Connected and Automated vehicles:
What are the implications of partial adoption?

Final Report

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DISCLAIMER

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16. Abstract

With increasing attention focused on connected and automated vehicles (CAVs), this study explores the opportunities and challenges associated with the adoption and use of such systems. CAVs represent the opportunity to greatly enhance safety and reduce both congestion and emissions. Adoption of new technologies is often messy, even if they follow the familiar S-shaped adoption curve. Among the challenges is how will partial adoption of automated technologies, characterized by levels 0 to 5, work in a transportation network? We develop simulations to help us understand the impacts of CAVs in transportation networks. Specifically, our research focuses on developing network simulations and algorithms to understand how variations in driving control impact safety and congestion. Specifically, this exploratory study uses novel tools to understand the implications of partial automation on the traffic network performance. This problem is made complex by the unpredictable nature of partial automation, where humans have different levels of involvement. The study accounts for traveler behavior under various automation scenarios and model the traffic flows at nodes in a network (merging facilities and intersections). In particular, the study develops simulations and algorithms to better understand how variations in driving control will impact safety and congestion.

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EXECUTIVE SUMMARY

While the economic loss of traffic crashes across the United States is estimated to be about 1 Trillion per year, the current state of the transportation potentially can be improved by automated vehicles (AVs) that perform control functions without driver input. However, AVs will be mixed in traffic streams with human-driven vehicles. The question that arises is: What are the safety impacts of interaction between human-driven vehicles and AVs with different levels of automation? In this study, we focused on addressing this problem at roadway intersections. A key objective of this study is building the behavioral framework to simulate different levels of automation and study the safety impact of these levels under different scenarios. A unique aspect of the study is that real-life connected vehicle data were incorporated to revise a car-following model. The model allowed simulation of human driven vehicles, mixed with low-level automated vehicles (LAVs), and highly-automated vehicles (HAVs).

To gain better understand regarding the current state of the AVs, the California AV report crashes were used. From October 2014 to May 2017, 31 crashes were reported. Analyzing these crashes revealed some important facts. First, human driven vehicles were at fault in almost all of the crashes, however, in one of the crashes which AV was operating in the autonomous mode, the AV was at fault. Second, 80.6 percent of crashes happened at intersections. Third, the most dominant manner of incident for AVs is rear- end crashes. Thus, we further investigated rear-end crashes at intersections. Therefore, the focus of this project is on the intersections and merging area where the interaction of human-driven and automated vehicles is inevitable.

In the first chapter, a simulation framework is developed to simulate human driven vehicles mixed with low-level automated vehicles and highly automated vehicles. The simulation results revealed that with increase in the market penetration of LAVs and HAVs, a substantial improvement in the safety performance at intersections can be achieved partly because of less conflicts and lower driving volatility. Focusing on LAVs, higher situational awareness and cautiousness than conventional vehicles, can lead to perceiving the leader's behavior from longer distances (than human-driven vehicles), improving performance. Additionally, HAVs can respond to the leader vehicles faster due to higher levels of automation technologies, and smoother driving, resulting in declines in conflicts and lower driving volatility.

In the second chapter, two coordination control systems are presented, and their performance (in terms of traffic flow, safety and fuel consumption) is compared. Based on the results, waves of stop and go operation are seen on the ramp road for the baseline, thereby reducing the outflow from the merging zone to 1765 vehicles per hour. Meanwhile, the coordination control systems limit the inflow into the merging zone maintaining the outflow from the merging zone at about 1973 vehicles per hour. From the perspective of traffic dynamics, both coordination control systems can reduce the TTS by about 50% and increase the TDT by about 9% over the baseline scenario. Furthermore, they can save TFC by about 25% (AFC is reduced by about 30%) as they resolve the stop-and-go waves. As expected, the fuel-optimal coordination control system provides increased fuel savings (2% in the overall traffic network and 6% in the control zone), when compared to the energy-optimal coordination control system.

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Chapter 1

Evaluating Safety with Automated Vehicles at Signalized Intersections: Application of Adaptive Cruise Control in Mixed Traffic[1, 2]

INTRODUCTION

The introduction and deployment of Automated Vehicles opens up a new world of possibilities and uncertainties. As Low Level of Automated Vehicles (LAV) are currently in the network, it is anticipated that in the near future, a widespread of LAVs and High-Level Automated Vehicles (HAV) will be available in the market. Waymo, a self-driving company that started as the google self-driving car project, is currently leading the on-road testing efforts with their self-driving vehicles which can be known as HAVs. Based on their reported AV crashes, the Waymo AVs were rear-ended by conventional vehicles (*2; 3*). This fact stresses the importance of exploring the interaction of human-driven vehicles with AVs. LAVs are receiving additional information and warnings regarding their environment leading to an increase in situational awareness and a decline in errors.

The main objective of this research is investigating the safety impact of HAVs when interacting with conventional and LAVs at signalized intersections. We are attempting to study the impact of variations in longitudinal control of the vehicles on the safety performance of an intersection using Adaptive Cruise Control (ACC) (*4*). To reach our objective, real-world connected vehicle (CV) data is used in order to modify and calibrate the Wiedemann car-following model to represent both, conventional human-driven vehicles and vehicles with enhanced warning and intervention systems, while an ACC model integrated in the traffic simulator VENTOS is used to represent HAV's. Finally, multiple scenarios are defined to simulate the mixed traffic environment where conventional, LAVs, and HAVs are interacting.

LITERATURE REVIEW

Before discussing the technical details of this study, a brief review of studies pertaining to AVs are discussed. The future of AVs has been studied from different viewpoints such as policy, society, public opinion, adoption, ethical issues, planning and so forth. A review of related studies of AVs (*5*) classifies the implication into a three-fold order. The first order of impacts are considered the issues related to traffic and travel cost, time, capacity as well as travel choices. Vehicle ownership and sharing, infrastructure, land use and location choices are classified as second order impacts. Finally, effects on safety, energy, fuel efficiency, public health etc. were classified as third-order impact. According to the results, AVs would reduce travel time, vehicle ownership, parking space requirement and emissions while will increase roads and intersections capacity, vehicle miles traveled, fuel efficiency and safety. It is interesting to note that AVs' impact on travel comfort, value of time, land use, long-term energy consumption and air pollution, social equity, economy and public health were concluded to be unknown. Apart from unknown impacts, it is clear that those benefits are unachievable unless some level of market penetration are realized. While use of AVs seem to be forthcoming, the pace of adoption is dependent on several factors such as public opinion, legal and policy barriers, cyber-security and safety. That said, there exist

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[1] Arvin, R., Khattak, A., & Rios Torres, J. *Evaluating Safety with Automated Vehicles at Signalized Intersections: Application of Adaptive Cruise Control in Mixed Traffic*. Presented at 98th Transportation Research Board Annual Meeting, 2019.

[2] Arvin, R., Kamrani, M., Khattak, A. J., & Rios-Torres, J. *Safety impacts of automated vehicles in mixed traffic*. Presented at 97th Transportation Research Board Annual Meeting, 2018.

number of studies to address those factors. For instance, public interests about AVs and CAVs were examined through estimation of willingness to pay (*6*) and survey (*7*). Given proper adoption of AVs, their impacts on travel demand and generally from planning perspective could be explored (*8; 9*).

To estimate AVs' impacts, one approach is to define different scenarios under which the modeling and simulation are performed. The definition of scenarios is necessary due to consequences of mix environment where different type of vehicles with different levels of automation and market penetration interact in the same environment. For instance, Strand *et al.* (*10*) studied the automation failure under semi and full automated environments. The results show the in case of failure, semi-automated driving will be safer than high-automated driving. The choice of time headway by human drivers were investigated if a platoon of CAVs exist around them by Gouy *et al.* (*11*). This study showed that presence of a truck platoon significantly affects the time headway chosen by human drivers. Participant in the study kept lower time headway as compared to normal driving environment that leads to higher chance of collision.

METHODOLOGY

This research explores the safety impact of AVs as they are gradually introduced into a network of conventional human-driven vehicles. The CV data from the Safety Pilot Model Deployment study in Ann Arbor, Michigan was used previously to modify and calibrate the Wiedemann model (*12*). In order to simulate the driving behavior of LAVs, it is assumed that the transmitted information and warnings to the drivers increase the cautiousness and situational awareness. On the other hand, to model the driving behavior of HAVs, the ACC model is included in VENTOS is used. Next, ten scenarios are defined with different market penetration of conventional vehicles, LAVs, and HAVs. Finally, two surrogate safety performance measures are used, i.e. number of conflicts and driving volatility, to quantify the safety performance of the network.

