Connected Eco-driving Technologies for Adaptive Traffic Signal Control

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Connected Eco-driving Technologies for Adaptive Traffic Signal Control

Final Report

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16. Abstract Signal phase and timing (SPaT) data enable eco-driving for vehicles both approaching and departing signalized intersections. The data are often presumed to be accurate as well as obtained from the conventional fixed-time signals that operate deterministically. In practice, however, it is common to have actuated or adaptive signals in which the signal timing is dynamic and thus less predictable. This leads to less-than-perfect SPaT containing uncertain signal timing information. A new eco-driving algorithm is formulated explicitly taking into consideration the uncertainty of SPaT data from adaptive signals. A rigorous methodology is further developed to generate meaningful SPaT in the context of a real-life adaptive control system. Two test sites, New York City and Arcadia of California, are selected for simulation studies. Results indicate that the new eco-driving strategy provides the benefits of fuel consumption savings and emission reductions even with less-than-perfect signal timing info from adaptive signals. A cyclic adaptive signal control system facilitates the predictability of future signal timing because of the cyclic nature and that the dynamic timing is known ahead of local zeros. Regardless of the accuracy of SPaT data, eco-driving may have negligible network benefits when traffic becomes oversaturated; vehicles cannot apply the needed speed adjustments with the constraints from surrounding vehicles in high density. It is revealed that the network benefits of eco-driving depend on the co-existence of both eco-driving and non-eco-driving vehicles. The latter provides the leeway for eco-driving vehicles to implement optimal speed adjustments. This means network benefits may diminish with the increase of market penetration of connected eco-driving vehicles.			
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Abstract

With the emergence of connected vehicles, it is possible to broadcast traffic signal timing data to approaching vehicles using SPaT (signal phase and timing) messages. This information makes it possible for vehicles to adjust their speed profiles, accelerations, and/or decelerations to minimize fuel consumption and carbon emissions. Unlike existing connected eco-driving studies that assume an environment using fixed-timing traffic signals, the objective of this project was to evaluate connected eco-driving at signalized intersections with adaptive traffic signals installed. To study the adaptive signals, which produce dynamic information and are less predictable than conventional fixed-timing signals, the team first developed a new connected eco-driving strategy and implemented it in TransModeler microscopic traffic simulator as a plugin. A new SPaT data generation and prediction algorithm was further formulated to rigorously measure the uncertainty of adaptive signal timing information and implemented as a SPaT data plugin of the TransModeler simulator. Two simulation test sites, the central business district (CBD) area in New York City and urban arterials around the City of Arcadia, were selected to represent different traffic flow conditions and network geometric features. Comprehensive traffic simulation studies were performed to evaluate the effectiveness of connected eco-driving in the context of adaptive traffic signals. Results indicate that the new connected eco-driving algorithm is able to provide the benefits of fuel consumption savings and carbon emission reductions; however, depending on the accuracy of the SPaT information with adaptive traffic signals, connected eco-driving may not always be able to provide significant benefits. The team further discovered that connected eco-driving may have negligible benefits as the traffic network becomes congested, typical of CBDs where individual vehicles cannot apply much of the needed speed profile adjustments with the constraints from surrounding vehicles. The benefits of connected eco-driving for urban arterials are more noticeable. Market penetration of connected vehicles and transportation network geometries were also found to be relevant to the effectiveness of eco-driving. Eco-driving in high-density traffic and multi-segment optimization in a CBD network may call for further research.

Keywords

Connected Vehicles, Connected Eco-Driving Application, GLOSA Algorithm, Adaptive Traffic Signal Control System, Signal Phase and Timing (SPaT)

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Acronyms and Abbreviations

AASHTO	American Association of State Highway and Transportation Officials
ACC	adaptive cruise control
AEB	automatic emergency braking
ATIS	Advanced Traveler Information System
ATR	automatic traffic recorder
C2X	car-to-car/car-to-infrastructure
CV	connected vehicle
CICAS	Cooperative Intersection Collision Avoidance System
CL	conflict likelihood
CMEM	comprehensive modal emission model
CTRA	confidence-based traversing
DSRC	dedicated short-range communications
FHWA	Federal Highway Administration
GLOSA	Green Light Optimal Speed Advisory
HMI	human machine interface
ITS	intelligent transportation system
IVS	in-vehicle signage
LOC	level of confidence
m/s	meters per second
m/s2	meter per second square
NHTSA	National Highway Traffic Safety Administration
OEM	original equipment manufacturer
PSA	personal signal assistant
RGA	robust GLOSA algorithm
SL	stopping likelihood
SPaT	signal phase and timing
TIMS	traffic incident management system
TJAW	traffic jam ahead warning
TLIO	traffic light info online
TMC	traffic movement count
TSCS	traffic signal control system
TSS	transport simulation systems
V2I	vehicle to infrastructure
V2V	vehicle to vehicle

Executive Summary

Eco-driving is a way of operating a vehicle that emphasizes fuel efficiency. Instantaneous traffic signal states and a prediction of when those states change in a future timeline are critical inputs to eco-driving logics at signalized intersections. With the emergence of connected vehicles, it is possible to broadcast traffic signal timing data to approaching vehicles using SPaT (signal phase and timing) messages. This information enables vehicles to adjust their speed profiles, accelerations and/or decelerations to minimize fuel consumption and carbon emissions.

Traffic signals, which operate in different ways—fixed-time, actuated, or adaptive, or any feasible combinations thereof—are the source of signal timing information for eco-drivers. Fixed-time signals update signal states based on a time of day schedule. Actuated signals, without being constrained by a time of day schedule, have more flexibility by responding to the actuations from traffic sensors to extend or terminate signal green in real-time. Adaptive signals, rather than responding to sensor actuations, pro-actively adjust signal timing based on the prevailing and predicted traffic flow conditions to minimize delay and number of stops for the benefits of mobility, safety, fuel savings, and carbon-emission reductions. It is inconsequential to obtain the current signal states and predict future signal state changes, and the dynamic nature of actuated and adaptive signals renders a similar prediction moot, compromising subsequent eco-driving decisions.

Unlike existing connected eco-driving studies (assuming fixed-timing traffic signals), the motivation of this research is to evaluate connected eco-driving with adaptive signals, through which the signal timing is more dynamic and harder to predict. This calls for the development of a new type of connected eco-driving algorithm that considers the "uncertainty" nature of adaptive signal timing, thus generating meaningful speed profiles accordingly. To that end, a new connected eco-driving algorithm is developed in this work. The algorithm explicitly considers the "uncertainty" of the received SPaT info that comes with adaptive traffic signals. It utilizes a data element called "Confidence" that has been defined in SAE J2735 SPaT message structure, yet the data element has not been fully explored in the existing literature nor in the existing connected eco-driving applications. This lack of utilization is because previous studies mainly utilized SPaT from conventional fixed-timing signals instead of adaptive ones. Since an adaptive signal controller introduces an extra level of uncertainty in SPaT predictions, this research contributes to the state of art by explicitly considering SPaT uncertainty from adaptive signals and by studying the impact of adaptive signal control system on the performance of eco-driving application.

A market analysis is performed to outline feasible commercialization approaches to implement the proposed new connected eco-driving algorithm. Human machine interface (HMI) and associated legal implications are documented for the relevant use cases where real-time signal timing information is provided to driver-assistance applications.

Two simulation test sites, a CBD area in New York City and urban arterials around the City of Arcadia, are selected representing different traffic flow conditions and network geometric features. Comprehensive traffic simulation studies are performed to evaluate the effectiveness of connected eco-driving in the context of adaptive traffic signals. Results indicate that the new connected eco-driving algorithm is able to provide the benefits of fuel consumption savings and carbon emission reductions; however, depending the accuracy of the SPaT information concerning adaptive traffic signals, connected eco-driving may not always be able to provide significant benefits. The team further discovered that connected eco-driving may have negligible benefits as the traffic network becomes congested, typical of CBDs where individual vehicles cannot apply much of the needed speed profile adjustments with the constraints from surrounding vehicles. The benefits of connected eco-driving for urban arterials (like those in Arcadia) are more noticeable. Market penetration of connected vehicles, and transportation network geometries, are also found to be relevant to the effectiveness of eco-driving. Eco-driving in high-density traffic and multi-segment optimization in a CBD network may call for further research.

1 Introduction

The rapid growth of passenger cars and freight volumes has resulted in higher traffic congestion that causes various traffic system operations, management, and environment-related issues such as capacity drop at bottlenecks, traffic gridlock, excessive emissions and fuel consumptions, etc. Global carbon emissions from fossil fuels have significantly increased (approximately 50% between 2000 to 2014) in past years (Boden, Marland, and Andres 2017). However, in the last 25 years, carbon emissions from fossil fuels in the United States have raised steadily, nearly 5% with a current declining rate (Desai and Harvey 2017). Despite the advancement in technology, greenhouse gas (GHG) emissions produced by transportation have not shown a declining trend yet, mainly due to significant increase in the number of vehicle miles traveled (VMT). As a result, GHG emissions from transportation accounted for about 27 percent of total U.S. greenhouse gas emissions in 2015, making it the second largest contributor of U.S. greenhouse gas emissions after the Electricity sector. More VMT leads to more traffic congestions and eventually more GHG emissions. In 2014, congestion wasted approximately 6.9 billion hours of extra time, 3.1 billion hours of wasted fuel, costing $160 billion in total or $960 per commuter (Schrank. et al. 2015). The cost would be much higher if we add the monetary value of the associated environmental degradations.

Extensive research efforts have been observed in recent years to make the transportation sector more advanced and sustainable in terms of fuel consumption and greenhouse emissions. These efforts include inventing and implementing new technologies (such as connected/automated vehicles), finding optimal operational strategies (such as optimal routing in terms of travel time and fuel economy, cooperative adaptive cruise control to improve traffic flow) and, developing eco-driving tool to reduce energy consumptions by achieving smooth speed profiles, and reducing unnecessary accelerations, decelerations, and idling situations.

An eco-driving tool utilizes signal phase and timing (SPaT) information to estimate optimal or near optimal speed profile for a vehicle and assists the driver by providing speed instructions ahead of time. With the emerge of vehicle-to-infrastructure (V2I) communication system, accessing SPaT information has become a lot easier than before. However, the challenge remains in the *accurate* prediction of signal states and thus the preparation of SPaT information for broadcast. In an urban network, pretimed signal controllers are not sufficient to better serve the traffic flow due to higher volatility in flow patterns. As a result, deployment of actuated or adaptive signal controllers are now very common where situation demands. These types of advanced controllers make the prediction difficult.

SPaT messages are broadcasted by Road Side Units (RSU) and received by aftermarket devices such as On-Board Units (OBU) installed on a connected vehicle and thus, utilized by the eco-driving application installed in the OBU. The messages can also be received by mobile applications, providing driving advisories. These applications are summarized in the next section, titled Market Analysis and Product Specification. Since the eco-driving tool's main input is the received SPaT information which requires some level of prediction depending on the controller types, the tool's efficiency relies on the accuracy of predicted SPaT. In general, SPaT itself is not a part of the typical eco-driving strategies development; existing studies directly utilize SPaT information, mostly based on fixed-timing signal plans with all timing parameters deterministic and known in advance.

Eco-driving is a well-studied topic with several initiatives to develop applications that aim to reduce fuel consumption and carbon emission through minimizing the abrupt change in vehicle's speed. Market analysis shows two feasible approaches in implementing the eco-driving strategy—a mobile application on a smartphone or an embedded application on the connected vehicles' on-board system. Previous research and pilot projects revealed a promising gain in CO_2 reduction by applying eco-driving strategy. Existing studies also showed a negligible gain with higher traffic density.

A smartphone application requires no extra hardware device except the phone itself. However, it does require a precise and accurate prediction algorithm to ensure its market/user acceptance and sustainability. Existing smartphone-based applications (e.g., SignalGuru and Enlightens) have suffered accuracy issue at some level which may have in return influenced the users' decision to accept and use the applications. It is thus important to fully appreciate the importance of accurate and reliable SPaT messages from both the viewpoints of users' mindset and eco-driving success.

Personal signal assistant (PSA), a data-service product of TTS, an Oregon based technological firm, provides an ideal example of a comprehensive onboard eco-driving application. PSA is a cloud-based data service available to auto-manufactures that can be integrated into on-board infotainment systems to provide driving advice and active engine management. The instantaneous and predicted signal timing, as retrieved from PSA server via proprietary 4G communication channel enables the vehicle to intelligently stop and start the engine if the remaining red signal time is more than a specific threshold. Although a smartphone application is not able to possess such direct engine access or flexibility, implementation of sufficient functionalities to achieve eco-driving would be reasonably possible with a smart phone application. However, the selection of onboard or smart-phone application is a secondary issue. Instead, the performance of eco-drive algorithm is a primary factor to decide its usefulness. Hence, this study not only focuses on recent research and application development initiatives to understand the market and specify the requirements to develop an eco-driving assistant for drivers, but also proposes an advanced algorithm that can utilize SPaT according to J2735 dedicated short-range communications (DSRC) Message Set Dictionary and provide better performance in terms of minimizing speed fluctuations, while considering the uncertainty elements brought by adaptive signals.

It should be noted again that existing literature on eco-driving did not sufficiently study the quantitative impact of traffic flow conditions on the effectiveness of eco-drive algorithms. Moreover, few efforts have been observed in studying the network-level impact of eco-driving algorithms. In addition, these studies haven't distinguished among the corresponding controller types—the conventional (e.g., fixed time, actuated coordinated, etc.) or adaptive traffic signal controller. Therefore, it is imperative to evaluate the feasibility of a new connected vehicle technology to enable eco-driving at intersections where the adaptive signal control system is in effect. This study utilizes a standard SPaT message, particularly the confidence of SPaT to deal with the uncertainty of SPaT prediction in both a conventional and an adaptive traffic signal control system. This research rigorously examined the impact of eco-driving algorithms from network level. It also inspected the effects of different traffic controller types on the performance of the algorithm. In the quest for these impacts it helped determining the underlying factors that may require further study in a continued research.

2 Market Analysis and Product Specification

With the emergence of connected vehicle technologies, it is possible to broadcast signal timing data to approaching vehicles, using SPaT (signal phase and timing) messages. SPaT messages contain information about the current phase of the traffic signal—red, green, or yellow and the start and end times of each. With the means of acquiring this information, vehicles can adjust their speed profile, acceleration and/or deceleration dynamics, intelligently in order to minimize fuel consumption and pollutant emissions, while avoiding abrupt changes to vehicle trajectories. This falls into the eco-driving category of connected vehicle applications and is believed to have great potential for significantly reducing fuel consumption and emissions. A thorough analysis of the potential market has been conducted and feature planning has been determined according to perceived market needs. Based on the needs analysis, a high-level specification of the proposed eco-driving device has been developed, including the overall functionalities needed, hardware and software required, and the cost control measures to ensure that the final product cost is reasonable (i.e., optimal market price)—without compromising the required functionalities. Current state of arts and practices of eco-driving can be analyzed from three different perspective: academic research, projects, and products.

2.1 Academic Research Analysis

For the past several decades, researchers are working relentlessly to achieve success in eco-driving through various strategies, process, and applications. One of their remarkable initiatives is the successful application of Green Light Optimized Speed Advisory (GLOSA). The basic concept behind GLOSA is to minimize the stop/go flow of traffic due to red lights at an intersection through advising drivers of the optimum speed. The GLOSA system has been thoroughly studied (De Nunzio et al. 2016; Seredynski, Mazurczyk, and Khadraoui 2013) from single segment to multi-segment and from simulation to real scenario (Katsaros, Kernchen, Dianati, and Rieck 2011). Researchers also studied the system as an optimization problem (De Nunzio et al. 2016) and solved the problem by minimizing energy consumption and by timing the travel through sequences of signalized intersections so that the green light consistently appeared, preventing the stop/go movement. Authors assume that the traffic lights timings are known and available to the vehicles via infrastructure-to-vehicle (I2V) communication. Among the significant research on the GLOSA algorithm, its application and evaluation, two selected studies are discussed here.

Konstantinos Katsaros et al. (Katsaros, Kernchen, Dianati, and Rieck 2011) have conducted a performance study of a GLOSA application using an integrated cooperative ITS simulation platform. In this simulation of urban mobility (SUMO), they integrated the microscopic Stefan Krauss (SK) model, a car-following model with two basic rules. The first rule is that a vehicle in free motion has a target speed and the vehicle should try to cruise at that speed. Under second rule, when a vehicle senses the distance to the vehicle ahead to be less than a certain threshold, it should slow down to keep a safe distance. The speed of the both vehicles is within a certain range [V-min, V-max] where V-min is the minimum speed that vehicles can cruise without causing further traffic congestion and V-max is the maximum speed that is forced by the speed limit of the area. The study shows significant improvement in reduced fuel consumption. Notable observations from this study include the following:

- In a mixed environment, higher GLOSA penetration rate (equipped vehicle) leads to higher benefits in reduction of both stop time and fuel consumption.
- The effects become more visible after GLOSA equipped vehicles reach 50% threshold.
- Increase of traffic density hinder the effect of GLOSA system.
- There is also an optimal activation distance where the GLOSA application should advise the driver.

Potentials and Limitations of GLOSA Systems has been studied by Eckhoff, Halmos, and German (2013). They evaluated GLOSA for different traffic patterns (free flow to dense) and found that the GLOSA doesn’t perform well in a dense traffic condition. Intuitively, a driver is unable to choose an optimal speed at dense traffic condition unless all the vehicles are equipped with GLOSA system and strictly follow the advice. However, the study lacks the density threshold for efficient use of the GLOSA system.

2.2 Project Analysis

In two recent projects in Europe, impacts of the GLOSA system have been evaluated and the results were found to be favorable. The following sections briefly discuss these projects.

2.2.1 Project Co-drive, France

Under the Co-Drive project (Lebre et al. 2015), a cooperative traffic light system was developed to make the link between the vehicle and infrastructure. The traffic system enables a safe intersection crossing with reduced CO_2 emission thanks to a GLOSA system. The project claimed that the GLOSA system improves traffic efficiency in the following ways:

- Reduced stop times for traffic fluidity.
- Provided more information about handling intersection for road safety.
- Avoided unnecessary acceleration to reduce CO_2 emission.

This kind of system can also be used to reach a green wave, where several traffic lights are coordinated by the infrastructure to ensure continuous flow of vehicles. In this project, the GLOSA system was implemented and tested on a testbed consisting of two traffic lights 1500 meters (m) apart. Results showed 13 to 14% CO_2 reduction with a maximum speed limit of 50 to 70 kilometers (km) per hour.

2.2.2 Project Drive C2X, EU

The field trials involving seven test sites all across Europe proved the safety and efficiency benefits of cooperative systems (Drive-C2X 2014). In-vehicle signage (IVS) on speed limit and GLOSA showed significant effects for both environment and traffic efficiency. Drivers reacted to the information by reducing their speed in most cases. The impact of IVS on speed limits grows with the penetration rate and has a large impact on fuel consumption and CO_2 which is reduced by 2.3% in the high-passenger car category. The use of GLOSA resulted in a small reduction in fuel consumptions and CO_2 emissions at the EU-level. It reduced driver speeds using IVS on speed limits and increased the delay in off-peak scenarios. Although drivers with traffic jam ahead warning (TJAW) reduced their speed earlier and with less sudden braking, no statistically significant traffic efficiency or environmental impact effects were found. However, the study requires stronger rationale to support the findings that deviate from mainstream research.

2.3 Product Analysis

GLOSA, an effective tool to achieve eco-driving success can be applied either in a vehicle's onboard unit or in a smartphone application. Both approaches have been applied in industry and academia. Other than the academic research application for eco-driving named Eco-GLOSA, SignalGuru is an academic approach to prepare the GLOSA tool for mass use. Another recent approach is the development of EnLighten, a free mobile-phone application to assist drivers in eco-driving. This application has had more user attention than other related applications and received positive and negative reviews from users. The forth tool, Personal signal assistant, is the most updated onboard version of GLOSA implementation. Detail descriptions of the tools are cited in the following sections.

2.3.1 Eco-GLOSA

Eco-GLOSA, a research purpose Android smartphone application, was developed by Yahui Ke of University of Alberta (Ke et al. 2016). Using Eco-GLOSA, a vehicle connected to the roadside unit (RSU) collects SPaT data while approaching an intersection. The SPaT data along with vehicle speed, distance to the intersection, and acceleration is processed in Eco-GLOSA and the results are displayed through a speedometer in the application. When the speed indicator points to the green color range, the vehicle's current speed is good to pass through the upcoming intersection. In contrast, the red color indicates that the current speed would not be appropriate for the intersection. The data in Eco-GLOSA is updated and recalculated at each second. Other than the speed status indication, the application uses voice notification to suggest the fuel saver speed. However, the study didn't consider adaptive signal-controlled intersections which require the prediction of signal timing, even after receiving real-time data from RSU. Due to focusing on pre-timed, signal-controlled intersections only, the study has failed to completely cover the real-world complexity of GLOSA implementation.

2.3.2 SignalGuru

Researchers from MIT and Princeton University have developed a system that uses dashboard-mounted smartphones to help drivers avoid red lights and reduce fuel consumption. The smartphone application called SignalGuru (Koukoumidis, Peh, and Martonosi 2011) predicts when a traffic signal is about to change and the speed at which the vehicle should be driven when approaching an intersection in order to cruise through without stopping. The application relies solely on a collection of mobile phones to detect and predict the traffic signal schedule. Based on the prediction of SignalGuru, the researchers applied a GLOSA algorithm to assist drivers, and concurrently, save time and energy. Authors also mentioned some other possible applications such as Traffic Signal-Adaptive Navigation (TSAN), Red Light

Duration Advisory (RLDA), Imminent Red Light Advisory (IRLA), and Red Light Violation Advisory (RLVA). On average, their application predicted within 0.66 sec. for a pre-timed traffic signal and 2.45 sec. for an adaptive signal. The study brought a promising result of 20.3% fuel savings despite of some erroneous detection of signal light by cameras on mobile phones. Instead of connecting to the traffic movement count (TMC) Controller, SignalGuru used past captured data of a signal light and its adjacent lights to predict signal timing.

2.3.3 Green Drivers: EnLighten

EnLighten (Connected-Signals 2016) is an application developed by an Oregon based company, Connected Signals, Inc. This free smartphone application is presently available as Enlighten for Android and IOS devices. Its basic functionality is to tell drivers how long they might be waiting at traffic lights by predicting when a red light will turn green. It provides, at no cost to users, access to the traffic light status and predictions needed to drive safely and smartly around town. Moreover, it can be used in municipalities currently integrating their Traffic Management System data with Connected Signals. The application gathers the SPaT information straight from TMCs.

EnLighten uses GPS technology to gather location data and analyze traffic information as well as calculates a car's velocity using a smartphone's accelerometer. The application is engineered to be non-distracting. Visual information is only shown when you are stopped at a red light. When you are driving, its distinctive tones tell you when you will make (or when you have missed) the next light. Indications are that this information reduces drivers' natural tendency to speed up when they see a green light ahead, even when the tone indicates the light will be missed. The application claims to dramatically improve the following:

- Driver safety and stress—it acts as a traffic calming technique.
- Fuel efficiency and carbon emissions—by avoiding hard acceleration and deceleration behavior.
- Urban traffic flow—by traffic flow balancing.
- Time to destination estimates—taking delay at signalized intersections into consideration.
- Autonomous vehicle safety.

In many cities, traffic light timing changes depending on real-time traffic, so the application generates a prediction based on a combination of factors. As from the comments on the app-store the application does not accurately predict signal timing especially when the signals are actuated. By bringing the real-time signal data along with map, GPS, speed limit information to the driver via cellular networks, it boasts of an approach which avoids the need to install costly municipal infrastructures such as DSRC for V2I and I2V communication. Cell phone GPS systems are typically noisy and relatively inaccurate, making it difficult to determine exactly where a user is and how fast they are going. This can be an issue when trying to determine which light a user is approaching.

The application is presently integrated into BMW's in-car infotainment system. For such vehicle-based applications, even more accuracy can be achieved by obtaining information from vehicle systems (GPS, speedometer, turn signals, brake pedal status, etc.), resulting in a broader range of supported functionality. To provide accurate traffic light information, the application needs to know the following:

- Where the lights are and how the streets are laid out.
- Which phase corresponds to each traffic movement phase map.
- Which timing plan (e.g., rush-hour, off-peak, game-day) is in effect.
- Other information, such as the location of stop signs, can also be useful.

In some cases, variations in timing plans, emergency vehicle preemptions, or other factors limit prediction accuracy. The predictive information is made available to applications and each application can then determine whether the prediction is strong enough for its intended purpose. The company offers a free hardware solution, an adapter named Vehicle to Infrastructure for Free (V2If) to broadcast the SPaT information to third party applications with complete control over the information by the agency. It acts as a switch sending information only in one direction, that is, outwards, avoiding installation of unwanted software and security risk. Connected Signals offers the following services free of charge:

- The V2If appliance itself.
- Maintenance and support as needed.
- No-cost rebroadcasting of your signal data to any third parties you wish.

The application was developed in partnership with BMW and originally featured in various journals and gained popularity by online tech blogs. It has the market potential in penetrating the "cars without infotainment" sector where the only means of accessing traffic signal systems is a smartphone. As such, it was downloaded nearly 5000 times within a year or so after it was first launched. However, users have expressed mixed reactions. Some user comments are provided:

- Application works but not really accurate with errors ranging from 1-5 seconds.
- The Apppplication drains the battery of the smart phone and is very buggy and low location accuracy.
- It blocks the use of other navigation applications.
- The application definitely covers Portland and Las Vegas, it does not let us know which cities are under the coverage, but it seems that the application works in nine cities right now.

As done with BMW, the application can be integrated with the onboard infotainment in cars, but this means an accurate fine tuning and testing of the software before the original equipment manufacturer (OEM) adopts it as a standard feature. It does not compete with DSRC, which offers two-way communication between infrastructure and vehicles. But it provides a good alternative to the vehicles that do not have smart infotainment systems on board helping the vehicles to connect to infrastructures without expensive hardware installation or any other related expenses. The ultimate solution would be to have DSRC mechanism but in the meantime, the market penetration of communication could be extended and refined through smartphone applications like Enlighten. The application seems to predict the SPaT based on the fixed-signal timings in its database and fails at actuated signals or when there is a change in the SPaT (e.g., during emergency vehicle preemption). The potential of the Enlighten can be enhanced by integrating with another navigation application and by collecting actual real-time SPaT signals. The only cost involved is software development which could run on smartphones and the related maintenance.

2.3.4 Personal Signal Assistant

The personal signal assistant (PSA) was developed by TTS and is a cloud-based data message (TSS 2015) service available to auto-manufactures for direct integration with the on-board systems, or for independent after-market devices. There are two components: a message containing information about the traffic signal state, or the Signal Phasing and Timing (SPaT), and a message with information about the geometry or topology of the intersections—also referred to as a MAP message. The SPaT message includes both the current signal state and a prediction of how long it will remain in that signal state (e.g., green, yellow, red). The application is based on acquiring the SPaT data from the TMC controller. But it also considers crowdsourcing to improve the accuracy of the prediction. TTS mainly uses traffic signal data, both in real-time and aggregated over time, to provide a prediction of the signal state.

The PSA uses the advanced technology available in the cars to access the traffic signal information to improve performance, fuel efficiency, and prepare for the future of connected vehicles. Presently engineers are working on devices that can communicate the traffic signal state to the vehicles. But TSS predicts that this technology will require huge investment and take substantial time to deploy and to harvest significant benefits. The advancement in communication technology on smartphones and on cars can be utilized to provide such benefits right now.

Fire trucks, ambulances, police vehicles, heavy rail, light rail, transit vehicles, and even passenger vehicles or pedestrians can cause the traffic signal controller to deviate from the normal plan. This is why real-time communication to the traffic signal controller is necessary. Parades, festivals, and sporting events are also a key component to predicting the traffic signal controller. By working with government agencies and owners of traffic signal systems, the model is able to tap the SPaT in real time as the TMC is in communication with the intersection.

