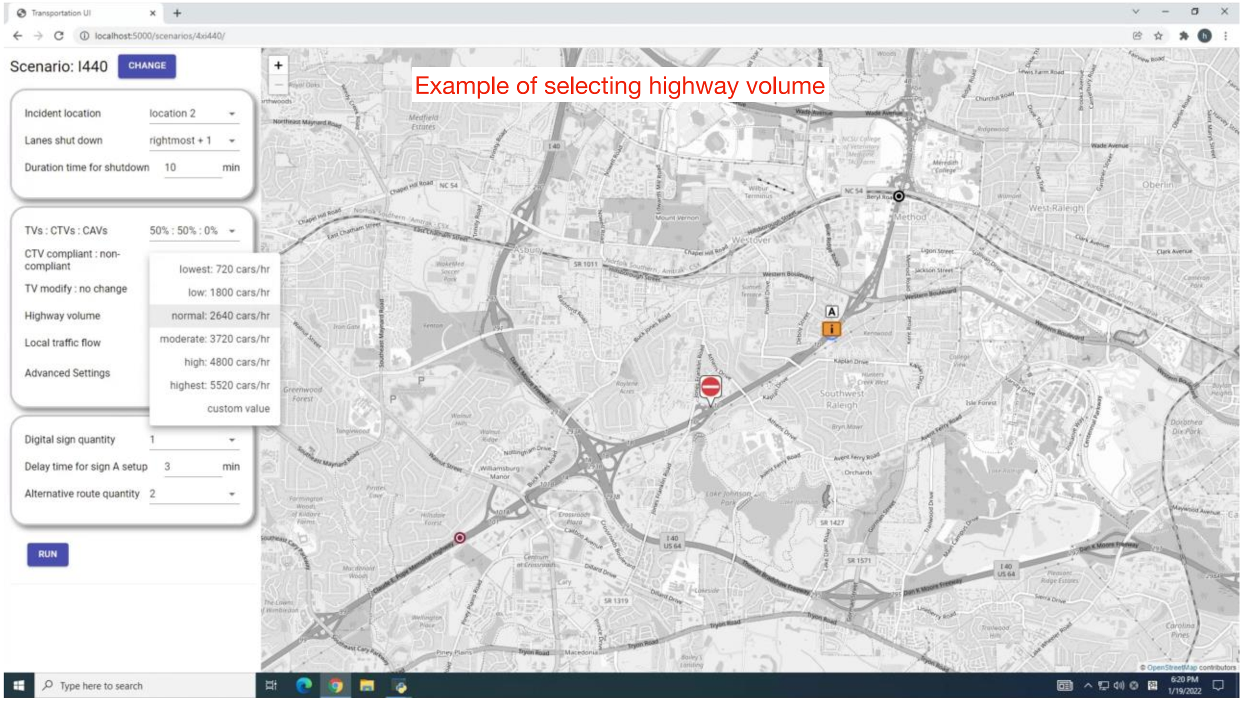


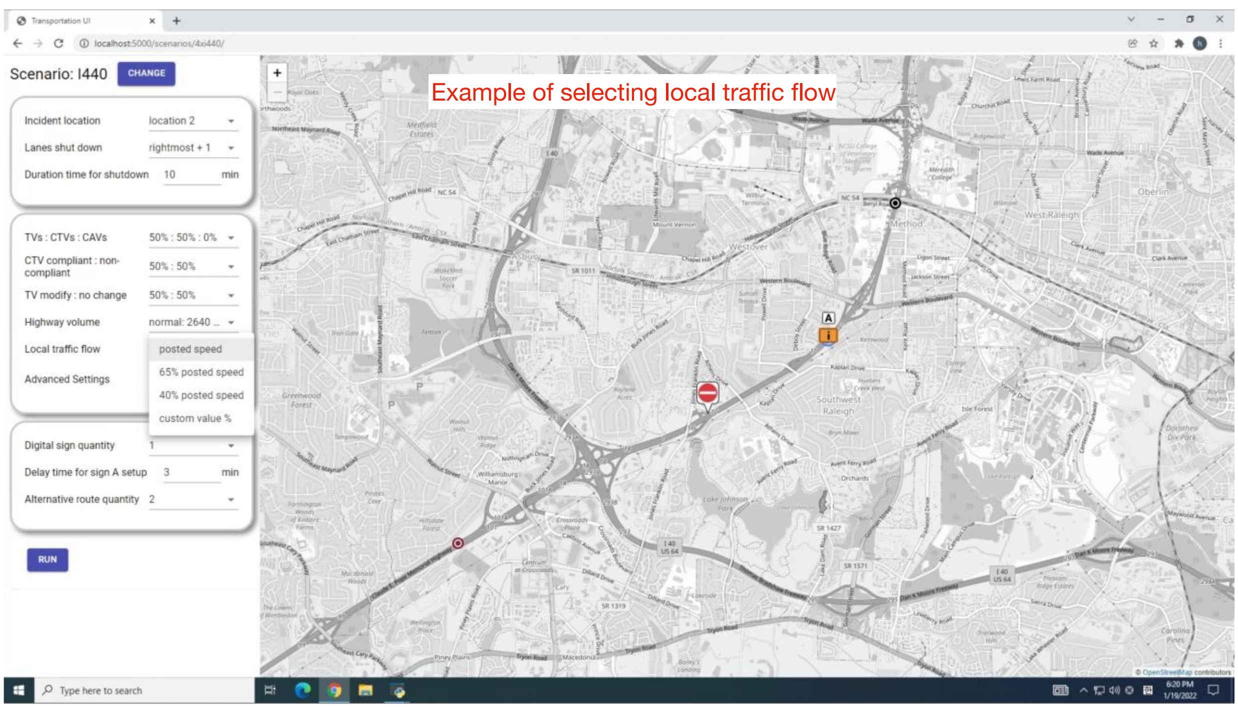

Scenario: I440
CHANGE
click to change scenario
Incident location
location 2
Lanes shut down
rightmost + 1
Duration time for shutdown
10
min
TVs : CTVs : CAVs
50% : 50% : 0%
CTV compliant : non-compliant
50% : 50%
TV modify : no change
50% : 50%
Highway volume
normal: 2640 ...
Local traffic flow
posted speed
Advanced Settings
Digital sign quantity
1
Delay time for sign A setup
3
min
Alternative route quantity
2
RUN
Type here to search

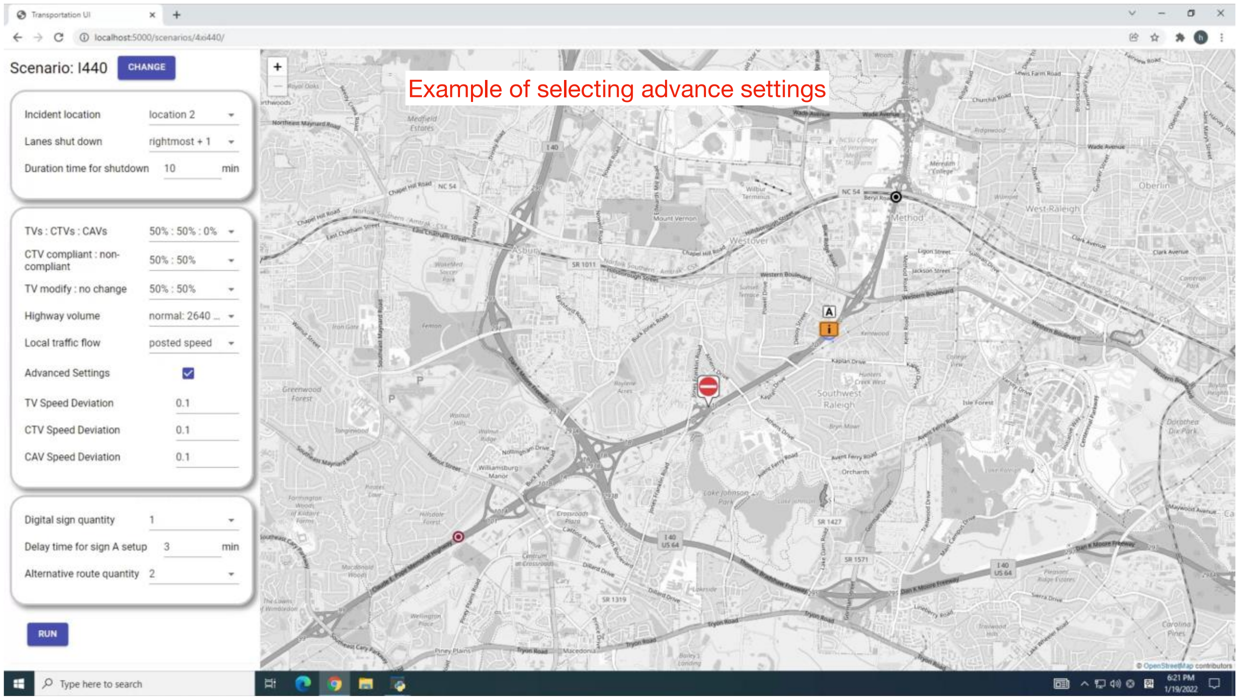

Scenario: I440
CHANGE
select scenario, at this time only I440 works
1
Scenario 1
I440 - Test I440 scenario
2
Scenario 2
3
Scenario 3
Scenario 2 & 3 are under construction
RUN
Type here to search

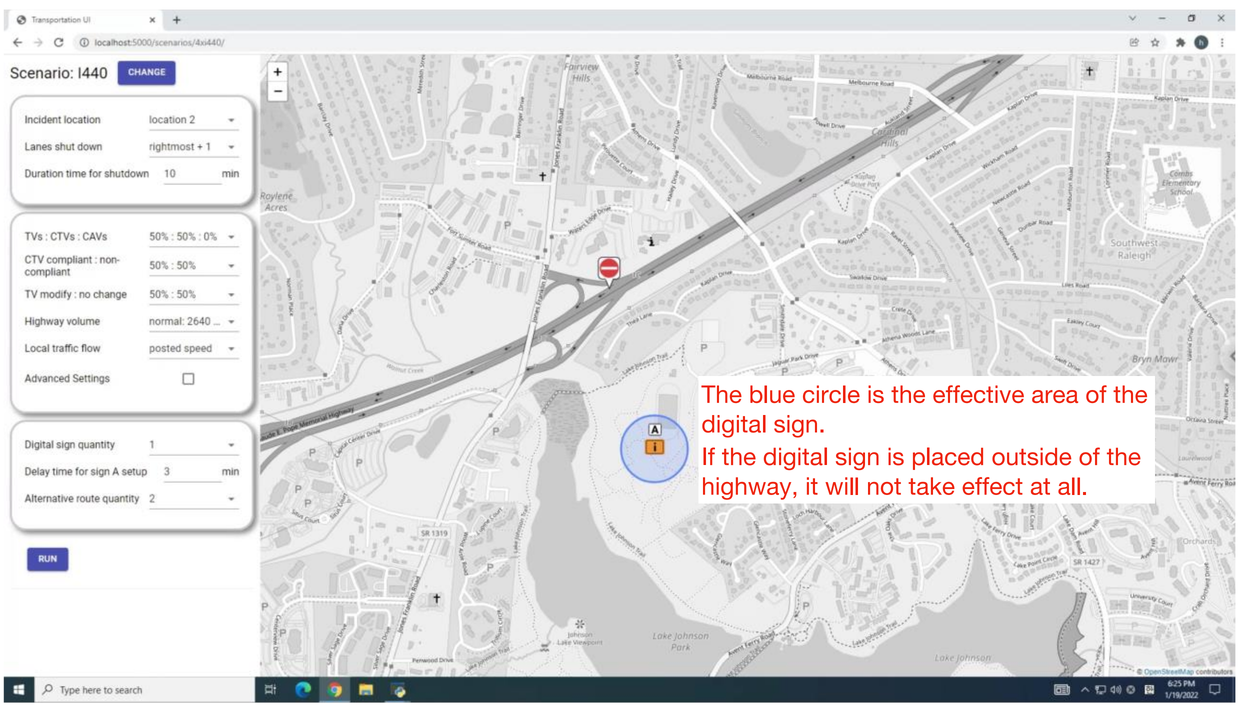

Scenario: I440
CHANGE
Incident location
location 2
Lanes shut down
rightmost + 1
Duration time for shutdown
10
min
Incident Parameters
TVs : CTVs : CAVs
50% : 50% : 0%
CTV compliant : non-compliant
50% : 50%
TV modify : no change
50% : 50%
Highway volume
normal: 2640 ...
Local traffic flow
posted speed
Advanced Settings
Traffic Parameters
Digital sign quantity
1
Delay time for sign A setup
3
min
Alternative route quantity
2
Sign & Route Parameters
RUN

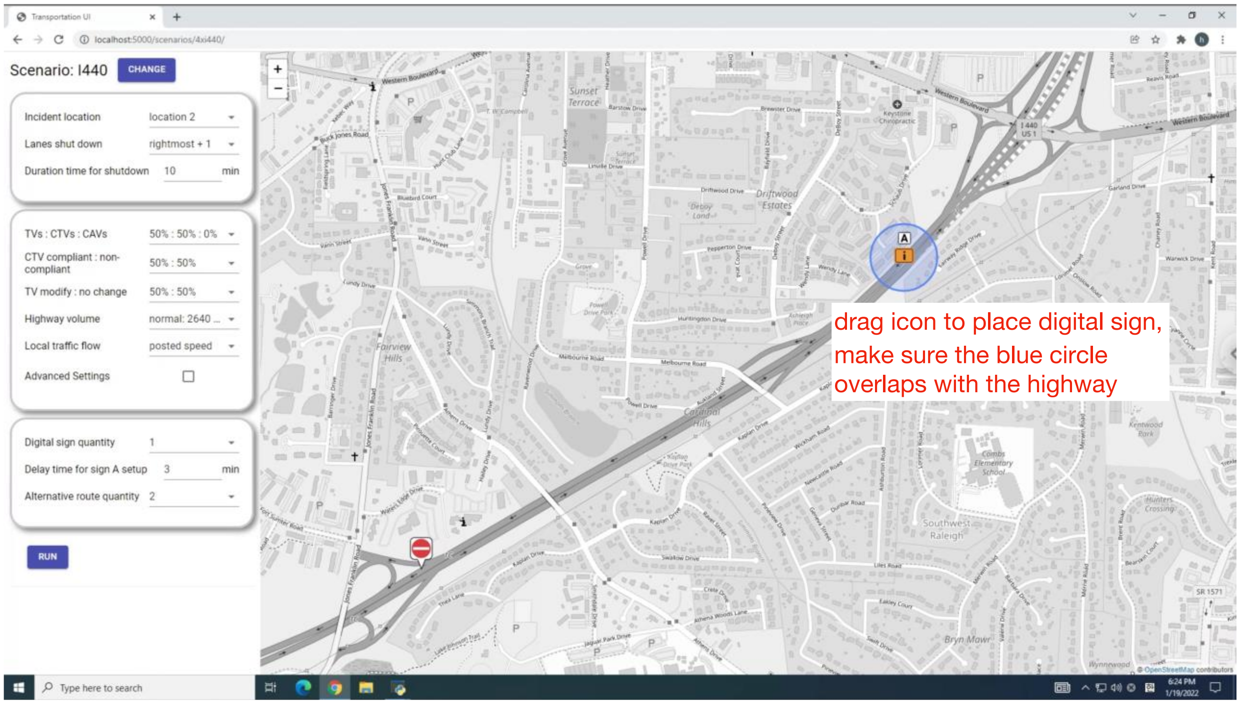

Scenario: I440
CHANGE
Incident location
location 2
select the incident location
Lanes shut down
rightmost + 1
select which lane(s) will be shut down
Duration time for shutdown
10
min
input lane(s) shutdown time
TVs : CTVs : CAVs
50% : 50% : 0%
CTV compliant : non-compliant
50% : 50%
select the percentage of CTVs rerouting vs. no rerouting
TV modify : no change
50% : 50%
select the percentage of TVs responding to digital sign vs. not responding
Highway volume
normal: 2640
select input car volume of highway
Local traffic flow
posted speed
select local traffic flow of areas surrounding the highway
Advanced Settings
select for advanced settings of speed variance for each vehicle type
Digital sign quantity
1
select digital sign quantity, you can change the sign location by dragging the icon in next step
Delay time for sign A setup
3
min
input how long the setup of sign A will take, you can enter up to 3 signs.
Alternative route quantity
2
select alternative route quantity, for no rerouting condition select 0
RUN