Real-world AV Crashes Analysis

Different companies are testing their AVs on public roads. Since September of 2016, the Google AVs (24 Lexus RX450h and 34 prototypes) are driven more than 2 million miles in autonomous mode on public roads. Google AV reports indicate that Google AVs' crash rate is 2.5 times greater than the national rate for "property-damage-only" crashes (*13*). In California State, every company testing their AVs on public roads have to report their car accidents to Department of Motor Vehicles (*3*) and these reports are accessible to the public. From October 2014 to May 2017, there are 31 crash reports that an AV was involved (both in autonomous and conventional mode) which are used as a database for analysis in this section. The dataset were examined by two persons for errors and the data was valid. Descriptive statistics for the crash reports are illustrated in Table 1. Among these 31 crashes, 21 crashes happened while the AV was operating in autonomous mode, and 10 crashes in conventional mode, however, one of them was operating in automated mode and disengaged by the driver just before the accident and we considered that as autonomous mode.

TABLE 1 Summary of California State crash reports

Crash Location	
intersection	25 (80.6%)
other	6 (19.4%)
Operation mode	
autonomous	22 (71%)
manual	9 (29%)
Crash type	
rear-end	19 (61.3%)
angle	5 (16.1%)
side-swipe	7 (22.6%)
Number of vehicles involved	
1	2 (6.5%)
2	28 (90.3%)
3	1 (3.2%)
Pedestrian or bike involved	
Yes	1 (3.2%)
No	30 (96.8%)
Severity	
property-damage-only	26 (80.6%)
minor injuries	5 (19.4%)
AV at fault	
Yes	5 (19.4%)
No	26 (80.6%)

Among these 31 crashes, there are 5 crashes that the AV vehicle was at fault among which, one of them happened when the vehicle was operating in autonomous mode. The cause of the crash was that the AV did not yield to the ongoing vehicle and collided with the side of the other vehicle's body. The other 4 crashes happened when the vehicle was operating in the conventional mode.

It is important to study the places that AVs' are prone to have an accident. We can observe that more crashes happened at intersections due to interrupted traffic flow. When it comes to crash types, 61.3 percent (19 crashes) were rear-ended, 16.1 percent (5 crashes) angle crashes, and 22.6 percent (7 crashes) were sideswipe. In Figure 1, the proportion of crash type by operating mode is shown. Considering crashes in autonomous mode (22 crashes), 73 percent of crashes were rear-ended, 18 percent was side-swipe, and 9 percent was angle crashes. On the other hand, 34 percent of AV crashes in conventional mode was rear-end, 33 percent side-swipe and 33 percent angle crash.

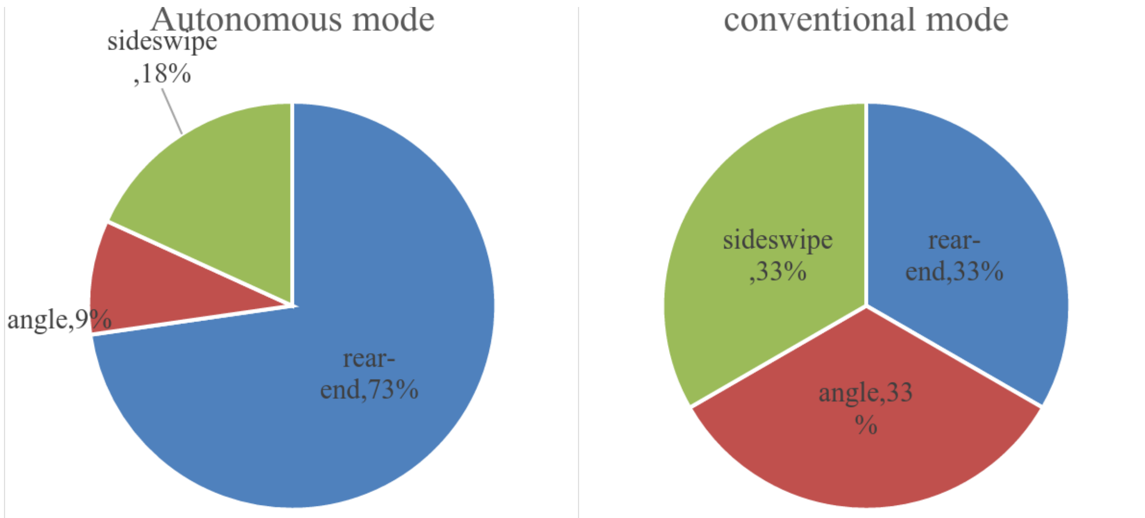


FIGURE 1 Percentage of crash type by operation mode at the accident time

In Table 2, the speed of the AV and the second vehicle (if applicable) is shown. AV vehicles are divided two autonomous mode and conventional mode. Focusing on crashes AV in autonomous mode (22 crashes), 61.9 percent of them occurred when the AV was stopped in the traffic, 19.3 percent with speed lower than 5 mph and 6.4 percent with speed higher than 5 mph. Average collision speed for these crashes is 2.7 mph which is significantly lower than the mean speed of the conventional mode.

TABLE 2 Speed of the vehicles at crash time

Speed	Autonomous Vehicle		Other vehicle
	Autonomous mode	Conventional mode	
0	12 (54.5%)	1	2
<=5 mph	6 (19.3%)	1	9
>5 mph	2 (6.4%)	5	13
Unreported	2 (6.4%)	3	4
Not Applicable	-	-	3
Mean speed (mph)	2.7	8	9.125
Total	22	9	31

The severity of the crashes indicates that 83.9 percent (26 crashes) were property-damage-only crashes, and 16.1 percent (5 crashes) were injury crashes. Crash severity based on the AV's operation mode is summarized in Figure 2.

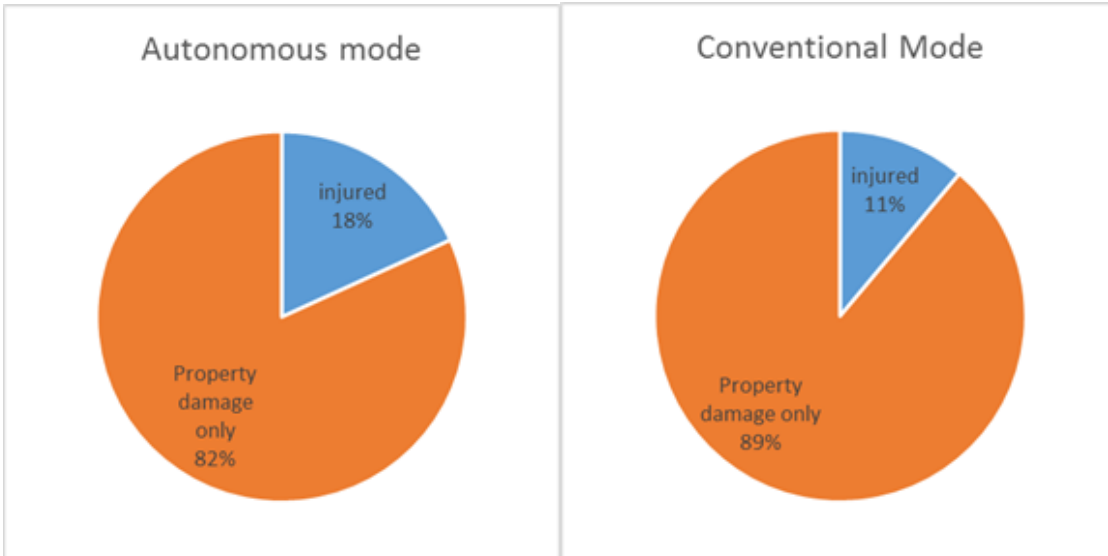


FIGURE 2 crash severity by operation mode

Analysis of California State crashes revealed some important facts about AV crashes in autonomous mode. First, in almost all of the crashes, the other vehicle was at fault. However, there is one crash that AV failed to yield the right of way to other car and led to the collision. Second, similar to conventional vehicles, AVs are more probable to have a crash at an intersection in comparison with other locations. Third, rear-end crashes are the most frequent type of the crashes.