Data packets already communicating to the traffic signal controllers are picked up and delivered second-by-second, twenty-four hours a day on every day of the week. Using a combination of data fusion and simulation as well as knowledge about traffic signal controller operations, the devices are trying to predict how long the traffic signal controller will remain in red or green states. Information about the performance of the traffic signal controller, as well as the traffic demand, both long term and short term, is stored and analyzed. The message package is delivered in the SAE J2735 format, the same as DSRC communication protocol. This data is finally provided to the user by regular cellular signal, whether by vehicle systems, aftermarket device, or by a smartphone with internet connection.

Potential applications of this product can be summarized as follows:

- Infotainment systems: The easiest way of returning the service to the driver. The information of red time left actually helps in reducing the startup loss time at the intersection, avoiding the time lost by an inattentive driver towards the signal lights.
- Engine management: The application is integrated into the engine start/stop system allowing the vehicle to stop running its engine if there is a long enough red time. The technology can be used by automated vehicles to break or accelerate on their own in a way to reduce fuel consumption.
- Routing: With the signal-timing plan in hand for every intersection, the time to destination can be more precisely estimated. This holds true for determining the route, which can be chosen to improve the travel time with less time waiting at intersections. This application is also useful in predicting bus and light rail transit travel time.
- Pedestrian and bicycle users: Pedestrians and bicycles can benefit from PSA by having a precise prediction of when a specific walk or bike signal will turn green. Most importantly, it provides pedestrians and bicyclists with a positive feedback in locations with phase actuations (e.g., push buttons, video, inductive loops, etc.) clearly letting them know that their presence has been detected by the control system.

TTS is working with vendors of the Advanced Traffic Management System (ATMS) such as Econolite, McCain, Siemens, Trafficware, TransCore. These ATMS are widely used by transportation administrative agencies (e.g., local department of transportation), and can communicate to the signals in the field directly, hence act as the raw data source to the PSA product. The specific communication workflow can be summarized as follows:

- Communication from signal controller hardware to ATMS (Closed Network)
- Communication from ATMS to TTS servers (IP)
- Computations for PSA product (Cloud-Based)
- Communication from TTS to Third-Party Servers/Applications (IP)

TTS claims that the liability exposure to the transportation administrative agency who manages field traffic signals by allowing access to signal timing data is no more than the current exposure experienced in the field by drivers or transportation end users. Audi has integrated the PSA data service into their traffic light info online (TLIO) service as part of their driver assistance systems and Car-2-X applications. TTS worked with the signal managing jurisdiction in Las Vegas, F.A.S.T., and Audi to demonstrate the PSA technology at the Consumer Electronics Show 2014, which won awards for new automotive technology by The Verge.

Current applications by the OEM are to provide assistance to the driver without adding any distractions. This is accomplished by providing the information in formats developed by human factors professionals by the OEM. The direct integration of the information into the Multimedia Interface (MMI) is overseen by the National Highway Traffic Safety Association (NHTSA) and the OEM. An example application by Audi is to hide the time-to-red-countdown timer during the last few seconds to force the driver to look at the signal state and not rely specifically on the displayed counter. Speed limit or speed suggestions are provided based on the navigation services information, or other OEM technologies, that does not contribute or provide motivation for speeding.

According to TTS the PSA system has no direct financial cost for the government agency. In exchange for the raw signal timing data provided by the government agency, TTS can offer free-of-charge system performance metrics that can be utilized to set benchmarks for traffic system operations. Examples of some performance metrics include: number of stops, arrivals on red/green, movement delay, pedestrian delay, etc. Further, basic communication metrics from the signals, such as downtime, mode of operations (flash), detector fails, will be summarized in intersection reports.

To conclude, previous research and projects suggest that the GLOSA system is an effective way to ensure eco-driving as well as reduce drivers' workload to some extent. Although onboard implementation of this system may require some investment and/or public-private collaboration, mobile phone-based applications would be the simple, but smart and effective solution in the pursuit of eco-driving. The most important user criticism regarding the EnLighten application was the prediction error (i.e., the time lag of 1 to 5 seconds). Hence, the successful implementation would require a robust prediction algorithm to ensure accurate prediction of signal timing, specifically, in case of an adaptive signal controller. Since confidence is the most precious element to gain user acceptance for such an application, it warrants a robust algorithm to ensure accuracy and precision of the advisory system. From a marketing viewpoint, user satisfaction should be one of the most critical concerns to achieve the eco-driving goal through such an application. Although connected technology has made substantial improvements for users, eco-driving success will partially depend on the compliance with the advisory, which is also subject to the traffic conditions and roadway characteristics.

3 Big Data Analytics Methodology

Big data analytics is the process of examining large data sets containing a variety of data types to uncover hidden patterns, unknown correlations, market trends, customer preferences and other useful business information. In the context of real-life, connected eco-driving applications, this study develops a big data analytics methodology in order to acquire and synthetize real-time adaptive signal control information. The methodology is established to determine traffic signal status at the next downstream intersection, as well as to predict the status of the subsequent intersections along the vehicle's route.

A new database architecture was developed that covers traffic conditions, network-wide signal operational status, real-time adaptive signal timing information, registered Transit Priority Preemption Requests, vehicle dynamics and engine economy data. The sources of the data include ITS roadway sensors, electronic toll collection tag readers, connected vehicle equipment and central adaptive signal control systems at the Traffic Management Center.

The database architecture implements a hybrid model: a long-term data manage system that archives permanent data and a short-term, in-memory cache. The in-memory database has the same definition of table structures as the on-disk database. It can be viewed as a mirrored memory image of on-disk tables, except the data are only several hours old, that is, any data with timestamps older than a certain time will be removed from memory. The in-memory database acts as the high-speed cache of the data that are most likely to be used in adaptive signal optimization and shared with the SPaT prediction engine. Because the data reside in memory, the latency in data input/output is much smaller than fetching the data from disk. Middle-tier servers are required to facilitate the core computation efficiency of the SPaT prediction engine.

Due to issues of confidentiality, details regarding the implementation of the big data analytics are omitted in this report.

4 Optimal Driving Strategies

Driving strategies refer to the mechanism of a user's driving behaviors and styles. Driving behavior is an instantaneous driving action of a driver such as acceleration or deceleration whereas driving style is the accumulation of these behaviors over a period of time such as the preferred time headway of a driver. In other words, driving style can be defined as the level of driving aggressiveness which includes the effects of the vehicle, driver, and driving environment (Berry 2010). Driving styles can be shaped by controlling one's driving behavior, that is, instantaneous acts behind the wheel. Mechanisms that influence a driver's driving strategies lie in controlling instantaneous behaviors which collectively represent the driving style.

Thus, "Optimal driving strategies" refers to the control mechanism that shapes a driver's behaviors as well as styles for an entire trip. The objective of a control mechanism depends on the project's focus. In this study, the goal was to optimize fuel consumption while driving. Thus, the term refers to "eco-friendly driving strategies." The following section summarizes previous works on this concept including industrial initiatives relating to building an eco-driving tool to apply these strategies. The discussion is followed by proposed strategies for optimal driving based on existing strategies.

4.1 Literature Review

The Green Light Optimal Speed Advisory (GLOSA) system assists drivers in attaining fuel efficiently when passing through an intersection. This classic concept of speed advisory focuses on each intersection individually and estimates optimum speed to pass through the intersection. Previously, a simple form of GLOSA, based on the theory of motion was studied (Katsaros, Kernchen, Dianati, Rieck, et al. 2011; Stevanovic, Stevanovic, and Kergaye 2013) and GLOSA's performance tested, mostly in a simulation environment (Eckhoff et al. 2013; Katsaros, Kernchen, Dianati, and Rieck 2011; Stevanovic et al. 2013). Stevanovic et al. used VISSIM—a microscopic multimodal traffic flow simulation software package—and validated the simulated data using travel time in the collected field data. The authors used the comprehensive modal emission Model (CMEM) to evaluate emissions. They estimated the speed using the following simple formula: travel time = distance/velocity (t = d/v) and considered queue status in their GLOSA decisions. Using SUMO, Katsaros (et al. 2011) integrated the microscopic Stefan Krauss (SK) model with a car-following model that had two basic rules: (1) a vehicle should try to cruise at its free-motion target speed and (2) when a vehicle senses the distance to the vehicle ahead to be less than a certain threshold, it should slow down to keep a safe distance. Katsaros et al. (2011) studied the performance of GLOSA algorithm. Eckhoff et al. (2013) studied the Institute of Electrical and

Electronics Engineers (IEEE) publication Potentials and Limitations of GLOSA Systems, evaluating the advisory system for different traffic patterns (free flow to dense) and found that the system doesn't perform well in a dense traffic conditions. Typically, drivers' have a difficult time choosing an optimal speed during dense traffic conditions unless all vehicles are equipped with GLOSA systems and strictly follow the advice. However, the study didn't consider a density threshold for the efficient use of a GLOSA system. There is a scope to enhance the existing GLOSA algorithms by taking into account different traffic conditions.

Besides the simulation-based research initiatives, real-world application development initiatives of GLOSA have been observed in Connected-Signals (2016), Drive-C2X (2014), Ke et al. (2016), Koukoumidis et al. (2011), Lebre et al. (2015), Raubitschek et al. (2011), and TSS (2015). In Lebre (et al. 2015), the GLOSA system was implemented and tested on a testbed consist of two traffic lights 1500 meters apart. Results showed a 13 to 14% CO_2 reduction with a maximum speed limit of 50 to 70 kilometers per hour. In Koukoumidis et al. (2011), authors use smartphone cameras and utilize vehicle-to-vehicle (V2V) communication through smartphone applications to predict signal timing, that is, generate SPaT information, and thus, apply GLOSA. Green Drivers: EnLighten (Connected-Signals 2016) is an application developed by an Oregon based company, Connected Signals, Inc. in partnership with BMW. Users have a mixed attitude towards Enlighten due to its accuracy level and corresponding cellphone battery charge consumption. The personal signal assistant, developed by TTS, acquires the SPaT data from the TMC controller and considers crowdsourcing to improve the prediction accuracy of signal timing (TSS 2015). Audi has implemented PSA into their Traffic Light Information Online (TLIO) service as part of their driver assistance systems and Car-2-X applications. Unfortunately, the algorithms used in most of these applications are not publicly known.

Eco-driving, a vehicle's route-based fuel optimization, refers to the network-level approach of GLOSA. This approach uses the vehicular dynamics-based, optimal-control theory to find the optimal speed. As an example, see Kamalanathsharma and Rakha (2013, 2016), Mahler and Vahidi (2014), De Nunzio et al. (2016), and Ozatay et al. (2014). This differs from GLOSA, which is based on a classical formula of motion. In Kamalanathsharma and Rakha (2013, 2016), Mahler and Vahidi (2014), and Ozatay et al. (2014), the authors use the Dynamic Programming (DP) approach to solve the optimal control problem. Unfortunately, these methods are costly in terms of central processing units (CPU) and memory use, and furthermore, often cannot be executed in real time (Wan, Vahidi, and Luckow 2016). In similar control theoretic approach, (Asadi and Vahidi 2011; Kamal et al. 2010, 2013; Samad Kamal et al. 2014) use Model Predictive Control (MPC) and (He, Liu, and Liu 2015) follow an approximation approach considering traffic light status and queue to find the optimal trajectories. Ozatay et al. (2012) formulate a linearized model of a vehicle's longitudinal dynamics and solve the problem analytically with given boundary conditions. Inspired by Ozatay, Wan et al. introduce a nonlinear model and solve the problem relying on Pontryagin's Minimum Principle (PMP) and kinematic constraints. They argue that their conclusion is similar to the conclusions found in Li et al. (2012) and Li and Peng (2012).

The differences between these two approaches are obvious. With the vehicle dynamics model, research that is oriented toward optimal control theory considers a different fuel consumption model. As an example see Kamalanathsharma and Rakha (2016) and Wan et al. (2016) which are based on the researchers' preference. These optimizations are directly connected to the corresponding fuel consumption model. In contrast, the classical approach optimizes the fuel consumption based on the underlying principles of the fuel consumption model. Due to the stochasticity in traffic patterns, the difference in their results are expected to be minimal. Another difference between the optimal control theoretic approach and classic approach is the optimization horizon. In general, the former one optimizes the fuel consumption as well as speed for the entire route whereas the later one focuses on each intersection individually. However, the end results are expected to be comparable considering the drivers natural tendency to drive the vehicle near speed limit. Considering the expected insignificant differences in the results, computational simplicity, reasonable runtime, and direct applicability, we adopt GLOSA and propose a classical theory of motion-based robust GLOSA algorithm (RGA) by combining and enhancing the available GLOSA algorithms. In this study, the RGA has been enhanced significantly by introducing safe deceleration rate and confidence-based cruising. The safe deceleration rate is estimated based on its distance from its follower connected vehicle. In confidence-based cruising, the confidence of SPaT information has been utilized to improve the RGA, which, to the best of our knowledge, has not previously been studied.

To estimate emissions, comprehensive modal emission Model (CMEM) and Motor Vehicle Emission Simulator (MOVES) are two different comprehensive tools developed by the researchers of the Center for Environmental Research & Technology, University of California, Riverside and the U.S. Environmental Protection Agency (EPA), respectively. Previously, the MOVES tool has been used in different studies (Papson, Hartley, and Kuo 2012), including green routing or eco-driving (Chen, Zhang, and Lv 2014; Guo, Huang, and Sadek 2013). Similarly, CMEM has also been utilized in many studies such as An et al. (1997), Barth et al. (1996), and Li et al. (2009). Since proposing a new emission model was beyond the scope of this study, an existing emission estimator, CMEM, was adopted because of its integration in the traffic simulator, the TransModeler.

4.2 Green Light Optimal Speed Advisory System

The prime objective of this advisory system is to assist a driver in optimizing fuel economy by providing speed recommendation near intersections. The speed (acceleration/deceleration) can't be completely controlled as the conditions of the driving environment are only partially automated which allows for the driver's choice and /or habits of driving. Therefore, suggesting the speed to the driver is advantageous since it is a parameter that is easily followed. If a vehicle complies with the advocated speed, and assumed acceleration/deceleration, the recommended speed won't change over time for a specific intersection. Since the process is recursive, it will be adjusted in next time-step (such as 0.1 simulation second). Thus, a vehicle will be able to maintain a relative steady speed over the entire area of interest/DSRC range near the intersection. However, advocating the speed in a simulation environment cannot be performed by advocating acceleration/deceleration since it is not a human driver. Instead, the acceleration/deceleration is automatically controlled as the position and speed of the leader and follower vehicles are tracked and measured.

The algorithm utilizes a vehicle's position, speed information along with the position and signal timing information of its downstream nearest intersection to find the best recommendation for the driver. It takes the prevailing traffic condition into consideration (e.g., queue situation) and incorporates a confidence level of signal phase and timing (SPaT) information into its decision-making process. Thus, it forms a logical decision tree and prepares a complex but robust eco-driving assistant. From a simplified perspective, the algorithm's main task is to find the best decision among the following scenarios to ensure relatively smoother speed profile: (a) do nothing to pass, (b) accelerate to pass, (c) decelerate to pass, and (d) decelerate to stop. When a vehicle comes closer to an intersection, the algorithm checks if the vehicle's current speed is good to pass (decision a) through. When a vehicle needs to accelerate to pass the signal (decision b) avoiding the stop/go situation, the algorithm recommends up to the maximum allowable speed unless the vehicle is tailgating its leader. In such a case, the vehicle should follow the leader vehicle instead of accelerating. Conversely, when a vehicle needs to decelerate (decision c), the algorithm assumes that the vehicle will decelerate first (based on an explanation provided later) and then will continue its traversing and pass the intersection at decelerated speed. If a vehicle is being tailgated by another vehicle, the algorithm finds a safe deceleration rate for few seconds (perception reaction time). The safe deceleration rate provides the follower vehicle sufficient reaction time to avoid a rear-end crash.

Otherwise, the algorithm calculates the near optimal speed using the American Association of State Highway and Transportation Officials (AASHTO) recommended comfortable deceleration rate. Decision d requires a vehicle to stop at intersection. There is no scope to optimize fuel economy in such a case and hence, a smooth deceleration rate to come to a full stop at an intersection or queue is estimated and recommended.

The inputs of the eco-driving assistance system come from two different sources: (a) the vehicle's onboard unit, which provides vehicle related information such as its position and speed and (b) the roadside unit (RSU), which broadcasts SPaT messages through vehicle-to-infrastructure (V2I) communication channel. According to J2735 dedicated short-range communications (DSRC) Message Set Dictionary, broadcasted SPaT messages may include minimum, maximum, and most likely end time (*minEndTime, maxEndTime,* and *likelyTime*) of all phases of an intersection. Moreover, it may also include the information about the confidence of broadcasting likely time and the time to next green indicator (*confidence*, and *nextTime*) for each phase. Among these five fields of broadcasted SPaT messages, while *likelyTime* and *nextTime* are utilized through the entire algorithm, the other three fields— *minEndTime, maxEndTime*, and *confidence*—are used in a specific module that handles confidence-based cruising (details included in later sections).

4.3 GLOSA Algorithm

The GLOSA algorithm activates when a connected vehicle (CV) enters the DSRC range of an intersection in the area of interest (AOI) (Figure 1). The algorithm continuously checks the distance of a CV from its nearest downstream intersection to inspect whether it has entered the AOI or not. Once a CV is found within the AOI, the algorithm goes into action. Based on queue condition, the algorithm separates the processing into two invisible sub-modules: Queue and No Queue. Then, it ends at three different decision modules: Acceleration, Deceleration, and Stop/Delay Module.

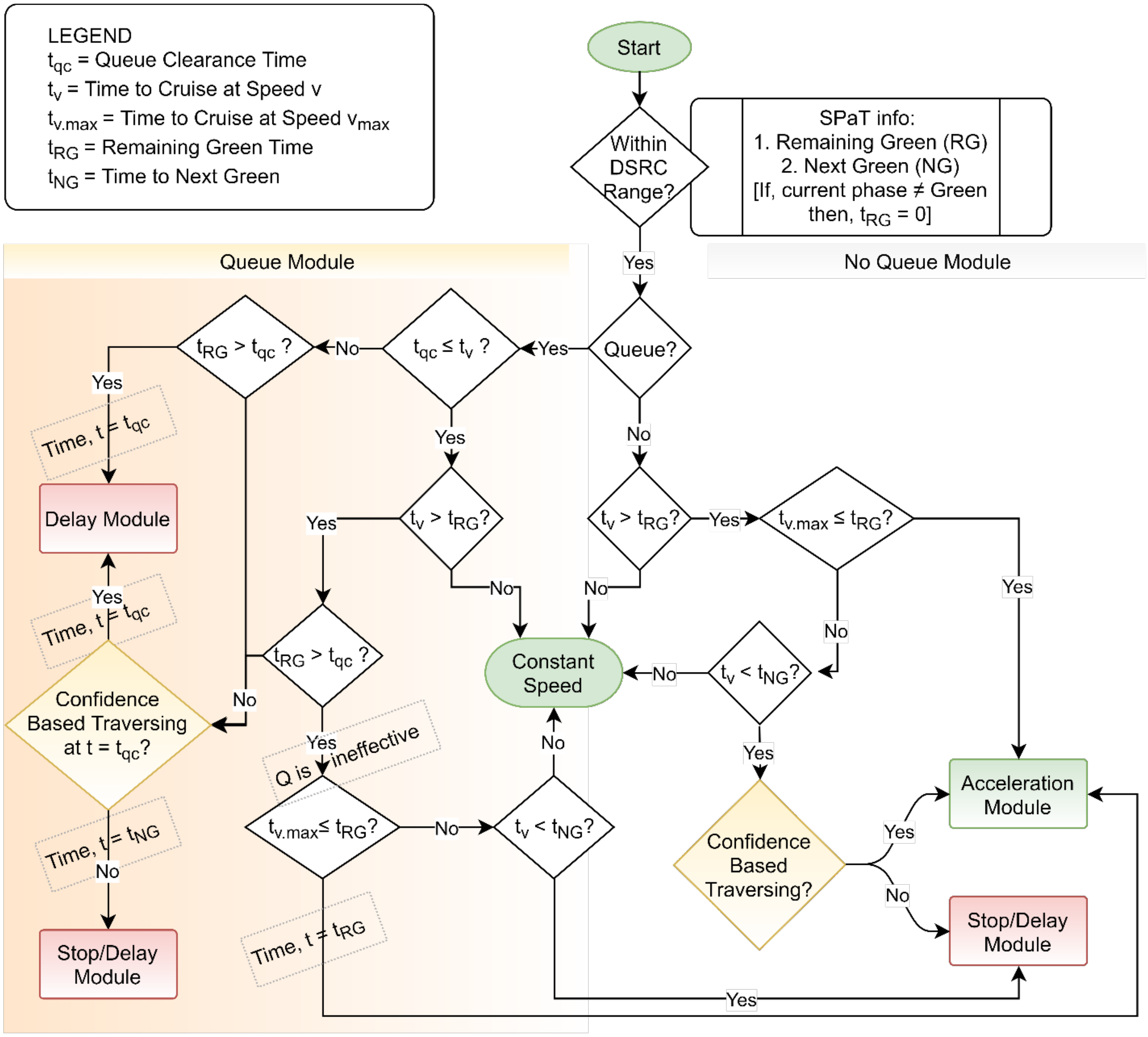
4.3.1 Queue Module

$Queue\ \&\ t_{qc} \leq t_v$: Initially, the algorithm checks if a queue exists. In case of queue, it checks if $t_{qc} \leq t_v$, that is, the total queue discharge/clearance time (t_{qc}) is less than or equals to the CV's cruise time (t_v) to the stop line at its current speed (v); otherwise it refers to the no-queue portion of the algorithm. It is worth mentioning that the total queue clearance time (t_{qc}) refers to the total time taken by the queued vehicles to enter the intersection after the signal light turns green.

$t_v > t_{RG}$: Although the CV won't be affected by the queue when $t_{qc} \leq t_v$, it may or may not be able to pass the intersection though current the green phase. Depending on the remining green and t_v, the vehicle needs to accelerate/decelerate if $t_v > t_{RG}$, otherwise, it needs maintaining the constant speed (since $t_{qc} \leq t_v \leq t_{RG}$).

$t_{RG} > t_{qc}$: Since $t_{qc} \leq t_v$ and $t_v > t_{RG}$ in previous steps lead to a point where t_v is greater than t_{qc} and t_{RG}. Consequently, the decision depends on the comparison between remaining green and the queue discharge/clearance time. Acceleration or deceleration is determined based on this condition and the next one. If remaining green is greater than the queue clearance time ($t_{RG} > t_{qc}$), queue is essentially ineffective (since $t_{qc} < t_{RG} < t_v$) while traversing at the end second of the current green. Conversely, if the remaining green is less than the queue clearance time (hence, $t_{RG} < t_{qc} < t_v$), traversability is checked using *confidence-based traversing* module. If traversing is possible within t_{qc} time, *Delay Module* is referred to estimate the decelerated speed and deceleration. Otherwise, *Stop/Delay Module* is recommended for the next green time.

Figure 1. GLOSA Algorithm



$t_{v_{max}} \leq t_{RG}$: Once queue is ineffective, possibilities of cruising at v_{max} speed are checked. If $t_{v_{max}}$ is less or equal to the remaining green, *Acceleration Module* is recommended. Otherwise, the speed is checked for accuracy in reaching the next green: if $t_v < t_{NG}$, *Stop/Delay Module* is referred, otherwise, constant speed is advocated.

$t_{RG} > t_{qc}$ (when $t_{qc} \leq t_v$ is false i.e. $t_{qc} > t_v$): At this point, the vehicle will be affected by queue for $t_{RG} > t_{qc}$ since it leads to $t_{RG} > t_{qc} > t_v$. Therefore, the algorithm refers to the *Delay Module*. Otherwise, $t_{qc} > t_{RG} > t_v$ leads to a point where the vehicle is unlikely to catch the current green due to the effective queue. In such a case, invoking the *confidence-based traversing* (CTRA) at the queue clearance time becomes necessary. If CTRA is possible, then the vehicle is delayed up to the queue clearance time, otherwise, *Stop/Delay Module* is referred for the next green.

Confidence based Traversing (CTRA) Module uses a probabilistic measure (*likelyTime*) of the current green interval; its *confidence* is employed to serve more vehicles through the current green in a case when the phase observes a prolonged current green beyond the estimated *likelyTime*. This *Module* is dedicated to reconsider traversing the vehicles that are seemingly unable to traverse through the current green. Based on the *confidence and* certainty range (*minEndTime,* and *maxEndTime*) the algorithm considers traversing the vehicles that are highly likely and safe to be traversed through current green. The rest of the vehicles, which are unlikely to traverse, and/or are in an unsafe position, are processed through the *Stop/Delay Module*.

4.3.2 No Queue Module

If a queue doesn't exist, the algorithm estimates the cruise time (t_v) to the intersection stop line for the CV at current speed v and compares it with the remaining green time (t_{RG}). If $t_v > t_{RG}$, further processing is required regarding acceleration or deceleration decision. Otherwise, the vehicle maintains constant speed to pass the intersection through the current green signal.

When a vehicle can't pass the intersection at v speed, the algorithm checks if a maximum allowable speed (v_{max}) can make it. If $t_{v_{max}} \leq t_{RG}$, the CV can catch the current green light by driving at v_{max}. In a such case, the algorithm suggests that the vehicle speeds up, subject to the distance from its leader vehicle (see the *Acceleration Module*). Otherwise, it checks if $t_v < t_{NG}$.

If traversing time (t_v) is not less than next green time (t_{NG}), constant speed is maintained to catch the next green. Otherwise, the *confidence-based traversing* (CTRA) at current green goes into effect. If CTRA is found feasible, the vehicle is instructed to speed up (to $t_{v_{max}}$), subject to the distance from its leader vehicle (see the *Acceleration Module*).

It is worth mentioning that when a vehicle with a speed v greater than v_{max} but unable to make the current green, the only viable option is to decelerate and plan to pass the intersection through the next green interval. Note that the v_{max} is set at 5 mph above the speed limit. Therefore, $v_{max} = v_{speed\ limit} + \Delta$ where Δ is a user defined threshold (5 mph for this study case). While calculating $t_{v_{max}}$, time to accelerate at v_{max} has also been considered. Thus, the relevant equations are: $t_{v_{max}} = t_1 + t_2$, $s = s_1 + s_2$, $t_1 = \frac{v_{max}-v}{a}$, $s_1 = \frac{(v+v_{max})t_1}{2}$, $t_2 = \frac{s-s_1}{v_{max}}$ where t_1 and s_1 are time and distance to accelerate, t_2 and s_2 are time and distance of constant speed trajectory respectively.

4.3.3 Acceleration Module

The *Acceleration Module* computes the minimum required acceleration using the following equation:

$$a_{req} = \frac{2(s - vt)}{t^2}$$

Where s = distance up to stop line or queue end point, and t = available time (remaining green time or queue clearance time).

Then, it checks the feasibility of acceleration by considering its leader vehicle's speed and position. If a leader exists, *Acceleration Module* computes the distance between them and the emergency breaking distance to achieve the leader's speed without hitting the leader. Note that, a leader exists only if the distance is below a threshold value which is defined by the traffic simulator. The following equation estimates the emergency minimum distance:

$$d_e = \frac{{v_{lv}}^2 - {v_{sv}}^2}{2a_{max.d}} + \delta_{e1}$$

Where v_{lv} and v_{sv} are the speed of the leader and the subject vehicles respectively, $a_{max.d}$ and δ_{e1} are maximum eco-friendly deceleration rate and minimum desired gap (after achieving the same speed as the leader) respectively. a and δ_{e1} are assumed to be 11.2 ft/s^2 and 20ft respectively.

If the subject vehicle is within the emergency distance, it starts decelerating immediately at the rate of $a_{max.d} + a_{lv}$ where a_{lv} represents the acceleration rate of the leader. The subject vehicle also stops acceleration (i.e., maintains constant speed) if it is within $d_e + \delta_{e2}$ distance where δ_{e2} = a user defined threshold = 30ft.