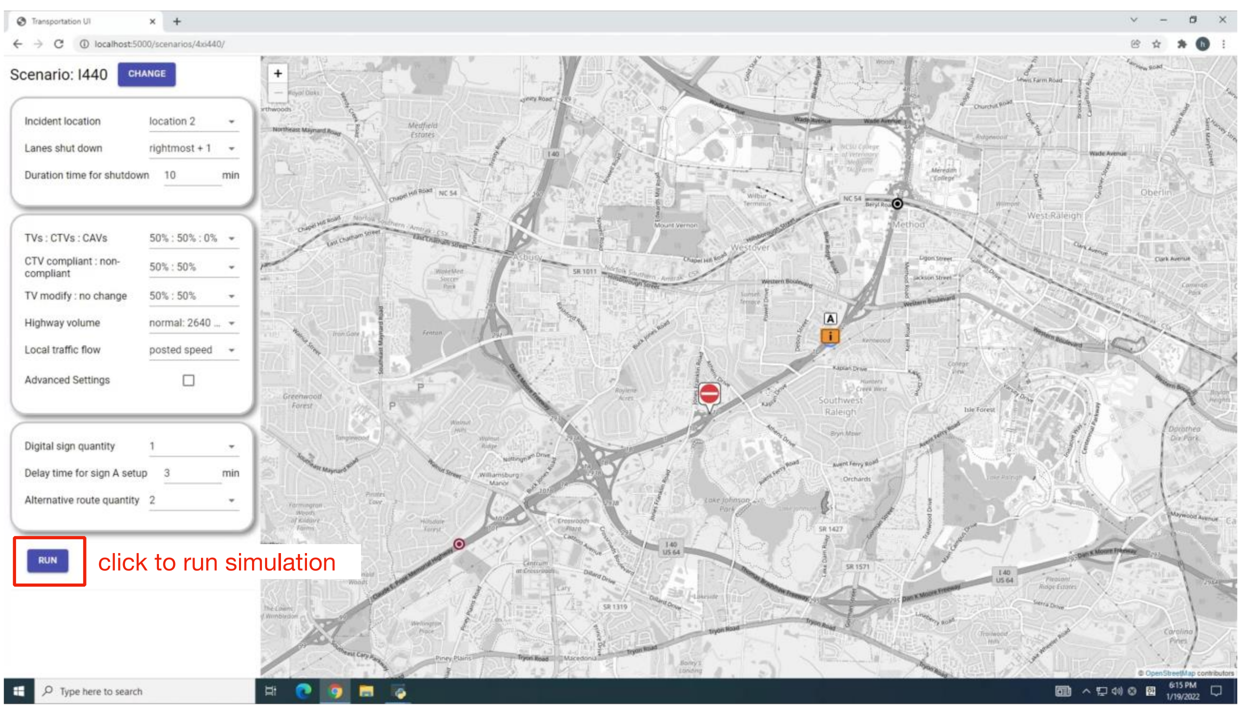

Example of selecting highway volume
Scenario: I440
CHANGE
Incident location
location 2
Lanes shut down
rightmost + 1
Duration time for shutdown
10
min
TVs : CTVs : CAVs
50% : 50% : 0%
CTV compliant : non-compliant
TV modify : no change
Highway volume
Local traffic flow
Advanced Settings
lowest: 720 cars/hr
low: 1800 cars/hr
normal: 2640 cars/hr
moderate: 3720 cars/hr
high: 4800 cars/hr
highest: 5520 cars/hr
custom value
Digital sign quantity
1
Delay time for sign A setup
3
min
Alternative route quantity
2
RUN
Type here to search

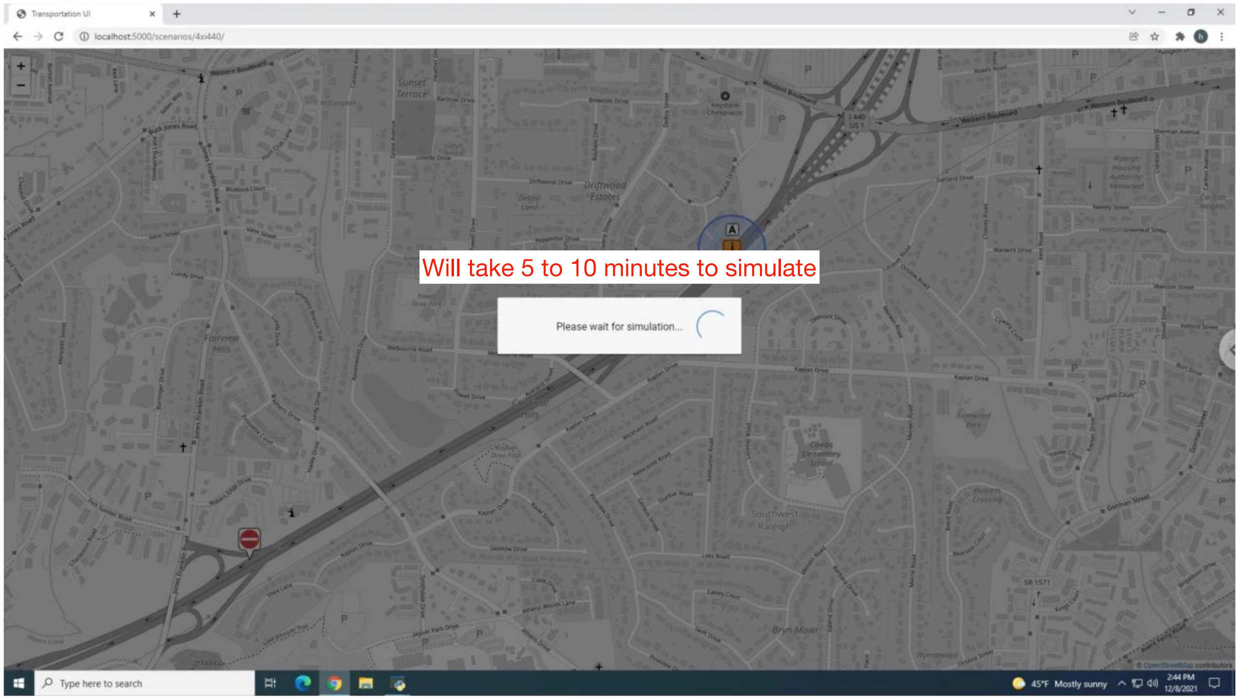

Example of selecting local traffic flow
Scenario: I440
CHANGE
Incident location
location 2
Lanes shut down
rightmost + 1
Duration time for shutdown
10
min
TVs : CTVs : CAVs
50% : 50% : 0%
CTV compliant : non-compliant
50% : 50%
TV modify : no change
50% : 50%
Highway volume
normal: 2640 ...
Local traffic flow
Advanced Settings
posted speed
65% posted speed
40% posted speed
custom value %
Digital sign quantity
1
Delay time for sign A setup
3
min
Alternative route quantity
2
RUN
Type here to search

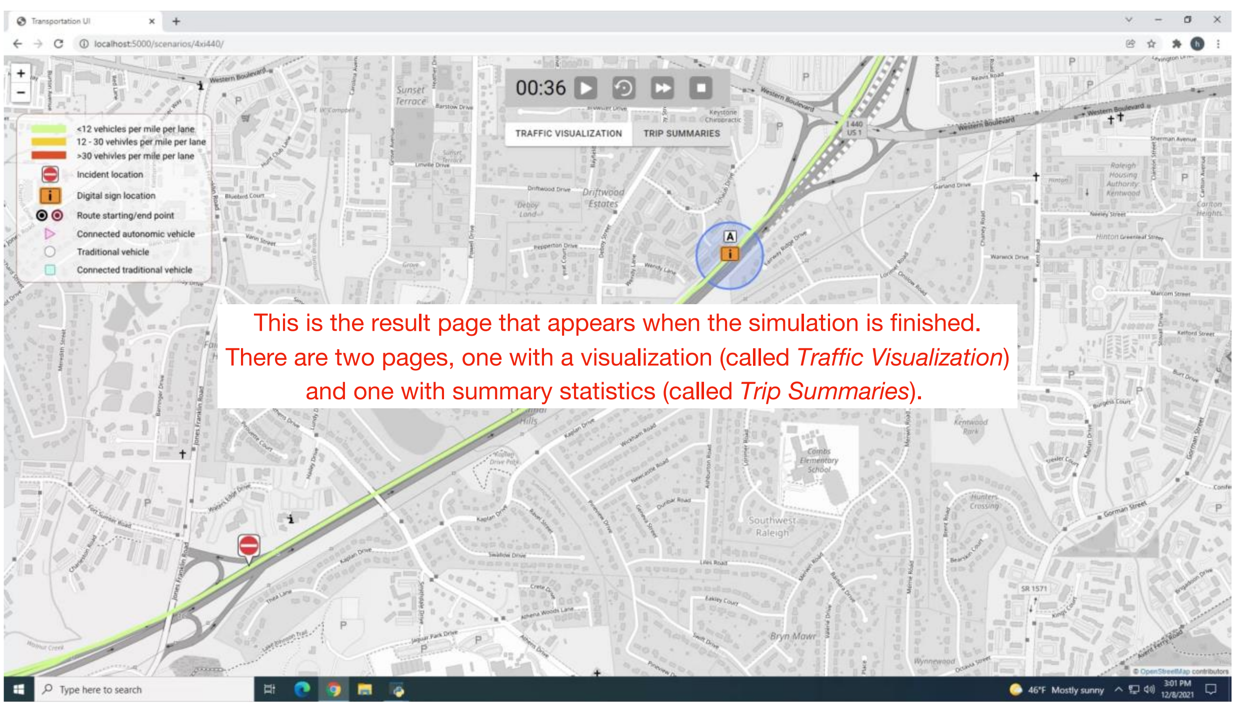

Scenario: I440
CHANGE
Incident location
location 2
Lanes shut down
rightmost + 1
Duration time for shutdown
10
min
TVs : CTVs : CAVs
50% : 50% : 0%
CTV compliant : non-compliant
50% : 50%
TV modify : no change
50% : 50%
Highway volume
normal: 2640 ...
Local traffic flow
posted speed
Advanced Settings
TV Speed Deviation
0.1
CTV Speed Deviation
0.1
CAV Speed Deviation
0.1
Digital sign quantity
1
Delay time for sign A setup
3
min
Alternative route quantity
2
RUN
Example of selecting advance settings

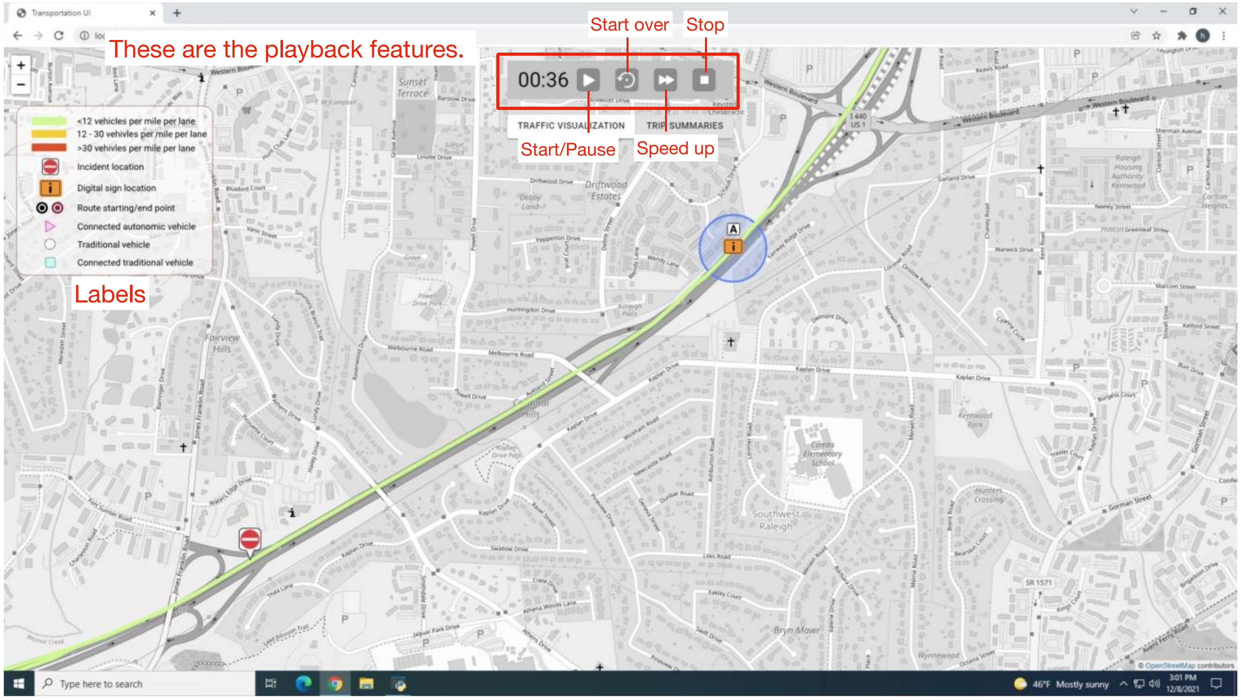

Scenario: I440
CHANGE
Incident location
location 2
Lanes shut down
rightmost + 1
Duration time for shutdown
10
min
TVs : CTVs : CAVs
50% : 50% : 0%
CTV compliant : non-compliant
50% : 50%
TV modify : no change
50% : 50%
Highway volume
normal: 2640 ...
Local traffic flow
posted speed
Advanced Settings
Digital sign quantity
1
Delay time for sign A setup
3
min
Alternative route quantity
2
RUN
The blue circle is the effective area of the digital sign.
If the digital sign is placed outside of the highway, it will not take effect at all.

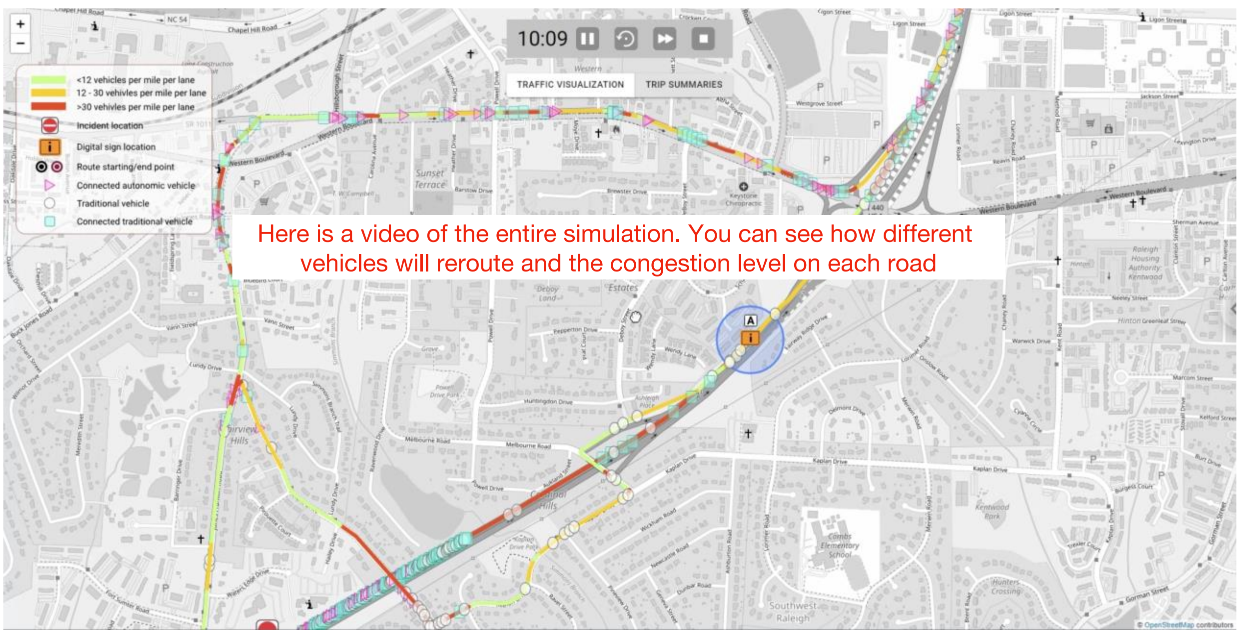

Scenario: I440
CHANGE
Incident location
location 2
Lanes shut down
rightmost + 1
Duration time for shutdown
10
min
TVs : CTVs : CAVs
50% : 50% : 0%
CTV compliant : non-compliant
50% : 50%
TV modify : no change
50% : 50%
Highway volume
normal: 2640 ...
Local traffic flow
posted speed
Advanced Settings
Digital sign quantity
1
Delay time for sign A setup
3
min
Alternative route quantity
2
RUN
drag icon to place digital sign, make sure the blue circle overlaps with the highway