Car-Following Model

Human-driven Vehicles (conventional and LAVs)

As per to Brackstone and McDonald (*14*), five groups of car-following models exist. The first and the most well-known model is Gazis-Herman-Rothery (GHR) model introduced by General Motors (*15*) that relates acceleration to speed of the leader vehicle, relative speed and gap space of vehicles, and driver reaction time. Collision-avoidance models (CA) are the second group first used introduced by (*16*), define safe following distance, which is a secure distance to avoid a collision, as a function of the leader and follower speed and driver reaction time. Linear models (*17*) assume that acceleration of the vehicle is relating to the desire following space gap, the speed of the host vehicle, relative distance and speed between the leader and the follower, and reaction time. Psychophysical or Action-Point model is introduced by Michaels (*18*) assumes that a driver performs an action within a threshold varying with speed and distance difference. These models are based on the drivers' perception ability that varies across different groups of people elaborating the process of estimation and calibration. Finally, fuzzy-logic-based models are the latest distinct stage in car-following model development by dividing the inputs of the model into some *fuzzy sets*. Each one of these sets should describe how adequately a variable fits the description of a *term*. This method initially used by Kikuchi and Chakroborty (*19*).

For this study Wiedemann model is selected due to the reason that the model is a function of perception and cautiousness of drivers which let us consider levels of automation with assuming higher perception and cautiousness of these vehicles.

Wiedemann Car-following Model is classified as psychophysical models originally introduced in 1974 by Rainer Wiedemann (*20*) and widely used by other researchers and software to simulate human driving behavior (*21; 22*). This model considers four regimes of movement for the following vehicle.

1- *Free-driving regime*: In this mode, the leading vehicle exerts no influence on the following vehicle's behavior. Reaching and maintaining the desired speed is the only task of the driver in this mode.
2- *Closing in regime*: in this mode, the following vehicle perceives that he/she is approaching a slower car in front and tries to adjust his/her speed to the leading vehicle.
3- *Following regime*: the following vehicle is maintaining its headway between maximum and safe headway. The follower car tries to accelerate and decelerate according to the behavior of the leader car.
4- *Emergency regime*: when the space gap between two vehicles is smaller than a threshold, the following vehicle decelerates to avoid collision with the front vehicle.

In Figure 3, graphical form of the Wiedemann model is illustrated. We can observe that different thresholds distinguish the boundaries of regimes. According to the figure, when the subject vehicle approaches the front vehicle (due to higher speed), it enters the perception area by crossing the SDV threshold and starts to reduce his/her speed. In this regime, the speed of the subject vehicle is still higher than leader one, and it crosses CLDV threshold and starts to react and decelerate to enter the unconscious reaction mode and follow the leading vehicle as long as the subject vehicle is in SDX, SDV and OPDV boundaries.

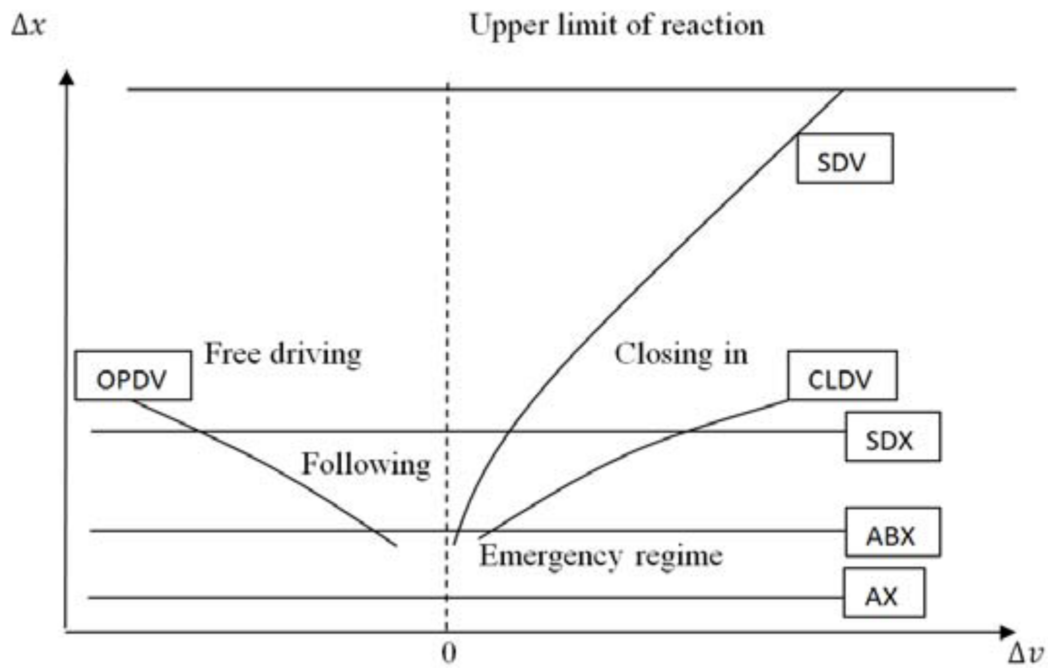


FIGURE 3 Thresholds and driving regimes in the Wiedemann model

Different formulation for Wiedemann model are presented by different studies. According to Werner (*23*) formulation, thresholds for each regime is a function of two important variables: driver cautiousness and driver's situation awareness. In addition, the model let the vehicles following Wiedemann model to collide inside the simulation, which is a unique feature of their simulation. Threshold definitions are shown in the following:

$$AX = L + 1 + 2 * ZF1 \tag{1}$$

$$ABX = AX + (1 + 7 * ZF1)\sqrt{v} \quad (2)$$

$$SDV = (\frac{\Delta x - AX}{CX})^2 \; where \; CX = 25 * (1 + ZF1 + ZF2) \quad (3)$$

$$SDX = AX + EX(BX - AX) \; where \; EX = 2 - ZF2 \quad (4)$$

$$CLDV = SDV * EX^2 \quad (5)$$

$$OPDV = CLDV - (-1 - 2 * rand) \quad (6)$$

Where:

AX: desired space gap between two stationary cars (minimum gap)
ABX: desired minimum following distance
SDX: maximum following distance
SDV: threshold indicating where driver perceive approaching slower vehicle (long distances)
CLDV: defines the threshold driver starts to react and decelerate (short distances)
OPDV: defines the threshold that driver perceives his/her speed is lower than in front vehicle
L: length of the vehicle
ZF1: level of cautiousness (called "security" in SUMO) (0 to 1)
ZF2: level of situation awareness (called "estimation" in SUMO) (0 to 1)
Rand: random number with mean 0.5 and standard deviation 0.15

Highly Automated Vehicles

In this paper, to model the driving behavior of HAVs, we used the Adaptive Cruise Control model (*24*) widely used by researchers to model the driving behavior of AVs (*25; 26*). We used VENTOS built-in ACC car-following model (*24; 27*).

Safety Surrogate Performance Measures

The safety performance of the system with the mixed traffic is evaluated by the number of conflicts and driving volatility, which is highly correlated with the frequency of crashes at intersections (*28*).

Number of conflicts

One of the common methods for quantifying the number of conflicts is time-to-collision (TTC), which can be written as (*4*):

$$TTC_{i,t} = \frac{(x_{i-1,t} - x_{i,t}) - L_{i-1,t}}{v_{i,t} - v_{i-1,t}} \quad (12)$$

where x_{i-1}, and v_{i-1} are the positions and speed of the leader, x_i and v_i are the speed and speed of the following vehicles, L_{i-1} is the vehicle length, and *t* refers to the time. In this research, a TTC lower than 0.5 seconds is considered as a serious conflict.

Driving Volatility

A new concept, named driving volatility, is recently introduced in the literature (*29*), which is intended to capture the variations in driving behavior. Multiple volatility measures are introduced (*30; 31*) and it has been shown that speed and acceleration volatilities are highly associated with the number of crashes at intersections (*28*). Given that, these measures are utilized to measure the safety performance of the intersection considering a mixed traffic environment.

Simulation setup and calibration

In this study, the open-source microsimulation software VENTOS (Vehicular network open simulator) is used (*32*). In order to evaluate the defined scenarios, the intersection of Huron parkway and Washtenaw Avenue in Ann Arbor, MI was selected. To calibrate the simulation to generate reasonable approximation of real-world condition at the selected intersection, the following steps are taken:

1- The Wiedemann car-following model is modified to generate more realistic acceleration and speed patterns.
2- The simulation is calibrated by incorporating safety measures for the conventional vehicles (base scenario).

RESULTS

Definition of scenarios

To study the interaction of HAVs with LAVs and conventional vehicles in a mixed traffic, ten scenarios are defined (Table 1). Prior to performing the simulation runs, the intersection was empty, and one-hour warm up is considered. Each simulation run was one hour, and the step-length was 0.1 second. For each scenario, the simulation was run 10 times, and the safety performance of each scenario was assessed.