If no leader exists or its distance is greater than $d_e + \delta_{e2}$, then the vehicle accelerates at the estimated minimum acceleration rate. In such a case, the desired speed is estimated as follows:

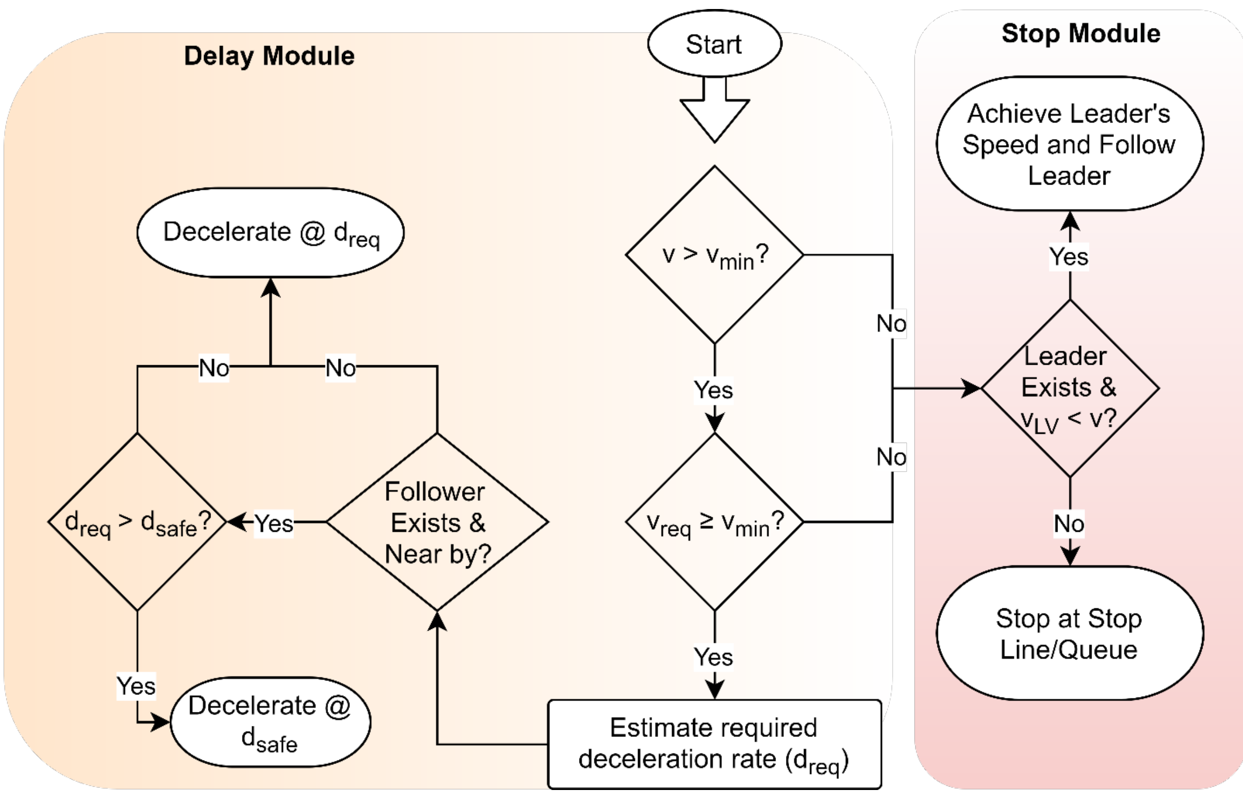
$$v_f = v + a_{req}t$$

Where v_f represents the final speed to pass the intersection or join the queue.

4.3.4 Stop/Delay Module

Stop/Delay Module decides whether a vehicle should slow down or stop to pass the intersection optimally on the next green interval (Figure 2).

Figure 2. Stop/Delay and Deceleration Modules of GLOSA Algorithm



Research shows that excessively high or low speeds increase the fuel consumption rate. According to several previous studies (Berry 2010; Biggs and Akcelik 1986; Davis, Williams, and Boundy 2017), a fuel-efficient, steady-speed range ($[v_{min}, v_{max}]$) lies between 20/25 mph to 55/60 mph. Therefore, the algorithm advocates stopping at the stop line (when no queue i.e. $t_{dq} = 0$) or the end of the queue (when $t_{dq} > 0$) if the near optimal speed estimated by *Deceleration Module* is below the minimum fuel-efficient speed (v_{min}), that is, 20 mph in this study.

At the beginning, this module checks if the speed of the subject vehicle is greater than the minimum eco-friendly speed (v_{min}). If so, it proceeds further to check if $v_{req} \geq v_{min}$ (*Delay Module*), otherwise it decides to stop near the intersection or at the end of the queue (*Stop Module*).

4.3.4.1 Stop Module

The algorithm checks if a leader vehicle exists (based on the simulator's threshold) and if the leader's speed is less than the subject vehicle's speed. If both are true, the algorithm finds the deceleration rate to achieve the leader's speed within a short distance (e.g., 10 ft. gap) from the leader to avoid a rear-end collision. The corresponding equation is as follows:

$$a_{sv} = \frac{{v_{lv}}^2 - {v_{sv}}^2}{2(d - \delta_{fd})}$$

Where v_{lv} and v_{sv} are the speed of the leader and the subject vehicles respectively, d is the distance between the leader and the follower vehicles, and δ_{fd} is the following distance at a lower speed when stopping near intersection.

However, if both are not true, it simply estimates the required deceleration rate to stop near the intersection (i.e., at the stop line or the end of the queue).

4.3.4.2 Delay Module

When the algorithm proceeds further to see if $v_{req} \geq v_{min}$, that is, the minimum required speed to pass the intersection is not less than the minimum eco-friendly speed (v_{min}), it refers to the *Stop Module* described above for $v_{req} < v_{min}$. Otherwise, it estimates the necessary deceleration rate ($-a_{req}$). Before implementing the required deceleration rate, it checks for its follower vehicle. If the follower exists within the perception reaction time distance ($v_{fv} * PRT$), the algorithm finds the safe deceleration rate, $-a_{safe}$

(see the following section for details) to avoid the risk of a rear-end crash. If the safe deceleration rate is smaller than the estimated required deceleration rate, the algorithm advocates the vehicle to follow the safe deceleration rate. Otherwise, it suggests decelerating at $-a_{req}$. Note that, the perception reaction time (PRT) is defined as 1.0 sec. when the follower is a CV and 2.5 sec. otherwise.

4.3.5 Safe Deceleration and Near Optimal Speed

It can be argued that the estimated required deceleration rate provides a **near optimal speed** profile to navigate through the intersection and thus, avoids stop/go situation. AASHTO recommends and expects a deceleration rate of $3.4ms^{-2}$ or $11.2fts^{-2}$. Hence, it is adopted as the maximum threshold/value of the eco-friendly deceleration rate. Thus, the near optimal speed profile is followed by avoiding the sharp deceleration, introducing safe deceleration, and ensuring a smooth trajectory (see the explanation in the following section).

4.3.5.1 Safe Deceleration Rate Estimation

It is assumed that the follower vehicle (FV) maintains constant speed (no acceleration or deceleration) while tailgating. Considering the tailgater's constant speed, the subject (i.e., tailgated) vehicle (SV) should decelerate at a rate so that the rear-end collision does not occur within the perception reaction time. It is also assumed that the tailgater will be able to press its brake pedal to reduce its speed within the PRT; and thus, will be able to avoid the potential crash. In other words, the rear-end collision won't happen if the collision, theoretically, occurs after the perception reaction time (PRT). If the sum of the distance traveled by the SV (s_{sv}) while decelerating at a and the bumper to head distance (d) between SV and FV is greater than the distance traveled by the FV (s_{fv}) at assumed constant speed for time $t = PRT$, a is termed as the safe deceleration rate. Mathematically, a = safe deceleration rate if $s_{fv} < s_{sv} + d$ where $s_{fv} = v_{fv}t$ = the distance traveled by the FV at assumed constant speed, v_{fv} for time $t = PRT$, $s_{sv} = v_{sv}t - \frac{1}{2}at^2$ = the distance traveled by the SV while decelerating at a from the speed, v_{sv} for time $t = PRT$, and d = the initial distance between SV and FV. In other words, the deceleration rate a is the safe deceleration rate if $v_{fv}t < v_{sv}t - \frac{1}{2}at^2 + d$ when $t = PRT$.

Therefore, $\frac{1}{2}at^2 < (v_{sv} - v_{fv})t + d$

Or, $a < \frac{2(v_{sv}-v_{fv})*PRT+2d}{PRT^2}$ [Since, t = PRT]

Or, $a < \frac{2(\Delta v*PRT+d)}{PRT^2}$

Therefore, the vehicle should decelerate at a rate of lower than $\frac{2(\Delta v*PRT+d)}{PRT^2}$ for $t = PRT$ while being tailgated by another vehicle. In such case, the algorithm recommends $v_{PRT} = v_{sv} - a * PRT$ for a short period, $t = PRT$ where $a < \frac{2(\Delta v*PRT+d)}{PRT^2}$. After the PRT, it updates speed based on the following near optimal speed calculation procedure. While both the vehicles are not CV, the algorithm mimics the actual behavior by assuming that the driver will use his/her own judgement to maintain and follow the safe deceleration rate.

4.3.5.2 Near Optimal Speed

Near optimal speed profile of a vehicle is based on the following simple but powerful principles:

- At each intersection, a vehicle decelerates only once when required to slow down.
- Since lower speed leads to longer travel time for same traveling distance, a vehicle decelerates first and then continues with the reduced speed.

Thus, a vehicle maintains possible maximum speed following a smooth trajectory at each intersection, which eventually leads to the minimum speed fluctuation over the entire journey. When a vehicle needs to slow down at an intersection, its smoothest possible trajectory consists of at least two different phases: Deceleration and constant speed: using the formula of motion:

$s = s_1 + s_2 = (ut_1 - \frac{1}{2}a{t_1}^2) + (u - at_1)t_2$ where t_1 = deceleration time,
t_2 = constant speeding time, $t = t_1 + t_2$ = total travel time,
s = total distance traveled within time t, u = initial speed, and a = deceleration rate.

The above equation can be rewritten as follows:

$s = u(t_1 + t_2) - \frac{1}{2}a{t_1}^2 - at_1t_2$

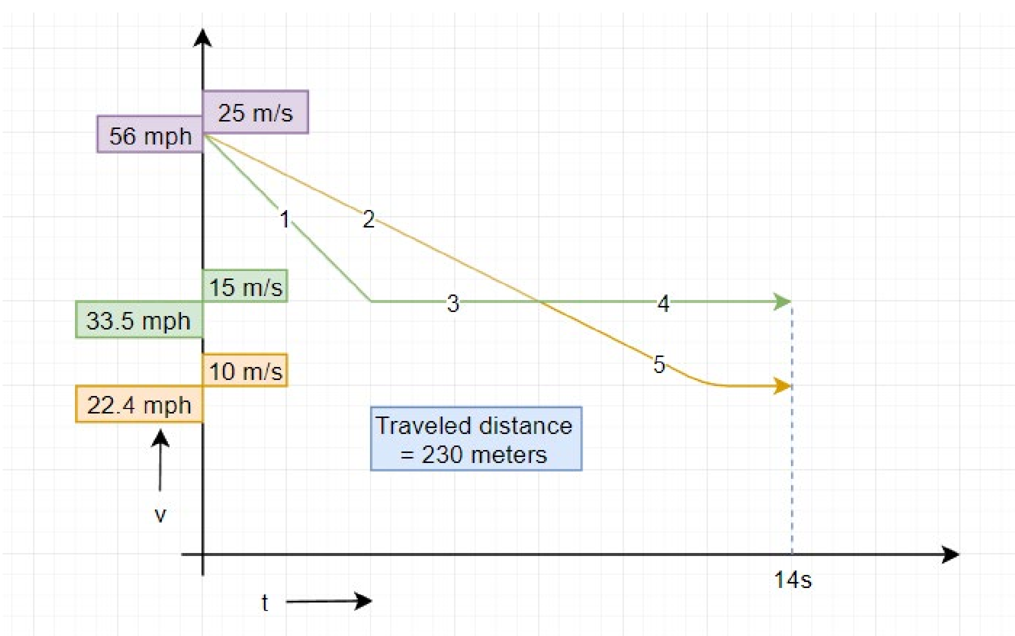
Or, $2s = 2ut - at_1(t_1 + 2t_2)$

Or, $a(t - t_2)(t + t_2) = 2ut - 2s$

Therefore, $a \propto \frac{1}{t^2 - {t_2}^2}$ for any given u, t, s. In other words, a is maximum when $(t^2 - {t_2}^2)$ is minimum or t_2 maximum (since $a > 0, t > 0, t_2 \geq 0$) for any given u, t, s. Thus, increasing a will increase t_2 or decrease t_1 which eventually leads to higher v since $v = u - at_1$. Hence, the final speed (v) can be expressed mathematically as a function of deceleration (a) for a given initial speed (u), travel time (t), and distance (s): $v = f(a/\, u, s, t)$. Note that the division of t into t_1 and t_2 depends solely on the value of a. Briefly, max v, i.e., $max\, f(a\ /\ u, s, t)$ requires max a.

To illustrate the previous theoretical discussion more clearly, the following graph visually explains.

Figure 3. Sharp Deceleration Helps Minimizing the Speed Reduction



In Figure 3, a vehicle represented by a hypothetical green trajectory decelerates at $2.5ms^{-2}$for 4s, and then travels at a constant speed, and another vehicle by another hypothetical yellow trajectory decelerates at $1.25ms^{-2}$for 12s, and then travels at constant speed. Both the vehicles have the same initial speed (56 mph) travel equal distances of 230 m within the same total time (14s) and reached a final speed of 33.5 mph and 22.4 mph, respectively. Clearly, it indicates that the sharp deceleration helps to minimize the speed reduction for a given travel time and a space, that is, distance which in a functional expression is $v = f(a/ u, s, t)$.

In general, the accelerate/deceleration rate required to achieve the advocated speed is subject to drivers' habits and preferences. It can be assumed that the drivers in a connected vehicle environment usually do not go beyond the comfortable acceleration/deceleration rate (recommended by AASHTO), while following the recommended speed. Moreover, in an automated vehicle, acceleration/deceleration can directly be controlled by the algorithm. Therefore, the range of the deceleration rate should be 0, a_{AASHTO}. Since the deceleration rate is subject to driver's habit and $v = f(a/ u, s, t)$, a_{AASHTO} ($3.4ms^{-2}$ or $11.2fts^{-2}$) is expected to be the maximum expected deceleration rate that will provide a near optimal trajectory near the intersection. Since it is the maximum possible speed to traverse the intersection without accelerating again within the given time (t) and space (s), it can be termed as the near optimal speed.

4.3.6 Confidence-Based Traversing

From the broadcasted SPaT messages, three pieces of information—*minEndTime, maxEndTime*, and *confidence*—have been utilized to make decisions regarding the confidence-based cruising through current green. Cruise time, *likelyTime, minEndTime,* and *maxEndTime* help to measure the ability to traverse, that is, measure the traverseability within the current green interval. Yellow and clearance time with the cruise time and *minEndTime* measure the safety of traversing, that is, measure the traverse safety. These two different membership functions, traverseability and safety, add to the level of confidence (LOC) and help introduce a fuzzy logic-based algorithm to make the cruising decision. It can be assumed that the current green won't end before *minEndTime* or after *maxEndTime*. In other words, the range of the current green interval is *minEndTime* and *maxEndTime* with a high-likely value of *likelyTime*.

4.3.6.1 Level of Confidence (LOC)

We utilize *confidence* directly to measure the LOC based on the following table:

Table 1. Fuzzifying the Confidence

SPAT Confidence		
Value	**Probability**	**Level of Confidence**
0	21%	Low (≤ 62%)
1	36%	
2	47%	
3	56%	
4	62%	
5	68%	Fair (≤ 85%)
6	73%	
7	77%	
8	81%	
9	85%	
10	88%	High (above 85%)
11	91%	
12	94%	
13	96%	
14	98%	
15	100%	

The confidence value and its corresponding probability is retrieved from J2735 DSRC Message Set Dictionary.

4.3.6.2 Stopping Likelihood (SL) and Traverseability

The inability to pass the intersection by current green can be measured by the ratio of Marginal Required Travel Time (MRTT) and Uncertain Extra Time (UET). Marginal required travel time is the portion of travel time that is required beyond the highly likely end-time of the current green phase (*likelyTime*); when $t_v > t_{RG}$. In other words, it is the difference between the estimated time to cruise and the remaining green (MRTT = *cruiseTime* – *likelyTime*). Uncertain extra time is the maximum possible extension of the current green time which is the difference between the maximum time and the likely time to end the current green (*maxEndTime* – *likelyTime*). Since it is the case that the higher the value of the ratio, the lower the chance of cruising, this scenario is termed as stopping likelihood (SL):

$$SL = \frac{\text{cruiseTime} - \text{likelyTime}}{\text{maxEndTime} - \text{likelyTime}}$$

Therefore, the higher value of SL indicates the higher chance of being stopped if considering cruising beyond the *likelyTime* of the current green. For example, stopping likelihood 0.1 indicates that the 10% of the maximum extendable time (*maxEndTime–likelyTime*) is required by the corresponding vehicle to traverse through the current green interval. The team fuzzified the SL based on the following table and defined it as the traverseability:

Table 2. Fuzzifying the Stopping Likelihood (SL)

Stopping Likelihood (SL)	Traverseability
≤ 0.1	Highest
0.1 < SL ≤ 0.25	High
0.25 < SL ≤ 0.50	Fair
0.50 < SL ≤ 1.0	Low
Above 1.0	Lowest/No

4.3.6.3 Conflict Likelihood (CL) and Traverse Safety

A driver following the advocated speed may ignore the signal indication such as, running at full speed, while observing yellow light. Hence, the projects obligation to measure the safety before advocating such traversing beyond the *likelyTime*. Whether a planned traversing beyond the *likelyTime* is safe or not can be estimated by the ratio of Marginal Shortage in Travel Time (MSTT) and Certain Extra Time (CET). Marginal shortage in travel time is the portion of travel time that may fall short in the case that the current green (i.e. *likelyTime*) ends earlier at *minEndTime* (when $t_v > t_{minEndTime}$). Certain extra time is the summation of yellow and all red interval. Similar to the stopping likelihood, the higher value indicates the lower safety of the cruising through the intersection. The term for this is conflict likelihood (CL):

$$CL = \frac{\text{cruiseTime} - \text{minEndTime}}{\text{Yellow} + \text{Clearance}}$$

Therefore, the higher value of CL demonstrates the higher chance of conflict if traversing through the current green. For example, conflict likelihood 0.5 indicates that the maximum shortage in cruise time due to the earliest termination of the current green is equal to the 50% of the buffer time, that is, the sum of the yellow and clearance/all red time. Similarly, CL = 1.0 suggests that the 100% utilization of buffer time is needed when current green ends at its earliest time (*minEndTime*). Therefore, cruising is unsafe if conflict likelihood > 1.0. The following table shows the fuzzification of conflict likelihood (CL):

Table 3. Fuzzifying the Conflict Likelihood (CL)

Conflict Likelihood (CL)	Traverse Safety
≤ 1.0	Yes
>1.0	No

4.3.6.4 Confidence-Based Traversing (CTRA) Decision

Confidence-based traversing decision is taken based on the three components discussed previously: (a) Level of confidence, (b) Traverse Ability based on stopping likelihood (SL), and (c) safety based on conflict likelihood (CL). Table 4 shows the fuzzy decision logics required to establish the CTRA.

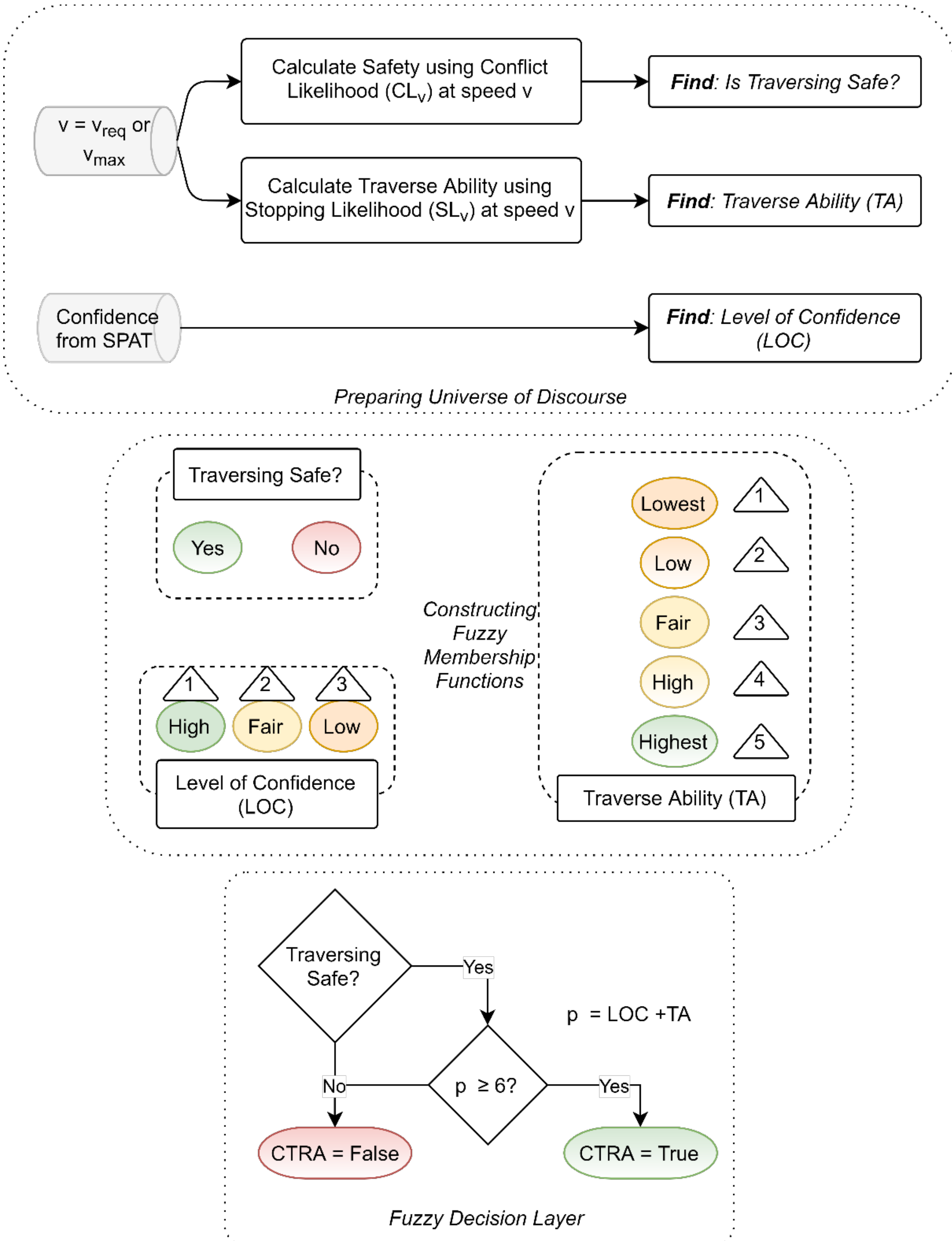
Table 4. Fuzzy Decision Logic

LOC	Traverse Ability	If it is safe, is it OK to traverse?
Low	Highest	Definitely Yes
	High	Yes
	Fair	Maybe Yes
	Low/Lowest	No
Fair	Highest	Definitely Yes
	High	Yes
	Fair/Low/Lowest	No
High	Highest	Yes
	High/Fair/Low/Lowest	No

4.3.6.5 Confidence-Based Traversing in GLOSA

GLOSA begins the process when it receives a target speed for traversing the intersection. Using the speed, it estimates the conflict likelihood and thus, finds the corresponding safety. GLOSA also estimates stopping likelihood and thus, finds traverse ability using corresponding fuzzifying table. Using the confidence from SPaT data, it also finds the information regarding the level of confidence (LOC). With this information, fuzzy membership functions can be constructed. The following diagram sketches the outline of the entire process.

Figure 4. Confidence-Based Cruising Algorithm



With the constructed fuzzy membership functions—traverse ability, traverse safety, and level of confidence—GLOSA uses the fuzzy decision logic table to decide the cruising possibility. Utilizing the reference cited in Table 4 and the researchers' engineering judgement, the sum of the level of confidence and the traverse ability, the team adopts six or higher to enable confidence-based traversing.

5 SPaT Structure Format

5.1 Standard Format

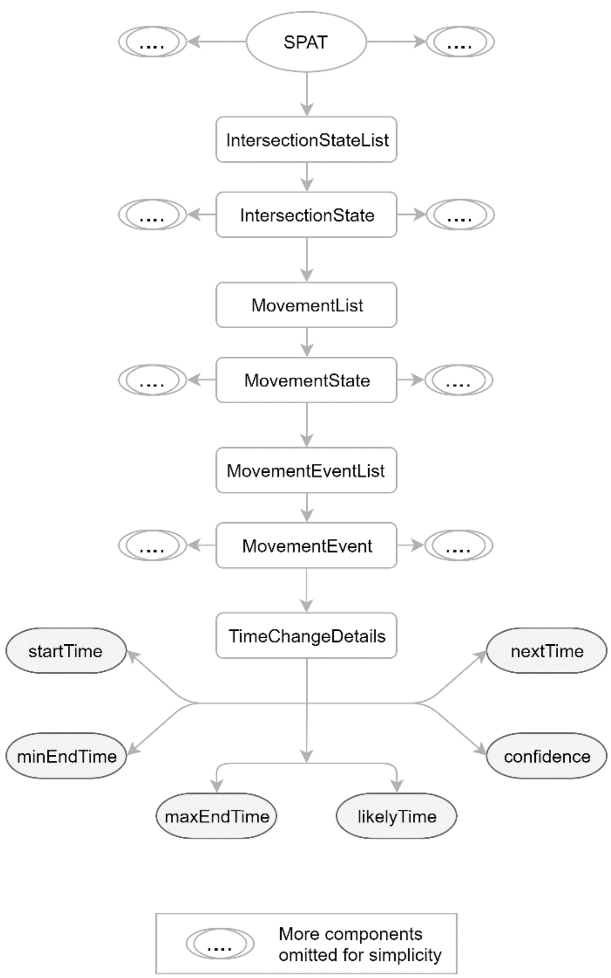
Signal phase and timing (SPaT) Message is one of the 17 messages defined in SAE J2735. In a connected vehicle environment, SPaT is the core V2I message broadcasted by the roadside unit (RSU) to convey current status data of one or more intersections. However, a vehicle needs another set of data named Map Data (which describes a full geometric layout of an intersection) to determine the state of the signal phasing it will encounter and when the following phase occurs. The SPaT message sends the current movement state of each active phase in the system as needed (such as values of what states are active and values at what time a state has begun, does begin, earliest time, etc. and what time a state is most likely expected to begin and end). The state of inactive movements is not normally transmitted. Movements are mapped to specific approaches and connections of ingress to egress lanes and by use of the Signal Group ID in the Map Data message.

SPaT can be used to develop intersection safety application and is commonly employed in in-vehicle applications such as the following:

- Cooperative Intersection Collision Avoidance System (CICAS) and its variants including CICAS-V (traffic signal violation) CICAS-SLTA (left turn across path, opposite direction), CICAS –TSA (traffic signal adaptation to extend all-red intervals to protect potential victims of red light runners) and right-turn assistance.
- Green Light Optimal Speed Advisory (GLOSA) based eco-driving application to assist drivers in maintaining relatively steady speed and thus, reducing fuel consumption.
- Intersection-based Trucker Advisory System, by which drivers are warned when they are approaching an intersection that has a high frequency of commercial vehicle crashes.
- Virtual advanced warning signals, particularly for commercial or heavy vehicles with longer stopping distances.

In traffic system operations and management, SPaT can be utilized to provide better estimates of point-to-point travel times based on real-time conditions. Moreover, dynamic information services based on SPaT can be introduced to transit systems, since it has the potential to significantly increase the predictability of transit trip time estimates, and it may also help to enable transit signal priority appropriately.

In general, SPaT should contain intersection SPaT data (mandatory), timestamp, human readable name, and regional extension (optional) data. Intersection SPaT data contains intersection state information which includes several optional fields along with three mandatory fields—intersection ID (a globally unique value that can be utilized to match the corresponding MAP data), revision status, and Movement List. Movement List contains Signal Group ID and Movement Event List as two mandatory fields. Signal Group ID is used to map to a list of lanes, and the Movement Event List consists of sets of movement data with Signal Phase State, Time Change Details, and etc. Among these, Time Change Details data contain all the required information about signal time changes for a particular Signal Group. It includes information about start time (when the phase first started), likely time (best predicted value when the current green would end), along with minimum end time and maximum end time (expected shortest and longest end time, respectively), confidence of above measures, and next time phase is expected tooccur again. The structure of the SPaT info in accordance with the standard proposed in J2735 document is presented in the following diagram.