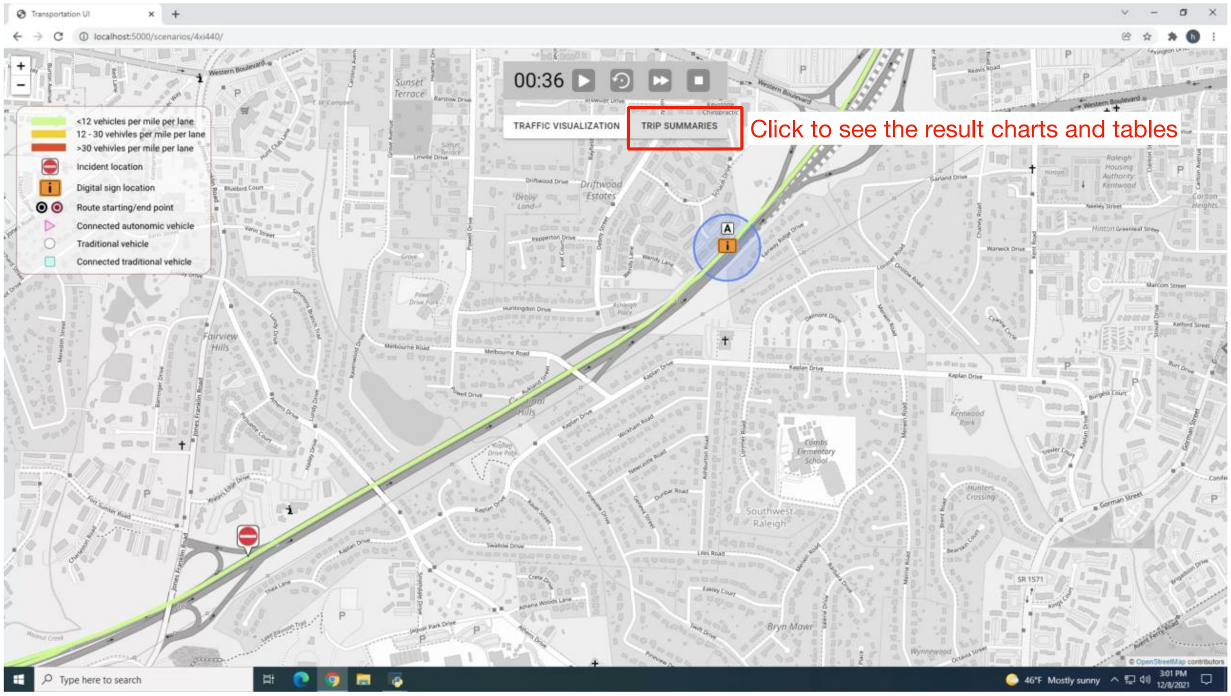

Scenario: I440
CHANGE
Incident location
location 2
Lanes shut down
rightmost + 1
Duration time for shutdown
10
min
TVs : CTVs : CAVs
50% : 50% : 0%
CTV compliant : non-compliant
50% : 50%
TV modify : no change
50% : 50%
Highway volume
normal: 2640 ...
Local traffic flow
posted speed
Advanced Settings
Digital sign quantity
1
Delay time for sign A setup
3
min
Alternative route quantity
2
RUN
click to run simulation


Transportation UI
localhost:5000/scenarios/4xi440/
Will take 5 to 10 minutes to simulate
Please wait for simulation...
Type here to search


Transportation UI
localhost:5000/scenarios/4xi440/
00:36
TRAFFIC VISUALIZATION
TRIP SUMMARIES
<12 vehicles per mile per lane
12 - 30 vehicles per mile per lane
>30 vehicles per mile per lane
Incident location
Digital sign location
Route starting/end point
Connected autonomic vehicle
Traditional vehicle
Connected traditional vehicle
This is the result page that appears when the simulation is finished.
There are two pages, one with a visualization (called *Traffic Visualization*)
and one with summary statistics (called *Trip Summaries*).
Type here to search


These are the playback features.
Start over
Stop
00:36
TRAFFIC VISUALIZATION
TRIP SUMMARIES
Start/Pause
Speed up
<12 vehicles per mile per lane
12 - 30 vehivles per mile per lane
>30 vehivles per mile per lane
Incident location
Digital sign location
Route starting/end point
Connected autonomic vehicle
Traditional vehicle
Connected traditional vehicle
Labels


10:09
TRAFFIC VISUALIZATION
TRIP SUMMARIES
<12 vehicles per mile per lane
12 - 30 vehivles per mile per lane
>30 vehivles per mile per lane
Incident location
Digital sign location
Route starting/end point
Connected autonomic vehicle
Traditional vehicle
Connected traditional vehicle
Here is a video of the entire simulation. You can see how different vehicles will reroute and the congestion level on each road



Shows all input traffic parameters

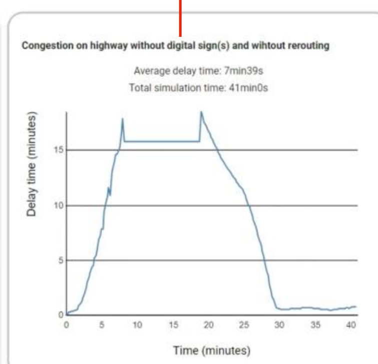
Delay of vehicles on highway due to congestion if no digital sign is placed and no rerouting happens. This is the baseline case.

Traffic conditions

TVs:CTVs:CAVs ratio	25% : 50% : 25%
CTV compliant : non-compliant	50% : 50%
TV modify : no change	50% : 50%
Highway Volume	high: 4800 cars/hr
Local traffic flow	posted speed
Lanes shut down	rightmost + 1
Duration for shut down	15 min
Advanced Settings	-
# of digital sign(s)	1
Delay time for sign setup	3 min
# of alternative route(s)	2

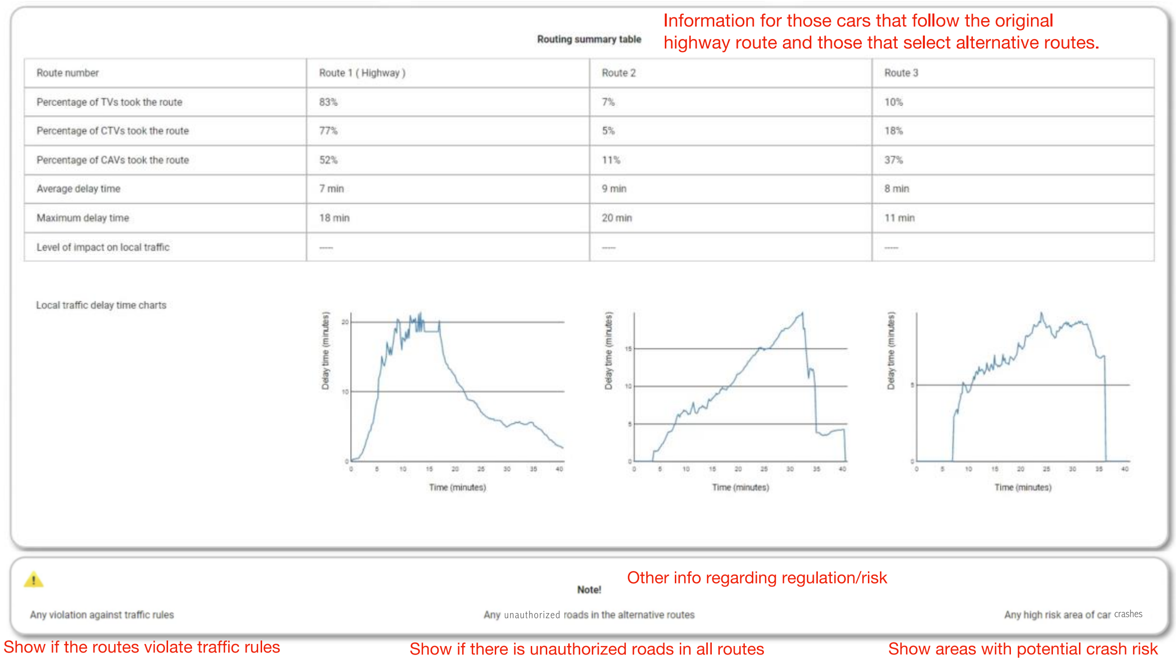
Vehicle summary table

	Type	Cars Arrived	Avg. Delay Time
TV	Modify	225	6min54s
	No Change	230	7min46s
CTV	Compliant	439	8min3s
	Non-compliant	482	7min45s
CAV	Compliant	478	7min58s
Total simulation time: 41min0s			

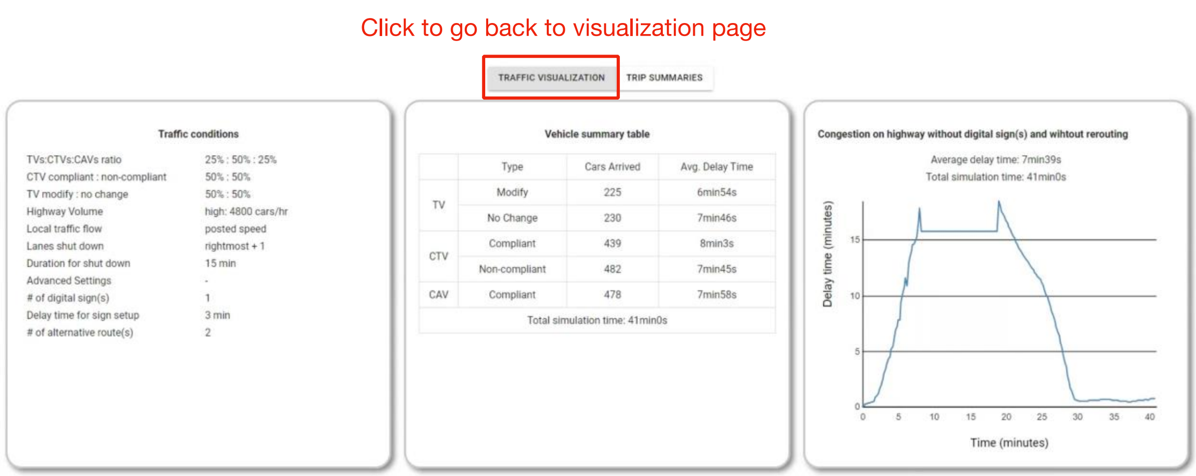


Arrived car number and average delay time for each vehicle type.

Total simulation time is the entire runtime with digital sign placement and vehicle rerouting. It's calculated based on the duration time for the length of the shut down and trip information.

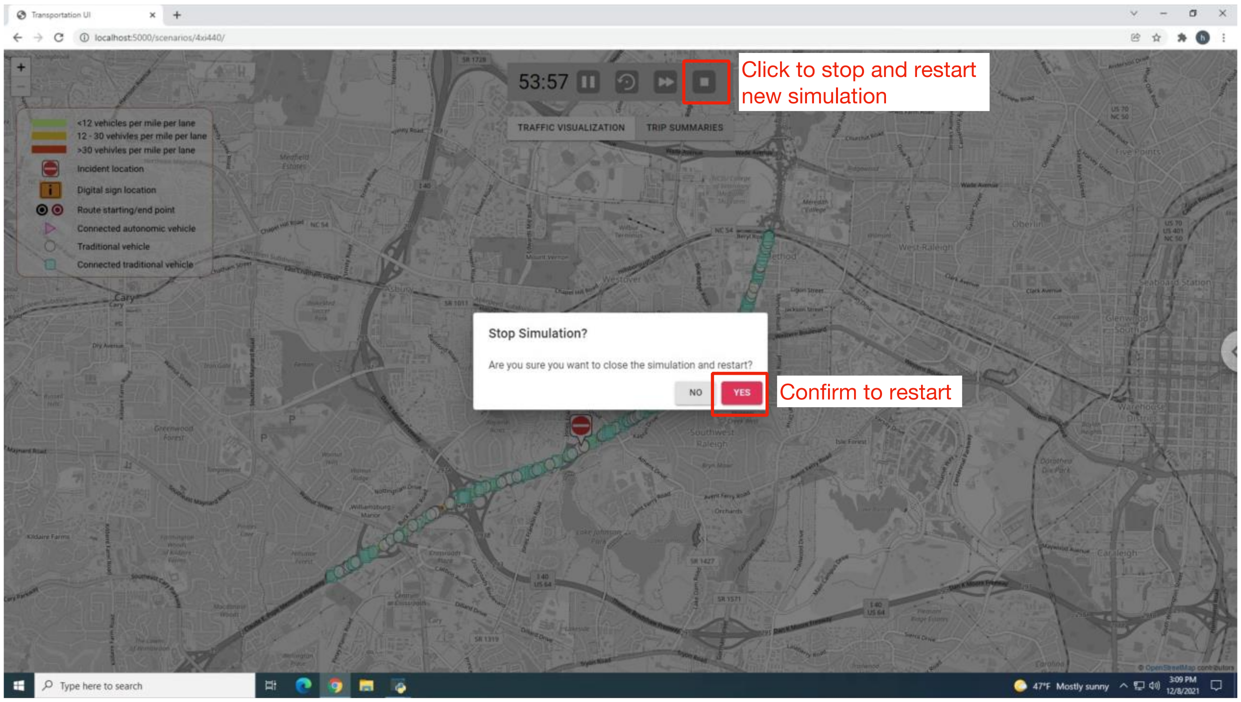


Route number	Route 1 (Highway)	Route 2	Route 3
Percentage of TVs took the route	83%	7%	10%
Percentage of CTVs took the route	77%	5%	18%
Percentage of CAVs took the route	52%	11%	37%
Average delay time	7 min	9 min	8 min
Maximum delay time	18 min	20 min	11 min
Level of impact on local traffic	----	----	----



Traffic conditions	
TVs:CTVs:CAVs ratio	25% : 50% : 25%
CTV compliant : non-compliant	50% : 50%
TV modify : no change	50% : 50%
Highway Volume	high: 4800 cars/hr
Local traffic flow	posted speed
Lanes shut down	rightmost + 1
Duration for shut down	15 min
Advanced Settings	-
# of digital sign(s)	1
Delay time for sign setup	3 min
# of alternative route(s)	2

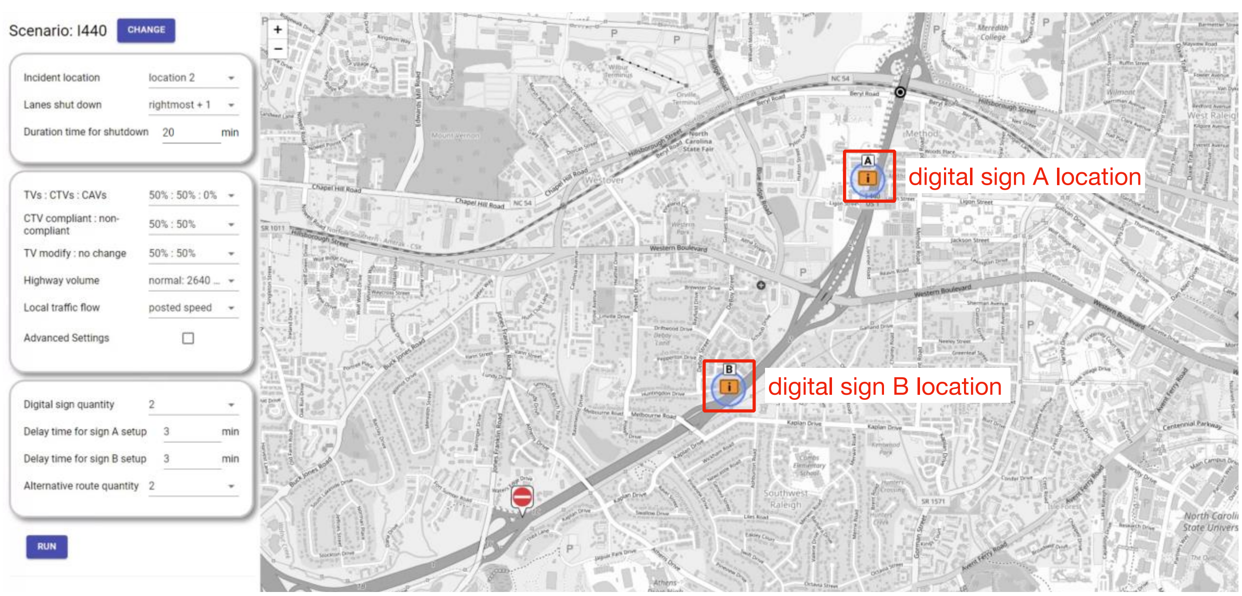
	Type	Cars Arrived	Avg. Delay Time
TV	Modify	225	6min54s
	No Change	230	7min46s
CTV	Compliant	439	8min3s
	Non-compliant	482	7min45s
CAV	Compliant	478	7min58s
Total simulation time: 41min0s			



TRY TO SOLVE THE FOLLOWING PROBLEMS

Problem 1

- Use CADS to determine whether adding signs at locations A and B significantly reduces delay time if there is an accident at location 2 with 20 minutes incident duration time. Please refer to the next slide for detailed input settings.
  - Example Input Page:



Problem 1 Solution

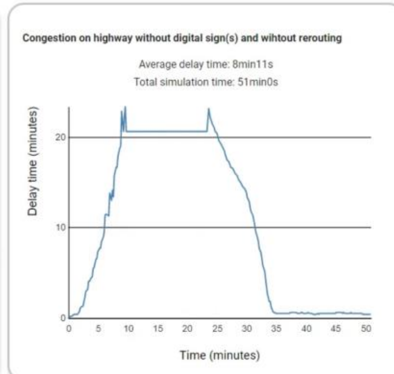
- You should obtain the following results:

Traffic conditions

TVs:CTVs:CAVs ratio	50% : 50% : 0%
CTV compliant : non-compliant	50% : 50%
TV modify : no change	50% : 50%
Highway Volume	normal: 2640 cars/hr
Local traffic flow	posted speed
Lanes shut down	rightmost + 1
Duration for shut down	20 min
Advanced Settings	-
# of digital sign(s)	2
Delay time for sign setup	3 min , 3 min
# of alternative route(s)	2

Vehicle summary table

	Type	Cars Arrived	Avg. Delay Time
TV	Modify	544	4min59s
	No Change	508	8min16s
CTV	Compliant	541	5min47s
	Non-compliant	505	8min43s
CAV	Compliant	0	-
Total simulation time: 51min0s			



- Given these results, if there is no digital sign placement and very few cars choose to reroute, the overall delay will be about 8 minutes. But if the sign is posted and people reroute per the input parameters, there will be a reduction in delay time for all rerouting vehicles. However, highway max delays could still be about 22 minutes on the original route.