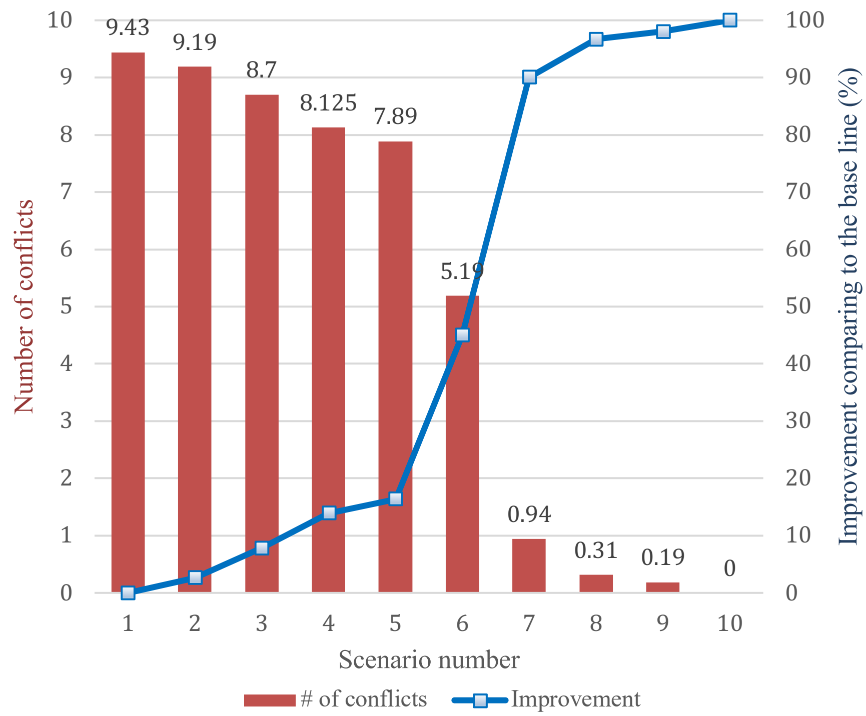
TABLE 1 Definition of scenarios.

	Sc1 (base)	Sc2	Sc3	Sc4	Sc5	Sc6	Sc7	Sc8	Sc9	Sc10
Conventional vehicles	100%	93%	85%	60%	40%	20%	0%	0%	0%	0%
Low level AVs	0%	5%	10%	25%	40%	50%	50%	30%	10%	0%
High level AVs	0%	2%	5%	15%	20%	30%	50%	70%	90%	100%

Simulation results

The summary of simulation runs is shown in Figure 1. Based on the results, in the baseline where all the vehicles are conventional, an average of 9.43 conflicts are observed. With increase in the penetration of LAVs and HAVs, the number of conflicts in the intersection dropped. When all the conventional vehicles are eliminated from the simulation (scenario 7), there is a 90.1% improvement compare to the baseline. Finally, in the last scenario where all the vehicles are HAVs, the intersection becomes conflict free.

The plot of the speed and acceleration volatilities for the scenarios is shown in Figure 1. Based on the results, it can be inferred that with increase in the penetration of LAVs and HAVs, the speed and acceleration driving volatilities are decreasing. The higher situation awareness and cautiousness of LAVs along with vehicle automation in HAVs leads to faster response to the stimuli and smoother driving which could help decrease the volatile movements of vehicles.



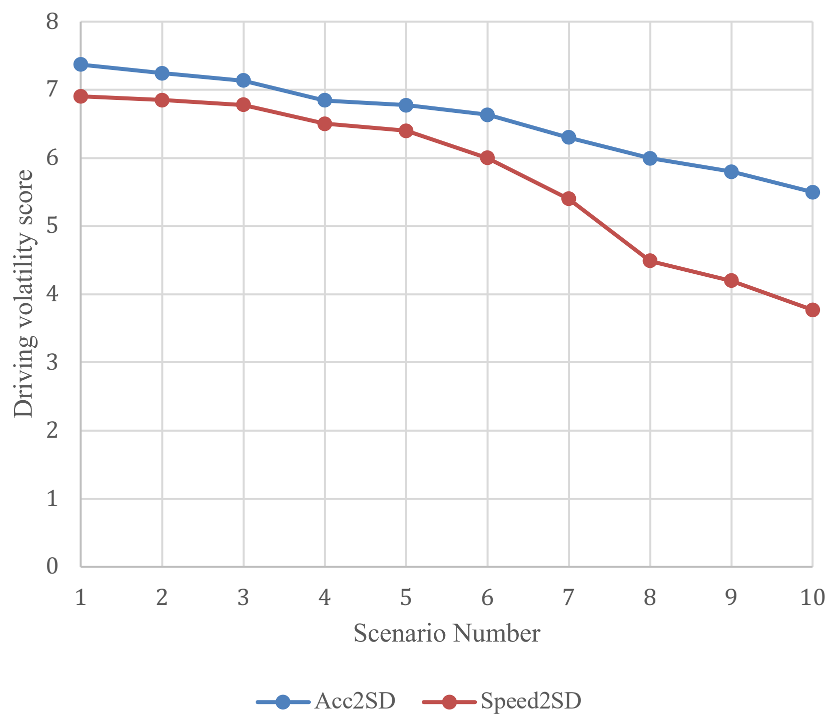


Figure 1 Simulation results for the defined scenarios number of conflicts and improvements comparing to the baseline (top), speed and acceleration volatility (bottom)

Conclusions

The interaction of HAVs with LAVs and conventional vehicles is studied by defining ten scenarios with different market penetration rates. The simulation results revealed that with increase in the penetration of LAVs and HAVs, a substantial improvement in the safety performance of the intersection can be achieved by decreasing the conflicts and driving volatility. Focusing on LAVs, higher situational awareness and cautiousness than conventional vehicles, lead to perceiving the leader's behavior from longer distances, improving the driver performance. On the other hand, HAVs can respond to the leader vehicles faster due to automation control, and smoother driving leading to declines in conflicts and driving volatility.

The study is timely and original by integrating and harnessing real-world CV data in a simulation to study the safety impacts of low-level and high-level of automated vehicles. The simulation results are valuable for researchers and experts by predicting the safety impact of emerging technologies, i.e. LAVs and HAVs, assuming different market penetration. The developed behavioral framework based on CV data is helpful for researchers to provide more realism in their simulations.

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Chapter 2
Safety Implications Analysis – Merging Scenario

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ABSTRACT
Connectivity and automation provide opportunities for implementation of innovative and effective system-level monitoring and control. Coordination control systems for vehicles merging at highway on-ramps can potentially improve traffic safety, efficiency and energy consumption. We present and assess the performance of two coordination control systems in terms of safety and efficiency. The systems allow connected and automated vehicles to merge onto the highway safely and smoothly by enabling a high-level controller to create a schedule for the vehicles to pass through the merge area based on a first-in-first-out queue. A low-level controller computes the optimal speed trajectory and provides the reference speed to be followed by the connected vehicles. The objective functions for each coordination system are the control input effort and the fuel consumption respectively. The optimization problems are solved analytically through application of Pontryagin's Minimum Principle. Control theory and microscopic traffic simulation are used to assess the impact of the two coordination control systems on safety, traffic flow, and fuel consumption. The simulation results show that, using the number of conflicts and driving volatility as safety indicators, the two optimal coordination control systems outperform the baseline case. Moreover, the two optimal coordination control systems can reduce total time spent and total fuel consumed. This study provides technical understanding and tools for enhancing connected and automated vehicle operations.

INTRODUCTION
It is estimated that a driver wastes an average of 40 hours per year stuck in traffic translating to about $1100 and a total cost in the U.S. of about $160 billion (*1*). Among the primary sources of bottlenecks, merging roadways are a major concern as drivers are required to execute and coordinate different maneuvers in a limited time period to safely merge, causing congestion and impacting the fuel consumption and travel time (*2*, *3*). To this end, a large body of research has been directed toward coordinating vehicles in merging roads and intersections (*4*). With the advent of connectivity technology, vehicles are able to communicate with each other (*5*) and have easier access to traffic information broadcasted by the infrastructure. Furthermore, connected and automated vehicles can be precisely and even cooperatively controlled, allowing them to reduce incidents caused by human errors and increase the traffic efficiency and safety while improving fuel economy. To enable safe and efficient operation of such vehicles, the objective of this paper is to present and evaluate two real-time coordination control systems that allow connected vehicles to merge onto a highway safely and smoothly. The problem is first formulated as an optimal control problem, solved analytically using Pontryagin's Minimum Principle, and then simulated to evaluate impacts. This study was informed by an extensive literature search on the development of optimal controls for vehicle merging coordination and measures of effectiveness (MOEs) related to traffic in networks, which are presented in the the next section.