In short, the structure of the transmitted SPaT message can be summarized as follows:

```
SPAT :: = {

        startTime     TimeMark      --When this phase 1st started
        minEndTime    TimeMark      --Expected shortest end time
        maxEndTime    TimeMark      --Expected longest end time
        likelyTime    TimeMark      --Best predicted value based on other data
        confidence    TimeIntervalConfidence -- Applies to above time elements only
        nextTime      TimeMark -- Estimate of time when this signal may next occur
}
```

5.2 Customized Format

In this research, a customized format was implemented as a SPaT Prediction Engine plugin in TransModeler traffic simulation software as follows:

```
[
  uuid(D75A1DA0-4A56-426D-AB61-8EB4394DD206),
  version(1.0),
  helpstring("Signal Phase and Timing Data Record.")
]
struct TTsmCvSPaTInfo
{
  double MinEndTime;
  double MaxEndTime;
  double LikelyTime;
  double NextTime;
  double Confidence;
  long ControllerID;
  double Timestamp;
  long TsmVehID;
  double Yellow;
  double AllRed;
  unsigned short CurState;
  double CurStateStartTime;
  double StartTime;
};

[
  uuid(C05A5DCD-350D-4C20-9B2D-1FD37C87F284),
  helpstring("Dispatch interface for TransModeler Connected Vehicle Application  Helper Class"),
  dual,
  oleautomation
]
interface ITsmCVApplicationHelper: IDispatch
{
  [id(0x000000C9), helpstring("Get relevant SPaT info for the specified vehicle.")]
  HRESULT _stdcall GetCvSPaTInfo([in] long aTsmVehID, [out, retval] struct TTsmCvSPaTInfo* aData);
};

[
  uuid(677414D1-AA89-4AB0-89ED-135D17F38D19),
  helpstring("TransModeler Connected Vehicle Application Helper Class")
]
coclass TsmCVApplicationHelper
{
  [default] interface ITsmCVApplicationHelper;
};
```

5.3 SPaT Generating Algorithm for Adaptive Signals

Adaptive signal control system is a traffic management strategy in which traffic signal timing changes, or adapts, based on actual traffic demand. Unlike conventional signal systems, adaptive signal control technology adjusts the timing of red, yellow, and green lights to accommodate changing traffic patterns and ease traffic congestion. The real-time adjustment of signal timing is performed either at every second or at each cycle. It rescinds the green time from one approach and provides to another signal that needs more green time. Consequently, SPaT prediction is an unpredictable process for any adaptive signal control system.

In the context of this project, a real-life Adaptive Control Decision Support System (ACDSS) is selected to investigate the feasibility of generating SPaT messages from adaptive signals. ACDSS has been deployed in the two selected test sites, New York City and the City of Arcadia. Cycle, offset, and splits are optimized on a cycle-by-cycle basis. A customized National Transportation Communications for ITS Protocol's (NTCIP) device, called a CIC object, is used to command controllers in the field to implement updated signal timing. The CIC object is guaranteed to be implemented by the local controller at the top of the next local zero. This means in the context of ACDSS adaptive control (or any similar cyclic adaptive control systems) the new signal timing parameters can be intercepted just in time.

The following are algorithmic steps on how to generate meaningful SPaT messages under ACDSS:

- Retrieve latest CIC object, and extract the active cycle, offset, and spits.
- Based on the active ring-barrier structure of the controller, determine the scheduled phase start time and phase end time based on the splits value.
- For each phase, depending on if it is a coordinated phase or non-coordinated phase, determine the force-off and yield point of that phase.
- Use the following procedures to calculate minEndTime, maxEndTime, likelyTime, and confidence:

```
IF curPhase IS non-coordinated THEN
   minEndTime :=  max {(curTime – curPhaseStartTime) – minPhaseGreen, 0} + passageTime
   maxEndTime := max {(scheduledForceOffTime – curTime), 0}
ENDIF

IF curPhase IS coordinated THEN
   minEndTime :=  max {(curTime – curPhaseStartTime) – split – ringExtension, 0} + passageTime
   maxEndTime := max {(scheduledYieldTime – curTime), 0}
ENDIF
```

Note: The scheduledForceOffTime is dependent on whether the controller is floating force-off or fixed force-off, while the scheduledYieldTime is dependent on the controller's permissive window settings as well as whether the phase is actuated-coordinated with early-yield.

The *likelyTime* is determined based on a bi-level, real-time optimization process: first the probability distribution of the time headways is derived in real-time over a rolling window using maximum likelihood estimation and high-definition detector events data as recorded by the traffic sensors; then based on the distribution, the number of vehicles (*N*) that has the highest possibility to pass over the sensor *consecutively* is determined. The *likelyTime* is set equal to the *N* * *passageTime.* Mathematically, this is expressed as: $\max_{\lambda} L(t_1,...,t_i,...,t_n;\lambda) = \prod_i f(t_i;\lambda)$. Here, $L(t_1,...,t_i,...,t_n;\lambda)$ represents the likelihood function of the time headway distribution $f(t_i;\lambda)$ with λ being the parameter of the distribution. Typically, exponential distribution is assumed for $f(t_i;\lambda)$. t_i is the time headway data as collected from traffic sensors. Each actuation of the traffic sensor extends the current green for an extra *passageTime.* $(t_1,...,t_n)$ is the set of time headway samples collected in the current rolling time window; this means the derived distribution is updated dynamically based on real-time data.

Once the time headway distribution is obtained, the probability of N consecutive vehicle actuations each extending the signal green for an extra passageTime (denoted as $T_{passage}$) is computed. The maximum probability P and the associated number N is the basis to calculate *likelyTime*:

$$\begin{aligned}
&\max_{N} P(t_i \le T_{passage}, \forall i = 1,...,N) \\
&s.t. \\
&P(t_i \le T_{passage}) = \int_0^{T_{passage}} f(t_i;\lambda) \\
&N \le T_{\max End} / T_{passage}
\end{aligned}$$

$T_{\max End}$ is the maximum end time as explained previously. Essentially, the above equation tries to find out the N consecutive actuations each having time headway less than passageTime to keep extending the signal until gap-out (or forced off). Among all possible scenarios, the combination with the highest possibility is used to derive the likelyTime and its associated standard deviation to be used by the following equation:

$$L = 10^{\frac{100.0}{82.5}\times(1.0-\frac{LT_{stdev}}{LT})} - 1.30$$

6 Human Machine Interface and Engine Control

6.1 Introduction

Human machine interface (HMI) is a component of certain devices that are capable of handling human-machine interactions such as, human-to-machine and machine-to-human interactions. The interface, in general, consists of different hardware and software that allow user inputs to be translated as signals for machines and thus, a machine performs different actions as desired by a human. HMI technology is not new, rather it has been well established in different industries for more than a century. HMI has been most commonly used in fields like electronics, entertainment, military, medical, and etc. In a vehicle, HMI is a communication channel between driver and vehicle's engine-to-perform driving.

An engine control unit (ECU), also known as an engine control module (ECM), is a type of electronic control unit that governors a series of actuators on an internal combustion engine to ensure optimal engine performance. Advanced driver-assistance systems are one of the fastest-growing segments in automotive electronics that can communicate with the engine to assist the driver and make driving more comfortable. As such, at a press of a button, a function in the in-car HMI electronics can take control of the power train, acceleration, breaking, steering—making the car momentarily a self-driving vehicle. This combination of HMI and direct engine control is a widely-debated topic considering the vulnerabilities that come along with such remote driverless capabilities. More details of HMI interactions and engine control are described in the following sections.

6.2 Human Machine Interface (HMI)

The nature of driving a car has not changed since the Austin 7 of the early 1920's. The archetypical automobile, with its specific driving position, steering and control scheme, gauges, and even its reliance on the internal combustion engine has not taken any major evolutionary steps in the last 80 years. However, this consistency has helped the automotive industry over the years in the sense that once someone has learned how to drive a car, learning to drive another car involves only minor adjustments. What has changed significantly is the integration of electronics, and more recently, computers into the vehicular environment, creating a Human Machine Interaction (HMI). These elements have introduced new layers of complexity to interactivity, completely changing cognitive models and expectations.

6.2.1 HMI in Automobiles

Modern vehicles are equipped with a complicated infotainment system comprising multiple data input and data output communication devices. Output communication devices represent data generated by an application to a driver or a passenger, and input communication devices receive date from a user. Examples of output communication devices are signal lights, analogue or digital displays, heads-up display, buzzers or loud speakers for voice output—or mechanical vibration units with a haptic output. Examples for input communication devices include keyboards, knobs, switches, jog dials, speech recognition input units, touch-sensitive displays, or visual gesture recognition units. Communication devices can also comprise a combined input and output unit, such as a touchscreen.

Figure 5. In-Car Infotainment System Cluster

Source: www.driverfocusedhmi.com

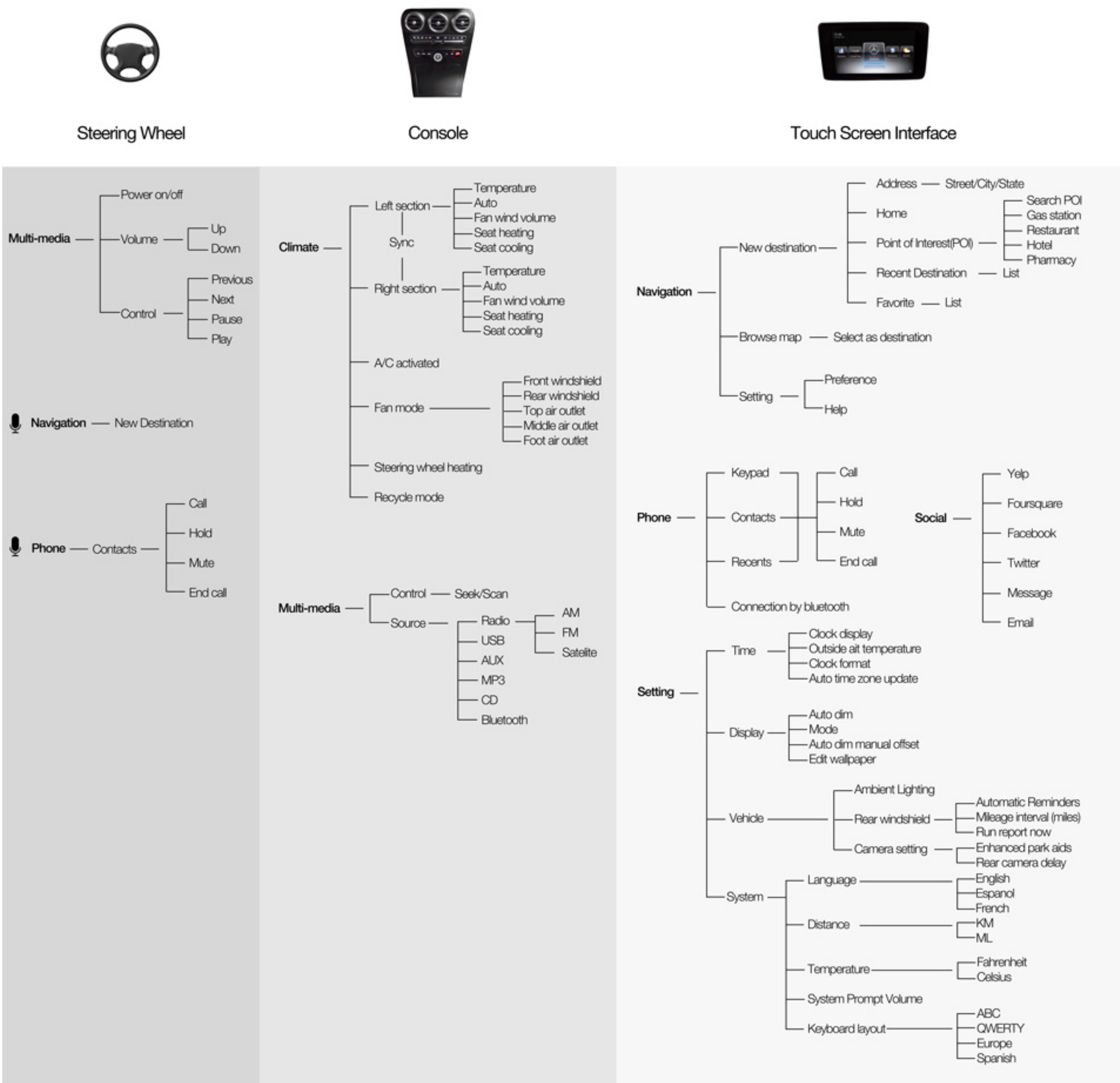
Driving and, in-particular, interaction with the infotainment systems in a car, gets more and more complex because of the increasing number of buttons, switches, knobs, or the multistage functionality of controls such as in BMW iDrive or Audi MMI. A possible consequence from the excessive information is cognitive overload, affecting driving performance, and finally resulting in driver distraction. This complexity-overload relation emphasizes the importance of novel solutions for future vehicular interfaces to keep the driver's workload low.

The operating environment should always be considered when designing an HMI. Latest technology in HMI helps in converting hardware to software, eliminating the need for mouse and keyboard and allowing kinesthetic computer-human interaction. The functionality achieved with digitizing a system with an HMI is unbeatable. The greatest advantage of HMI is the user-friendly graphical user interface (GUI). An HMI provides a visual representation of a control system and provides rea- time data acquisition. The GUI contains color coding that allows for easy identification of the situation. Pictures and icons allow for fast recognition, easing problems for user unfamiliar with the interface.

Vehicles can represent more complex information and adopt more and more applications that originate from mobile and fixed internet devices. Therefore, the HMI of complex mobile I/O devices, such as smart phones, mobile computers, portable navigation systems or mobiles multimedia devices, must be adapted to the constraints of the vehicle's information and entertainment system.

Figure 6. Mapping of Controls and Options Available to a Driver in a Regular Car

Source: www.driverfocusedhmi.com



Adapting the HMI unit for different embedded vehicles and mobile communication devices to various driving conditions usually requires an in-depth understanding of the software and the hardware of both the communication device and the vehicle's infrastructure—and that usually leads to a complicated and costly adaptation of each device to a specific vehicle infotainment system.

Therefore, it is desirable to simplify the adaption of HMI to provide smooth and easy interaction between application, communication device and human user. It is important to enable general application developers to understand specifics of each vehicle and all optimal ways to communicate holistically.

6.2.2 HMI Technologies

In recent years with the advancement in computational capacity of in-car computers, a wide variety of HMIs have become available. But many of them are still being studied as researchers explore the best way to develop the interface. The following are some of the types of advanced HMI technologies that are available at present.

Haptic controllers with embedded touch surfaces and hybrid interfaces: BMW went on to introduce the improved i-Drive Touch in 2013 by introducing a touch interface on the control knob itself. This form of hybrid interaction presents a significant improvement because it allows more active and tangible control of the on-screen GUI.

Touch screens with haptic feedback: Touch screens are promoted as the sole mode of control in automotive HMI, as demonstrated in the large-screen iterations in the Porsche 918 and the Tesla Model S. Although they appear to offer a simple alternative, they are in fact problematic because they are difficult to learn. They can also be very distracting, because the driver must rely on visual feedback all the time and therefore cannot spend time reinforcing a muscle memory or map of the controls.

3D Gesture control with visual, aural, haptic feedback loops: Using gestures to control certain aspects of HMIs is an exciting concept. This is primarily because it presents an opportunity to bring back the direct control and feedback which existed in early cars, although it is not without problems. The sensing of 3D gestural data is getting progressively easier, not only because of low-cost sensors and processors, but also as better algorithms become available. One can detect not just macro changes in physical characteristics, like nodding, facial positions, and hand gestures but also micro changes like eye movements. However, the new interaction patterns emerging from low-cost computer vision have not been fully cataloged and understood, which poses a challenge when mapping and learning a gestural interface. However, the rich feedback of physical interactionslike clicking buttons, the movement of levers, and gears falling into placehave not yet translated well into the fuzzy digital space.

Voice Controlled Interfaces: Though it is far from achieving human-like conversations with machines, due to continuous advances in natural language processing and recognition, the last few years have seen several high-fidelity consumer applications. Siri and Google Now in mobile OS's have also been playing a strong role with in-car interactivity. The promise of voice control lies with two factors, one in replacing physical and digital controls, which will displace user interface, and lead to the possibility of freely conversing with HMI. This will minimize the distractions which come from the manual operation of HMI and in turn increased safety.

It may seem obvious that voice recognition technology will be the best solution for the next generation of user interfaces, but studies are needed to critically understand the implications before designing new models.

Discrete and continuous control: The terms refer to the difference between on and off states of a button or switch versus the continuous rotation of a knob. Voice can play a large role in activating the discrete control function, for example, a simple demand such as, "turn on radio" or "radio," is effective, but may not be as useful with commands that operate over time or a range. An example would be directives to change the volume, such as, "increase volume," "make it higher," "higher." These requests are abstract, analogue, and an inexact notion—making continuous control more suited.

The problem with "strings" and "lists": There is a challenge in dealing with the input of strings of sentences. Though one would think this is where voice input could be ideal since it eliminates the need to enter text via a keypad, studies suggest the contrary. Research carried out at the MIT AgeLab and the New England Transportation Center, point out that the distraction and engagement levels of voice are comparable to that of manual operations and the subjects of the study rated these parts of voice interfaces to be as demanding as using knobs and buttons.

Recognizing emotion in voice: This seems to be the next step in natural language processing—where mood and emotion are triggers for in-car reactions.

6.2.3 Types of Interactions

In-car interactions can be split into two distinct types: hard and soft.

Hard interactions: can be defined as deliberate manipulative actions performed by the driver. Examples are changing the drive position using a button, using an infotainment system via a GUI, and inputting location data into a navigation device dependent on satellites.

Soft interactions: can be defined as the actions performed by the machine as non-deliberate inputs provided by the user. Self-cancelling turn signals and self-dimming interior lights are an example of soft interactions—where the machine autocompletes a sequence of actions without any user input.

The latter type of interaction, especially, has been coming into prominence with the advent of embedded interior sensors and the notion of the connected car. Some of the possibilities have been exploited with contextual information displayed in HUDs (Heads-Up Displays), even experimental tracking of closed eyelids. These interactions require the greatest amount of care and appropriateness in execution since there is a thin line between when the application provides assistance and when it becomes a distraction. A combination of meaningful hard and soft interactions is the key to getting the best out of HMI in a car.

Soft interactions aided by computer vision

The ability of cameras to track micromovements in pixel data allows sensors in the car's interior to detect a driver's physiological data. Infrequent movement can signify a tired driver and thus a car might prompt the driver to take a break or offer the driver directions to the nearest motorway services.

Soft interactions—contextual information on secondary displays supported by eye/gaze tracking

For instance, information can be broken down into several displays to provide turn-by-turn navigation data when a driver requires it, perhaps using HUDs. This information can also be displayed where the driver is looking, via gaze detection techniques. Use of secondary displays in cars, like HUDs, for providing information on or near the driver's line of sight have been in use since the late 1980s.

The Land Rover Discovery's invisible bonnet concept is a more recent idea, where a combination of contextual on-road information and actual off-road imagery from grille cameras is viewed through a HUD.

6.2.4 Advent of Mobile Phones

If someone asks which consumer technology market has changed and advanced most in the past decade, the answer must be the mobile phone sector. Thanks to the game-changing user experiences delivered through touch screens, the market has rapidly evolved, giving rise to products such as tablets and phablets. Along with advances in chip, display, and web-based technologies, mobile devices have become more and more affordable, achieving unprecedented mass adoption. It seems only natural that they have found their way into the cars we drive today. Similarly, there is much potential for in-car HMI, but we have yet to see a similar revolution in UI in the automotive industry.

The car infotainment system is now equipped with cellular data connectivity, Wi-Fi hotspots for multiple devices, applications for various audio content sources and applications to connect to navigate or otherwise enhance the mobility experience. The only reason cars have had this boost in technology is the evolution of smartphones and consumer demand for the same connectivity choices in their cars as in their pockets.

In the past, Apple, Microsoft, and Google have entered the in-car space with their own custom HMI concepts. The media has focused on the potential for new user experiences within the connected car and the likely emergence of a strong in-car application market.

As people become ever more dependent on smart devices, they begin to expect more of embedded technology elsewhere in their lives. However, in the haste to get on-trend, car manufacturers have simply used screens to replicate previous technology, rather than taking an empathetic, intelligent approach.

6.2.5 Safety Issues

Another early downside of this mobile technology is distracted driving. Market research has shown that operating a hand-held cellular phone while driving is one of the most common causes of distractions that can significantly increase the risk of collision. As a solution, many automotive vehicle manufacturers now offer hands-free cellular phone capability, where the vehicle occupant can place and answer calls without the need to press tiny buttons or read tiny displays. Many vehicles also have audio systems that employ a speech recognizer that interprets the user’s speech and issues the necessary hands-free commands to cause the phone to initiate a call. Once the call is established the user can hold the conversation by simply stating a command within the vehicle—without the need to physically handle the phone. While almost all cars come with this feature by default, menu navigation and phone book navigation are two weak points.

At present BMW is experimenting with a touchpad that has character/stroke recognition capability by which menu navigation and phone book name selection can be made through hand drawing characters on the touchpad with the fingertip. The touchpad must be within comfortable reach of the driver and can be used in conjunction with speech to give the user excellent control over navigation choices.

In fact, minimizing distraction and reducing driver error has been the focus of law and policy makers worldwide. The rules for safe vehicle operation require that driver distraction be at a minimum and well controlled. Specific HMI methods that are convenient for a passenger are not necessarily applicable to the driver. Incoming messages, navigation data, traffic news or vehicle state information relevant for the driver must be prioritized based on the driving condition. While passenger can be free to use a communication feature, such as email, or watch a video clip, such information access should be suppressed for a driver during driving. Highly relevant information concerning driver safety, such as traffic news, vehicle failure warning, or navigation information, should be clearly and directly represented to the driver. Such information should be represented adaptively in the form of audible, visual, and/or mechanical information using different levels of intensity considering the urgency of the message.

Figure 7. Available Controls when Car is Stationary

Source: www.driverfocusedhmi.com

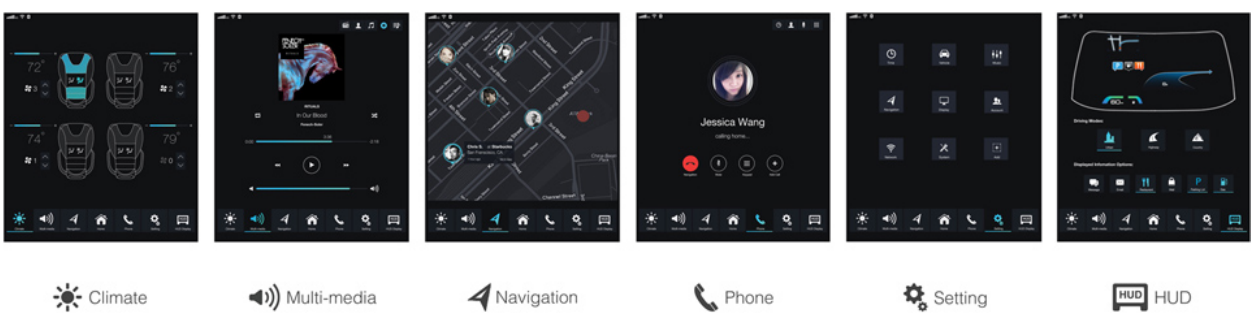
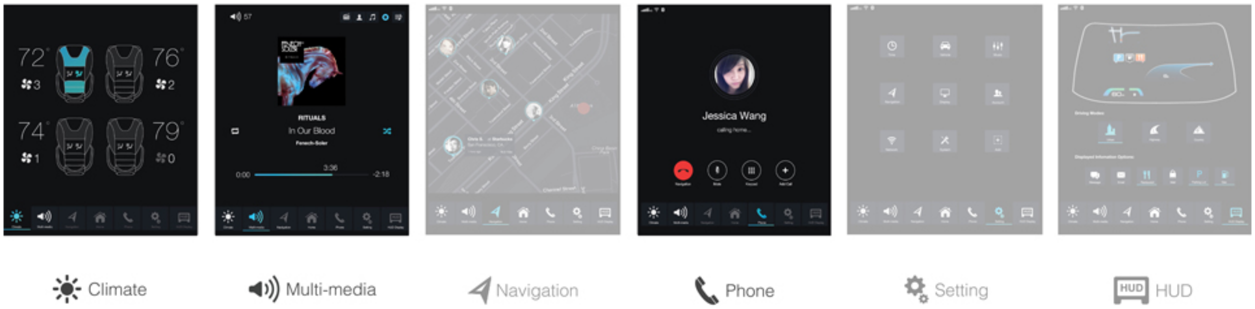


Figure 8. Available Controls During Driving

Source: www.driverfocusedhmi.com



Efforts are being made to curb the use of distracting devices (e.g. mobile interfaces), which in turn also influence the design of HMI. The following is a statement of principles on in-vehicle HMIs issued by the Commission of the European Communities:

- The system should be designed to support the driver and should not give rise to potentially hazardous behavior by the driver or other road users.
- The system should be designed in such a way that the allocation of driver attention to the system displays or controls remain compatible with the attentional demand of the driving situation.
- The system should be designed so as not to distract or visually entertain the driver.

Similarly, in the U.S. the National Highway Traffic Safety Administration guidelines state the following:

- The driver's eyes should usually be looking at the road ahead.
- The driver should be able to keep at least one hand on the steering wheel while performing a secondary task (both driving-related and non-driving related).
- The distraction induced by any secondary task performed while driving should not exceed that associated with a baseline reference task (manual radio tuning).
- Any task performed by a driver should be interruptible at any time.
- The driver, not the system/device, should control the pace of task interactions.
- Displays should be easy for the driver to see and content presented easily discernible.

6.2.6 Design Considerations

This section deals with the current state of HMI and the corresponding organizational, cognitive, and regulatory issues. The automotive industry brings high-level concepts to life with the aim of impressing motor show attendees to increase sales. This approach overlooks all the requirements that users who have a high degree of interaction with modern technology need. To get these experiences right, we need to develop the user experience with real users, in near-real situations.