Route number	Route 1 (Highway)	Route 2	Route 3
Percentage of TVs took the route	79%	11%	10%
Percentage of CTVs took the route	79%	11%	10%
Percentage of CAVs took the route	0%	0%	0%
Average delay time	7 min	6 min	6 min
Maximum delay time	22 min	10 min	10 min
Level of impact on local traffic	—	—	—

Problem 2

- Use CADS to determine whether congestion is worse under high traffic volumes when the vehicle mix of TVs: CTVs: CAVs is 25%: 25%: 50% (with no accident and no digital sign) as compared to normal highway volumnes.
  - Hint: Use 1 minute incident time to represent a no accident situation
  - Example input page:

Normal Highway Volume Results

Traffic conditions

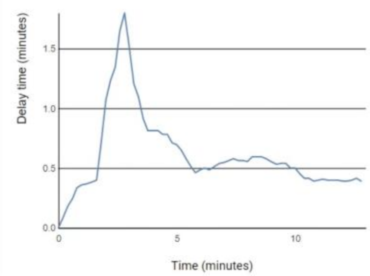
TVs:CTVs:CAVs ratio	25% : 25% : 50%
CTV compliant : non-compliant	50% : 50%
TV modify : no change	50% : 50%
Highway Volume	normal: 2640 cars/hr
Local traffic flow	posted speed
Lanes shut down	rightmost + 1
Duration for shut down	1 min
Advanced Settings	-
# of digital sign(s)	0
Delay time for sign setup	-
# of alternative route(s)	0

Vehicle summary table

	Type	Cars Arrived	Avg. Delay Time
TV	Modify	49	0min40s
	No Change	56	0min44s
CTV	Compliant	54	0min41s
	Non-compliant	39	0min39s
CAV	Compliant	232	0min41s
Total simulation time: 13min0s			

Congestion on highway without digital sign(s) and wihtout rerouting

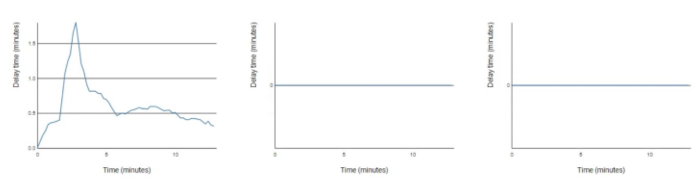
Average delay time: 0min41s
Total simulation time: 13min0s



Routing summary table

Route number	Route 1 (Highway)	Route 2	Route 3
Percentage of TVs took the route	100%	0%	0%
Percentage of CTVs took the route	100%	0%	0%
Percentage of CAVs took the route	100%	0%	0%
Average delay time	0 min	0 min	0 min
Maximum delay time	1 min	0 min	0 min
Level of impact on local traffic	---	---	---

Local traffic delay time charts



High Highway Volume Results

Traffic conditions

TVs:CTVs:CAVs ratio	25% : 25% : 50%
CTV compliant : non-compliant	50% : 50%
TV modify : no change	50% : 50%
Highway Volume	high: 4800 cars/hr
Local traffic flow	posted speed
Lanes shut down	rightmost + 1
Duration for shut down	1 min
Advanced Settings	-
# of digital sign(s)	0
Delay time for sign setup	-
# of alternative route(s)	0

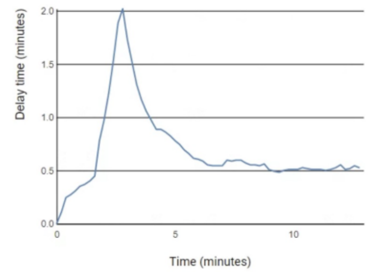
Vehicle summary table

	Type	Cars Arrived	Avg. Delay Time
TV	Modify	58	0min45s
	No Change	62	0min48s
CTV	Compliant	63	0min42s
	Non-compliant	47	0min43s
CAV	Compliant	258	0min47s

Total simulation time: 13min0s

Congestion on highway without digital sign(s) and wihtout rerouting

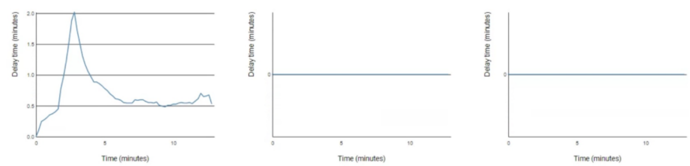
Average delay time: 0min46s
Total simulation time: 13min0s



Routing summary table

Route number	Route 1 (Highway)	Route 2	Route 3
Percentage of TVs took the route	100%	0%	0%
Percentage of CTVs took the route	100%	0%	0%
Percentage of CAVs took the route	100%	0%	0%
Average delay time	0 min	0 min	0 min
Maximum delay time	1 min	0 min	0 min
Level of impact on local traffic	—	—	—

Local traffic delay time charts



- Given these results, for normal traffic volume on highway, the average delay is around 41 seconds, while for high traffic volume, the delay is about 45 seconds, only 4 seconds difference. Additionally, the maximum delay in highway is 1 minute for both normal and high volumes. Considering the trip time from starting point to end point is much larger than 1 minute it appears that under high traffic volumes the congestion is relatively the same level as normal traffic volumes with this mix of vehicles.

Vehicle summary table

	Type	Cars Arrived	Avg. Delay Time
TV	Modify	49	0min40s
	No Change	56	0min44s
CTV	Compliant	54	0min41s
	Non-compliant	39	0min39s
CAV	Compliant	232	0min41s

Total simulation time: 13min0s

Normal Traffic Volume

Vehicle summary table

	Type	Cars Arrived	Avg. Delay Time
TV	Modify	58	0min45s
	No Change	62	0min48s
CTV	Compliant	63	0min42s
	Non-compliant	47	0min43s
CAV	Compliant	258	0min47s

Total simulation time: 13min0s

High Traffic Volume

Route number	Route 1 (Highway)
Percentage of TVs took the route	100%
Percentage of CTVs took the route	100%
Percentage of CAVs took the route	100%
Average delay time	0 min
Maximum delay time	1 min
Level of impact on local traffic	—

REFERENCES

[1] Bastian J. Schroeder, Part 5 - Traffic Operations, Highway Engineering, Butterworth-Heinemann, 2016, Pages 255-432, ISBN 9780128012482,

Table 5.7 LOS thresholds for basic freeway and multilane highway segments

Level of service	Description	Density range (passenger cars/ mi per lane)
A	Completely free-flowing condition with efficient operating speeds	0–11
B	Stable flow for a freeway or major highway	>11–18
C	Reasonable and uniform flow but with lower operating speeds	>18–26
D	Approaching unstable flow with low operating speeds	>26–35
E	Unstable flow	>35–45
F*	Forced flow or the stop-and-go movement	>45

*LOS = F also applies any time demand exceeds capacity.

[2] Highway Capacity Manual. TRB, National Research Council, Washington, D.C., 2000.

TABLE 1 LOS Criteria for Urban Arterial (*1*, Exhibit 15-2)

	Average Travel Speed by Class			
	I	II	III	IV
Range of free-flow speeds (FFS)	55–45 mph	45–35 mph	35–30 mph	35–25 mph
Typical FFS	50 mph	40 mph	35 mph	30 mph
LOS				
A	>42	>35	>30	>25
B	>34–42	>28–35	>24–30	>19–25
C	>27–34	>22–28	>18–24	>13–19
D	>21–27	>17–22	>14–18	>9–13
E	>16–21	>13–17	>10–14	>7–9
F	≤16	≤13	≤10	≤7

Appendix B

B1. TERMS AND DEFINITIONS

The metrics from Fig. 9 are defined in Table 7, with detail following.

Table 7: Glossary of Terms for Surrogate Safety Assessment

Parameter	Unit	Description
$a_L(t)$	m/s^2	Acceleration rate of the leading vehicle at time t
$a_F(t)$	m/s^2	Acceleration rate of the following vehicle at time t
$\Delta a(t)$	m/s^2	Relative acceleration rate of the pair of interacting vehicles at time $t, \left(a_F(t) - a_L(t)\right)$
d_{Lmax}, d_{Fmax}	m/s^2	Maximum deceleration rate applied by leading and following vehicles. A value of 3.4 m/s^2 is used for passenger cars (AASTHO,2009)
$D(t)$	M	Inter-vehicular spacing of the vehicle pairs at time t
$DSS_i(t)$	M	Difference between space distance and stopping distance of the i^{th} following vehicle at t.
DSS^*	M	DSS threshold is 0 m; when DSS is below zero, it defines a traffic conflict
$DRAC_i(t)$	m/s^2	Deceleration rate to avoid crash of the i^{th} (following) vehicle at time instant t
$DRAC^*$	m/s^2	Defined threshold for $DRAC$. At time instant t, if $DRAC$ is beyond $DRAC^*$, then t is considered as time in conflict.
$DRAC_{max}$	m/s^2	Maximum observed $DRAC$ over the experiment time
DV	m/s	Driving volatility expressed as speed volatility in this research
μ		Friction factor of the pavement
g	m/s^2	Gravitation acceleration (9.81 m/s^2)
L_i	M	Length of the following vehicle
L_{i-1}	M	Length of the leading vehicle
MAD_i		Mean absolute deviation of the i^{th} (Subject) vehicle. It quantifies variations in the data by measuring the distance between observations and their central tendency (mean of vehicular speed in this research).
$MTC_i(t)$		Margin to collision of the i^{th} (following) vehicle at time instant t
MTC^*		Margin to collision threshold; normally taken as 1.
$MTTC_i(t)$	S	Modified time to collision of the i^{th} (following) vehicle at time instant t, in seconds.
$MTTC*$	S	Threshold of modified time to collision.
N	Count	Number of vehicles counted within the experiment time interval T
RT_F	S	Response time of following vehicle

$RCRI_i(t)$	M	Rear end crash index of the i^{th} (following) vehicle at time instant t
$SSD_L(t)$	M	Safe stopping distance of the leading vehicle at time t
$SSD_F(t)$	M	Safe stopping distance of the following vehicle at time t
τ	S	Experimental time step, in this study it 0.1 s.
t		A time instant
T	S	Total experimental time
$TTC_i(t)$	S	Time to collision (TTC) of the i^{th} (following) vehicle at time instant t, expressed in seconds.
TTC^*	S	Defined threshold for TTC. At any time, instant t if the TTC value for a vehicle is below TTC^*, then t is considered as time in conflict.
TTC_{min}	S	Minimum observed TTC over the experiment time T.
TIT	s^2	Time integrated time to collision.
$TIDRAC$	m/s	Time integrated deceleration rate to avoid crash
$TERCRI$	S	Time exposed rear-end crash risk index
Δt	S	Response time lag
V_i(t)	m/s	Speed of subject vehicle i at any time instant t
V_L(t)	m/s	Speed of the leading vehicle at any time instant t
V_F(t)	m/s	Speed of the following vehicle at any time instant t
ΔV(t)	m/s	Relative speed of the pair of interacting vehicles
$\bar{V}_i$	m/s	Average speed of the i^{th} vehicle.
$X_i(t)$	M	Vehicle position of the subject vehicle measured form front bumper at time instant t
$X_{i-1}(t)$	M	Vehicle position of the leading vehicle measured form front bumper at time instant t
$x(t)$, $y(t)$		Value of any $x(t)$ and $y(t)$ time series at time $t, t = 0,1,2,3, \ldots \ldots \ldots T$

Time to Collision (TTC) and Minimum Time to Collision (TTC_{min}): TTC at an instant *t* is defined as the time that remains until a collision between two vehicles on the same lane would have occurred if the collision course and speed differences are maintained, provided that the following vehicle has greater speed than the leading vehicle (82). A car-following scenario is unsafe when the TTC value drops below a certain threshold value (83). TTC assumes that consecutive vehicles will maintain current speeds and there must exist a collision course between them (84). One of the main limitations of TTC is that it can report only the number of traffic conflicts but not their severity (45). Therefore, TTC_{min} is introduced which reports the minimum TTC value observed within a time interval, as an indication of its severity (77). TTC can be expressed in Equation (1) below:

$$TTC_i(t) = \begin{cases} \frac{X_L(t) - X_F(t) - L_F}{V_F(t) - V_L(t)}, & V_F(t) > V_L(t) \\ \infty, & otherwise \end{cases} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (1)$$

Time Integrated Time to Collision (TIT): TIT expresses the level of traffic conflict severity by using the integral of the following vehicle's TTC-profile during the time it is below the threshold TTC* (Minderhoud & Bovy, 2001). Experimental time step for TIT for is 0.1 s for this study. Equation (2) illustrates the TIT computation:

$$TIT = \sum_{t=0}^{T} \sum_{i=1}^{N} (TTC^* - TTC_i(t))\ \tau\, \delta_{i,t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (2)$$

where $\delta_{i,t} = \begin{cases} 1, & when\ 0 \le TTC_i(t) \le TTC^* \\ 0, & Oterwise \end{cases}$

TTC thresholds typically vary between 1.5 and 4 seconds (Minderhoud & Bovy, 2001) for TVs. For this study we selected a TTC* threshold of 1.5 s.