LITERATURE REVIEW
According to Athans (*6*) coordinating vehicles in merging roadways involves two fundamental problems: 1) at the high level, the vehicles must be scheduled to define a merging sequence and 2) at the low level, the vehicles should be controlled in such a way that the desired schedule is achieved in a safe and efficient way. The high-level problem aims at avoiding any collisions with

a surrounding vehicle at the merging area by defining a merging sequence with proper safety headway times, but other factors such as fuel consumption, traffic flow efficiency, etc. could also be included without compromising the safety (*7*, *8*). The low-level problem can be treated as a vehicle driving control problem, which formulates an optimal control problem mimizing a desired cost function such as fuel consumption, control effort, drivability, travel time, etc.

Several researchers have used model predictive control (MPC) based on direct optimization methods to obtain near-optimal speed trajectories. The most predominant research involves adaptive cruise control (ACC) (*9*, *10*) and platooning control (*11*). This type of control is generally executed for short prediction horizons and, the shorter the horizon the closer to the optimal the solution will be. However, there is a trade-off between the horizon size and the computing time. Another commonly used approach is dynamic programming (DP) which allows to handle more complex problems while guaranteeing global optimality but it imposes a heavy computational burden (*12–14*).

More recently, the derivation of analytical solutions to the optimal control problem has been addressed through application of Pontryagin's Minimum Principle (PMP) and different types of vehicle models. Among those, a second order longitudinal model was used in (*15–17*), a linearized vehicle model was used in (*18*, *19*), and a nonlinear vehicle model in (*20*). The advantage of using analytical solutions is that they are suitable for real-time implementation. According to these studies based on analytical solutions, if the cost function is defined as a quadratic function of the acceleration, the optimal control effort solution corresponds to a parabolic speed trajectory. On the other hand, if the cost function is the fuel consumption, the analytical fuel-optimal solution corresponds to "bang-(singular)-bang" trajectory for traction control and "bang-bang" trajectory for braking control (A bang-bang controller-also known as an on-off controller- switches between predefined states). These kind of solutions require switching between intervals including maximum acceleration, maximum braking, coasting with engine shut-down, and constant speed cruising (*21*, *22*). A similar conclusion was reached in (*23–25*) by using numerical optimization.

The contribution of this paper compared to our previous work (*16*, *22*, *26*, *27*) is the quantification of a broader range of impacts, i.e., safety, traffic flow efficiency and energy consumption on the performance of two formulations of the optimal coordination control sytem.. The first control strategy uses control effort, i.e., acceleration, as the cost function while the second uses fuel consumption. These coordination systems could be implemented in real world using a roadside unit with dedicated short-range communication (DSRC) capabilities, to serve as a scheduler. The scheduler will transmit the optimal schedules to the vehicles inside its range. All the vehicles will need to be connected and able to follow optimal speed advisories. The latter requirement could be accomplished by having onboard a driving assistance system to guide the driver or vehicles with SAE L3-L4 automation capabilities. Given the momentum and widespread interest on CAVs, this work is timely and its originalitly lies on the combination of mobility, safety and energy impacts of CAVs.

OPTIMAL COORDINATION PROBLEM

The merging scenario considered for this study is illustrated in Fig. 1. We define a *control zone* of length L where the vehicles will be controlled to keep appropriate headways and to minimize an objective function. We assume that once the vehicles enter the control zone, they can share their states, i.e., speed and position, with a central coordinator that will assign a vehicle index. This vehicle index will be decided by the schedule controller and will determine the sequence to leave the control zone. A *merging zone* of length S is also defined where the vehicles will complete the merging maneuver while keeping a safe distance from each other. Once each vehicle reaches the merging zone it will continue driving at constant speed to form a stable platoon.

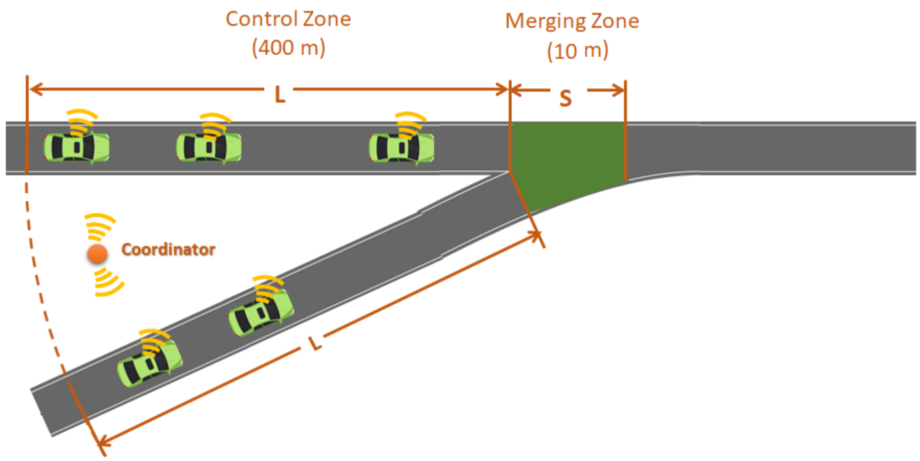


FIGURE 1 Merging at highway on-ramps considered in this study.

The aim of the control system is to optimally coordinate the vehicles driving inside the control zone until they reach the merging zone while keeping appropriate headways. We evaluate two objective functions and the optimal coordination problems are solved in two phases. First, the desired time to reach the merging zone (TTMZ) is determined such that rear-end or lateral collisions between consecutive vehicles inside the merging zone are avoided. Second, an optimal control problem is analytically solved to find the optimal control policy that minimizes a desired objective function for the vehicles driving inside the control zone.

Time to reach the merging zone

Once a vehicle i enters the control zone at some time t, the coordinator assigns an index $N(t) \in \mathbb{N}$ which is determined by a first-in-first-out (FIFO) principle. Let us denote the FIFO queue as $\mathcal{N}(t) = \{1, \cdots, N(t)\}$. Defining average travel speed as v_d, we can express the TTMZ as

$$t_{f,i} = t_{0,i} + \frac{L}{v_d} \qquad \forall i \in \mathcal{N}(t), \tag{8}$$

where $t_{0,i}$ is the time at which the vehicle i enters the control zone.

When the vehicles reach the merging zone, their headway time must be larger than the safety headway time δt_s, to ensure absence of collisions:

$$t_{f,i} - t_{f,i-1} = \delta t_i \geq \delta t_s. \tag{9}$$

Therefore, the TTMZ can be computed as:

$$t_{f,i} = \max\left(t_{0,i} + \frac{L}{v_d}, t_{f,i-1} + \delta t_s\right) \ \forall i \in \{2, \cdots, N(t)\}, \tag{10}$$

where $t_{f,1} = t_{0,1} + \frac{L}{v_d}$ is used when there is not preceding vehicle in the control zone or the preceding vehicle is very far from the follower (in which case there is not reason to accelerate to get closer to it), and then, the recursive calculation starts when the vehicle $i = 2$ enters the control zone.

Analytical solutions to optimal control problems

The two optimal control problems at the core of each optimal coordination control strategy are formulated below and their solution is derived using the Pontryagin's Minimum Principle (*30*).