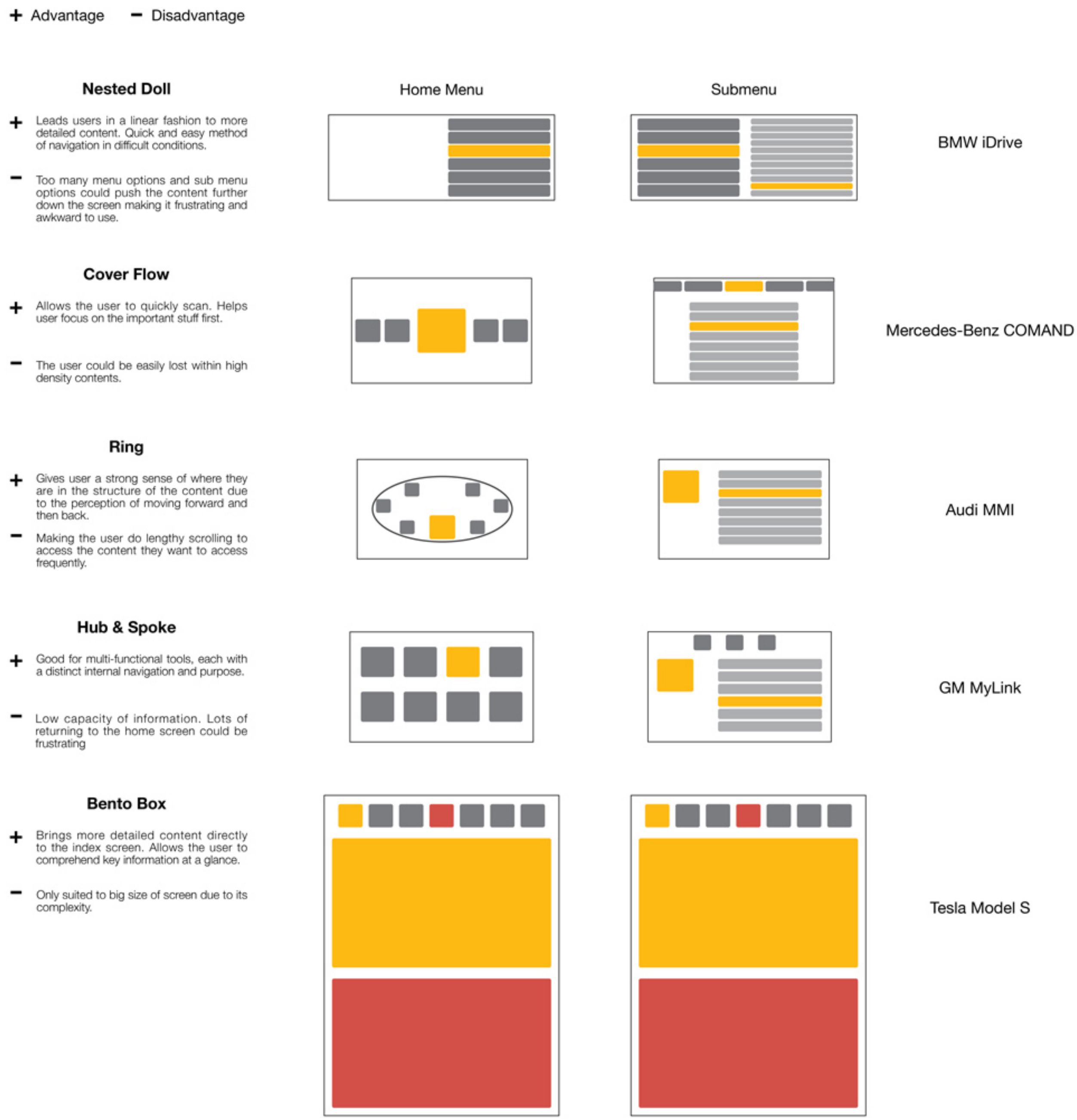
Nowadays, there is a mix of both tangible and graphical user interfaces (GUI), with the GUI behaving as the primary source of feedback with multiple modes for different in-car functions and systems. With such multimodal HMIs, drivers are now faced with an unprecedented level of complexity, as well as the added pressures of congested driving. Therefore, HMI interface should try to address the following issues:

1. **Shifting between modes:** Modes and learning that do not allow for a single mental map to be built up over time.
2. **Ease of Mapping or Learnability:** Where are the controls and what are their functions? Can they be learned easily?
3. **Affordances:** How does moving a circular knob relate to movement between modes on the screen?
4. **Feedback:** At present, there is a reliance on visual feedback in the GUI which can be distracting.
5. **Consistency and muscle memory:** If a person changes car models or even manufacturers, they must relearn some of the basic controls from scratch.

While designing such HMI concepts it should be remembered that there is a limitation to human cognition. It is necessary to consider how people consciously engage with the world by building long-term and short-term memories and their retrieval over time. The Working Memory Model put forward by Baddeley & Hitch in 2000 (first in 1974) describes the interplay between a "crystallized" long-term memory system, a "fluid" short-term memory system and a limited capacity "episodic buffer." The crystallized long-term memory system comprises language, knowledge of shapes and forms, and muscle memory, whereas fluid memory tends more to the visual and auditory.

Figure 9. Pros and Cons of GUI Architectures Available in Various Car Models

Source: www.driverfocusedhmi.com



The act of driving is crystallized, since it uses long-term muscle memory. The information consumed around that task of drivingis the episodic buffer. The episodic buffer has a limited capacity for taking in visual, auditory, and motor cues, so a HMI which does not allow for the easy construction of skill or muscle memory will easily be overtaxing. This in turn leads to bad decision-making and frustration.

Human–computer interaction studies have suggested several key methods for tackling the problem of cognitive overload. One such method is "Chunking" as proposed by George Miller in 1956, by which an individual can remember or process only seven chunks of information, in their correct serial-order, in his working memory. This essentially means that grouped items are easier to remember, because grouping assists phonological and visuospatial memory [e.g., 5355902256 versus (535) 590 2256].

As pointed out previously, in typical interaction design fashion, the following aspects must be considered while designing HMI for in vehicular environment:

- **Controls**: Intelligent choice of tools or devices which offer control of in-car functions (e.g., a knob or a touchscreen).
- **Affordance**: To preserve the simplicity manipulating a control, while performing an action (e.g., a knob can be turned about on an axis).
- **Feedback**: The change or reaction brought about by the controller should be crisp and affirmative (e.g., the change in volume when the knob is turned).
- **Mapping**: To ease the process of developing a "feel" for controls—the ability to understand what a control does and where it is located (muscle memory).
- **Learnability**: It should be easy to understand the way a control behaves over time (e.g., knob can also be used to control brightness or volume.).
- **Modes**: The number of ways a tool or device can be used and repurposed by switching to a new function (e.g., when a button and a knob are fused together, turning the knob manipulates volume and pressing the same knob selects a song in a different context).

Old generation cars have spatial arrangement of the dials and knobs that allowed for a mental map of the HMI to be developed over time and in turn built into muscle memory. Learnability was always a factor, but less controls made it very simple to learn. With modern HMI, there are many more controllable elements, for instance, navigation systems, ride control and infotainment systems to name a few. Building hardware, software, and the HMI interface from ground up allows for deep integration of control systems available in the car. But most of the automotive manufactures use software platforms built by third-party companies to manage and integrate devices. For example, Ford used Microsoft's platform for their Ford Sync HMI systems. Currently, we also see automotive manufacturers adapting popular operating systems widely, such as Android Auto and Apple car play, which in turn ties the user to the same platform for all devices.

Android pay and Apple car play look promising since they provide better utility and consistency across car types; furthermore, using them may be the quickest and most practical way of getting a modern UI into a vehicle system, but being bound to a single platform may constraining for the user. Other issues include the steep learning curve for comprehending the peculiarities of each operating system, mobile devices update more frequently than a car's software and hardware update cycles, and the software cannot be transferred from phone to vehicle because of safety issues.

In GUI certain controls or switches are designed as they would physically appear to help the driver learn its functionality. This is called "skeuomorphism." By retaining a few ornamental design cues from the original interface, the driver comprehends the purpose of the control (e.g., depicting a button with depth helps communicate that it is press-able). Skeuomorphism was widely adapted in the previous generation of GUI; however, adopting more relevant and effective options such as speedometers would be in order today. There are better ways to represent speed; for example, showing if the current speed is within fuel-efficient driving range and/or within the speed limit. Alternatives to the circular dial with a pointer arm, even on digital screens, should be considered.

The HMI also must be crafted in such a way to require a minimum range of attention from the driver, known as "micro-dwell communication." Audio and haptic feedback removes the requirement of visual communication in some instances, and in instances where visual communication is necessary, the HMI must be designed so that the driver looks at the visuals for as little time as possible. There are several design alternatives that can help reduce the time the driver must focus on the device, such as the following:

Readability and Legibility: Text should be short and as readable as possible using font type, contrast, and scale.

Grouping or Chucking: Information related to a specific context or a scenario can be grouped. For example, all the music controls at one place or all navigation options in one screen.

Hierarchy and Quantity: Information should be prioritized and displayed as little as possible at any time. Normally, no more than three pieces of information are displayed at the same time for optimal delivery of data within the dwell time.

Interactions: The interaction between the user and the input devise or the output and the user should be easy and quickly performed without demanding much of user's attention. Also, the feedback delivered should be concise and crisp.[1]

Figure 10. Increasing Legibility and Reduced Number of Options During Driving

Source: www.driverfocusedhmi.com

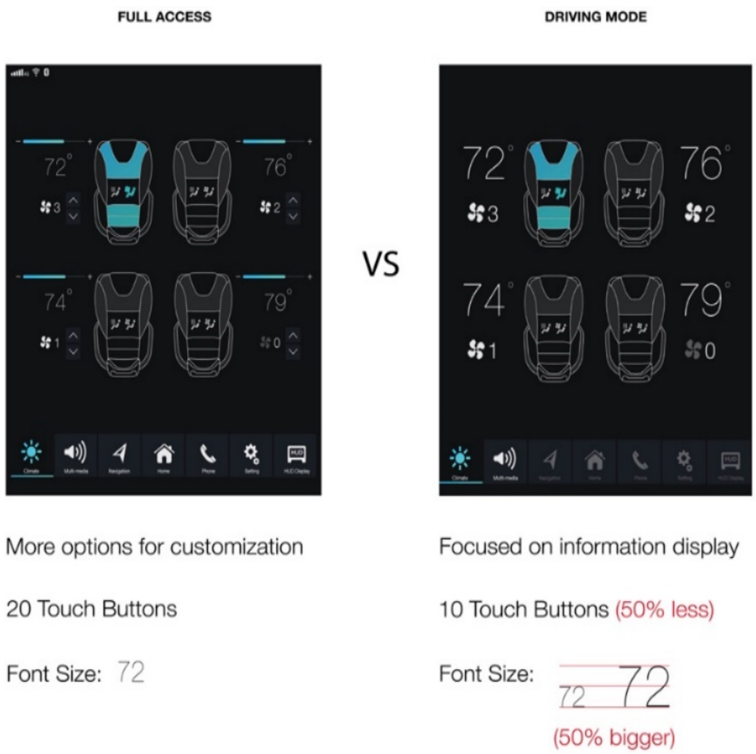
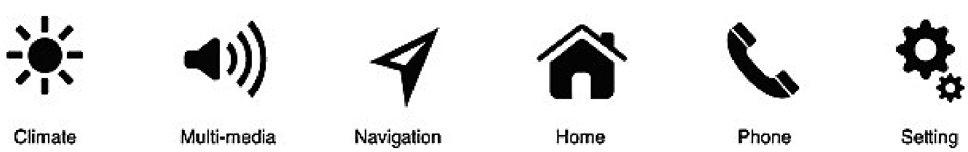


Figure 11. Chucking or Categorization of Menu Options Available in Infotainment System

Source: www.driverfocusedhmi.com



[1] The definitions are taken from https://medium.com/@autoustwo/our-experience-approach-to-hmi-design-6859a32d8aaf

Infographics, a way of representing functions using icons and contrasting images, proved to be effective in communicating information while reducing the length of time the user must look at the screen. User friendly designed icons will influence a HMI positively in several ways. They are easy to memorize, can be recognized quickly with even peripheral vision, and need less text and are not bound to any languages

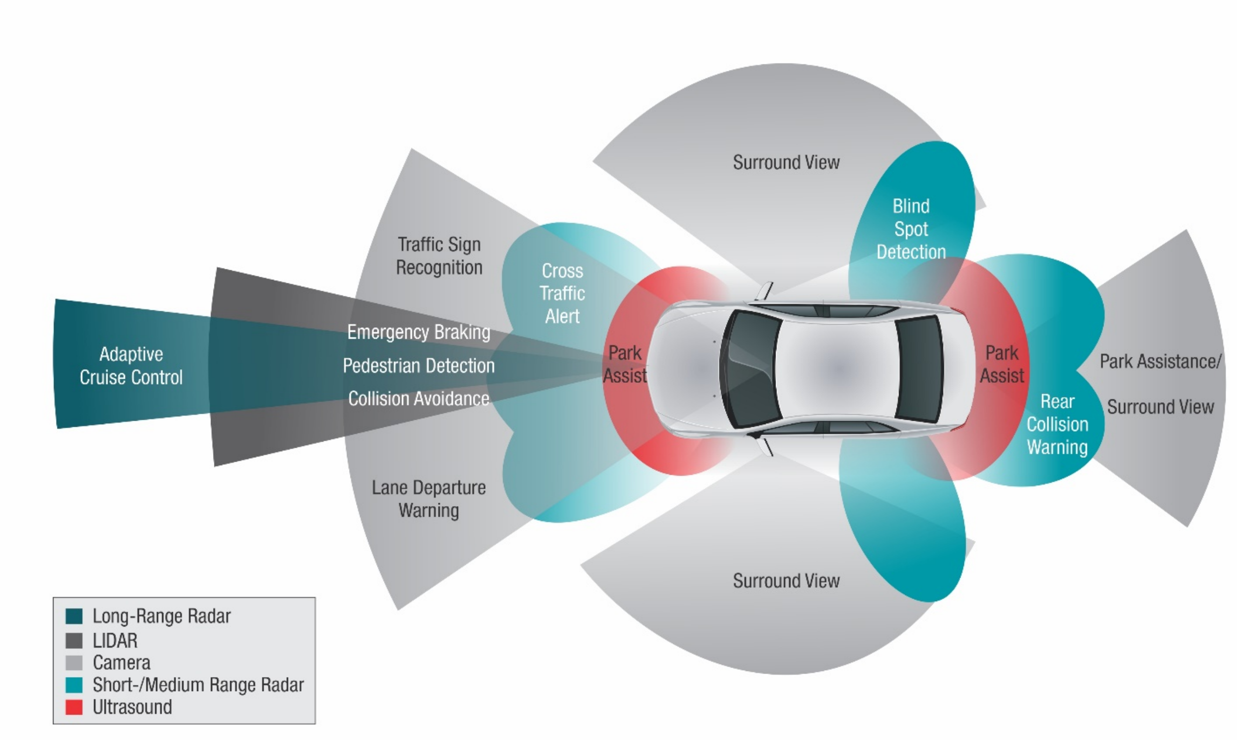
But if the icon is not obvious and not entirely captured on the screen, could result in erroneous choices. Therefore, Icons must be designed aiming to achieve task adequacy, self-descriptiveness, conformity to expectations and learning supportiveness.

6.3 Acceptance of Direct Engine Control Technologies

Today, by just a stroke of a figure, cars can park themselves, avoid collisions with obstacles, keep themselves from drifting out of lanes, follow the car in front with a safe following distance, and even drive remotely with the use of cell phones. Advanced driver-assistance systems are one of the fastest-growing segments in automotive electronics, with steadily increasing rates of adoption and industry-wide quality standards. Thus, at a press of a button a function can be activated through HMI in the in-car electronics that can take control of the power train, acceleration, breaking, steering, making the car momentarily a self-driving vehicle. This combination of HMI and direct engine control is a widely-debated topic considering the vulnerabilities that come along with such remote driverless capabilities.

Figure 12. Driver Assistance Systems

Source: Texas Instruments (www.ti.com)



Any level of automation achieved in the direction of driverless, self-driving vehicles must be powered by innovation in HMI, sensors, mechanical aspect of direct engine control, and coupled with the software that holds them together. We already have such models available commercially. Most of them belong to Level 3 (discussed in next section) Automation where the driver is still in control of the vehicle. Examples of such Automation technologies include functions such as adaptive cruise control (ACC), automatic emergency braking (AEB) and Lateral Keeping/Centering Assist (LKA/LCA). These automated technologies will first notify the driver of any imminent danger of crashing into an obstacle or crossing a lane marking. Accordingly, the driver is still captain of the ship in which all of the devices provide driving assistance. The driver still has the ability to either push the break or swerve around obstacles. But if the driver doesn't react, the automated technology will engage. At this instance, for a very brief moment, the driver will not have any control of the vehicle. The vehicle is expected to do the best to minimize the impact of an accident, and in the best-case scenario the accident may be totally avoided. Such an ability renders these technologies crucial for safe driving—and should be installed in every new car put on road in future. To better understand the acceptance of these technologies, it is important to look at how the technology operates and examine the advantages and disadvantages of adopting such an innovation.

6.3.1 Driverless Vehicle Technologies

Five groups of technologies are combined to create a driverless environment, partially or in full capacity.

- Human vehicle interface.
- Sensors that provide data about internal operations of the vehicle and its parts.
- Sensors that provide location and real-time external roadway environment data.
- Automated controls over vehicle functions and operations.
- Artificial intelligence that integrates in-vehicle operational data with external roadway data" and activates automated vehicle controls. AI is the most important feature to create a completely autonomous environment.

The latest in HMI technologies have been discussed in the earlier sections. However, in the context of self-driving cars, it is likely that, at least at first, driverless vehicles will involve a simple HMI that provides no choices other than to use the driverless vehicle or not. The driver would simply select a destination. At some point in their development, driverless vehicles may provide more complex interactions between humans and automated controls. Although default driverless vehicle programming is expected to be both safe "and most [of the] time…fuel efficient, while obeying all traffic laws," programming alternatives are inevitable—making the driving at times aggressive or causing the system to overlook some minor regulations.[2] HMI in cars with advanced driverless features may be complicated as discussed in previous sections; these cars can also require a steep learning curve to operate.

Sensors that detect and process the operation of various vehicle parts, such as the brakes, transmission, steering, throttle, and tires are already embedded in modern vehicles. With the increase in computational power and decrease in the production cost of the sensors along with advanced information processing algorithms, present-day virtual driver assistance systems have become a reality. However, one of the weaknesses of the automated system is the way in which internally facing sensors provide points of access for intruders to insert malicious code that could misdirect or even take control of a driverless vehicle.

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[2] The quotation on page 59 of this document is taken from Dorothy, Robert, Kyle. 2015."A *Look at the Legal Environment for Driverless Vehicles*"

Precise real-time mapping, tracking, and other environmental awareness technologies are essential to safe vehicle operation. These capabilities usually receive updates at frequent intervals. Poor weather conditions may interfere with many sensors that require line of sight. To supplement the sensors, wireless communications are expected to supply roadway situation information. The latest beacon technologies can transmit information to vehicles regarding signs, warnings, low bridges, tight curves or lane closures. But in a multiconnection wireless communications setting, identifying, isolating, and preventing security threat from hackers, malware, defective equipment and other cybersecurity threats are especially difficult.

So far automated controls in conventional vehicles appear to have been remarkably reliable in accomplishing specific vehicle operations from anti-lock brakes to electronic stability control. But reports about technical experiments enabling remote access to automated vehicles controls have eroded public confidence in such automation. Hackers used this communications feature in a Jeep Cherokee to tap into vehicle control systems so that they could remotely takeover operational control of the vehicle while it was being driven on a highway. Such vulnerabilities, associated with car hacking, present legal as well as technical challenges for the driverless vehicle. Indeed, automated controls and the potential for car hacking have proven to be the most vulnerable aspect of vehicle automation.

Artificial intelligence decisions have consequences in terms of safety and economic and environmental impacts; this aspect of driverless cars are likely to be subjected to extensive legal regulations. At present, the legal system does not specifically regulate any of the parameters in which driverless vehicle artificial intelligence will be permitted to operate. The law likely will evolve to respond to the capabilities of vehicles that incorporate increasingly sophisticated autonomous functionalities. And people will likely embrace the technology while harboring reluctance in giving up vehicle control. But any failure of any magnitude will make it difficult for the public to accept the technology and may delay its subsequent deployment. In addition to psychological hesitancy to relinquish control over personal mobility, legal consequences of having no human driver in control, or potential control, of a passenger car are pervasive. In some areas of law such as vehicle regulation and insurance, driverless vehicles may require entirely new legal rules.

In 2013, the U.S. Department of Transportation—through the NHTSA—issued its Preliminary Statement of Policy Concerning Automated Vehicles ("NHTSA Policy"). In it, the NHTSA set a path for future research and laid out a framework classifying five "levels" of autonomous capability. These levels are designed to track advances in autonomy in an organized fashion, stagger research goals, and facilitate the promulgation of rules for each level. The following chart presents the Automation levels defined by NHTSA.

Table 5. Levels of Automation as Defined by NHTSA.

Automation Level	Description
No Automation (Level 0)	The driver is in complete and sole control of the primary vehicle controls—brakes, steering, throttle and motive power—at all times.
Function-Specific Automation (Level 1)	Automation at this level involves one or more specific control functions. Examples include electronic stability control or pre-charged brakes, where the vehicle automatically assists with braking to enable the driver to retain control of the vehicle or stop faster than possible if acting alone.
Combined Function Automation (Level 2)	This level involves automation of at least two primary control functions designed to work in unison to relieve the driver of control of those functions. An example of combined functions enabling a Level 2 system is adaptive cruise control in combination with lane centering.
Limited Self-Driving Automation (Level 3)	Vehicles at this level of automation enable the driver to cede full control of all safety-critical functions under certain traffic or environmental conditions to rely on the vehicle to monitor changes in those conditions requiring transition back to driver control. The driver is expected to be available for occasional control, but with sufficient transition time. The Google car is an example of limited self-driving automation.
Full Self-Driving Automation (Level 4)	The vehicle is designed to perform all safety-critical driving functions and monitor roadway conditions for an entire trip.

Today's commercially viable, partially automated systems include the following driving assistant features that are proving to be very useful in avoiding driving stress and preventing accidents in multiple cases. However, Automakers insist the driver will always be in charge and the current liability in case of an unexpected failure, still lies with the operator of the vehicle.

- Adaptive cruise control (ACC)
- Automatic emergency braking (AEB)
- Lateral Keeping/Centering Assist (LKA/LCA)

6.3.1.1 Adaptive Cruise Control (ACC)

Adaptive cruise control (ACC) improves conventional cruise control systems by controlling the engine, power train, and service brakes in order to follow a leading vehicle at a pre-selected distance. Frequently, ACC systems rely only upon input from on-board sensors, typically radar or laser/LIDAR.[3] GPS-aided ACC further integrates navigation data to help interpret the intentions of slowing vehicles (e.g., a car slowing to exit a freeway off ramp). Cooperative adaptive cruise control (CACC) integrates V2V communication with ACC in order to better determine the acceleration or deceleration of other vehicles and will allow the "platooning" of vehicles into a condensed convoy.

6.3.1.2 Automatic Emergency Braking (AEB)

Automatic emergency braking, also known as Advanced Emergency Braking System, uses a system to "sense" an imminent collision with another object. Upon detection of an object, the system automatically applies brakes without any human intervention. The system uses sensors such as radar, LIDAR, video cameras, or infrared sensors to detect the oncoming object. In some applications, GPS input also is used to detect fixed objects such as approaching stop signs. The NHTSA has announced that beginning with model year 2018 vehicles, AEB will be recommended as part of the 5-Star Rating System. The systems that take over braking early enough to prevent crashes is preferable, but that's the exception these days. Automakers are being cautious about full automatic braking, in part, because if the car brakes and there's no emergency it could cause another crash because other drivers may not be expecting a sudden stop.

6.3.1.3 Lane Departure Warning, Lateral Keeping, Centering Assist

There are three categories of lateral road lane assistance: Lane Departure Warning (LDW), Lane Keeping Assist (LKA), and Lane Centering Assist (LCA). Most systems rely upon a video camera to monitor lane markings. LDW provides the driver a visual, audible, or haptic alert when the vehicle crosses a lane marking. It does not integrate vehicle steering. Whereas LKA and LCA both are integrated with the vehicle's electrically powered steering. LKA will correct course with a counter-steer torque for a vehicle that is drifting out of the road lane. LCA goes further to continually reapply a force to maintain the vehicle centered in the lane.

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[3] LIDAR is a detection system that works on the principle of radar—using light from a laser.

At present, all the semi-autonomous driver assistance systems fit the general federal motor vehicle standards. But for future autonomous technology, manufacturers should consider playing a role in crafting the types of regulations necessary for a successful—yet safe—transition from the testing process to the public roadways. Considerations could include the following:

- **Critical standards and definitions**: How one state defines an autonomous vehicle feature, or other key terms within their motor vehicle laws, like "driver," could differ from its neighboring state's definition. Uniform Standards and common definitions will make the features readily acceptable among developers and legislators alike.
- **Permitting requirements**: Will drivers need special qualifications? Drivers may need special licenses or special permits or may have to undergo a training program to be able to drive or own an autonomous vehicle.
- **Geographical restrictions**: Is the technology safe to be driven anywhere? Initially and until the long-term consequences are well known, the vehicle operation in driverless mode should be restricted to specific location like interstate highways.
- **Emergency situations**: In the event of an emergency, what will be required of the human occupant, the car itself, and the technology it utilizes?
- **Liability**: As discussed in another section, in the event of an accident involving an autonomous vehicle and a human-driven vehicle, how is liability apportioned? As the human element decreases in functional importance and the manufacturer's hardware and software increases, who bears the risk of an accident?
- **Insurance regimes**: What will insurance on autonomous vehicles look like?

If Congress embraces autonomous vehicles as a major improvement to transportation safety, it could consider passing legislation that provides qualified immunity for OEMs, thereby assuaging concerns over potential liability.

In the NHTSA Policy, the NHTSA noted as much: "because Level 4 automated systems are not yet in existence and the technical specifications for Level 3 automated systems are still in flux, the agency believes that regulation of the technical performance of automated vehicles is premature at this time." NHTSA thinks that both state and federal governments run a real risk of stifling technological innovation by trying to regulate too far into the future.

The first wave of driverless vehicles will be capable of driverless operation only in certain areas and may be precluded by law or design from operation in driverless mode elsewhere. It is likely that initially the driverless technology would be allowed on segregated roadways with few or no pedestrians or other road users, where all vehicles are capable of similar driverless functionality. This may be the most efficient near-term way to deploy driverless vehicles, study their long-term consequences, and develop subsequent policies. Driverless vehicles initially will be available only to a limited audience or be deployed only in particular contexts such as providing shared transportation for hire in urban areas.

Adoption of self-driving cars may present serious challenges to companies writing traditional personal automobile policies. The threat to their business models is noted. It is quite possible that at level 4 many OEMs will not sell cars to individuals, but rather will sell them to operators of fleet of cars. Users will subscribe to use the vehicles as needed. One would expect the insurance burden, then, to fall on the commercial insurers of the OEM and/or the fleet owners. It may be possible that the OEM's would partner with insurance agencies to offer a policy of their own, which could benefit both the parties, because the insurance will encourage people to buy cars with driverless capabilities and the more automated cars on the road would provide OEMs more feedback to improve their product.

6.3.2 Manufacture and Sales

It is quite possible the components to build a driverless vehicle including parts and systems will not be manufactured by a single OEM. Presently, vehicle manufacturers and many other software and vehicle parts suppliers are developing driverless and automated vehicle parts and modules. Software, in driverless vehicles such as mapping, is likely to require continued maintenance and more frequent updating than physical aspects of the vehicle. Frequent software and firmware updates for driverless vehicles are expected to be wirelessly downloaded from manufacturers. Continuing need for updates, mapping, and other programming modifications may tether a driverless vehicle to its manufacturer throughout the life of the vehicle. The software associated with driverless vehicles will be marked as and generally understood to represent, a product distinct from a vehicle's physical hardware.

To preempt automakers and the users initially, the self-driving vehicles may be eligible for something similar to "No fault insurance laws" of 1960s and 1970s where claims that allege only minor property damage or modest personal injuries bypass the tort system altogether and are instead compensated by first party insurance on a no-fault basis.

Some commentators ask whether it is or will become good policy to pre-empt or limit the tort liability of the manufacturers of the driverless vehicles. But the preemption of tort liability would eliminate an incentive for the manufacturers of driverless vehicles to improve their product's safety.

6.4 Legal Implications of Direct Engine Control

Recently introduced automated systems that control some or all vehicle operations for part of a journey or in specific roadway environment are available. However, for now, human drivers remain in overall control, particularly in emergencies. Thus, a human driver remains both legally and practically required to be present and capable of positive operational control of these vehicles.

Capable of operating without human control over their operations, driverless vehicles are anticipated to have numerous advantages in terms of safety, convenience, mobility and environmental protection, relative to their conventional counterparts. The likelihood that driverless vehicles soon will appear on the nation's roads raises questions about the application of existing legal rules to these devices and whether these vehicles may lead to significant changes in the prevailing legal culture. To understand how the system could change to accommodate the future of self-driving cars, we need to understand how the present-day legal framework has been established. Actually, transition from conventional vehicles to driverless vehicles echoes the "horseless carriages" name for human driven automobiles over a hundred year ago. The present-day legal framework regarding automobiles is a result of accident mitigation measures that evolved over time.

6.4.1 Evolution of Law

When the roads were shared by horses and motored vehicles, the driver of the motored vehicles were instructed to drive carefully so as not to frighten the horse. If the horse was frightened and became injured, the driver was responsible for the incident. Eventually, as horses got used to sharing the road with new machines, "the frightened horse lawsuits" were replaced by vehicle crashes and collisions. Some rules or litigations which appear to be important tend to change with time and eventually become obsolete as technologies evolve. This evolution is the same in the case of speed limits. Initially when the speed limit was introduced for motor vehicles, it was set at 8 miles per hour (mph). As the car manufacturers produced faster cars and engineers built safer roads, speed limits were gradually increased to what we see today.