Deceleration Rate to Avoid Crash (DRAC): DRAC represents the deceleration rate applied by a following vehicle in response to the actions of a leading vehicle, to come to a timely stop or attain a matching lead vehicle speed to avoid a crash. Like TTC, DRAC requires a threshold to differentiate between safe and unsafe driving. According to AASHTO, the DRAC threshold should be 3.40 m/s^2 (AASHTO, 2009). Archer (2005) proposed that if a vehicle's braking exceeds 3.35 m/s^2, it should be defined as a conflict. Based on the review of literature, a DRAC threshold of 3.40 m/s^2 was adopted in this study. DRAC is expressed as in Equation (3), per (Almqvist et al., 1991):

$$DRAC_i(t) = \frac{(V_F(t) - V_L(t))^2}{2 * \{(X_L(t) - X_F(t)) - L_F\}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

In addition, we have used time integrated deceleration rate to avoid crash (TIDRAC), which characterizes the severity of a conflict using the integral of the following vehicle's DRAC-profile during the time it is above the threshold DRAC*. Experimental time step for $TIDRAC$ is 0.1 s for this study.   The estimation of TIDRAC is shown below:

$$TIDRAC = \sum_{t=0}^{T} \sum_{i=1}^{N} (DRAC_i(t) - DRAC^*)\ \tau\, \varepsilon_{i,t} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

where $\varepsilon_{i,t} = \begin{cases} 1, & when\ DRAC_i(t) \ge DRAC^* \\ 0, & Oterwise \end{cases}$

Modified Time to Collision (MTTC): Ozbay et al. (85) proposed a modified time to collision (MTTC), whose application is similar to TTC; however, unlike TTC, MTTC considers acceleration or deceleration discrepancies within a given interval of time to report traffic conflicts. The theoretical concept and the equation to estimate MTTC are described below:

$$0.5 * \Delta a(t)t^2 + \Delta V(t)t - D(t) \geq 0$$

$$t_1 = \frac{-\Delta V(t) - \sqrt{\Delta V^2(t) + 2\Delta a(t)D(t)}}{\Delta a}$$

$$t_2 = \frac{-\Delta V(t) + \sqrt{\Delta V^2(t) + 2\Delta a(t)D(t)}}{\Delta a}$$

$$MTTC_i(t) = \begin{cases} t_1; (t_1 < t_2, \Delta a(t) \neq 0) \\ t_2; (t_1 \geq t_2, \Delta a(t) \neq 0) \\ t_1; (t_1 > 0 \ and \ t_2 \leq 0, \Delta a(t) \neq 0) \\ t_2; (t_2 > 0 \ and \ t_1 \leq 0, \Delta a(t) \neq 0) \\ \frac{D(t)}{\Delta V(t)}; (\Delta a(t) = 0, \Delta V(t) > 0 \end{cases} \qquad \text{..........(5)}$$

As shown above, when the relative acceleration/deceleration between the vehicle pairs is zero within the given time, the MTTC value reverts to the conventional TTC. For this study we selected a MTTC* threshold of 1.5 s.

Difference between space distance and stopping distance (DSS): DSS shows the freeze position of the following and leading vehicles when the leading vehicle brakes suddenly, and then the following vehicle brakes to avoid the collision (Okamura et al., 2011). The equation below calculates DSS at any instant (t):

$$DSS_i(t) = \left(\frac{V_F(t)^2}{2\mu g} + D(t)\right) - \left(V_L(t)RT_F + \frac{V_L(t)^2}{2\mu g}\right) \ldots\ldots\ldots\ldots \text{(6)}$$

DSS is easy to calculate and is mostly used to report rear-end traffic conflicts. However, DSS cannot evaluate the severity of traffic conflicts. To overcome the shortcomings of DSS, we used a time integrated difference between space distance and stopping distance (TIDSS) measure that computes the integration of the time profile of the difference between the DSS^* and DSS value measured at each time step. The threshold of value for DSS (DSS^*) is zero. Therefore, the greater the value of ($DSS^* - DSS$), the more severe the traffic conflict. Experimental time step τ for $TIDSS$ is 0.1 s for this study.

$$TIDSS = \sum_0^T \sum_0^N (DSS^* - DSS)\tau\theta_{i,t} \ldots\ldots\ldots\ldots \text{(7)}$$

Where $\theta_{i,t} = \begin{cases} 1, \ when \ \ DSS_i(t) < DSS^* \\ 0, \qquad\qquad Oterwise \end{cases}$

Margin to collision (MTC): MTC represents the collision risk of the following vehicle when the leading vehicle brakes suddenly. Mathematically, MTC is the ratio of the summation of the inter-vehicular distance of vehicle pairs and the stopping distance of the preceding vehicle divided by the following vehicle's stopping distance. Mathematically *MTC* is calculated as follows:

$$MTC_i(t) = \frac{D(t) + SSD_L(t)}{SSD_F(t)} \ldots\ldots\ldots\ldots \text{(8)}$$

where,

$$SSD_L(t) = D(t) + \frac{V_L(t)^2}{d_{Lmax}} \quad (9)$$

$$SSD_F(t) = V_F(t) * RT_F + \frac{V_F(t)^2}{d_{Fmax}} \quad (10)$$

An MTC less than 1 indicates a traffic conflict.

Rear End Crash Index (RCRI): To avert a rear end crash the stopping distance of the following vehicle should be smaller than the leading vehicle. Therefore, RCRI can be mathematically expressed as follows:

$$RCRI_i(t) = \begin{cases} 1, & SSD_F(t) \geq SSD_L(t) \\ 0, & Otherwise \end{cases} \quad (11)$$

Time Exposed Rear End Crash Index (TERCRI): Is a measure that gives the total experimental time the vehicle was in rear-end traffic conflict, which is expressed by equations (12) and (13):

$$TERCRI_i = \sum_{t=0}^{T} RCRI_i(t).\tau \quad (12)$$

$$TERCRI = \sum_{i=1}^{N} TERCRI_i \quad (13)$$

Experimental time step τ for $TERCRI$ is 0.1 s for this study

Driving Volatility (DV): DV reports on the microscopic driving variations that affect the vehicle's longitudinal control. DV measures can be applied to speed, acceleration, or jerk variations. Increases in DV indicate an increase in collision probability (31). Mahdinia et al. (53) introduced speed volatility as an SSM to assess the longitudinal traffic safety of vehicles involved in car-following situations. We use the mean absolute deviation (MAD) of speed to quantify *relative speed volatility* that shows variations in speed data by measuring the distance between each observation and to their mean and then aggregated across all vehicles in a platoon, as per Equations (14) and (15).

$$MAD_i = \frac{1}{T}\sum_{t=0}^{T} |V_{it} - \bar{V}_i| \quad (14)$$

$$MAD = \frac{1}{N}\sum_{i=1}^{N} MAD_i \quad (15)$$

The *relative speed volatility* measure indicates whether the speed variation emanating from the lead vehicle is increasing or decreasing for the following vehicles when normalized based on the lead vehicle's (either platoon or immediate lead vehicle) MAD.

In the subsequent discussion, the number of longitudinal traffic conflicts is reported on a per-km basis in order to enable a comparison across the selected platoons and car-following scenarios that have different travel times and distances.

Response time lag estimation for a following vehicle

The acceleration/deceleration *response* of the following vehicle lags by response time lag Δt to the *stimulus* enacted by a leading vehicle (86). In this study, we rely on the Gasiz-Herman-Rothery car-following model assumption that the acceleration or deceleration of the following vehicle depends on the relative speed, the inter-vehicular spacing between the leading and following vehicle, and the speed of the following vehicle (86).

Therefore, we can state:

$$a_F(t+\Delta t) = \alpha \frac{V_F(t)^l}{(X_L(t)-X_F(t))^m}\left(V_F(t)-V_L(t)\right),\ where \ldots\ldots\ldots\ldots \quad (16)$$

$a_F(t+\Delta t)$ = response of the following vehicle

$\frac{V_F(t)}{(X_L(t)-X_F(t))}\left(V_F(t)-V_L(t)\right)$ = stimulus

α = Sensitivity term

l, m = Model parameters, for this study we are using $l = m = 1$

We used the cross correlation (87) method to estimate the Δt. Cross- correlation is a technique for comparing two time series and finding objectively how they match up with each other, and when the best match occurs. The technique takes the two-time series and lines them up to determine the lag that produces the highest similarities between the two series. The lag refers to how far the series are offset, and its sign determines which series is shifted. Consider, two time series $x(t)$ and $y(t)$ lag by a time interval d, where $t \in \{0,1,2,3, \ldots \ldots \ldots . n\}$. The cross-correlation r at lag d, $r(d)$ as follows:

$$r(d) = \frac{\sum_t[(x(t)-\mu_x)*(y(t-d)-\mu_y)]}{\sqrt{\sum_t(x(t)-\mu_x)^2}\sqrt{\sum_t(y(t-d)-\mu_y)^2}} \ldots\ldots\ldots\ldots \quad (17)$$

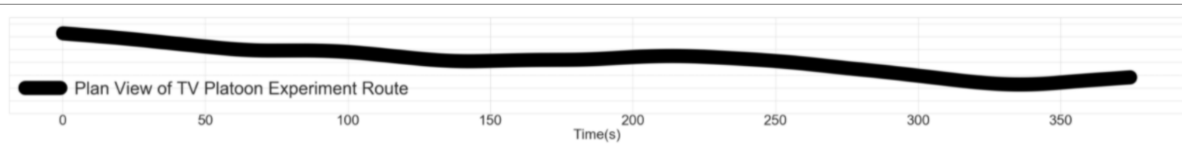
where μ_x and μ_y are the means of the corresponding series. When the above equation is computed for all lags, $d = 0,1,2,\ldots n$, it produces a cross-correlation series of twice the length as the original series. The range of lags d and thus the length of the cross-correlation series can be less than N, if for example the goal may be to test cross correlation for short lags only. The denominator in the equation (17) tends to normalize the correlation coefficients such that $-1 \leq r(d) \leq 1$, the bounds indicating maximum correlation and 0 indicating no correlation.

B2. DATA ON VEHICLES IN THE FIELD TEST

Table 8: Experimental vehicle description

Vehicles	Max power (kW)	Drive-Fuel	Engine displacement (cc)	Battery capacity (kWh)	Propulsion type	Top speed (km/h)	Model year
Hyundai (Ioniq hybrid)	104	gasoline	1580	1.56	HEV	185	2018
Mitsubishi (SpaceStar)	59	gasoline	1193	-	ICE	173	2018
KIA (Niro)	77.2	gasoline	1580	8.9	PHEV	172	2019
Mitsubishi (Outlander PHEV)	99	gasoline	2360	12	PHEV	170	2018
Peugeot (5008 GT Line)	130	diesel	1997	-	ICE	208	2018
VW (Golf E)	100	electricity	-	35.8	BEV	150	2018
Mini (Cooper)	100	gasoline	1499	-	ICE	210	2018

Table 9: Exclusive TV platoon experiment

<table>
<tr><th></th><th>Vehicle Model</th><th>Driving Mode</th><th>Total Experimental Time (s)</th><th>Total Distance (m)</th></tr>
<tr><td>Leader</td><td>KIA Niro 2019</td><td>Human</td><td rowspan="4">374.4</td><td rowspan="4">`11075</td></tr>
<tr><td>1st Follower</td><td>Peugeot 5008 GT Line 2018</td><td>Human</td></tr>
<tr><td>2nd Follower</td><td>VW Golf E 2019</td><td>Human</td></tr>
<tr><td>3rd Follower</td><td>Mini Cooper 2018</td><td>Human</td></tr>
<tr><td colspan="5">Plan view of the exclusive TV platoon route</td></tr>
<tr><td colspan="5">
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<tr><td colspan="5">Elevation profile of the exclusive TV platoon route</td></tr>
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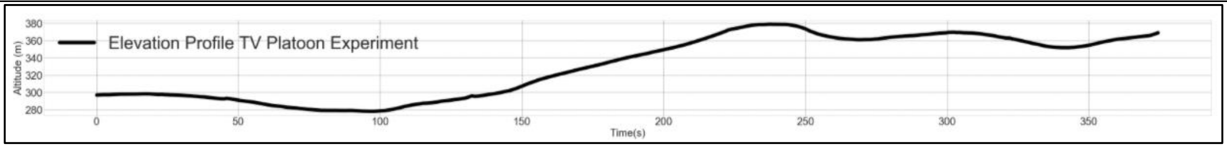
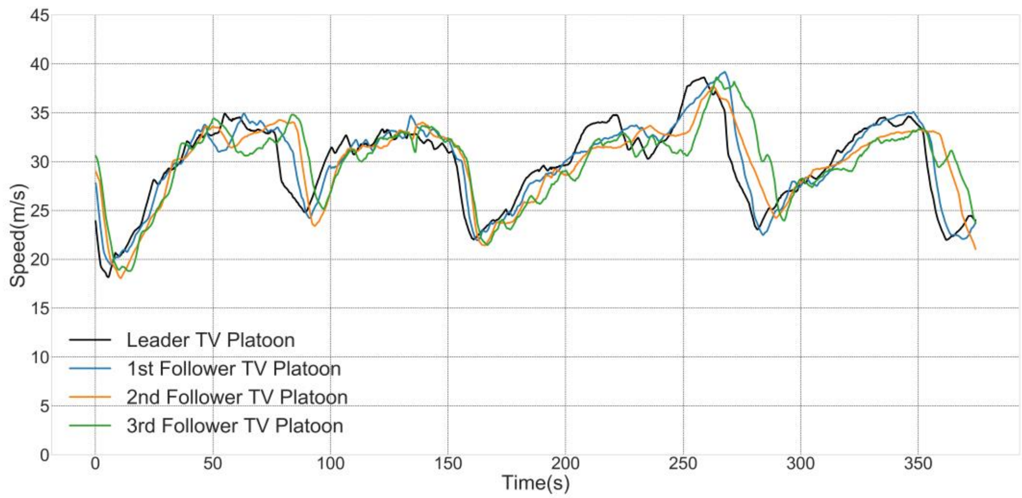


Speed profile of the exclusive TV platoon



Speed distribution TV platoon

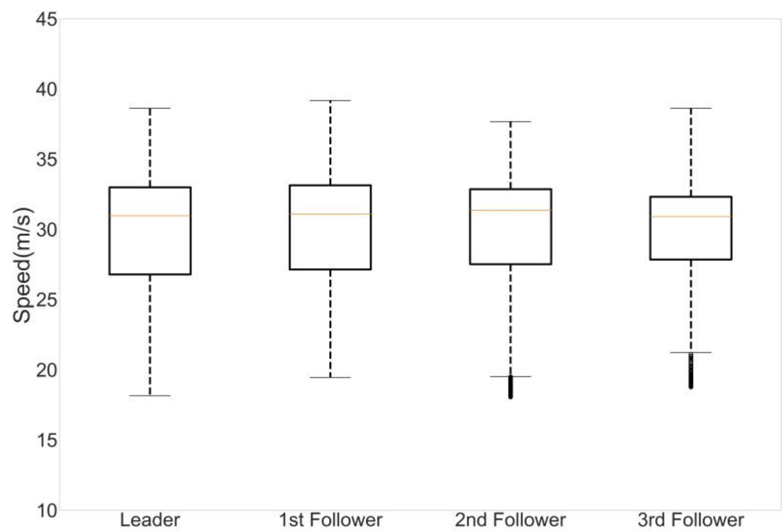
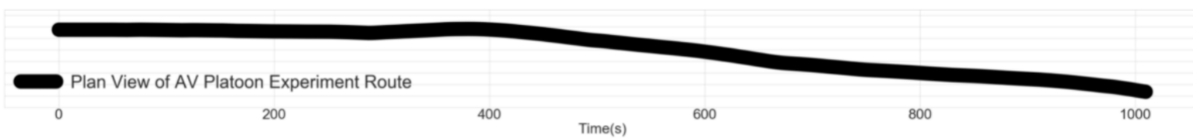


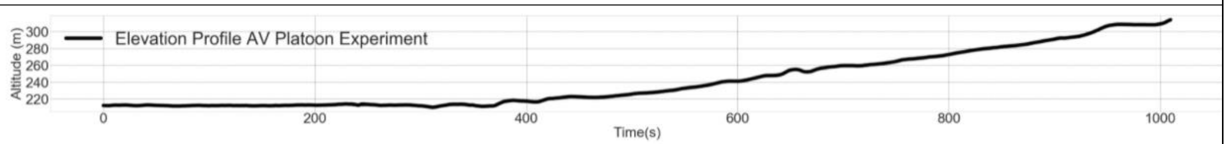
Table 10: Exclusive AV platoon experiment

	Vehicle Model	Driving Mode	Total Experimental Time (s)	Total Distance (m)
Leader	Ford S Max 2019	ACC (SAE Level 2)	1009.7	20549
1st Follower	Peugeot 5008 GT Line 2018	ACC (SAE Level 2)		
2nd Follower	KIA Niro 2018	ACC (SAE Level 2)		
3rd Follower	Mitsubishi OutlanderPHEV 2018	ACC (SAE Level 2)		