We consider a second-order vehicle longitudinal dynamic:

$$\dot{p} = v, \quad (1)$$

$$\dot{v} = F_t - F_b - F_a - F_{rr} - F_g = a_t - a_b - \frac{\rho_a c_d A_f v^2}{2m} - g(c_r \cos\alpha(p) + \sin\alpha(p)), \quad (2)$$

where p and v are the vehicle's position and speed, respectively; F_t and F_b are the traction force and the friction braking force at the wheels; the resistance forces F_a, F_{rr}, and F_g are the aerodynamic drag resistance, the rolling resistance, and the hill climbing resistance at the wheels, respectively; the traction and braking accelerations are defined as $a_t = F_t/m$, $a_b = F_b/m$, m is the vehicle mass, ρ_a is the external air density, A_f is the vehicle frontal area, c_d is the aerodynamic drag coefficient, c_r is the rolling resistance coefficient, g is the gravity acceleration, and α is the road slope as a function of position.
Assuming a constant road grade, $\alpha(p) = \alpha$, the vehicle dynamics $\dot{v} = f_1$ can be simplified as

$$f_1 = a_t - a_b - c_1 v^2 - c_0 \quad , \quad (3)$$

where $c_1 = \frac{\rho_a A_f c_d}{2m}$ and $c_0 = g(c_r \cos\alpha + \sin\alpha)$. If the aerodynamic drag is neglected, i.e., $c_1 = 0$, the model can be further simplified as:

$$f_2 = a_t - a_b - c_0, \quad (4)$$

Fuel consumption model
We assume that all vehices are engine-powered and the fuel consumption is described by:

$$m_f = \int_0^{t_f} \dot{m}_f(\omega_e, T_e), \quad (5)$$

where the fuel rate, $\dot{m}_f(\omega_e, T_e)$, is provided by an engine map (*28*). Following (*29*) and based on the assumption of maintaining maximum engine efficiency, the engine map $\dot{m}_f(\omega_e, T_e)$ can be converted to $\dot{m}_f(v, a_t)$, as follows:

$$\dot{m}_f(v, a_t) = \begin{cases} \sum_{i=0}^{3} q_i v^i + a_t \sum_{j=0}^{2} r_j v^j & a_t \geq 0 \\ 0 & \text{else} \end{cases} \quad (6)$$

where the coefficients, q_i and r_j are estimated with the least square fitting method. The Willans' approach is used to further simplify this relationship as

$$\dot{m}_f(v, a_t) = \begin{cases} k_0 + k_1 a_t v & a_t \geq 0 \\ 0 & \text{else} \end{cases}, \quad (7)$$

where the coefficients, k_0 and k_1, are obtained by least-square fitting method.

Optimal coordination control strategy 1
This strategy aims to minimize the control effort defined by the square of the control input, i.e., $l_{1,i} = \frac{1}{2} u_i^2$. Subject to the longitudinal vehicle dynamics (Equations 1-2)

Defining the control input as $u_i = a_{t,i} - a_{b,i}$, the optimal control problem is mathematically stated as:

$$\text{Minimize} \quad \int_{t_0}^{t_{f,i}} l_{1,i}\, dt, \quad (8)$$

$$\text{Subject to} \quad \dot{p}_i = v_i, \quad \dot{v}_i = f_{2,i}, \quad (9)$$

$$-u_{min} \leq u_i \leq u_{max}, \tag{10}$$

where t_0 is current time, and $t_{f,i}$ is the TTMZ. With boundary conditions:

$$v(t_0) = v_0, \quad s(t_0) = s_0, \tag{11}$$

$$v(t_{f,i}) = v_f, \quad s(t_{f,i}) = L, \tag{12}$$

where v_0 and s_0 are current speed and position, respectively.

Following (*16*, *21*), the optimal control policy u_i^* is derived through application of PMP.

Optimal coordination control strategy 2
This strategy aims to minimize the fuel consumption (Equation (6)). By defining the control inputs as $u_{t,i} = a_{t,i}$ and $u_{b,i} = a_{b,i}$, the corresponding optimal control problem is stated as:

$$\text{Minimize} \quad J_i = \int_{t_0}^{t_{f,i}} l_{2,i}\, dt, \tag{13}$$

$$\text{Subject to} \quad \dot{p}_i = v_i, \quad \dot{v}_i = f_{1,i}, \tag{14}$$

$$-u_{min} \leq u_i \leq u_{max}. \tag{15}$$

With boundary conditions (11) and (12).

The optimal control policy $u_i^* = u_{t,i}^* - u_{b,i}^*$ is again derived through application of PMP.

SIMULATION FRAMEWORK

To evaluate the performance of the two coordination control systems, we created a merging scenario (Figure 1) in PTV VISSIM. A baseline scenario in which all the vehicles are assumed to be human-driven is used to test the effectiveness of the coordination control systems.

Human driver model

To represent the longitudinal driving behavior of humans in the baseline scenario, we used the psycho-physical driver behavior model developed by Wiedemann included in VISSIM. This model has four driving modes: free-driving, approaching, following, and braking. In the free-driving mode the driver accelerates to reach and maintain a desired speed as a preceding vehicle is not present. In the approaching mode, the driver adjusts the speed to that of a preceding slower vehicle. In the following mode, the driver accelerates/decelerates according to the behavior of the preceding vehicle to keep a safe headway. The braking mode is activated whenever the distance gap with respect to the preceding vehicle is less than a predefined threshold. For this study, we used the default values for the Wiedemann 99 parameters in VISSIM: standstill distance d_0 =1.5 m and headway time δt_h =0.9 s.

Coordination control systems

The optimal coordination systems are implemented via the VISSIM component object model (COM) interface. The COM interface allows MATLAB to receive (and sent back) data from the VISSIM environment. Such data is used to compute the optimal reference speed which is fed back to the corresponding vehicle in the VISSIM environment. Due to the dynamics of the Wiedemann 99 model, the resulting speed trajectories might have deviations from the optimal trajectories fed by MATLAB (the Wiedemann model attempts to track the optimal speed)

We consider a control zone of length $L = 400$ m and a merging zone of length $\mathrm{S} = 10$ m and assume that all the vehicles on the scenario are homogeneous. Furthermore, we use a safety headway time of $\delta t_s = 1.6$ s for scheduling the TTMZs, which corresponds to a safe traffic outflow from the merging zone of $Q_{\mathrm{MZ},s} = 1/\delta t_s = 2250$ veh/h. The control input bounds are set as: $u_{max} = 3$ and $u_{min} = -3$. For the remaining of the paper the two coordination control systems based on the optimal control effort and the fuel-optimal solutions are identified as 'CECS' and 'FCCS', respectively.

Traffic network parameters

To model the traffic network in VISSIM, we selected the W I 94/N US 23 On-Ramp in the Washtenaw county in Ann Arbor, Michigan. According to (*32*), this merging point has an average Annual Average Daily Traffic demand on the main and ramp roads of (Q_m, Q_r) = (19,800, 13,800) veh/d. Following (*33*), the traffic demand at peak hour is estimated to be about (1900, 1300) veh/h. Assuming a fixed ratio between Q_m and Q_r, we considered a saturated traffic demand of (1200, 800) veh/h. The speed limit for both roads is 40 mph (~64.4 km/h), thus we set the desired speed before the vehicles reach the control zone on the main and ramp roads in simulation to 60 km/h and 50 km/h, respectively. The total simulation time is 30 min including a warm-up time of 5 min. We conducted ten simulation runs with different seed number for each scenario.

Assessment indicators

During the simulation, the speed and acceleration trajectories for each vehicle are logged and the vectors obtained at the end of the simulation are used to compute the assessment indicators.

Driving volatility and number of conflicts

Since the cars should follow predefined behaviors (car-following models), the simulation environment is collision free. Therefore, various surrogate safety measures are utilized to study the safety impact of different traffic scenarios. In this study, two safety indices were utilized to address the safety performance of the merging area. The safety analyses were conducted on main and ramp segments separately, since the regimes of movements are different. The details for each index are included next.

Number of conflicts. Since accidents are a subset of conflicts between vehicles, the number of conflicts is a common approach to measure the safety performance in traffic simulation (*34*). Previous studies have widely used time-to-collision (TTC) as a measure to quantify number of conflicts, which can be written as (*35*):

$$TTC_i(t) = \frac{(x_{i-1}(t) - x_{i,}(t)) - l_{veh_{i-1}}}{v_i(t) - v_{i-1}(t)} \tag{16}$$

where $TTC_i(t)$ is the time to collision at time t for subject vehicle *i*, $x_i(t)$ and $v_i(t)$ are position and speed of subject vehicle, $x_{i-1}(t)$ and $v_{i-1(t)}$ are position and speed of leader vehicle, and $l_{veh_{i-1}}$ is length of leader vehicle. We have considered TTCs lower than 0.5 seconds as a conflict. In case the coordination system is implemented using a driving assistance system instead of an automated vehicle, the threshold to define conflicts should be higher.

Driving volatility. This measure attempts to capture the variations in instantaneous driving movements. Various measures of volatilities are introduced and utilized by researchers (*36–38*), applying to speed, acceleration, and vehicular jerk. In this study we use speed and acceleration volatilities. Using these two measures, by counting the number of outliers lying beyond the defined threshold, we can quantify the times that vehicle movements are erratic. For the speed volatitlity we can write:

$$\text{Speed volatility} = \frac{k > threshold}{n} * 100 \tag{17}$$

where *k* is number of speed outliers, *n* is number of observations, and threshold is:

$$\text{threshold} = \bar{v} \pm 2 * S_{dev} \quad (18)$$

where $\bar{v}$ and S_{dev} are average speed and standard deviation of vehicles speed passing the merging area. Acceleration volatility can be formulated as:

$$\text{Acceleration volatility} = \frac{m > threshold}{n} * 100 \quad (19)$$

where *m* is number of acceleration outliers, and threshold can be defined as:

$$threshold = \bar{a} \pm 2 * S_{dev} \quad (20)$$

where $\bar{a}$ and S_{dev} are average and standard deviation of acceleration.