In the beginning of 20th century, as automobile accidents became increasingly common, state legislatures enacted rudimentary laws regarding their registration, use, required equipment, established maximum speed limits, and required simple safety equipment such as breaks, lamps, and a bell horn or other signals. These early statutes with instructions for motorists on how to behave on roads were quickly accepted by all states. From the beginning, the benefits of having personal mobility stacked higher than the disadvantages that automobiles produced.

Finally, as the number of accidents exploded, along with the volume of automobile accident litigations, the formation of the automobile workers' compensation programs—which eventually evolved as the present-day "accident/collision insurance"—became a prerequisite for operating a vehicle on roads and highways.

Eventually, the code of conduct for motorists was accepted by all states and standardized under federal government. It consisted of The Uniform Motor Vehicle Registration Act, The Uniform Motor Vehicle Anti-Theft Act, The Uniform Motor Vehicle Operators' and Chauffeurs' Act and The Uniform Act Regulating the Operation of Vehicles on the Highways.

With the soaring number of automobiles came recognition of new forms of anti-social behaviors such as automobile theft, hit-and-run incidents and driving while intoxicated. Early criminal laws prohibited driving while intoxicated describing it as unlawful conduct in general terms. These laws were refined after a series of studies which clarified the correlation between impairment and blood alcohol concentration levels.

After establishing a law regarding being drunk under the influence (DUI), attention turned to how auto makers might design their motor vehicles to reduce occupant injuries in the event of an accident. The federal government introduced the regulatory code for motor vehicle design by passing National Traffic and Motor Vehicle Safety Act. And established the National Highway Safety Administration. Personal injury lawsuits against automobile manufacturers took longer to appear. Persons injured in early automobile accidents may not have perused claims against manufacturers because they could not identify any negligent behavior by the automaker. By mid-1960s almost all states recognized that these automobile companies could be held strictly liable in tort to consumers when their unreasonably unsafe product designs led to injuries.

Like our transition from horse carts to automobiles, the law will emerge from every innovation and the direction of the future of self-driving cars will become apparent.

First, new technologies can prompt a variety of policy responses, differing along dimensions that include their timing and the branch and level of government responsible for them. Second, the policy responses to new technologies often evolve over time, early efforts to address the risks associated with innovations are subjected to review and revisions as the technologies develop, expectations shift and initial efforts at risk regulation prove inadequate or ill-fitting to changed conditions. Third, these policy responses commonly track changing attitudes regarding the perceived benefits and drawbacks of a technology. Fourth, a discrete and unpredictable incident can play a key role in catalyzing policy, at least when these episodes are sufficiently notorious and occur at opportune times. Fifth, notwithstanding the iterative nature of policy making within any particular forum, early measures may have a long-term impact on the development of the law applicable to a technology. Sixth, policymakers rely upon process of analogy in perceiving and addressing the pros and cons of a new technology and often view innovations in a light of comparable quantities of substitute technologies. Seventh, and finally, specific innovations may produce in the law that ultimately sweeps more broadly then initially anticipated.

Today's Code of Federal Regulations fill thousands of pages with federal motor vehicle standards. Many—if not all—of those standards were drafted with human drivers in mind. With the recent snowballing momentum of autonomous vehicle technological innovation, however, the federal government has realized that it needs to re-evaluate these rules. This far, the agent of change has not been Congress but, rather, the Department of Transportation and, specifically, the National Highway Traffic Safety Administration ("NHTSA").

Google is one of the pioneers in the technology of self-driving. When it approached NHTSA about putting their self-driving cars on roads, NHTSA stated that "NHTSA recognizes that it can take substantial periods of time to develop rulemaking proposals and final rules... NHTSA further understands that the time it takes to conduct rulemakings may, in some instances, make such proceedings ill-suited as first-line regulatory mechanisms to address rapidly evolving technologies …. as a result, Google may wish to explore the interim step of seeking exemptions."[4] Lastly, and perhaps most importantly, the NHTSA's letter to Google signals that the NHTSA is seriously considering what regulatory changes may be required for this growing industry. But currently in this regulatory vacuum, states are moving forward with their own regulations for testing and driving EVs.

6.4.2 Civil Liability and Types of Product Liability Claims

Even if driverless vehicles are safer than other methods of transportation, they will still get into accidents. When this happens, questions will arise regarding who should have to bear the costs of these accidents. Assuming an absence of either a state or federal legislative framework addressing liability, OEMs will be forced to operate under traditional theories of product liability.

The Restatement (Third) of Torts states that product liability requires that a product must be found to have at least one of three categories of "defect" before liability can be imposed:

- Manufacturing defect
- Design defect
- Inadequate instructions or warnings

A product liability suit can allege any or all three theories. To understand the applicability of torts to self-driving capable vehicles, we need to first understand the technology involved in making a vehicle self-driving. The complexities of these technical systems will present unusual challenges to courts and legislatures tasked with creating and applying legal rules regarding driverless vehicles.

The first category of defect, however, presents a major hurdle to plaintiffs: no courts have applied manufacturing defects to software, because nothing tangible is manufactured. Therefore, if the alleged defect stems from an error in the autonomous software or algorithm, plaintiffs may be unable to avail themselves of traditional product liability law on manufacturing defects. An understanding of the technology and how it interfaces with other components or systems will be essential to determining whether a manufacturing defect theory can be pursued.

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[4] The quotation on page 68 of this document is taken from Cristina, Pillip, Steven. 2016. "Autonomous vehicles: The legal landscape in the US"

The second category of defect, and perhaps the most significant for autonomous vehicles, is a design defect. The standard for a design defect is that "the foreseeable risks of harm posed by the product could have been reduced or avoided by the adoption of a reasonable alternative design and the omission of the alternative design renders the product not reasonably safe." This is called the "risk-utility test." It necessitates the plaintiffs determining the design cause of an accident, whether it be an actual product or component, or the software involved in the process. Showing that a safer design would have prevented the accident could create an incredibly high burden of proof; however, it could be difficult to find qualified experts with legitimate experience.

The third defect, often referred to as "failure to warn," applies "when the foreseeable risks of harm posed by the product could have been reduced or avoided by the provision of reasonable instructions or warnings and the omission of the instructions or warnings renders the product not reasonably safe." Most jurisdictions limit this duty to warn of risks that could be "reasonably" known at the time of sale.[5]

The particular circumstances and the vehicle's level of autonomy will likely dictate the viability of a claim against the "operator." For instance, if the technology is such that a person can simply input directions, then sit back while the car operates itself completely, it may be harder to find fault with the person when the car collides with a pedestrian. In a different scenario, what if an autonomous vehicle has alerted the occupant of a malfunction, but the occupant is unable to disengage autonomous mode and take control before an accident occurs? Liability of the occupant in that instance will likely hinge on whether the occupant is viewed more like the engineer of a train, whose role is to monitor and react to certain circumstances, or more like a passenger, who has little or no control of the vehicle's behavior.

Analysts have reached the shared conclusion that a proliferation of driverless vehicles eventually will lead to an upward shift in the locus of civil liability for everyday accidents, away from drivers and toward the manufacturers of these devices and the software used in them. Accordingly, analyst forecast that the earliest claims against manufacturers of driverless vehicles will likely resemble those lodged against the makers of conventional vehicles.

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5 https://www.wired.com/2012/01/ff_autonomouscars

There may be a lag before a substantial number of sophisticated defect claims appear that specifically attack driverless features and functions. However, any early case will likely prove important in directing the future path of the law. Significantly, in the long run the total number of personal injury lawsuits involving these vehicles should drop.

In early cases, it could be possible that generic tort principles do not properly account for the unique risks and benefits of driverless vehicle technologies. Pressure will build for the reevaluation and possible alterations of these rules whether through federal preemption or otherwise.

Software may produce early and easy product-defect litigation when it leads to palpably improvident outcomes such as a vehicle turning abruptly and unexpectedly into oncoming traffic, running a red light, or crossing over a sidewalk when making a turn, in which case a defect of some sort will be difficult to deny.

As for claims against the users of driverless devices, plaintiffs may try to restyle existing theories of negligence commonly directed against drivers of conventional vehicles, like criticizing the users of driverless vehicles as inattentive towards circumstances that arguably require hands-on driving.

In general, the immaturity of the technology and evolving claim consciousness of plaintiffs point toward lawsuits that (1) criticize decisions made by the drivers of automated vehicles with driverless capacities and decisions associated with the engagement and maintenance of the driverless functionalities or (2) allege that there was a failure to provide sufficient warnings by the manufacturer regarding risks associated with these devices or (3) allege there were defects in a vehicle's sensors, actuators, and other hardware, as well as defect claims that attack flaws in the software that translates information derived from sensors into driving instructions.

Certain features of driverless vehicles may accelerate the normally gradual process through which plaintiffs develop claim consciousness. Information collected or relayed by driverless vehicles may shorten the feedback loop through which data regarding a product's dangerous qualities is gathered and translated into possible improvements.

Litigations: A period may witness the emergence of more sophisticated claims against users, such as allegations that users have overridden safety directions programmed within the vehicle or selected unreasonably aggressive driving mode. The prodigious amount of data generated by driverless vehicles, together with the connected attributes of these devices, will create incentives and opportunities for business and individuals to collect and use this information for profit which would look like exploitation of personal data. Although most of the resulting cases will be resolved by reference to evolving consumer protection and privacy torts. Some of these disputes may challenge the collection or dissemination of information by vehicle manufacturers or software providers. Finally, depending on the path that driverless vehicle technologies follow, new claims may emerge against third parties who do not manufacture driverless vehicles, but are in other ways responsible for their operation on highways. Such as counterparts to present day navigation applications, that promise to enhance the efficiency or otherwise direct the performance of driverless vehicles manufactured by a different company. At some very matured claiming environment, where it is unclear who is to be held liable for a particular claim, a different compensation system may well be created similar to the national childhood vaccine injury act of 1986.

Criminal Liability: Driverless vehicles will develop a complicated multifaceted relationship with federal and state criminal law and procedure. Current state laws typically make the driver or operator of a vehicle liable for failing to stop at a stop sign. If a driverless vehicle fails to obey such sign, the human user of the vehicle could conceivably continue to be held liable. Continued assignment of liability to users seems likely insofar as level 3 vehicles are involved. At advanced stages, it is possible that an interregnum period will appear in which drivers will be permitted to claim a defense by ascribing an improper traffic maneuver to a self-driving function, but no direct liability will attach to the manufacturer or anyone else for this error.

Cyber crimes: Their potential for use as unmanned drones suggests that these vehicles could be deployed for terrorist purposes. Terrorist or other third parties also may try to hack individual vehicles or the system in which these vehicles operate-either to trigger collisions or simple confusion or to gain access to data compiled by driverless cars for purpose of surveillance or profit. Yet these concerns about new criminal capabilities remain speculative at this point.

Criminal investigations: If they become common, driverless vehicles also will have an important effect on police investigations. These devices will alter the existing equilibrium between privacy and security by enabling both new crimes and new methods of surveillances. These arguments will implicate what is presently a contested area of privacy laws. Under the Fourth Amendment the government engages in a search when the alleged crime intrudes upon an individual's subjective expectation of privacy, to the extent that society is prepared to regard such an expectation as reasonable. In this regard, the culling of digital evidence from driverless vehicles by police may prove particularly sensitive.

6.4.3 Insurance of Driverless Vehicles

Insurance issues arising from the relationship among driverless vehicles, insurers, manufacturers and policymakers will present a host of interesting challenges. The reduction in injuries and the reduced responsibility and liability on the part of operators will benefit the public and the operators, but it will also present challenges to the business plans of many insurers. As vehicles become more connected, cyber risks will present a new set of insurance challenges.

It is likely that self-driving cars will not be totally autonomous for several years. They will operate in a shared driving mode (level 3) in which the driver may trust the driving to the car but must be available on adequate notice to take over the driving. As vehicles move towards driverless capabilities, there will be a transitional period of shared driving experience—some driving in manual mode and some in automated mode. Insurance will depend on the number of miles driven in each mode. But again, gathering this information may present some privacy issues. If the vehicle causes an accident while operating in driverless mode, under present products liability law, the responsibility would be allocated to those in the commercial chain (dealers, OEM, possibly the programming entity if different) rather than the driver. For that portion of the shared driving experience in which the operator manually drives the automobile, insurance and the calculation of insurance rates should be straightforward. It helps the consumers with lower rates, and lower rates encourage the purchase of these safer vehicles. If, however, insurance savings over the life of the vehicle offset the additional cost of equipping the vehicle, cost should neither dete, acceptance nor create two classes of drivers. There will be a considerable amount of guesswork going into initial rate making. At present, insurers have little or no data on which to base a rate, even if it was clear where liability would lie. Presently, insurance rates primarily depend upon (1) drivers driving record (2) the number of miles driven per year and (3) the number of years of driving experience. The driving information gathered from the vehicles may be useful to improve insurance policies and products. Ideally, an insurer would rate a policy based on real knowledge about the driver, the vehicle, and other hazards that it might present. It is impractical however to put an observer in each vehicle. But with continuous information flowing back and forth between a driver and the OEM, it might be possible to price policies so that the premium better matches the actual exposure. OEM's may find it in their interest to offer their own policies or they may share the information with affiliated insurers.

In a recent study by the Boston Consulting Group, their survey showed that despite the added expense for the technology, 44 to 55% of those polled would buy either a partially or fully autonomous car. For partially autonomous cars, lower insurance costs were the top reason for making the purchase, safety was second. For fully autonomous cars, lower insurance was the second ranking reason, with safety in the first place.

In time there will be a growing database, however it will likely be much less static than databases used to rate current vehicles. OEMs will continually improve and update their algorithms, and these will be downloaded to all the vehicles in the fleet. This could happen daily or perhaps virtually continuous bases. Therefore, yesterday's self-driving car will not be the same as today's or tomorrow's.

6.4.3.1 Cyber Insurance

At present, there is little financial motive to hack into cars, but this may change. As a consequence, NHTSA is doing focused research on hacking and hacking defenses at its transportation research center. There is considerable doubt whether standard commercial general liability (CGL) policies cover cyber risk. The issue may surface whether there was property damage or merely damage to electronic media and records. In any event, insurers will start to add cyber exclusions to the policies to avoid any ambiguity with respect to the issue.

6.4.3.2 Privacy Law

Drivers privacy protection Act (DPPA), Fair Information Practices (FIP), Electronics Communication Privacy Act (ECPA), Consumer Proprietary Network Information (CPNI), Federal Trade Commission Act and Personal Information Protection act from Privacy breaches are a few to name that protect an individual's personal information contained with either the Department of Motor Vehicles (DMV), an insurance provider, or the OEM. Over time these laws must become increasingly strict. They will apply to driverless vehicle manufacturers, sellers, ride service companies, and indeed all entities that collect personal information associated with driverless vehicles. The GPS Act would prohibit businesses from disclosing geographical tracking data.

6.4.3.3 Security Laws

As driverless vehicles become advanced, they become an integral and critical part of nations transportation infrastructure. Driverless vehicles communication should be protected from possible interceptions and hacking threats. Although legal policies questions about how best to assure the security of driverless vehicles have been asked, there is yet, no legislation or regulation requiring specific type or levels of security for driverless vehicles.

6.5 Conclusions

The modern cars are equipped with a complicated infotainment system with touchscreens and a multi-stage functional human machine interface. The design of such a system should be accomplished by extensive testing with real people in real scenarios. Adapting the HMI of different embedded devices and mobile communication devices to various driving conditions usually require an in-depth understanding of the software and hardware. However, in the haste to get on-trend, car manufacturers have simply used screens to replicate what has been before, rather than taking an empathetic, intelligent approach. A possible consequence of such an ill-designed HMI is cognitive overload, affecting driving performance and driver distraction. Today's HMI can definitely be improved and perfected by considering various aspects of safety, affordability, learnability, and with intelligently designed UIs.

Present day cars are equipped with advanced driver-assistance systems which can be activated by a press of a button and perform activities such as parking by themselves, avoid collisions, avoid drifting out of lanes, follow cars at safe distance and so on. This combination of HMI and direct engine control is a widely-debated topic, considering the vulnerabilities that come along with such remote driverless capabilities. However safer and enjoyable, the features come with side-effects such as a difficult learning curve, dependence on sensors and software, vulnerability to hacking and helplessness in case of equipment malfunction or complex scenarios. Currently, advanced semi-autonomous systems are available commercially with ill-conceived standards that treat them to be under Level 3 Automation. One such controversial issue is Tesla's fatal accident of Joshua D. Brown in early May 2016. All experts in the field agree that it is not possible to expect human drivers to continuously supervise driving automation software and correct its shortcomings and errors at split-second notice when problematic traffic situations occur. Unfortunately, the driving automation frameworks were heavily influenced by the perceived needs of the auto industry which already had driver assistance systems on the road and favored a gradual evolution of their systems towards fully autonomous driving. Tesla introduced their vehicle with auto-pilot software on the market. It was presented as a small step from cruise control to full lateral and acceleration/deceleration control. The human is still expected to be in full control and bears full responsibility which means that the driver will always be responsible if something goes wrong and the vehicle does not have the ability to perform all tasks by itself. But they overlook the key difference: the software now handles the driving task continuously—for longer stretches of time without the need for human action. There is a fundamental difference between continuous driving systems versus ad-hoc, short-term operations of driver assistance systems, that is, parking, emergency braking, lane warning etc. which only take over driving functions for short periods of time. But the key problem is not a software issue. It is the mindset which offloads the responsibility from the driving software to the driver. Developers will be much more inclined to release imperfect software if they can expect the driver to fill any gap.

Capable of operating without human control over their operations, driverless vehicles are anticipated to have numerous advantages in terms of safety, convenience, mobility, and environmental protection relative to their conventional counterparts. However, even if driverless vehicles are safer than other methods of transportation, they will still get into accidents. When this happens, questions will arise regarding who should have to bear the costs of these accidents. Assuming an absence of either a state or federal legislative framework addressing liability, OEMs will be forced to operate under traditional theories of product liability. The likelihood that driverless vehicles will soon appear on the nation's roads raises questions about the application of existing legal rules to these devices and whether these vehicles may lead to significant changes in the prevailing legal culture. Analysts have reached the shared conclusion that a proliferation of driverless vehicles eventually will lead to an upward shift in the locus of civil liability for everyday accidents, away from drivers and toward the manufacturers of these devices and the software used.

It is likely that self-driving cars will not be totally autonomous for a number of years. They will operate in a shared driving mode with conventional cars. As vehicles move towards driverless capabilities, there will be a transitional period of shared driving experience—some driving in manual mode and some driving in self-driving mode. Insurance will depend on the number of miles driven in each mode. There will be a considerable amount of guesswork going into initial rate making. The driving information gathered from the vehicles may be useful to improve insurance policies and products; however, this poses a threat to the privacy aspect.

Another shortcoming of connected vehicles is the vulnerability of being hacked. In a recent case, researchers demonstrated that certain connected cars can be hacked and that hackers can remotely control vehicle functionality by exploiting security defects in the vehicle's software. This susceptibility of the connected car to malfunction or to be remotely accessed is a legitimate and important concern that can be addressed. At present, there is little financial motive to hack into cars, but this may change. As driverless vehicles become advanced, they become an integral and critical part of the nation's transportation infrastructure. Driverless vehicles' communication systems should be protected from possible interceptions and hacking threats.

Studies have identified that the distinctive feature of different degrees of automation is the permanent attention of the driver to the task of driving as well as the constant availability of control over the vehicle. Partial automation meets these requirements. As far as higher degrees of automation imply hands-free driving, further research in terms of behavioral psychology is required to determine whether this hinders the driver in the execution of permanent caution.

7 Traffic Simulation Testing

Traffic simulation refers to the imitation of the real-world traffic system operations. The act of simulation the requires a model that represents the key characteristics, behaviors, and functions of a transportation system. The model/simulator represents the system itself, whereas the simulation represents the operation of the system over time. Several simulators with different purposes and potentials are available commercially (such as AIMSUN, Citilabs CUBE, Synchro, TransModeler, VISSIM etc.) or free (such as SUMO) to simulate the transportation system. In this research, an advanced microscopic traffic simulator called TransModeler is selected as the simulation platform to test the eco-driving strategies. TransModeler provides full-featured GIS functionalities, user-friendly graphical user interface, high-fidelity microscopic driver behavior models, and a COM-based powerful Application Programming Interface (API). TransModeler has an integrated emission model named comprehensive modal emission model (CMEM) useful for quantifying the fuel consumption and carbon emissions as effected by eco-driving strategies.

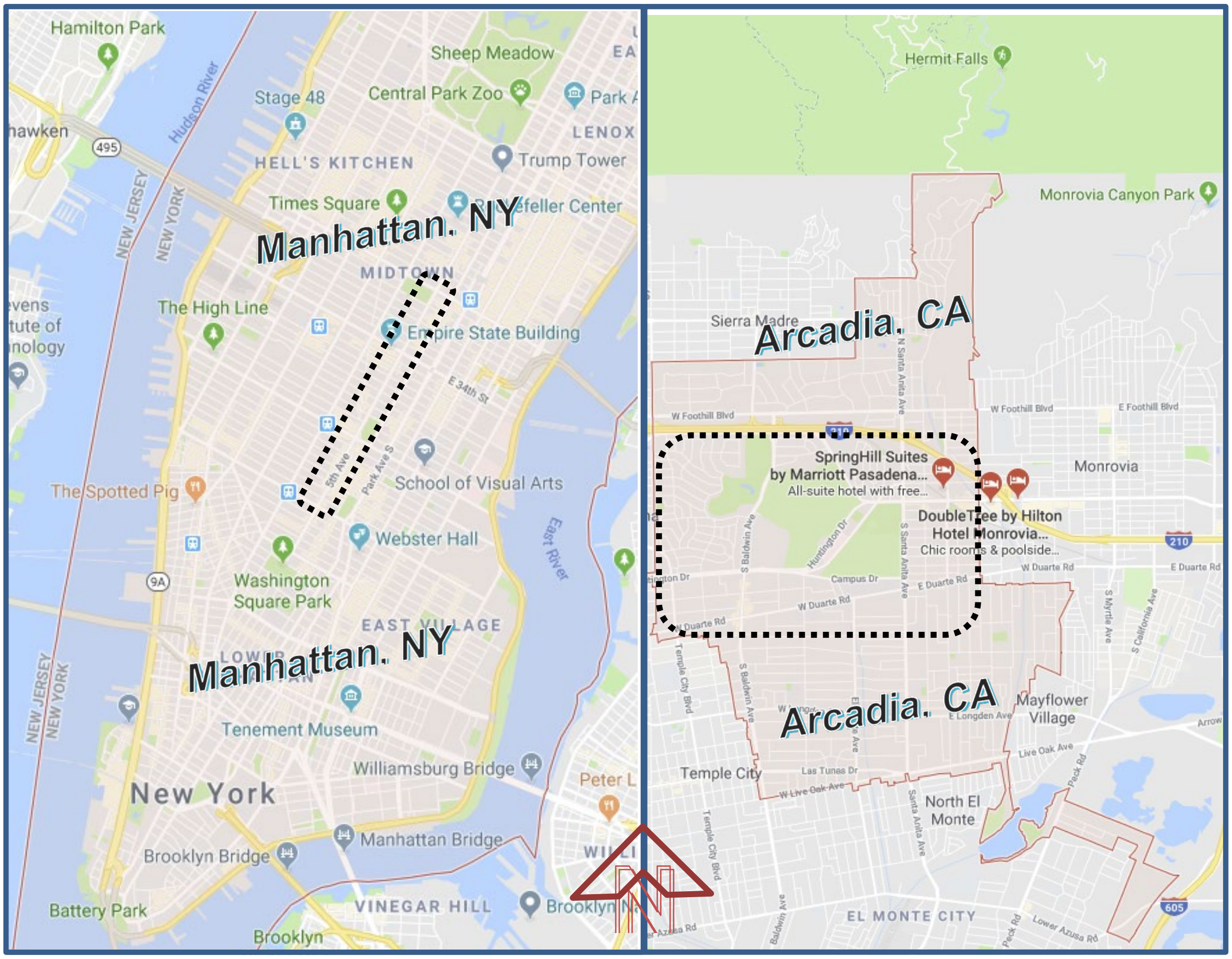
An API is a set of subroutine definitions, protocols, and tools for building application software. In other words, an API of a software/program supports communication with its core program from other compatible add-in programs. An API support is mandatory to develop and test the eco-driving tool since the API provides the passage to communicate with the core program and implement the advised speed.

7.1 Study Area

In terms of traffic dynamics, selected study areas—Arcadia, CA and Manhattan, NY—are significantly different from each other. As such, compared to Arcadia, Manhattan is highly dense with a lot of business activities. Although the road networks follow grid patterns, grid size in Manhattan is nearly a quarter of the grid size in Arcadia. Within the boundary of the selected study area, several major corridors have been included in the Arcadia, CA network that consists of 33 signalized intersections. These corridors include Huntington Drive, W. Duarte Road, S. Baldwin Avenue, Santa Anita Avenue, and S. 1st Avenue etc. In contrast, a single corridor (5th Avenue from 14th Street to 42nd Street) has been selected in Manhattan, NY, which includes a total of 29 signalized intersections. Figure 13 represents the study areas. A dotted black rectangle highlights the actual study area within Manhattan, NY and Arcadia, CA respectively.

Figure 13. Study Area

Source: Google Map



7.2 Data Preparation

Arcadia, CA and Manhattan, NY roadway networks have been drawn in TransModeler. Different roadway features such as speed limit, intersection geometries, and lane use etc. are obtained from Google map, and then incorporated into the simulation networks.

7.2.1 Arcadia, CA

Traffic detector data from 31 intersections have been collected and processed to prepare turning movement count (TMC). TMC can be utilized directly into the TransModeler as its input. Intersections in Arcadia have either stop-line detector only or both stop-line and advanced detectors in place. If precise TMC wasn't found or inferred for each approach, total volume has been divided into left turn, through traffic, and right turn volume when the downstream has three directional movements. The division was roughly based on a ratio of 15%, 70%, and 15% of the total volume, respectively. However, engineering judgement-based different ratios were used in some cases where the default ratios seemed to be unrealistic or the downstream had three directional movements. Moreover, missing data was extrapolated from two adjacent intersections. Thus, TMC data for 33 intersections was generated from the available 31 intersections' detector data.

TransModeler generates O-D matrix from the turning volume and uses it as simulation input matrix. Due to limited data availability, unsignalized intersections were mostly removed from the network. It is assumed that the removal of unsignalized intersections hardly plays any role in the efficacy of eco-drive algorithm testing. The study routes are the major roads with stop control to most unsignalized side streets. Therefore, negligible traffic is expected to enter and leave the corridor from these side streets.

Fifteen-minute interval data was used to replicate the actual stochasticity of traffic volume into the simulation environment. Actual signal configurations and detector locations from the field have been collected and coded into the network. Thus, maximum precision has been maintained while replicating the field condition. The study period includes three different time settings, each of them three hours: morning/AM Peak (6 a.m.–9 a.m.), off-peak/midday (9 a.m.–12 p.m.), and evening/PM peak (3:30 p.m.–6:30 p.m.).

7.2.2 Manhattan, NY

TMC data has been collected from NYSDOT Traffic Incident Management System (TIMS). As was the process in Arcadia, missing data has been extrapolated based on TMCs or automatic traffic recorder (ATR) counts of adjacent intersections in Manhattan. The analysis period (AM Peak, Midday, and PM Peak) and traffic data interval (15 mins) also remained same as Arcadia. The analysis time settings have been changed due to the different dynamics of Manhattan. Analyzed morning peak, off-peak, evening peak are set to be 7 a.m.–10 a.m., 11a.m.–2 p.m., and 4:00 p.m.–7:00 p.m., respectively.