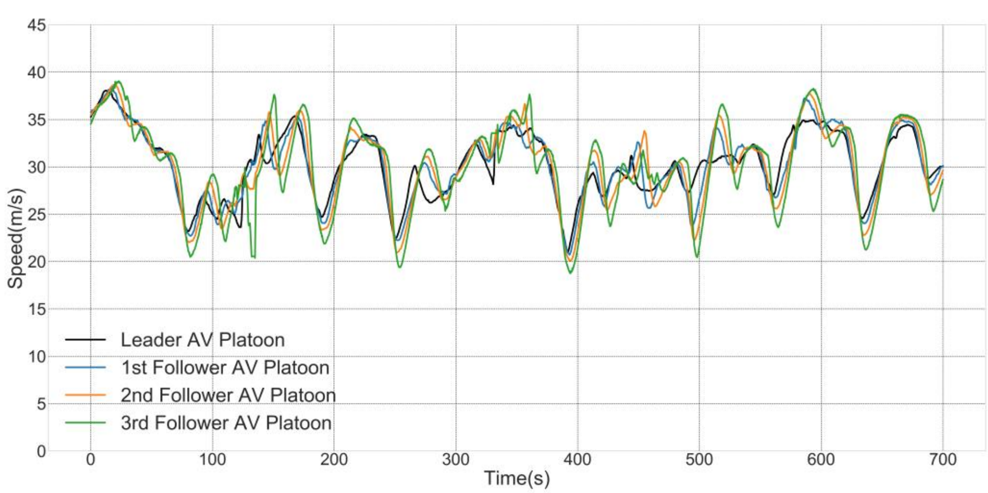
Plan view of the exclusive AV platoon route



Elevation profile of the exclusive TV platoon route



Speed profile of the exclusive AV platoon



Speed distribution AV platoon

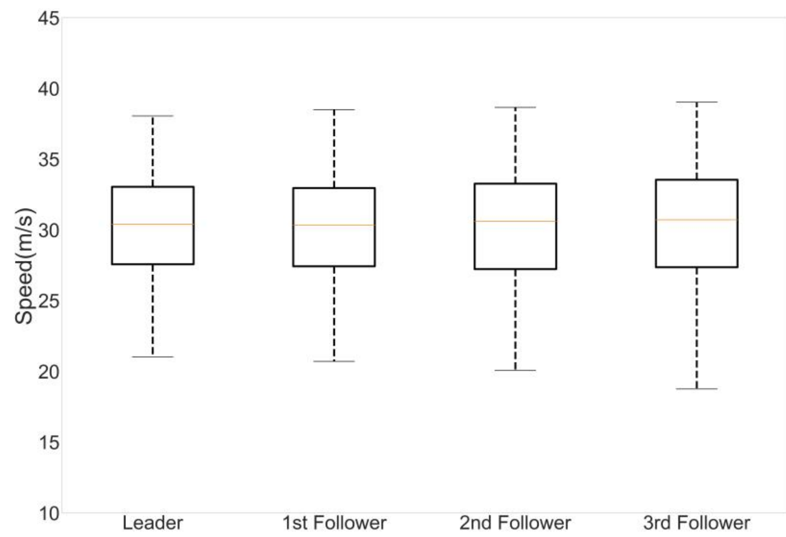
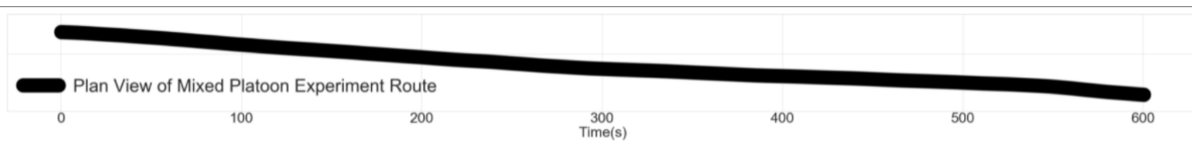


Table 11: Mixed platoon experiment

<table>
<tr><th></th><th>Vehicle Model</th><th>Driving Mode</th><th>Total Experimental Time (s)</th><th>Total Distance (m)</th></tr>
<tr><td>Leader</td><td>Mitsubishi SpaceStar 2018</td><td>Human</td><td rowspan="5">600.5</td><td rowspan="5">17184</td></tr>
<tr><td>1st Follower</td><td>Ford S Max 2019</td><td>ACC
(SAE Level 2)</td></tr>
<tr><td>2nd Follower</td><td>Peugeot 5008 GT Line 2018</td><td>ACC
(SAE Level 2)</td></tr>
<tr><td>3rd Follower</td><td>KIA Niro 2018</td><td>ACC
(SAE Level 2)</td></tr>
<tr><td>4th Follower</td><td>Mini Cooper 2018</td><td>Human</td></tr>
<tr><td colspan="5">Plan view of the Mixed platoon route</td></tr>
<tr><td colspan="5">
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<tr><td colspan="5">Elevation profile of the exclusive mixed platoon route</td></tr>
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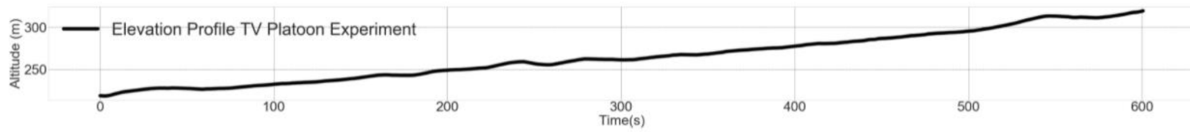
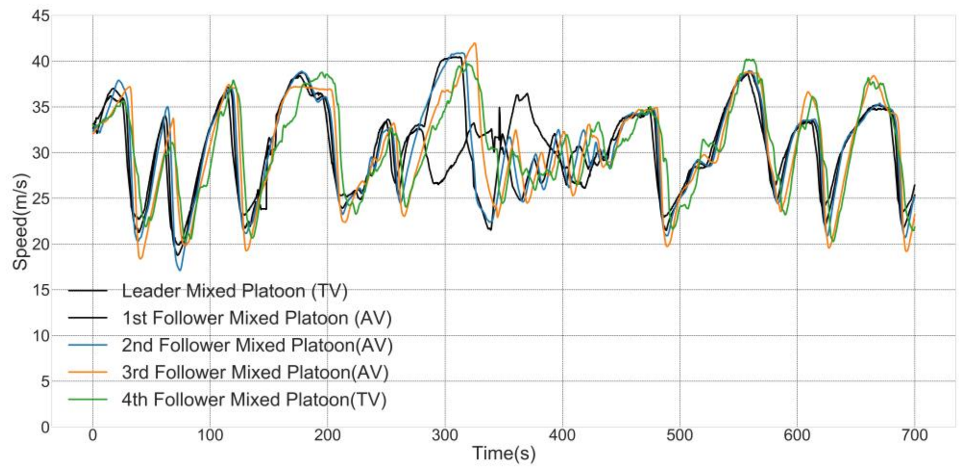


Speed profile of the exclusive Mixed platoon



Speed distribution Mixed platoon

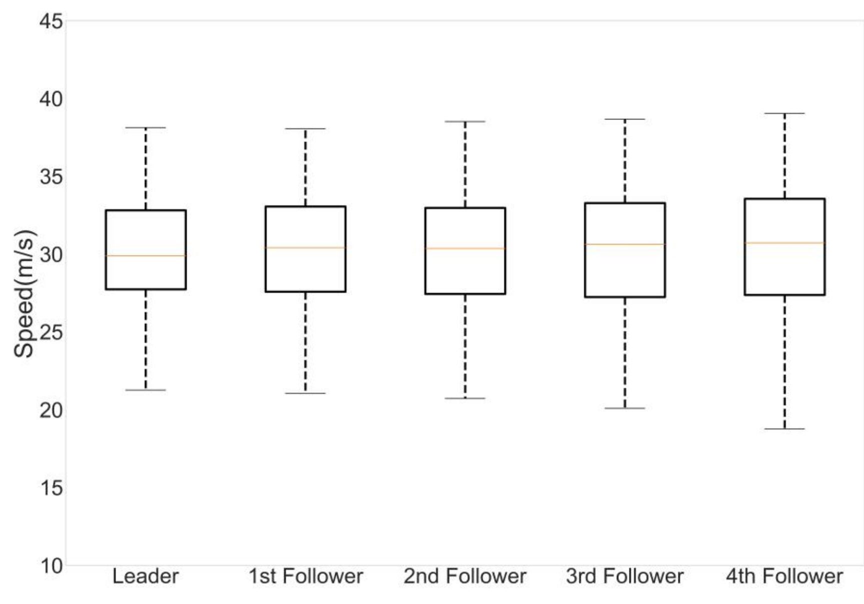
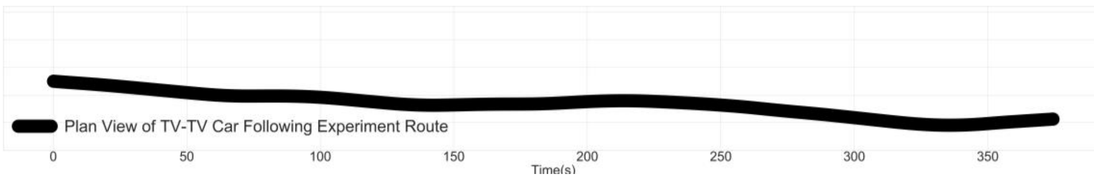


Table 12: TV-TV car following experiment

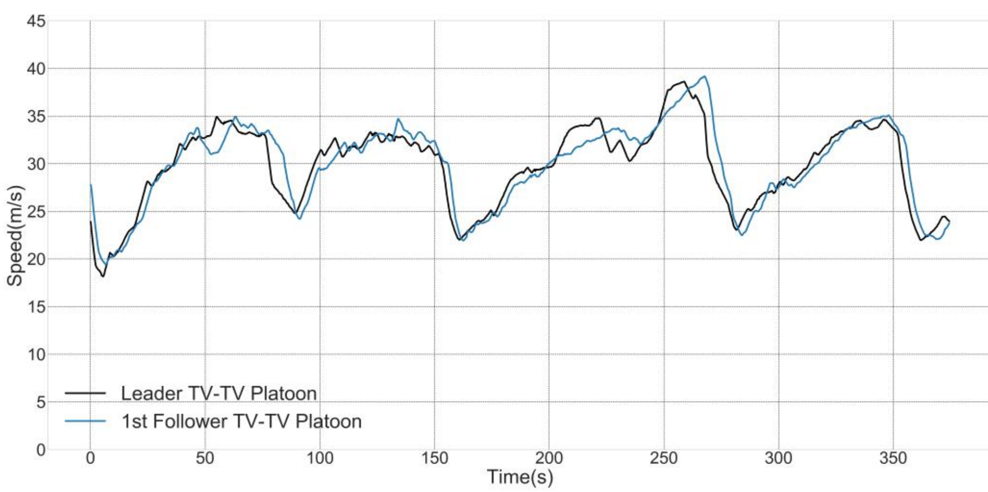
	Vehicle Model	Driving Mode	Total Experimental Time (s)	Total Distance (m)
Leader	KIA Niro 2019	Human	374.4	`11075
1st Follower	Peugeot 5008 GT Line 2018	Human		

Plan view of the TV-TV platoon route



Elevation profile of the TV-TV platoon route

Speed profile of the TV-TV platoon



Speed distribution TV-TV platoon

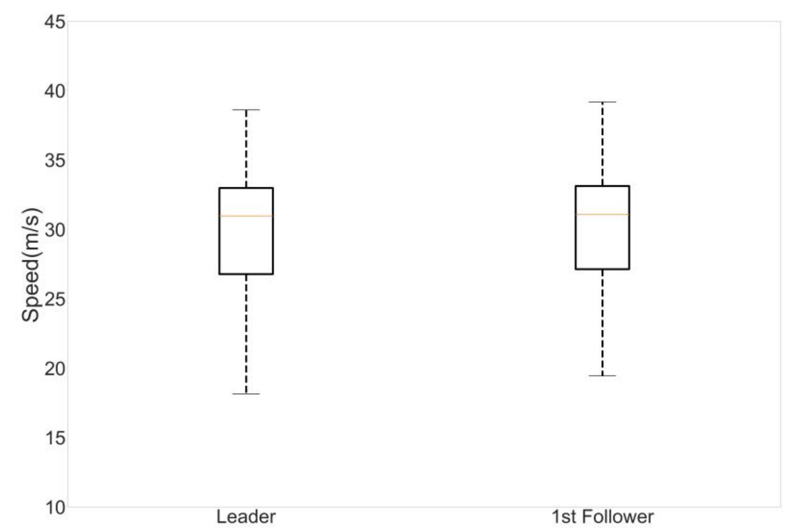
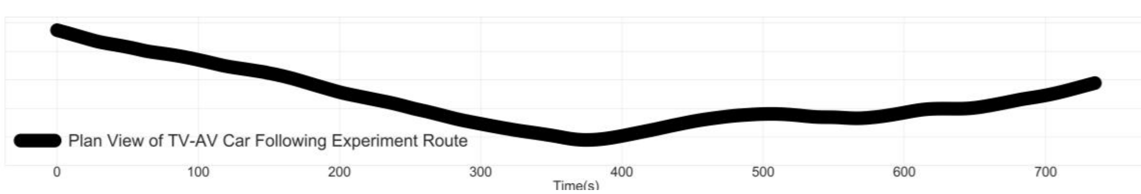


Table 13: TV-AV car following experiment

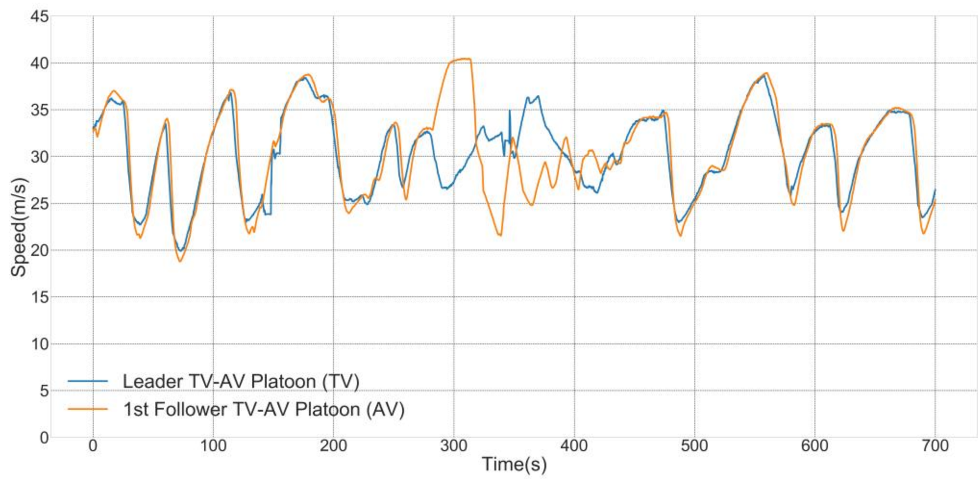
	Vehicle Model	Driving Mode	Total Experimental Time (s)	Total Distance (m)
Leader	Mitsubishi SpaceStar 2018	Human	734.8	22401
1st Follower	Ford S Max 2019	ACC (SAE Level 2)		

Plan view of the TV-AV platoon route



Elevation profile of the TV-AV platoon route

Speed profile of the TV-AV platoon



Speed distribution TV-AV platoon

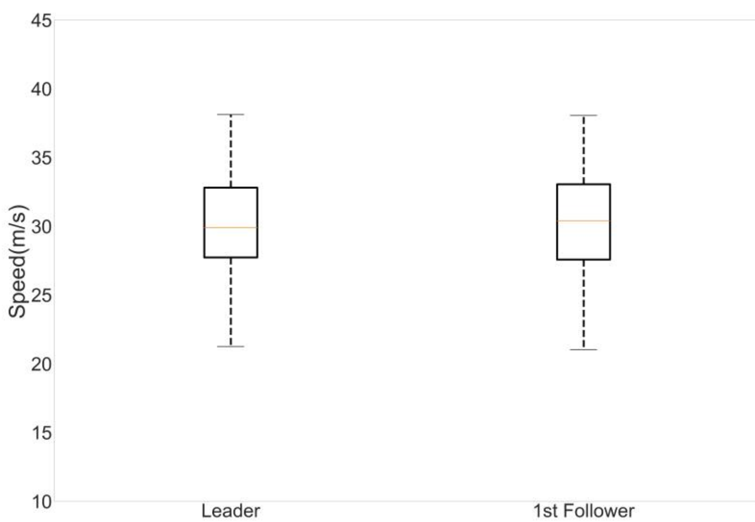
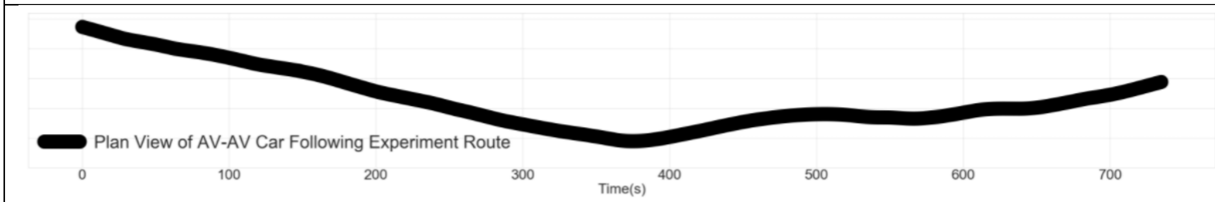