Total distance travelled (TDT) and total time spent (TTS)
The TDT is computed by

$$\text{TDT} = \sum_{i=1}^{N_v} \text{DT}_i, \quad (21)$$

where DT_i is distance travelled by vehicle i, and N_v is the number of vehicles in the traffic network. The TTS is computed by

$$\text{TTS} = \sum_{i=1}^{N_v} \text{TS}_i, \quad (22)$$

where TS_i is time spent by vehicle i.

Total fuel consumption (TFC) and average fuel consumption (AFC)
To consider the effect of aerodynamic drag resistances in the fuel consumed, the required traction acceleration $a_{t,i}^r$ for the respective vehicle speed trajectory v_i is computed by $a_{t,i}^r = \dot{v}_i + c_{1,i}v_i^2 + c_{0,i}$ (derived Equation (3)). Then, the polynomial model in Equation (6) is used to compute the final fuel consumption, $\text{FC}_i = m_{f,i}\left(a_{t,i}^r, v_i\right)$. The TFC and the AFC are computed by

$$\text{TFC} = \sum_{i=1}^{N_v} \text{FC}_i, \quad (23)$$

$$\text{AFC} = \text{TFC}/\text{TDT}. \quad (44)$$

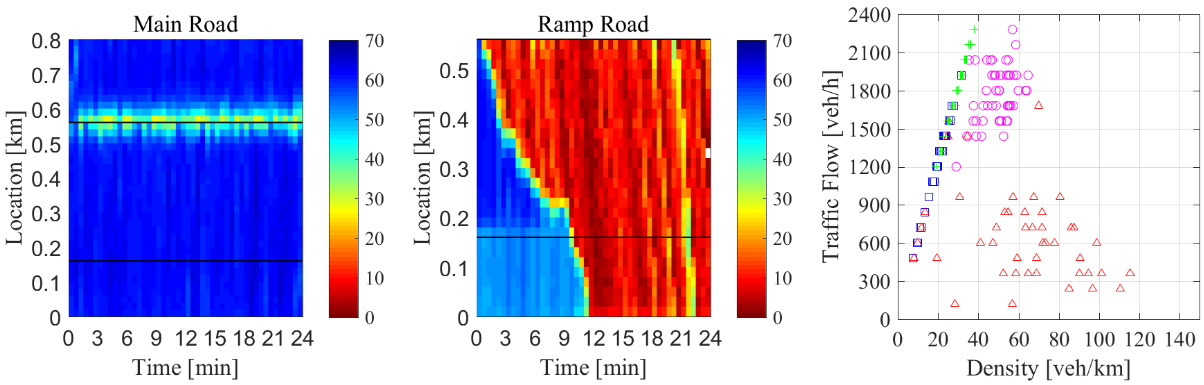
SIMULATION RESULTS

Traffic dynamics in the traffic network

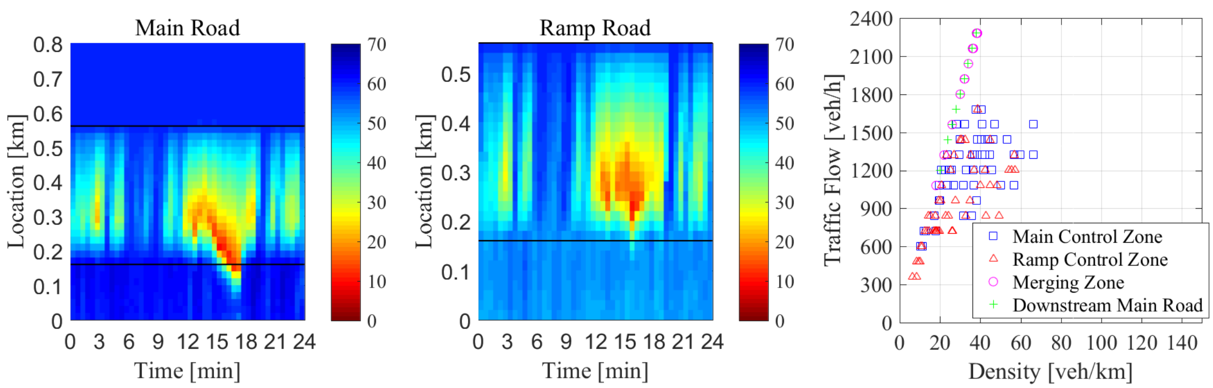
To investigate the traffic impacts of optimal coordination, collected the traffic flow Q and the mean speed v_m every 30 seconds. Figure 2 shows the spatio-temporal time mean speed contour plots and the flow-density relations. In the flow-density relations, we have determined the density ρ using the relation of $Q = \rho v_m$, and selected four different cross-sections to analyze inflow and outflow based on the merging zone: the main and ramp control zone located at 300 meters, the merging zone located at 560 meters, and downstream of the main road located 800 meters (the exit of the simulated traffic network). The average traffic flow and speed at the merging zone and downstream of the main road (Q_{MZ}, $v_{m,\text{MZ}}$, Q_{out}, and $v_{m,\text{out}}$), which are averaged over the total simulation time, are reported in Table 1.
In the baseline case, main road vehicles reduce speeds up to 20 km/h near the merging zone, while ramp road vehicles repeat stop-and-go driving waiting for a proper timing to pass through the merging zone (Figure 2a). A decrease in speed due to high inflow into the ramp road increases the density near the merging zone, limiting traffic outflow from the merging zone. Moreover, the

frequent stop-and-go driving on the ramp road causes severe congestion starting from the merging zone and results in queue formation. Notably, this queue propagates upstream, and may result in a spill back to local streets/intersections. After vehicles leave the merging zone, they start to accelerate again to the desired speed of 60 km/h. However, larger headways are observed between vehicles in the acceleration interval which lead to a reduction of the traffic outflow in the merging zone.

In contrast, the two coordination systems enable smoother traffic flow by limiting the inflow to the merging zone by assigning longer TTMZs. As a result, the average speed is decreased but the traffic density on the control zone is increased particularly on the main road, which is represented in Figure 2 (b and c, right) by the traffic flow points scattered over the density axis below the free traffic curve. This confirms that limiting the inflow in the coordination systems can significantly mitigate traffic congestion on the ramp roads and increase the traffic outflow in the merging zone (about 1973 veh/h in average) with respect to the baseline (see Table 1). Notably, the CECS require the vehicles to follow lower reference speeds compared to the FCCS but generates smoother acceleration/deceleration patterns over time. The lower speeds in the CECS can eventually lead to short traffic jams due to increased density, as it is observed in Figure 2(b) from 12 to 17 min (main road). FCCS is able to mitigate this condition as a result of the slightly higher average speed. It is worthy to consider that the CECS was implemented using a more simplified vehicle dynamic model than the one used for the FCCS. Using the same model might slightly change these results. Ongoing research is exploring this and how the two coordination systems perform under higher traffic demands, especially near capacity.



a)



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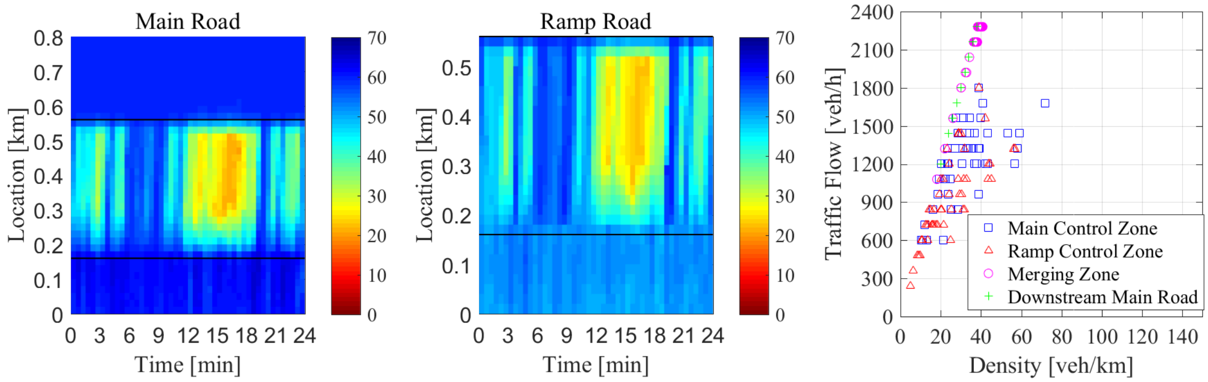


c)

Note: Four different cross-sections, i.e, the main and ramp control zone, the merging zone, and downstream of the main road are shown for three cases: a) baseline, b) CECS, and c) FCCS. Area between black lines indicate the control zone.