7.3 Eco-drive Plugin Development

The eco-driving application was developed in C# programming language, and a compiled DLL (ECO-DLL) loaded into TransModeler to integrate and apply the eco-driving strategies into the simulator. The ECO-DLL receives SPaT messages from a separate SPAT-DLL which is developed independently using Delphi programming language. SPAT-DLL deals with the controller logic and predicts the signal timing of an intersection. To get the signal timing info of a specific vehicle, ECO-DLL calls a method defined as *GetCvSPaTInfo()*. SPAT-DLL then figures out the nearest intersection that the vehicle will pass through and the phase it will be served. Thus, it gets back to the ECO-DLL with the corresponding signal timing information.

The plugin has configurable user parameters such as:

- DSRC range (i.e., eco-driving enabler) which defines the plugin activation distance from the nearest intersection
- DSRC interval which defines the DSRC message transection interval
- CV vehicle class index which gives a user flexibility to design a custom vehicle class and use that class or classes as CV
- Two operating modes—Connected and Automated Vehicle. In automated vehicle mode, the plugin controls vehicles' acceleration instead of desired speed. Unfortunately, controlling the desired speed provides TransModeler much freedom to override the eco-driving application's decision. Therefore, the plugin was operated in Automated Vehicle mode which essentially replaced the simulator's default car following model for time being only.
- δv to allow vehicle's maximum cruising speed above speed limit ($v_{max} = v_{speed\ limit} + \delta v$)
- v_{min} to set the minimum eco-friendly speed
- Eco-friendly max acceleration and deceleration
- Perception reaction time for both CV and non-CV
- Enable test mode and set test mode speed to check if the module works properly. If the test mode is enabled and a test speed is set, all the vehicles in the network will have same speed which verifies the successful loading of the plugin.

The plugin instantiates TransModeler interface (TSM) and subscribes necessary event (simulation and vehicle events) in its constructor. Based on the subscribed vehicle events, it stores and removes the ID of a connected vehicle once the vehicle enters and leaves the network respectively. For each of the stored CV vehicles, the plugin estimates the optimal speed and updates at every 0.1 simulation second. Although the implemented algorithm considers queue length to estimate the advisory speed, TransModeler API doesn't have any direct support to get a queue length a vehicle may experience. Hence, a complex queue estimator module was introduced to overcome the limitations of TransModeler API. Since a vehicle's next turn lane is not available in its path info (in TransModeler), the next turn lane for a desired turn was determined in real time by mapping current links, lanes and next links of all the vehicles. Then, the first vehicle of the turn segment was detected, and the following recursive methods were used to determine the number of queued vehicles:

Figure 14. Sample Code Snippets

```
// Estimate the number of vehicles in Queue including Q length
private int VehiclesInQueueLength(TsmVehicle pVehicle, int laneId, bool metric)
{
    if (pVehicle.Back is TsmVehicle pBackVeh)
    {
        if (pBackVeh.Lane.id == laneId)
            return (pBackVeh.Speed < 5) ? 1 + VehiclesInQueueLength(pBackVeh, pBackVeh.Length, true, metric) :
                VehiclesInQueueLength(pBackVeh, 0f, false, metric);
        else
            return VehiclesInQueueLength(pBackVeh, laneId, metric);
    }
    else
        return 0;
}


private int VehiclesInQueueLength(TsmVehicle pVehicle, float length, bool Q, bool metric)
{
    if (pVehicle.Follower is TsmVehicle pFollower)
    {
        if (pFollower.Speed < 5)
        {
            length = length + ((length > 0) ? (metric? 3: 10) : 0) + pFollower.Length;
            _config.QueueLength = length;
            return 1 + VehiclesInQueueLength(pFollower, length, true, metric);
        }
        else
            return Q ? 0 : VehiclesInQueueLength(pFollower, length, false, metric);
    }
    else
        return 0;
}
```

7.4 Simulation Settings

To measure the effectiveness of the eco-drive algorithm, a before and after comparison needs to be done for each scenario. Considering signal timing plans and traffic patterns, the study consists of three different scenarios—AM Peak, PM peak, and Midday—for each of two different signal controller settings—conventional (i.e., actuated or fixed time control) and adaptive. Before considering the penetration rate of connected vehicle (CV), the study comprises a total of twelve different scenarios by running each of these six scenarios in two settings—with and without eco-drive plugin. Moreover, each of these twelve cases has been iterated five times, based on CV penetration rates (10%, 30%, 50%, 80%, and 100%). Hence, the study comprises a total of sixty different scenarios/cases. Since each of AM Peak, PM peak, and Midday scenarios are three hours long, a single iteration for each scenario/case provides a total of 180 hours of simulation for each study area. The excessive computation associated with CMEM emission model and the eco-drive plugin has reduced the simulation speed significantly. Considering the vast amount of time to finish running the simulation and post processing the data, a fixed seeding approach has been adopted in this study. Theoretically, a fixed seeding approach re-generates same outputs, that is, vehicle trajectories for multiple runs in same settings. Instead of multiple iterations, exactly two iterations—with and without eco-drive plugin—have been performed using the fixed seeds with exactly same simulation settings to ensure an apple to apple comparison. A brief discussion of other relevant settings for each simulation/scenario has been cited in the following sections.

7.4.1 Project Settings

Default 0.1 sec state step size was used in the TransModeler and the eco-drive plugin to control the vehicles. Different scenarios are summarized below:

- Three major scenarios based on signal timing plans are—AM Peak, PM peak, and Midday.
- Traffic signal controller type-based scenarios/iterations are conventional and adaptive.
- CV penetration rate-based cases are 10%, 30%, 50%, 80%, and 100% to study the sensitivity of CV penetration rate in terms of emission while using eco-drive application.
- With and without eco-drive plugin for comparison purpose.

7.4.2 Vehicle Classification

In general, a traffic simulator requires to classify the vehicles in terms of their physical appearance such as size, shape etc., and mechanical characteristics such as power/weight ratio etc. The study utilizes the default vehicle classes of TransModeler and prepares the distribution of different vehicle classes for Arcadia, CA based on the distribution provided in CMEM user guide (Scora and Barth 2006) and another work[6] done for the California Department of Transportation. Assuming the similarity in terms of traffic characteristics in Arcadia and Riverside urban area, these statistics were utilized to interpolate the following distribution:

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6 Final report on Modeling the Effectiveness of High Occupancy Vehicle (HOV) Lanes at Improving Air Quality, prepared for California Department of Transportation, Project PS-06, Contract Number: RTS 65A0196 (December 2006).

Table 6. Distribution of Vehicle Classes in Arcadia, CA

Class	Description	Percentage (%)
PC1	High Performance Passenger Cars	12
PC2	Middle Performance Passenger Cars	18
PC3	Low Performance Passenger Cars	24
PU	Pickup Trucks, Van and SUVs	40
ST	Single-unit Trucks	2.2
TT	Trailer Trucks	1.3
B	Buses	0.3
M	Motorcycles	2.2
Total		100

These eight classes have been extended to fourteen classes to accommodate connected vehicles and CMEM emission types in the most reasonable way. The updated classification is provided in the next section.

Vehicle classification of Manhattan, NY has been carried out based on TMC classification data and engineering judgement. TMC has higher level classification of vehicles such as car, truck, buses etc. However, it doesn't classify the cars based on size/shape or emission patterns. TMC's vehicle classification and engineering judgment-based distribution of vehicle classes are listed in the table below:

Table 7. Distribution of Vehicle Classes in Manhattan, NY

Class	Description	Percentage (%)
PC1	High Performance Passenger Cars	15
PC2	Middle Performance Passenger Cars	18
PC3	Low Performance Passenger Cars	20
PU	Pickup Trucks, Van and SUVs	35
ST	Single-unit Trucks	4
TT	Trailer Trucks	1
B	Buses	5
M	Motorcycles	2
Total		100

7.4.3 CMEM Configurations

CMEM requires the vehicles to be classified based on their emission characteristics. It supports more than 30 different classes for cars and light duty trucks mostly to reflect the actual emission nature of a vehicle fleet as close as possible. The study has adopted the CMEM default values—80 and 75—for soak time and humidity parameters respectively. The following table shows the mapping of different TransModeler vehicle classes to the CMEM emission category in this study:

Table 8. Mapping between TransModeler and CMEM Vehicle Classes

TransModeler Vehicle Class	Vehicle Class Description	CMEM Emission Category
PC1	High Performance Passenger Cars	Ultra-Low Emission Vehicle (ULEV)
PC2	Middle Performance Passenger Cars	Tier 1, >50K miles, low power/weight
PC3	Middle Performance Passenger Cars	Tier 1, >50K miles, high power/weight
PC4	Low Performance Passenger Cars	3-way Catalyst, FI, >50K miles, high power/weight
PU	Pickup Trucks, Van and SUVs	Tier 1 LDT2/3 (3751-5750 LVW or Alt. LVW)
ST	Single-unit Trucks	Excluded
TT	Trailer Trucks	Excluded
B	Buses	Excluded
M	Motorcycles	Excluded
CV PC1	Connected High Performance Passenger Cars	Ultra-Low Emission Vehicle (ULEV)
CV PC2	Connected Mid Performance Passenger Cars	Tier 1, >50K miles, low power/weight
CV PC3	Connected Mid Performance Passenger Cars	Tier 1, >50K miles, high power/weight
CV PC4	Connected Low Performance Passenger Cars	3-way Catalyst, FI, >50K miles, high power/weight
CV PU	Connected Pickup Trucks, Van and SUVs	Tier 1 LDT2/3 (3751-5750 LVW or Alt. LVW)

7.5 Results and Analysis

In following sub-sections, simulation results are explained separately for conventional and adaptive signal control system. Each system contains results of different CV penetration rates (10%, 30%, 50%, 80%, and 100%). The results answer the following two key questions for connected vehicles, regular vehicles, and both, that is, overall:

- What type of effect—positive, negative, or neutral—does the eco-drive application have on CVs, regular vehicles, and overall in terms of emission and fuel consumptions?
- Is the eco-drive application sensitive to the penetration rate of CVs?

The study includes two different types of signal systems: conventional and adaptive. Conventional signal control system (conventional TSCS) includes all types of non-adaptive signal control systems. The eco-drive application has been tested with two different signal control systems—actuated and fixed time—for two selected study areas—Arcadia, CA and Manhattan, NY respectively. The effects of the eco-drive application on the traffic network with coordinated actuated signals in Arcadia, CA and fixed time signals in Manhattan, NY have been interpreted from the perspective of two broad vehicular categories— connected and regular passenger cars. Therefore, the results are summarized as (a) effects on connected vehicles, (b) effects on regular vehicles, and (c) overall effects. The same classifications of the results have also been maintained for adaptive traffic signal control systems (adaptive TSCS). The following sections include detailed results.

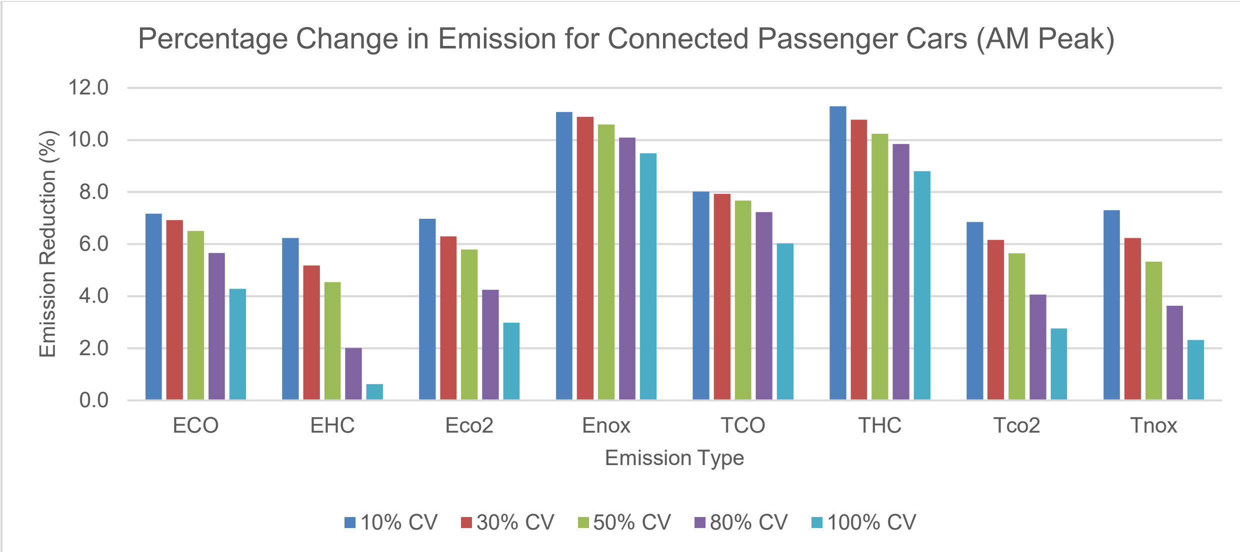
7.5.1 Conventional Traffic Signal Control System in Arcadia, CA

The following figures represent the percentage change in different types of emissions considering connected passenger cars/pickup and trucks/SUVs (CV) at different CV penetration levels. ECO, EHC, Eco2, and Enox represent engine carbon-monoxide, engine hydro-carbons, engine carbon-dioxide, and engine nitrogen-oxide, respectively. In addition, TCO, THC, Tco2, and Tnox represent the same types of tailpipe emission rather engine emission.

7.5.1.1 Effects on Connected Passenger Cars in Arcadia, CA

In AM Peak, effects of conventional traffic signal control system (TSCS) on connected passenger cars in Arcadia, CA are presented in the following graph.

Figure 15. Emission Effects on CV in Arcadia, CA (AM Peak/Conventional TSCS)



In the figure above, reduction in emissions lessen, that is, emissions increase with the increase in CV penetration rate in the AM Peak. Similarly, Midday (shown in the Figure 16) continues the same trend with less randomness such as less emission (i.e., more reduction in emission) at 50% penetration rate. In PM peak, more randomness has been observed. Hence, in PM peak, up to 50% penetration rate provides seemingly reasonable reduction in emission. To conclude, 30–50% CV penetration rate in Arcadia, CA shows a stable and reasonable improvement in reducing the emissions. However, fuel consumptions and network volumes are yet to be considered before drawing a more concrete conclusion.

Figure 16. Emission Effects on CV in Arcadia, CA (Midday/Conventional TSCS)

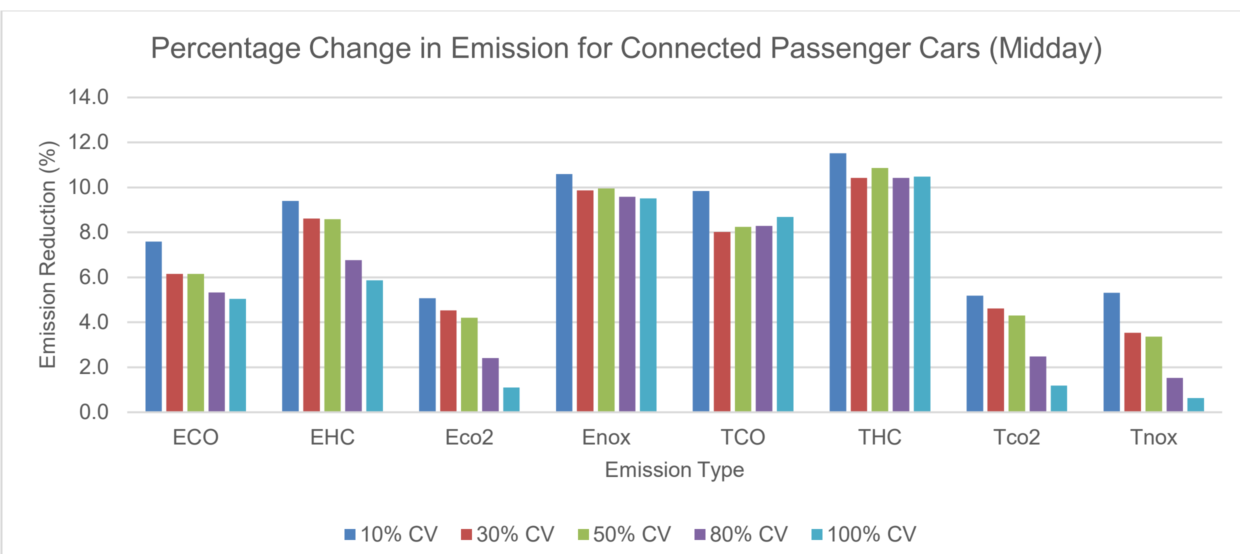
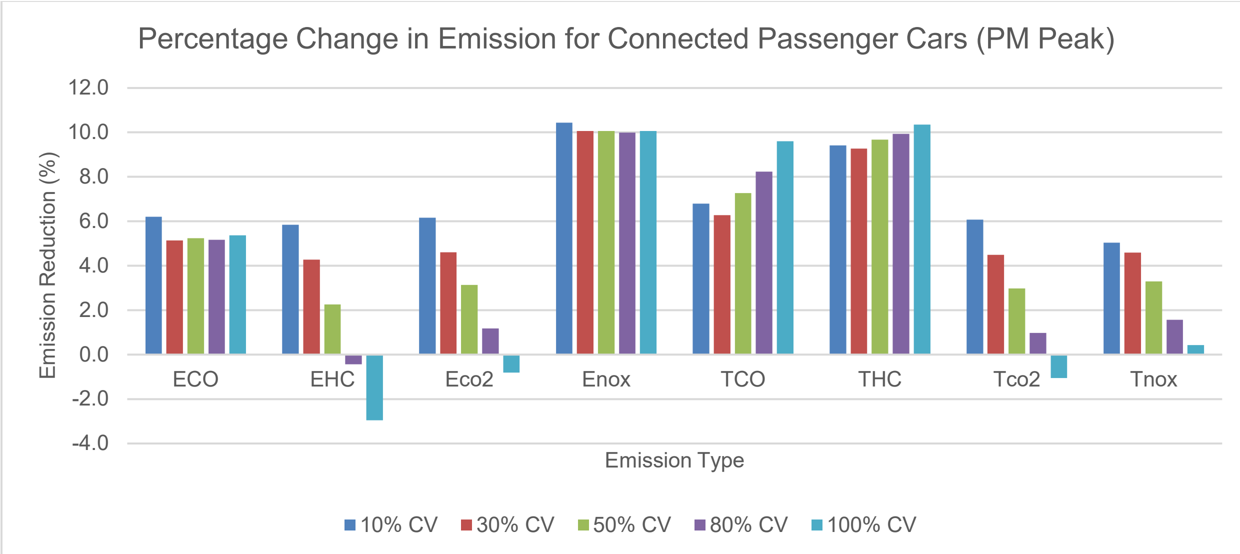
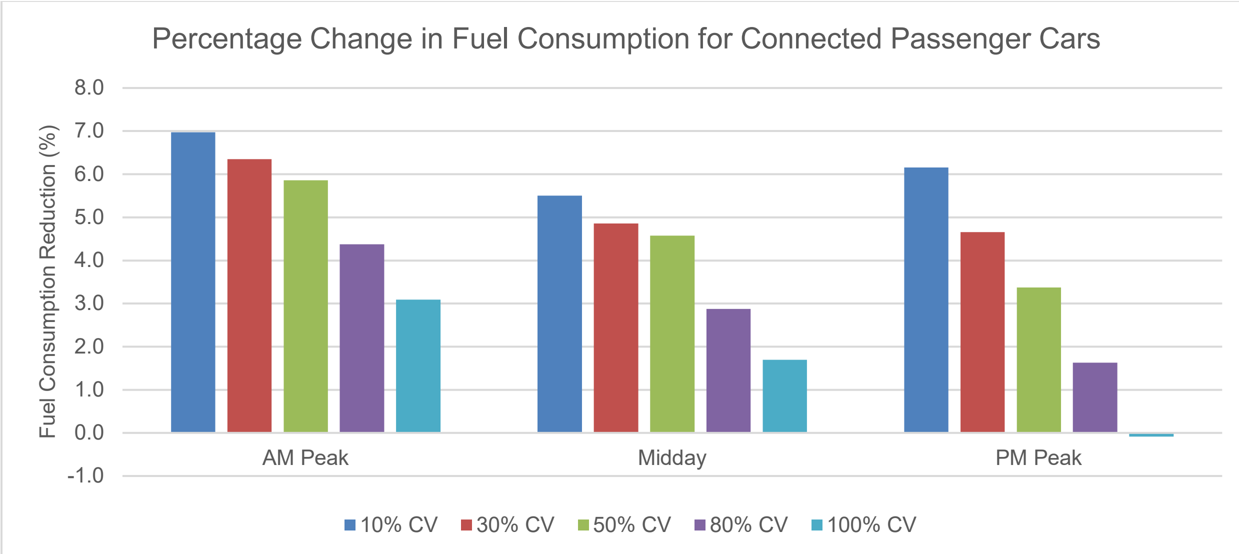


Figure 17. Emission Effects on CV in Arcadia, CA (PM Peak/Conventional TSCS)



The following figure summarizes the fuel consumption reduction for connected passenger cars. It shows that the reduction in fuel consumption decreases gradually with the increase of CV penetration rate. Eventually, fuel consumption has increased in the PM Peak when penetration rate is 100%. Further investigation reveals an interesting finding that such randomness could possibly be the results of higher/saturated traffic flow rate. It is observed that the total traffic network volume is much higher in PM Peak than AM Peak. Compared to AM Peak, traffic volumes are 15% and 57% higher in midday and PM peak respectively. Therefore, it won't be erroneous to infer that the traffic volume, that is. flow rate has a significant effect on the efficacy of the eco-drive application. Intuitively, in a saturated condition, it would be hard to follow the instructions of the eco-drive application when gap is unavailable.

Figure 18. Fuel Consumption Effects on CV in Arcadia, CA (Conventional TSCS)



Overall, 50% penetration rate is a good threshold where the reduction in emission and fuel consumption is relatively higher for connected vehicles.

7.5.1.2 Effects on Regular Passenger Cars in Arcadia, CA

The following figures represent the percentage change in different types of emission considering regular passenger cars/pickup trucks/SUVs at different CV penetration level. Contrary to the previous findings, the eco-drive application has negatively affected the regular vehicles while it controls CVs. The emission increases with the increase of CVs and it becomes severely high at 80% penetration rate.

Figure 19. Emission Effects on Regular Cars in Arcadia, CA (AM Peak/Conventional TSCS)

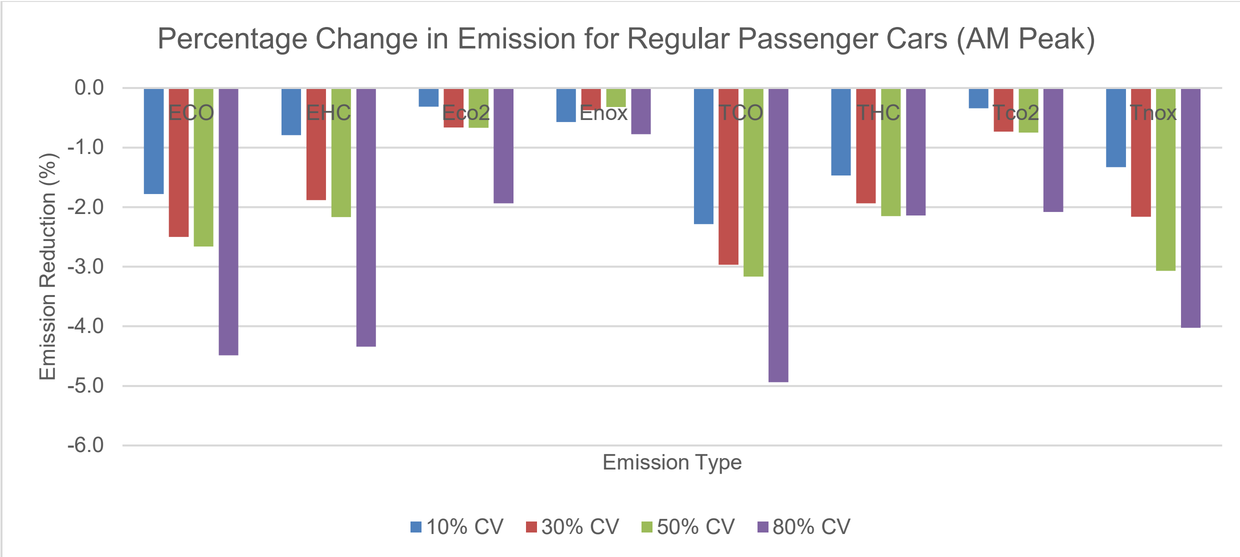


Figure 20. Emission Effects on Regular Cars in Arcadia, CA (Midday/Conventional TSCS)

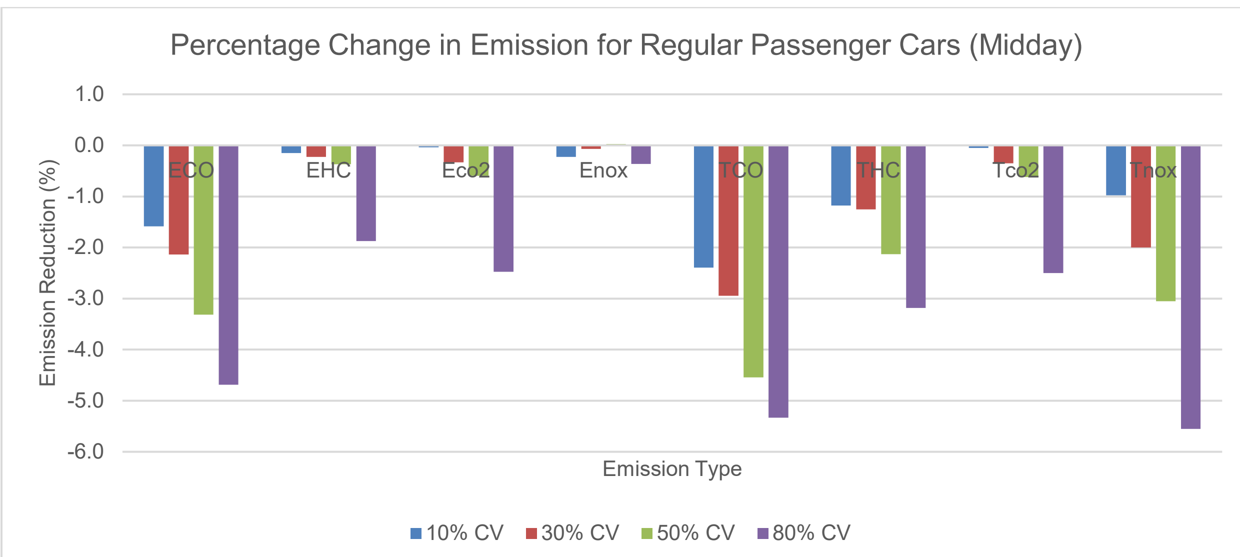
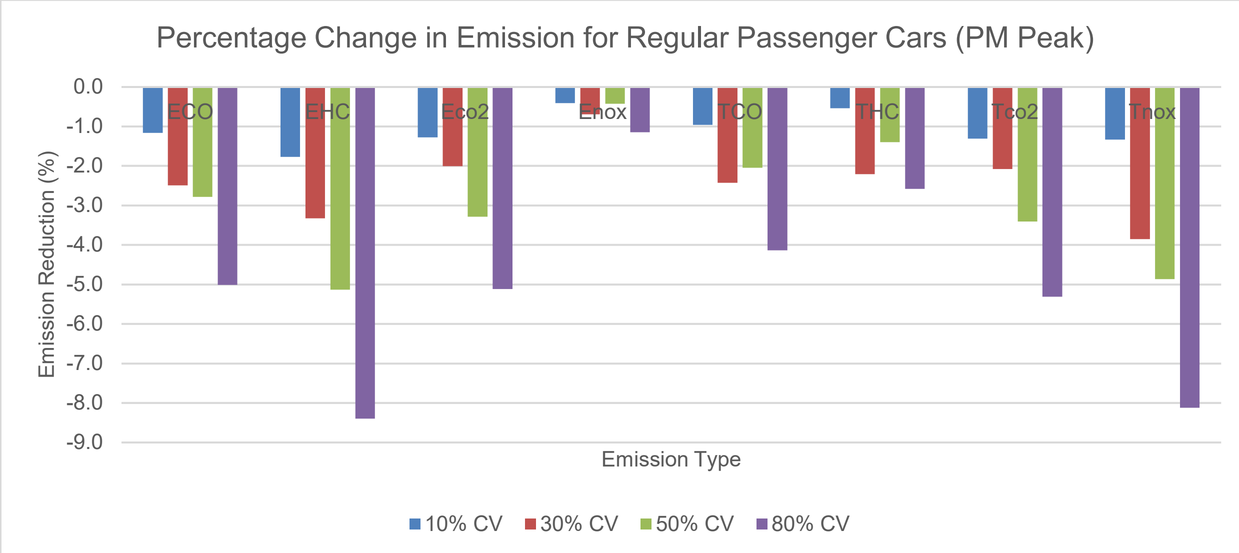
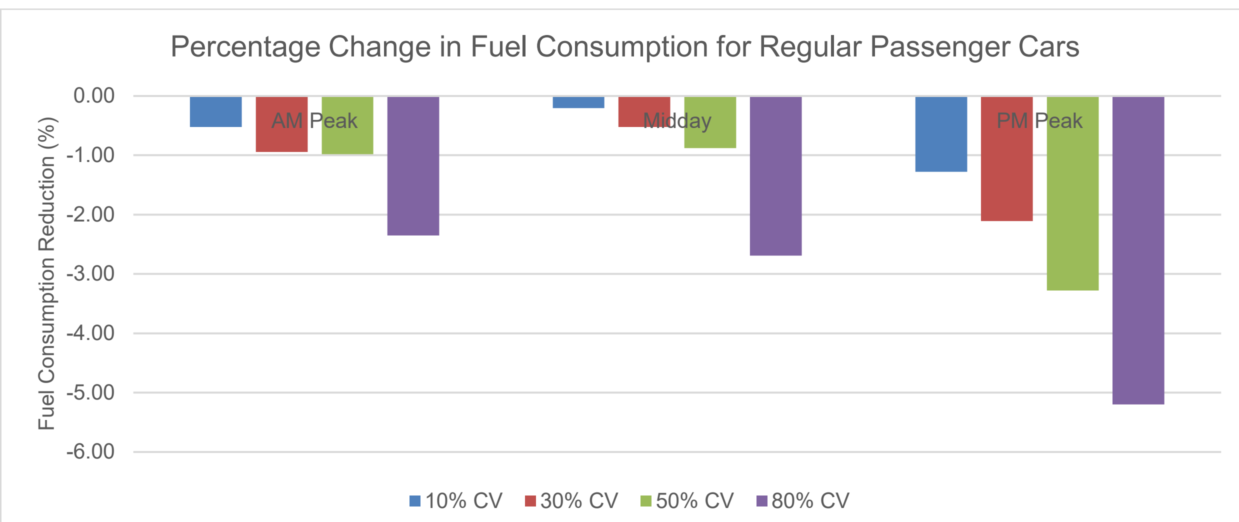


Figure 21. Emission Effects on Regular Cars in Arcadia, CA (PM Peak/Conventional TSCS)



The following chart shows that up to 50% penetration rate of CVs in the vehicle fleet provides relatively less increase in fuel consumption of regular vehicles.