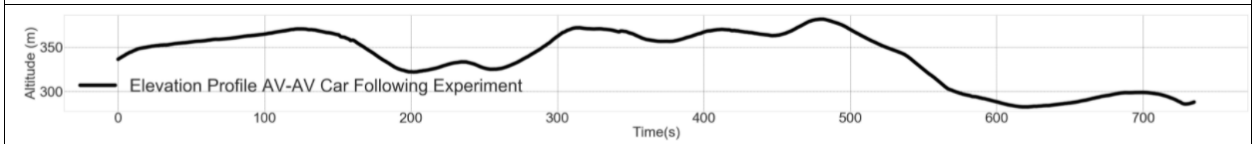
Table 14: AV-AV car following experiment

	Vehicle Model	Driving Mode	Total Experimental Time (s)	Total Distance (m)
Leader	Peugeot 5008 GT Line 2018	ACC (SAE Level 2)	734.8	22401
1st Follower	KIA Niro 2018	ACC (SAE Level 2)		

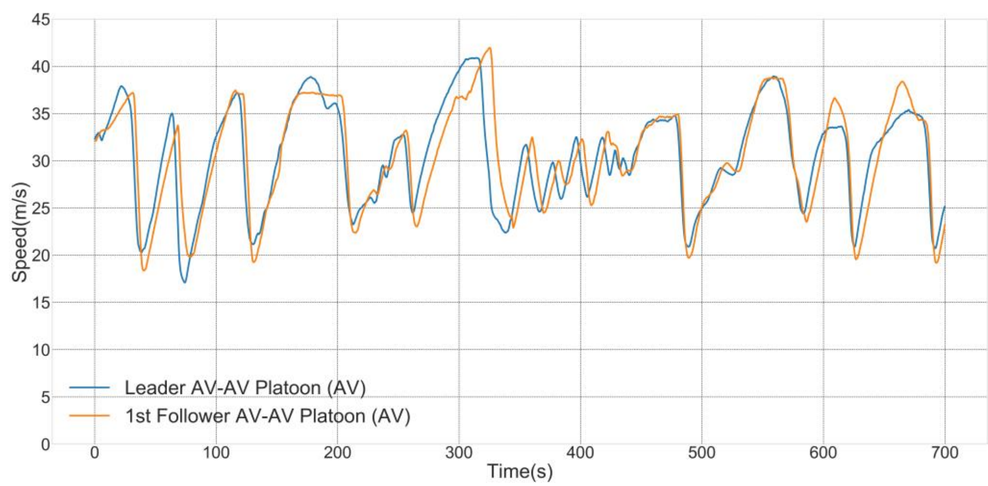
Plan view of the AV-AV platoon route



Elevation profile of the AV-AV platoon route



Speed profile of the AV-AV platoon



Speed distribution AV-AV platoon

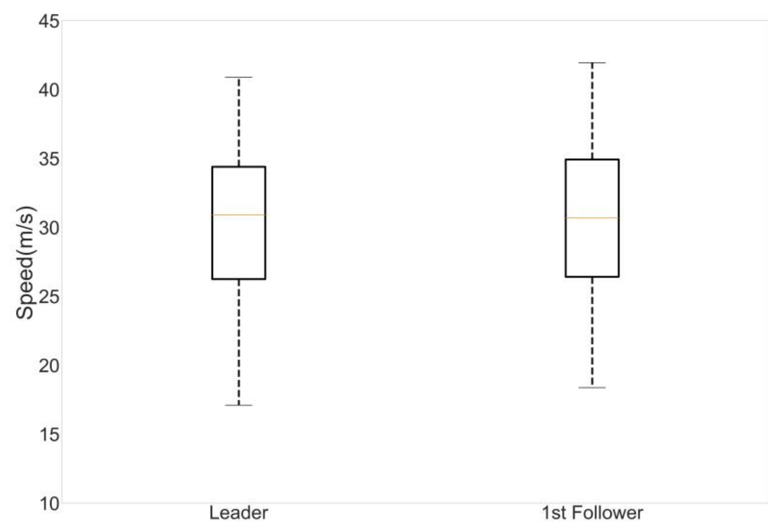
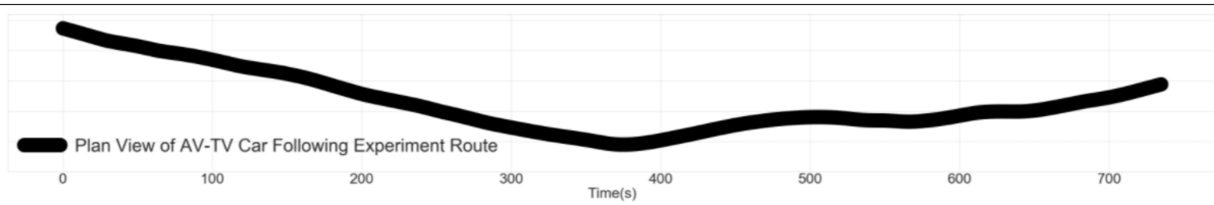
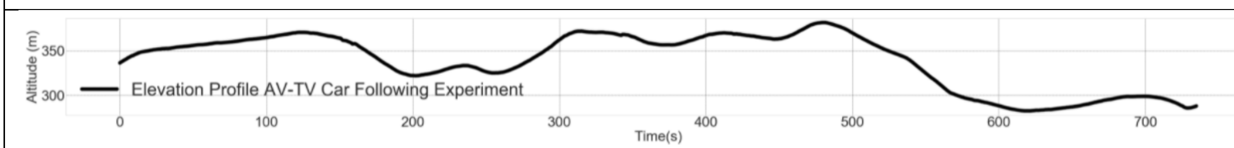


Table 15: AV-TV car following experiment

<table>
<tr><th></th><th>Vehicle Model</th><th>Driving Mode</th><th>Total Experimental Time (s)</th><th>Total Distance (m)</th></tr>
<tr><td>Leader</td><td>KIA Niro 2018</td><td>ACC
(SAE Level 2)</td><td rowspan="2">734.8</td><td rowspan="2">22401</td></tr>
<tr><td>1st Follower</td><td>Mini Cooper 2018</td><td>Human</td></tr>
<tr><td colspan="5">Plan view of the AV-TV platoon route</td></tr>
<tr><td colspan="5">
</td></tr>
<tr><td colspan="5">Elevation profile of the AV-TV platoon route</td></tr>
<tr><td colspan="5">
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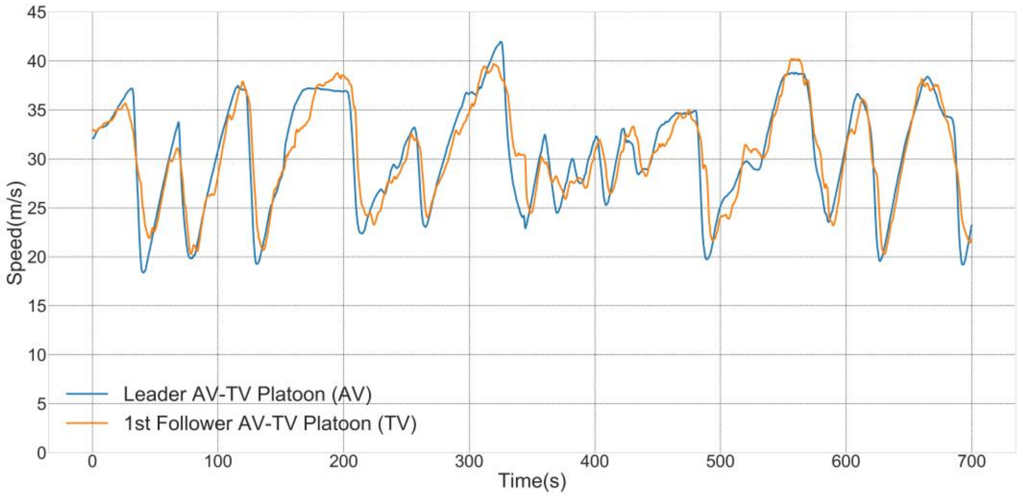
<tr><td colspan="5">Speed profile of the AV-TV platoon</td></tr>
</table>



Speed distribution AV-TV platoon

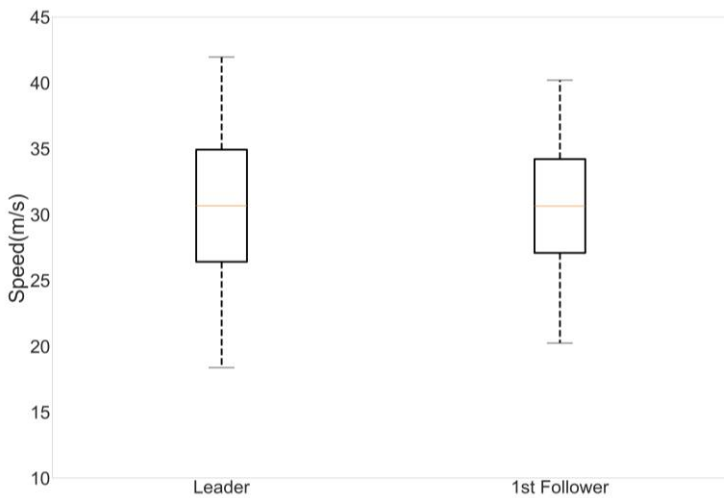
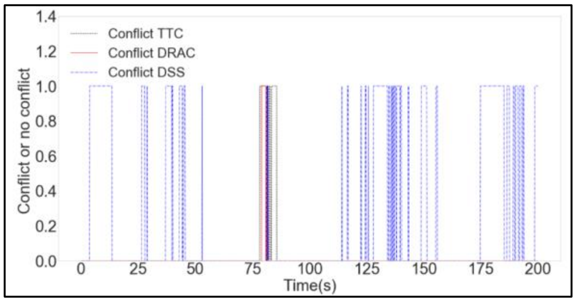


Table 16: K-S two-sample tests for multi vehicle and two vehicle platoons

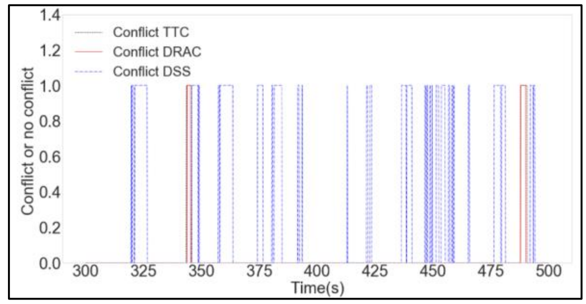
	Sample 1 Speed Profile	Sample 2 Speed Profile	Statistic	P Value
1	Leader of exclusive TV platoon	Leader of exclusive AV platoon	0.332	0.873
2	Leader of exclusive TV platoon	Leader of mixed platoon	0.362	0.874
3	Leader of exclusive AV platoon	Leader of mixed platoon	0.190	0.873
4	Leader of AV-AV platoon	Leader of TV-TV platoon	0.226	0.874
5	Leader of AV-AV platoon	Leader of AV-TV platoon	0.192	0.874
6	Leader of AV-AV platoon	Leader of TV-AV platoon	0.312	0.868
7	Leader of TV-TV platoon	Leader of AV-TV platoon	0.291	0.876
8	Leader of TV-TV platoon	Leader of TV-AV platoon	0.381	0.891
9	Leader of AV-TV platoon	Leader of TV-AV platoon	0.201	0.882

B3. SSM DISCUSSION

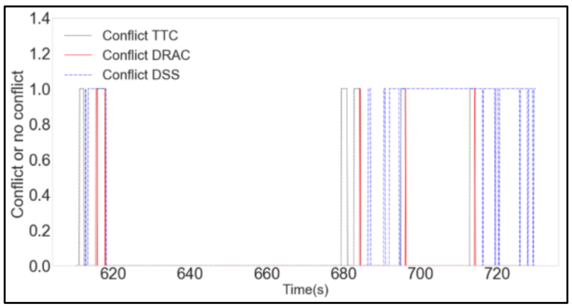
Each SSM has its own definition and measurement methodology. Therefore, use of a single SSM represents only a portion of traffic events (Ismail et al., 2011). As a result, traffic conflicts reported by a single SSM may not accurately reflect the overall safety of the investigated locations, resulting in a biased traffic conflict evaluation. Figure 28 (d) shows that as per DSS, the traffic interaction between 5 s to 20 s is flagged as traffic conflict. Nonetheless, as per DRAC or TTC, the traffic interaction between 5 s to 20 s is not flagged as traffic conflict. Similarly, the traffic interaction between 77 s to 80 s is flagged as traffic conflict only by TTC, though, DSS, DRAC and TTC all three SSMs measure the rearend traffic conflicts. As a result, a single SSM traffic conflict reporting is only a portion of the overall safety picture. Consequently, researchers have used different sets of SSMs to report traffic conflict.



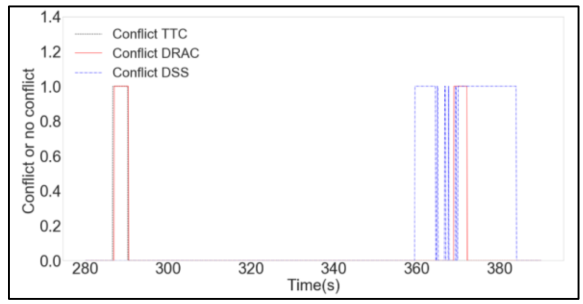
(a): Leader: TV; Follower: TV



(b): Leader: AV; Follower: TV



(c): Leader: AV; Follower: AV



(d): Leader: TV; Follower: AV

Assumed Values: TTC threshold 1.5s; DRAC threshold 3.4 m/s^2; RT 1 s

Figure 28: Conflict reporting by three SSMs versus time in experiment

Appendix C

The three car-following models selected for evaluation in this study are presented in this section.

C1. INTELLIGENT DRIVER MODEL (IDM)

The IDM model was first proposed by Treiber et al. (88). It gives the acceleration characteristics of the vehicle in car-following and free flow situations. The IDM acceleration is a continuous function incorporating different driving modes for all velocities in freeway traffic (69). The IDM acceleration function is shown below by Equations 1 and 2.

$$a_{IDM,F}(t) = \frac{dv}{dt} = a[1 - \left(\frac{v_F(t)}{v_0}\right)^{\delta} - \left(\frac{s^*(v_F(t),\Delta v(t))}{s(t)}\right)^2 \text{ .... } (1)$$

$$s^*(t) = s_0 + \max(v_F(t)T + \frac{v_F(t)\Delta v(t)}{2\sqrt{ab}}, 0) \text{ .... } (2)$$

where,

$a_{IDM,F}(t)$ = Acceleration of the follower at time t in m/s^2

$a_{brake}(t)$= Emergency deceleration at time t in m/s^2

$a_{free}(t)$= Free acceleration at time t in m/s^2

a = Maximum acceleration of the follower in in m/s^2

b = Desired deceleration of the follower in in m/s^2

v_0 = Desired speed in m/s

$v_F(t)$ = Actual speed the follower at time t

δ = Free acceleration exponent

s_0 = Jam Distance in m

T = Desired time gap in s

$\Delta v\ (t)$ = Relative Speed in m/s^2

$s(t)$= Inter vehicular distance between the leader and follower measured from leader's rear bumper to follower's front bumper

$a_{free}(t) = a[1 - (\frac{v(t)}{v_0})^{\delta}]$ along with a deceleration strategy

$a_{brake}(t) = -a(\frac{s^*}{s(t)})^2$

The latter becomes relevant when the gap to the leading vehicle is not significantly larger than the effective 'desired (safe) gap' $s^*(t)$. The free acceleration is characterized by the desired speed v_0, the maximum acceleration a and the exponent δ characterizing how the acceleration decreases with velocity ($\delta = 1$ corresponds to a linear decrease while $\delta \rightarrow \infty$ denotes a constant acceleration).