FIGURE 2. Spatio-temporal distribution of time mean speed contour plots of main and ramp road and flow-density relations.

TABLE 1 Assesement indicators averaged over ten simulation runs for the baseline and the coordination cases under the condition of (1200, 800) veh/h.

Cases		**TDT [km]**	**TTS [h]**	**TFC [l]**	**AFC [ml/km]**	Q_{MZ} **[veh/h]**	Q_{out} **[veh/h]**	$v_{m,\text{MZ}}$ **[km/h]**	$v_{m,\text{out}}$ **[km/h]**	N_v
Traffic network	**Baseline**	739.50	30.10	46.02	62.23	1765	1724	37.56	60.74	841
	CECS	806.30	14.99	34.50	42.79	1973	1973	59.62	60	862
		9.03%	***-50.20%***	***-25.03%***	***-31.24%***	***11.78%***	***14.44%***	***58.73%***	***-1.22%***	***2.50%***
	FCCS	806.60	14.97	33.58	41.63	1974	1932	58.92	60	862
		9.07%	***-50.27%***	***-27.03%***	***-33.10%***	***11.84%***	***12.06%***	***56.87%***	***-1.22%***	***2.50%***
Control zone	**Baseline**	320.00	19.73	20.37	63.63					
	CECS	342.10	7.12	16.38	47.87					
		6.91%	***-63.92%***	***-19.59%***	***-24.77%***					
	FCCS	342.40	7.10	15.04	43.93					
		7.00%	***-63.99%***	***-26.17%***	***-30.96%***					

Note: The numbers in italic bold represent percentage difference with respect to baseline.

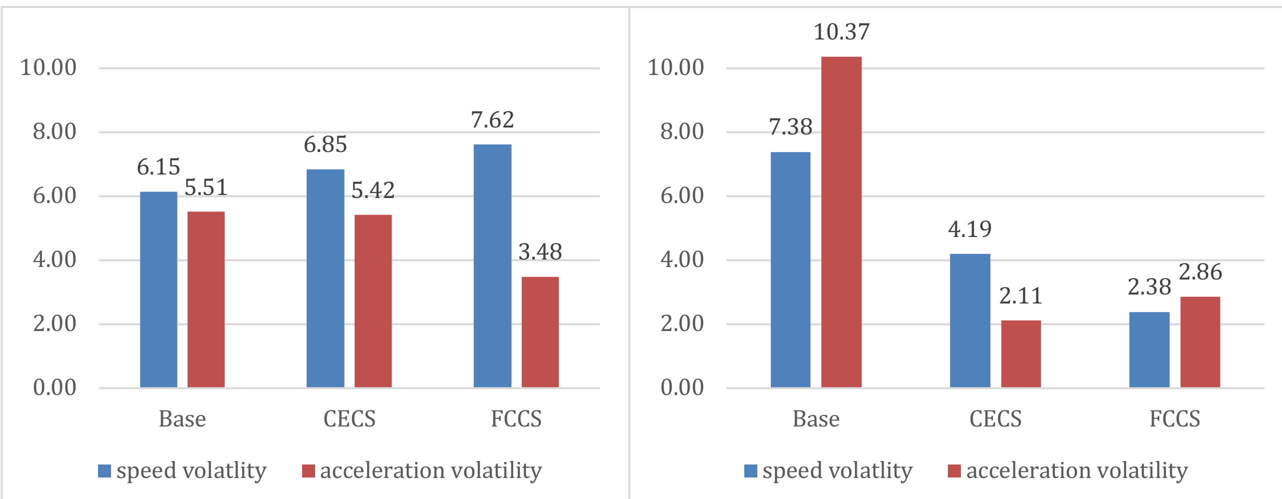
Number of conflicts

To quantify number of conflicts in the simulation environment, TTC values lower than 0.5 seconds are considered as a serious conflict. To achieve more precise understanding regarding the safety performance of the merging area, the number of conflicts for the main road segment and ramp are measured separately. Focusing on the base scenario, the number of conflicts in the ramp area (about 10.1) is significantly higher than those on the main road (about 0.2). However, by introducing the coordination strategies, the number of conflicts in both main road and ramp sections decrease to zero, indicating the good performance of the two coordination systems in controlling the vehicles and eliminating the longitudinal conflicts.

In case the coordination systems are implemented throught a driving advisory system, it is important to consider the driver reaction time, therefore the threshold to consider TTC values as conflicts should be higher. This case needs further exploration.

Driving volatility

Driving volatility is one of the surrogate safety measures that can be incorporated to assess the safety performance of developed coordination compared to the baseline. Figure 3 illustrates the safety analysis on the defined scenarios for the main road and ramp segments. It can be observed that speed and acceleration volatilities are higher in the ramp compared to the main road. This is because some of the merging vehicles usually decelerate to lower speeds to find a safe gap on the main road to merge. Once a safe gap is detected, the vehicles accelerate in a short time to adjust their speed with the ongoing flow in the main road, leading to volatile driving behavior. However, the safety analysis revealed that under any of the two coordination strategies, the volatilities on the ramp drop significantly. Speed and acceleration volatilities in both coordination systems are lower than the baseline scenario.



(a) (b)

FIGURE 3 Speed and acceleration volatilities for the baseline, CECS, and FCCS in the (a) main road, and (b) ramp for ten simulation runs

Focusing on the main road segment, the results revealed that acceleration volatility of the segment is reduced under both coordination systems (FCCS achieves the lowest acceleration volatility on the main road compared to the CECS), while the speed volatility increases for both coordination systems. This is because ongoing vehicles from the highway segment should adjust their speed to provide appropriate gaps for the vehicles in the ramp, leading to an increase in the speed volatility. Focusing only on the coordination systems, as expected, the FCCS has lower speed volatility on the ramp than the CECS as the minimum speeds reached under this coordination mode are higher. However, considering only the highway segment, the speed volatility is higher for the FCCS. On the contrary, CECS has lower acceleration volatility than the FCCS on the ramp segment, while FCCS achieves lower acceleration volatility on the highway segment.

CONCLUSION

In this paper we presented two coordination control systems and compared their performance, in terms of traffic flow, safety, and fuel consumption, with respect to a baseline uncoordinated scenario. We assumed that the vehicles driving in the traffic network are all connected and investigated how the differences in the speed and acceleration/deceleration trajectories for each coordination system affect the traffic network. According to the results, waves of stop and go operation are seen on the ramp road for the baseline, thereby reducing the outflow from the merging zone to 1765 veh/h. Meanwhile, the coordination control systems limit the inflow into the merging zone maintaining the outflow from the merging zone at about 1973 veh/h. From the perspective of traffic dynamics, both coordination control systems can reduce the TTS by about 50% and increase the TDT by about 9% over the baseline scenario. Furthermore, they can save TFC by about 25% (AFC is reduced by about 30%) as they resolve the stop-and-go waves. As expected, the fuel-optimal coordination control system provides increased fuel savings (2% in the overall traffic network and 6 % in the control zone), when compared to the energy-optimal coordination control system.

To evaluate the safety performance of the coordination systems, two surrogate safety performance measures are utilized: number of longitudinal conflicts and driving volatility. Safety analysis revealed that, compared to the baseline scenario, both coordination systems enhance the safety performance of the merging area by eliminating the number of longitudinal conflicts. In addition, driving volatility significantly dropped under both coordination systems for the ramp segment, indicating improved safety performance. Both coordinators eliminated the conflicts, while there was an increase in the main road speed volatility as the vehicles should adjust their speed to provide appropriate gaps for the vehicles merging in the traffic.

To implement any of the coordination systems, a roadside unit using DSRC can be used with information from the infrastructure to compute the optimal schedules and transmitting them to the vehicles inside its range. In such scenario, all the vehicles need to be connected and be able to follow optimal speed advisories.

Ongoing work is analyzing implications of increasing the traffic demand, and of having partial penetrations of connected vehicles in the traffic network.

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