The effective minimum gap s^* is composed of the minimum distance s_0 (which is relevant for low velocities only), the velocity-dependent distance $v_F(t) * T$, which corresponds to following the leading vehicle with a constant desired time gap *T*, and a dynamic contribution, which is only active in non-stationary traffic corresponding to situations in which $\Delta v(t) \neq 0$. This last contribution implements an 'intelligent' driving behavior that, in normal situations, limits braking decelerations to the comfortable deceleration b. In critical situations, however, the IDM deceleration becomes significantly higher, making the IDM collision-free (88).

C2. ADAPTIVE CRUISE CONTROL MODEL (ACC)

The ACC model uses the acceleration framework developed by (55) to model the longitudinal response of AVs. Response is explicitly divided into four modes (Fig. 29), explained next.

Speed control mode

The speed control mode is designed to maintain the driver's desired speed and is activated when there are no preceding vehicles in the range covered by the sensors or preceding vehicles exist in a spacing larger of 120 m. The motion equation for this mode is shown below in equation (3):

$a_{ACC}(t) = k_{sc} * (v_{des} - v(t))$.. (3)

Gap control mode

The gap control mode seeks to keep the time gap between the ACC-equipped vehicle and its predecessor consistent. The mode is activated when the gap and speed deviations (with respect to the preceding vehicle) are concurrently smaller than 0.2 m and 0.1 m/s, respectively.

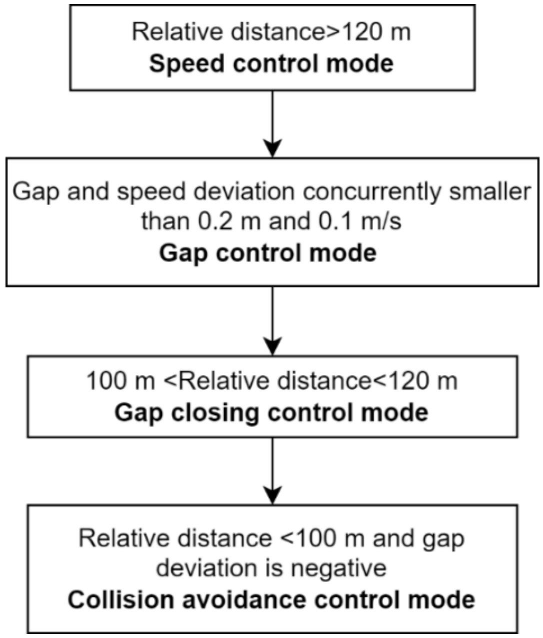


Figure 29: Different modes of ACC car following (55)

Gap-closing control mode

The gap closing controller allows for a smooth transition from speed control mode to gap control mode and is activated when the distance between vehicles is less than 100 m. If the distance between the vehicles is between 100 and 120 meters, the ACC-AVs preserves the previous control technique to provide hysteresis in the control loop and a seamless transition between the two methods.

Collision avoidance control mode

When there are safety critical situations, the collision avoidance mode prevents rear-end collisions. This option is activated when the gap to the prior vehicle is less than 100 m, the gap deviation is negative, and the speed deviation is less than 0.1 m/s.

The calculated AV acceleration based on gap control mode, gap closing mode and collision avoidance mode where k_s and k_v have different values based on the different response mode, shown below in equation (4):

$$a_F(t) = k_s * \underbrace{(x_L(t) - x_F(t) - T * v_F(t))}_{\text{Gap deviation}} + k_v\underbrace{(v_L(t) - v_F(t))}_{\text{Speed deviation}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (4)$$

where,

$a_F(t)$ = acceleration of the subject AV in m/s^2,

k_s, k_v = distance and speed feedback gain,

$x_L(t)$ = position of the leading vehicle in m,

$x_F(t)$ = position of following vehicle in m,

T = desired time-gap in seconds

$v_F(t)$ = speed of following vehicle in m/s,

$v_L(t)$ = speed of the leading vehicle in m/s

C3. WIDEMANN 99 MODEL (W99)

In this study, the shadow algorithm cited in Zhu et al. (70) was applied to code the car-following algorithm of W99. In general, W99 has four driving modes: free, close in, follow, and emergency braking. The model clearly specifies each of these regimes based on certain criteria, as shown in Fig. 30. The terms ΔX and ΔV indicate the distance and speed differentials (Leader minus Follower) between the leading and following vehicles, respectively.

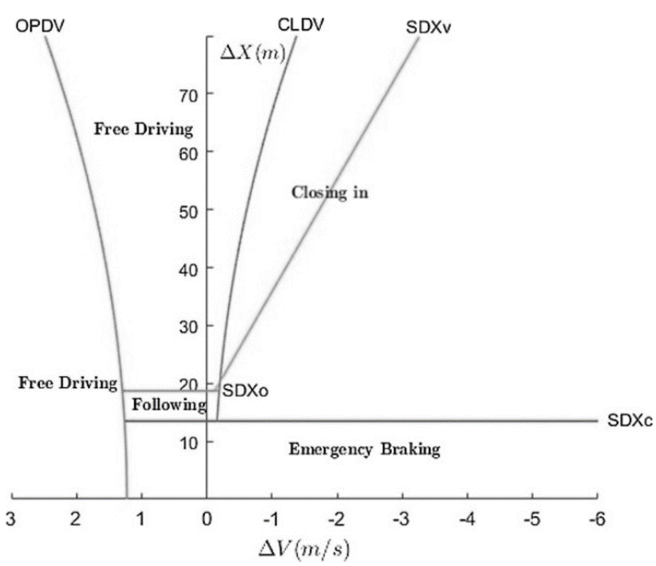


Figure 30: Wiedemann 99 model with various driving regimes and thresholds (70)

The follower vehicle's response to stimuli generated by the lead vehicle varies depending on the driving regime. The instantaneous acceleration rate of the following vehicle is the model output in the current investigation. Figure 31 depicts the prediction acceleration rate at a time (t+1), $or\ a_n\ (t+1)$ calculation procedure in various driving regimes based on the inputs from the current time step t.

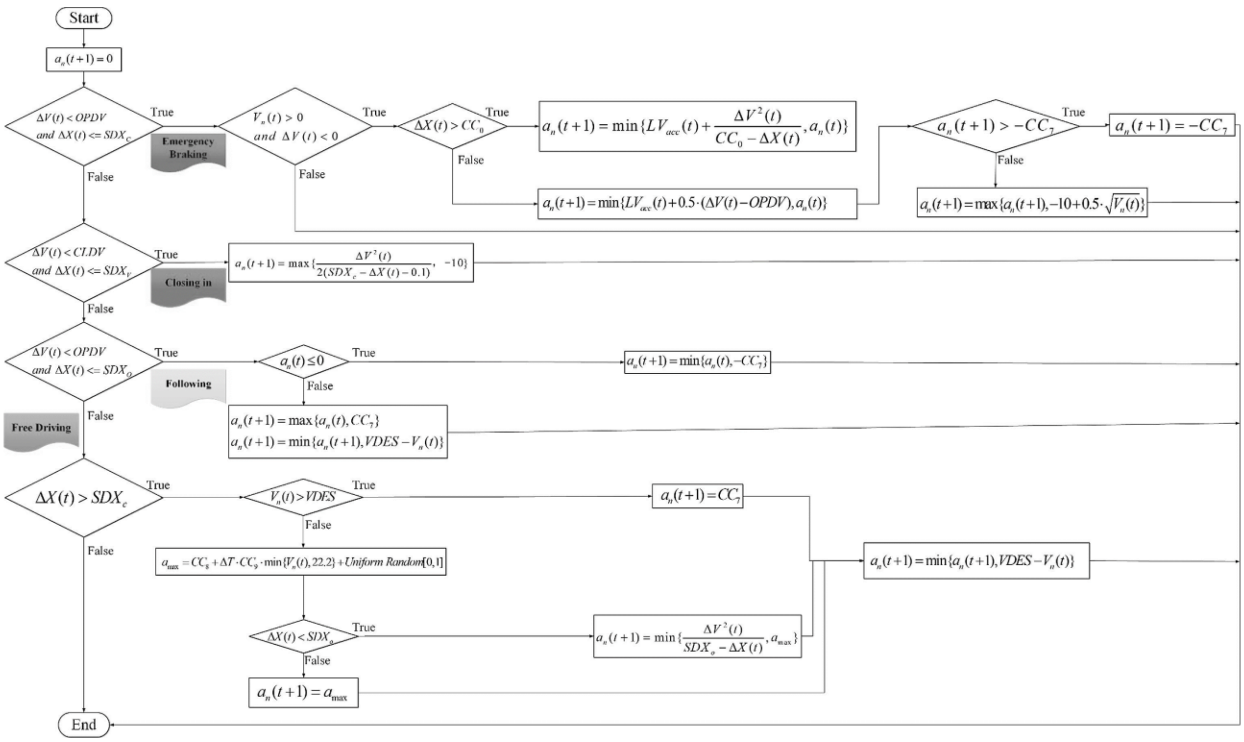


Figure 31: Calculation process of acceleration in the Wiedemann 99 model (70)

Where,

$\Delta x(t) = x_L(t) - x_F(t) - L_F$

$\Delta v(t) = v_L(t)$- $v_F(t)$

SD$X_c(t)$ =C$C_0 + CC_1 * v_{SL}(t)$

$$v_{SL}(t) = \begin{cases} v_F(t) & if\ \Delta v\ (t) > 0\ and\ a_L(t) < -1\ m/s^2 \\ v_L(t) - \Delta v\ (t).RND & otherwise \end{cases}$$

$RND = Uniform\ Random[-0.5, 0.5]$

$SDV(t) = CC_6(\Delta x(t) - L_F)^2$

$SDX_0(t)$ =$SDX_c(t) + CC_2$

$SDX_v(t) = SDX_0(t)$ +$CC_3(\Delta v\ (t) - CC_4)$

$$CLDV(t) = \begin{cases} -SDV(t) + CC_4 & if\ v_F(t) > 0 \\ 0 & otherwise \end{cases}$$

$$OPDV(t) = \begin{cases} SDV(t) + CC_5 & if\ v_F(t) > CC_5 \\ SDV(t) & otherwise \end{cases}$$

$x_L(t), x_F(t)$= Position of leading and following vehicle at time t in m

$\Delta x(t)$= Inter-vehicular distance at time t in m

$v_L(t), v_F(t)$= Speed of leading and following vehicle at time t in m/s

$\Delta v(t)$= Relative speed at time t in m/s ($v_F(t)$-$v_L(t)$)

L_F= Length of the following vehicle in m

$SDX_c(t)$= Minimum safe following distance at time t in m

$a_L(t)$= Acceleration of the lead vehicle at time t in m/s^2

$SDV(t)$= Perception threshold for speed difference at time t in m/s

$SDX_0(t)$= Maximum following distance at time t in m

$SDX_v(t)$= Distance threshold of following vehicle perceiving its approach to a slower leader at time t in m

$CLDV(t)$= Perception threshold of speed difference at short decreasing distances at time t in m/s

$OPDV(t)$= Perception threshold of speed difference at short but increasing distances at t in m/s

$VDES$= Desired speed of following vehicle in km/h

a_{max}= Maximum acceleration in m/s^2

CC_0 to CC_9= Model parameters listed in the car-following models' parameter section

The W99 car following algorithm was coded based on published research work (70). We subsequently verified our script with that of SUMO. As mentioned earlier, the experiment was conducted at off-peak hours with no overtaking and no intrusion of side vehicles. To simplify, we created a one-lane basic freeway segment to mimic the experimental scenario. Figure 32 shows the basic segment in SUMO's Netedit (89).

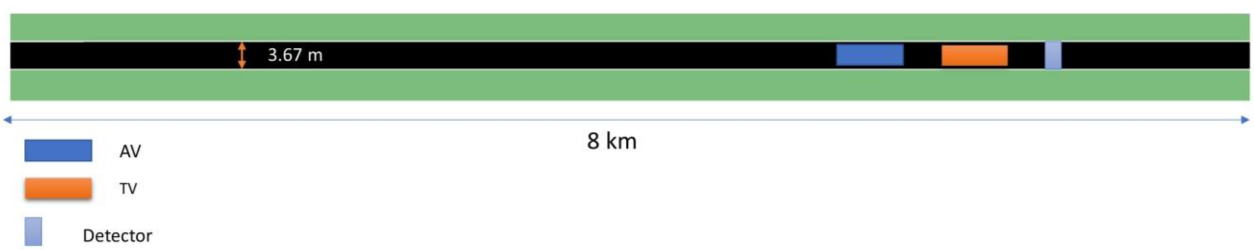


Figure 32: Simulation Setup (Freeway Basic Segment)

The leading vehicular trajectory of TV was given as input using SUMO TRACI (90). Moreover, the following AV followed the leading TV with parameters shown in Table 17. We simulated platoon 2 both using our script of W99 and SUMO's inherent W99 model. Comparing the trajectories, we found that the coded speed profile and simulated speed profile (Fig. 33) did not differ significantly at a 95% confidence interval. As such, the W99 model was validated and used for the remaining parts of the study.

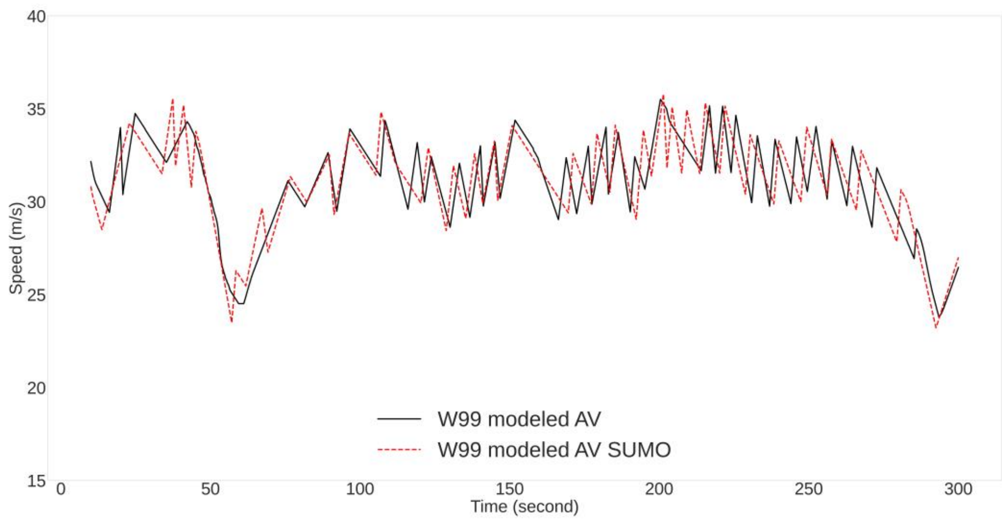


Figure 33: Comparison of coded W99 speed profile with SUMO generated speed profile

C4. CAR-FOLLOWING MODELS' PARAMETERS

In the case of the ACC and IDM models, we used the default parameter values given in Milanés and Shladover (55) to model ACC-AVs. However, we used a desired speed value of 40 m/s to match the maximum speed value in the OpenACC platoon datasets. For the W99 model parameters, we used the proposed parameter values documented in the CoEXist project (75). Table 17 lists the model parameters used in this study.

Table 17: Applied car-following model parameters

Car-following models	Parameter names		Values
ACC	Speed control mode	Speed feedback gain, k_{SC}	0.4 s^{-1}
	Gap control mode	Distance feedback gain, k_{s1}	0.23 s^{-2}
		Speed feedback gain, k_{v1}	0.07 s^{-1}
	Gap closing mode	Distance feedback gain, k_{s2}	0.04 s^{-2}
		Speed feedback gain, k_{v2}	0.8 s^{-1}
	Collision avoidance control mode	Distance feedback gain, k_{s3}	0.80 s^{-2}
		Speed feedback gain, k_{v3}	0.23 s^{-1}
	Desired speed, v_d		40 m/s
	Minimum time, t_d		1.10 s
IDM	Desired speed, v_d		40 m/s
	Maximum acceleration, a		1.00 m/s^2
	Desired deceleration, b		2.00 m/s^2

	Free acceleration exponent, δ	4
	Jam distance, s_0	0 m
	Desired time gap, t_d	s
Wiedemann 99	Stand still distance, CC_0	1 m
	Headway time, CC_1	0.6 s
	Following variation, CC_2	0 m
	Threshold for entering following, CC_3	-6
	Negative following threshold, CC_4	-0.1
	Positive following threshold, CC_5	0.1
	Speed dependency of Oscillation, CC_6	0
	Oscillation Acceleration, CC_7	0.1 m/s^2
	Standstill Acceleration, CC_8	4.0 m/s^2
	Acceleration with 80 km/h, CC_9	2.0 m/s^2