Figure 22. Fuel Consumption Effects on Regular Cars in Arcadia, CA (Conventional TSCS)

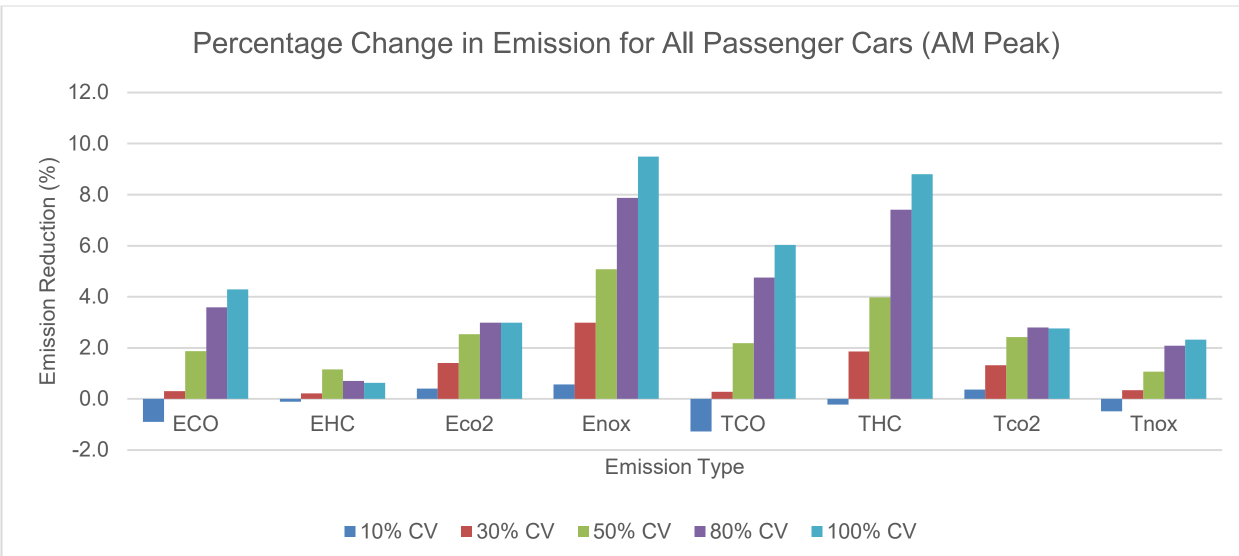


Overall, 50% penetration rate is a good threshold where the increase in emission and fuel consumption is relatively lower for regular vehicles.

7.5.1.3 Overall Effects on All Passenger Cars in Arcadia, CA

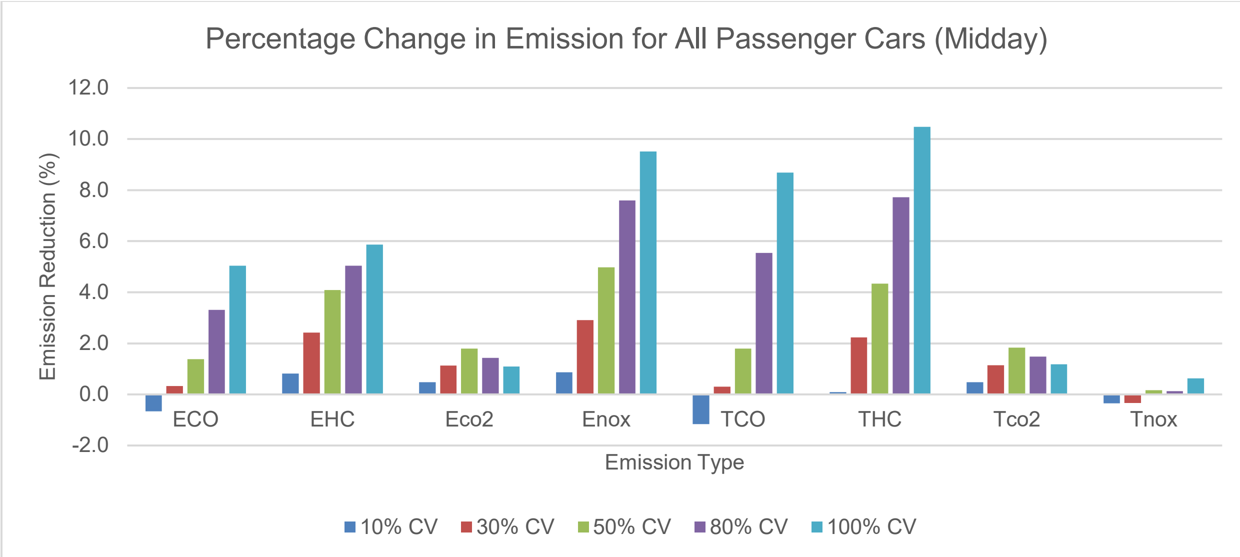
The following figures represent the percentage change in different types of emission considering all the cars at different CV penetration level. Overall effects on all passenger cars in Arcadia, CA exhibit gradual increase in reduction of emission with the penetration rate of CVs in case of AM Peak and Midday. In AM Peak, there is not much difference in terms of emission reduction between 80% and 100% penetration rate of CVs. Therefore, traffic flow pattern of AM Peak would perform better at 80% penetration rate.

Figure 23. Overall Emission Effects in Arcadia, CA (AM Peak/Conventional TSCS)



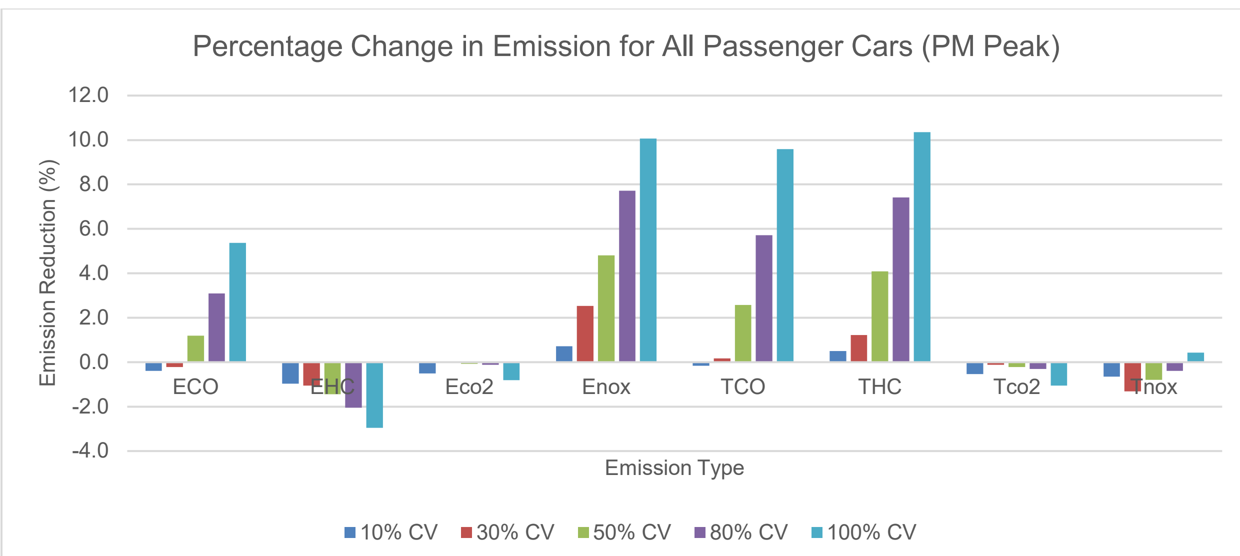
In Midday, 100% penetration rate scenario shows better performance by pushing the 80% penetration rate case in second place.

Figure 24. Overall Emission Effects in Arcadia, CA (Midday/Conventional TSCS)



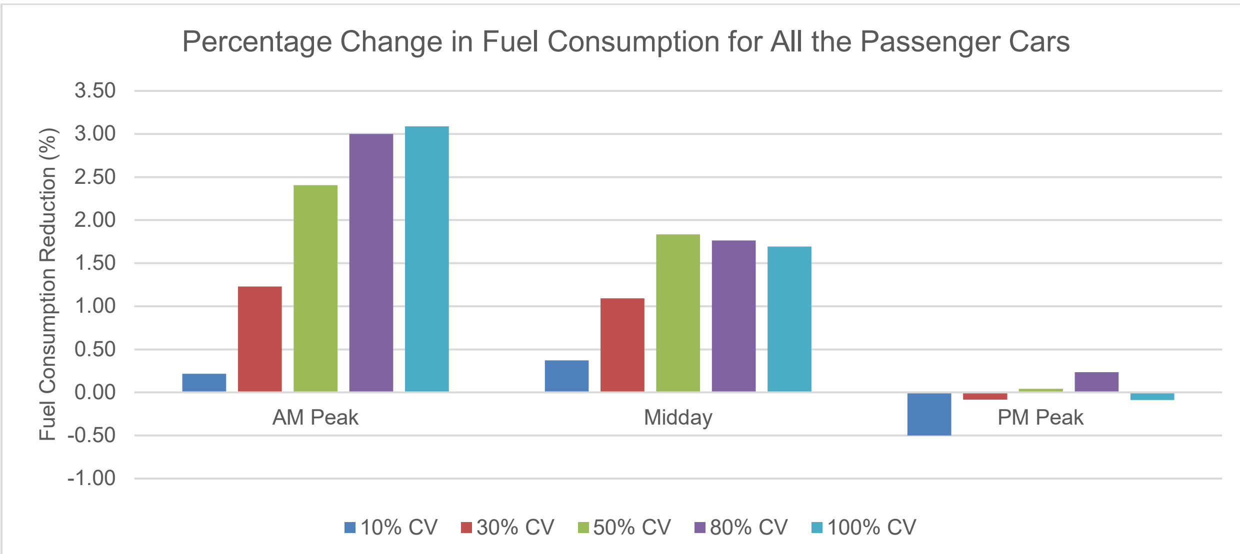
Due to the higher traffic flow rate in PM Peak, performance is somewhat random. It shows an increase in some emission types and decrease in others. Seemingly, 80% penetration rate increases emission at a lower rate and decreases emission at a relatively higher rate.

Figure 25. Overall Emission Effects in Arcadia, CA (PM Peak/Conventional TSCS)



The following figure shows the fuel consumption for all the passenger cars, indicating that the 50% or more CV penetration rate provides better fuel economy in AM Peak and Midday. It also indicates that the sensitivity reduces once 50% CV penetration level is reached. Although the PM Peak remains unpredictable due to the higher flow rate, it shows a significant reduction in fuel consumption at 80% penetration rate.

Figure 26. Overall Effects on Fuel Consumption in Arcadia, CA (Conventional TSCS)



7.5.2 Adaptive Signal Control System in Arcadia, CA

Adaptive signal control system is a traffic management strategy in which traffic signal timing changes, or adapts, based on actual traffic demand. Unlike conventional signal systems that use pre-programmed daily signal timing schedules, adaptive signal control technology adjusts the timing of red, yellow, and green lights to accommodate changing traffic patterns and ease traffic congestion. According to FHWA website,[7] the main benefits of adaptive signal control technology over conventional signal systems include the following:

- Continuously distribute green light time equitably for all traffic movements.
- Improve travel time reliability by progressively moving vehicles through green lights.
- Reduce congestion by creating smoother flow.
- Prolong the effectiveness of traffic signal timing.

7 https://www.fhwa.dot.gov/innovation/everydaycounts/edc-1/asct.cfm

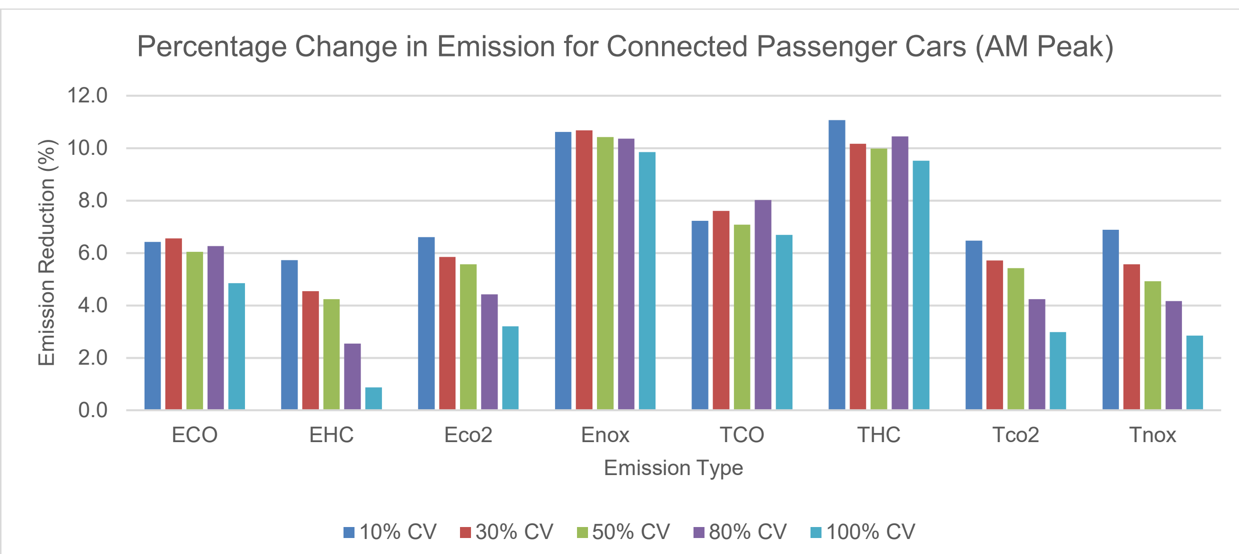
The real-time adjustment of signal timing is performed either at every second or at each cycle. It rescinds the green time from one approach and provides the green time to another approach as needed. Consequently, SPaT prediction becomes volatile for any adaptive signal control system. Incorporating this volatility in SPaT message is an alternate of designing and implementing adaptive controller in a simulation environment. Hence, this study has adopted a statistical approach to mimic the uncertainty of adaptive signal control system and incorporated it into SPaT messages.

Results from the adaptive signal control system have also been subdivided into (a) effects on connected vehicles, (b) effects on regular vehicles, and (c) overall effects. The following sections describe the findings in detail.

7.5.2.1 Effects on Connected Passenger Cars in Arcadia, CA

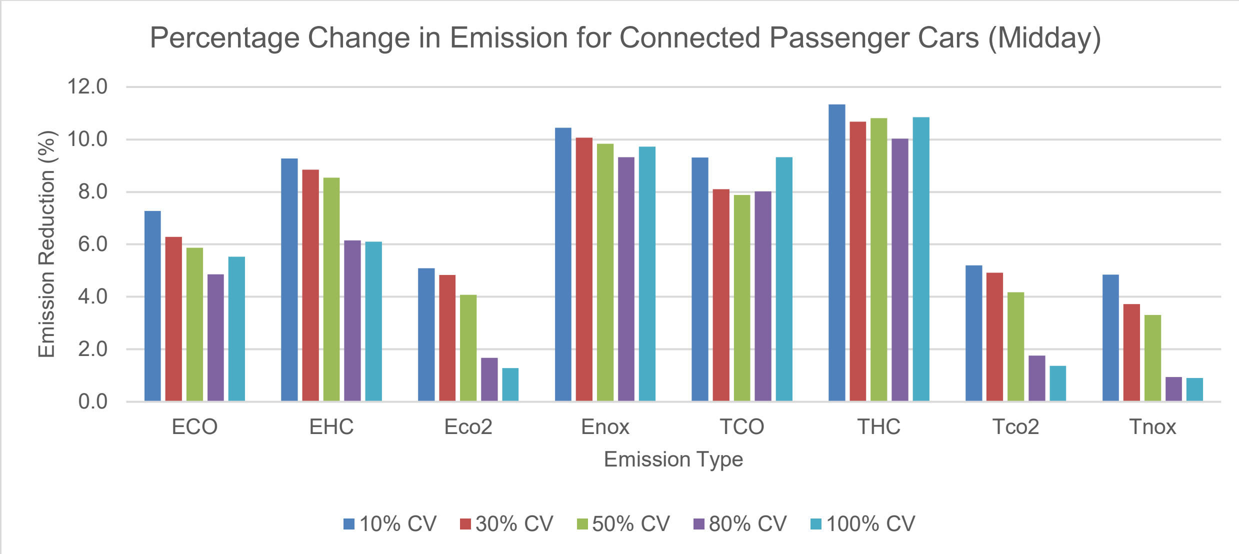
The eco-driving application shows mostly similar performance in both conventional and adaptive signal control system. Similar to the results of actuated coordinated system in Arcadia, CA, adaptive system shows significant fuel savings and less emissions in AM Peak and Midday. In addition, PM Peak shows somewhat variable results as indicated previously. Up to 80% penetration rate of CVs, AM Peak traffic has continued significant reduction in different emissions of connected passenger cars:

Figure 27. Emission Effects on CV in Arcadia, CA (AM Peak/Adaptive TSCS)



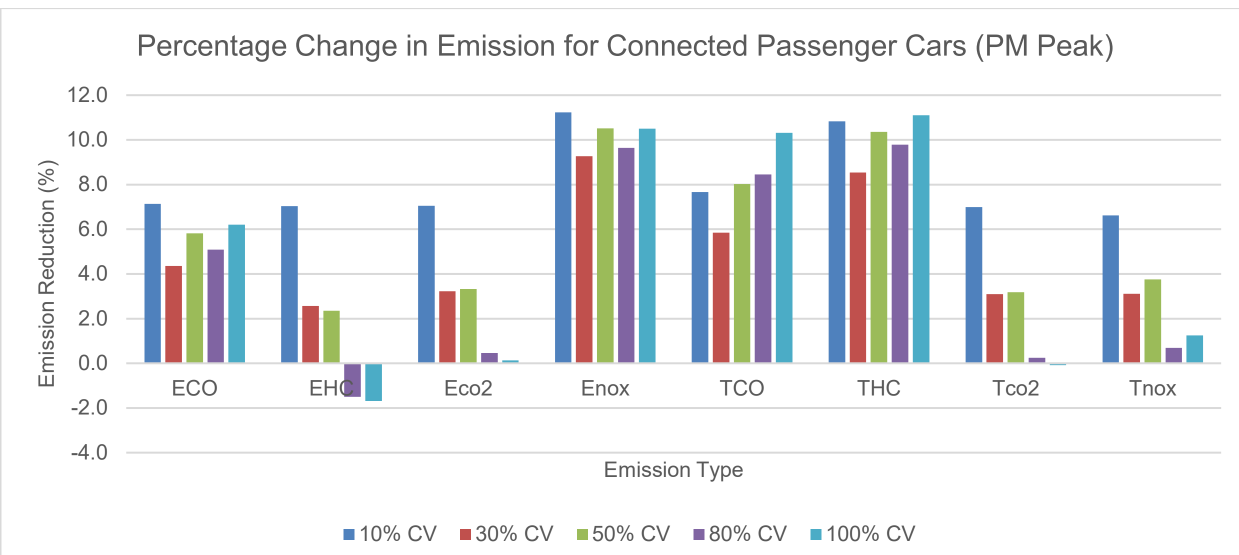
In Midday, the superior performance in terms of emission reduction has continued up to 50% penetration rate of CVs.

Figure 28. Emission Effects on CV in Arcadia, CA (Midday/Adaptive TSCS)



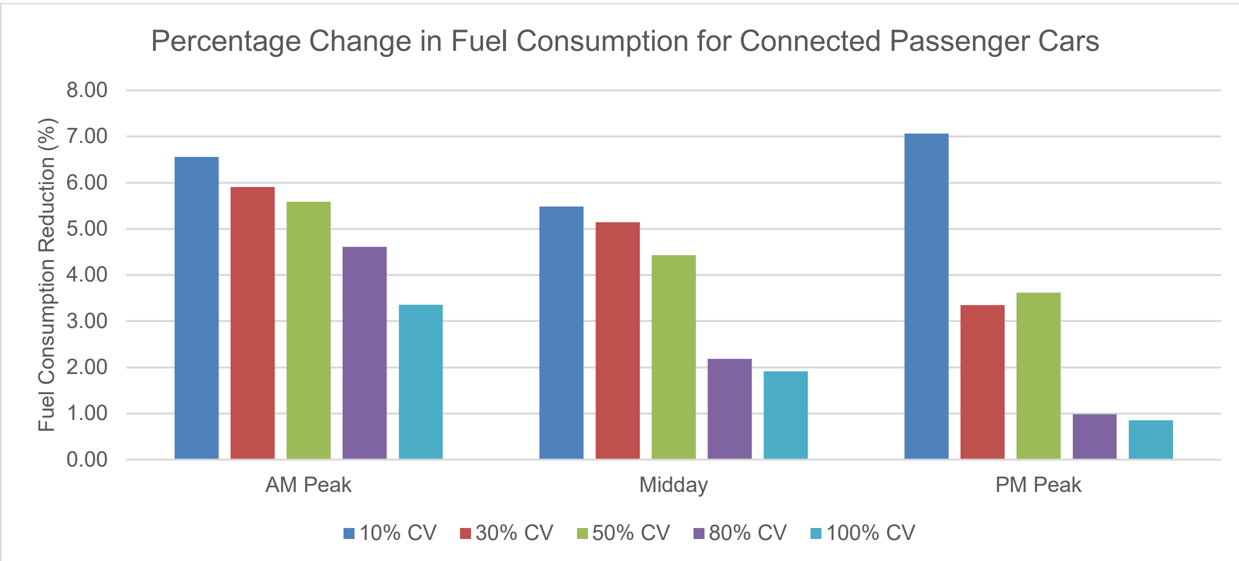
As in the case of a conventional traffic signal control system, the performance trend in an adaptive system is somewhat inconsistent for PM Peak when the traffic volume is nearly 60% higher than that of AM Peak. However, a consistent reduction in emission for all different emission types has been observed up to 50% penetration rate of CVs.

Figure 29. Emission Effects on CV in Arcadia, CA (PM Peak/Adaptive TSCS)



In AM Peak, fuel consumption reduction follows a consistent downward trend among connected passenger cars. However, 80% and 100% penetration rates do not show much difference in percentage change in fuel consumption rate. Moreover, it seems that the 50% penetration rate shows higher reduction in fuel consumption in all scenarios including saturated PM Peak.

Figure 30. Fuel Consumption Effects on CV in Arcadia, CA (Adaptive TSCS)



Therefore, 50% penetration rate can be considered as a good threshold where the reduction in emission and fuel consumption is consistently higher regardless of the time of day (i.e., AM Peak, PM Peak, and Midday) for connected vehicles.

7.5.2.2 Effects on Regular Passenger Cars in Arcadia, CA

As with a conventional traffic signal control system, adaptive system also shows increase in emissions for regular passenger cars when CVs uses eco-drive application. The increment in emissions varies with the penetration rate of CVs. Regardless of the time of day, emission increases gradually with less variation between 30% and 50% penetration rates of CVs, and maximum emission at 80% penetration rate.

Figure 31. Emission Effects on Regular Cars in Arcadia, CA (AM Peak/Adaptive TSCS)

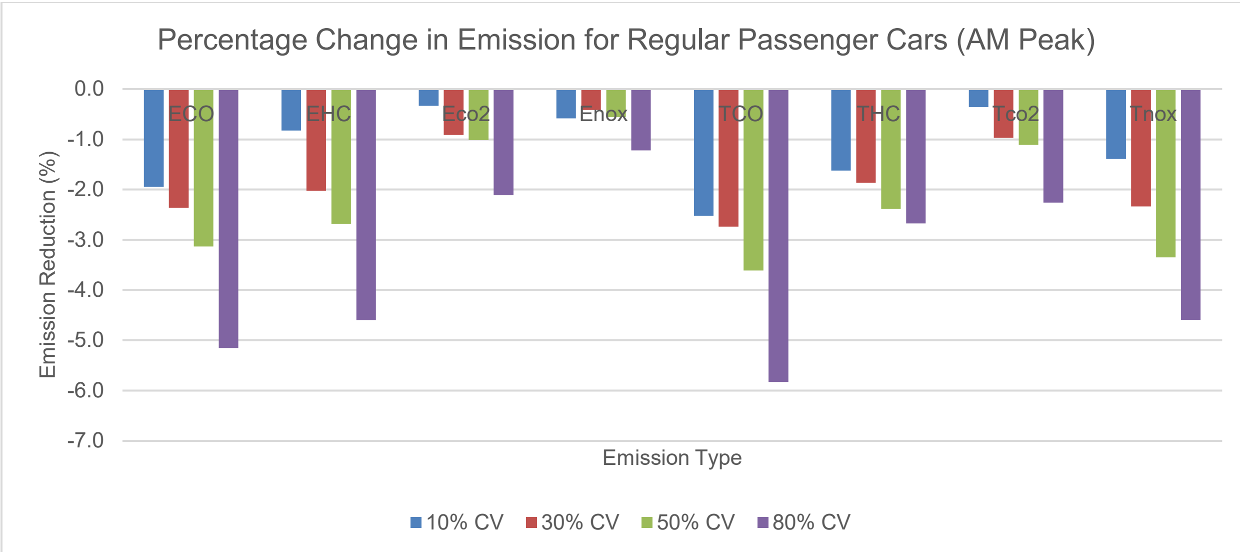


Figure 32. Emission Effects on Regular Cars in Arcadia, CA (Midday/Adaptive TSCS)

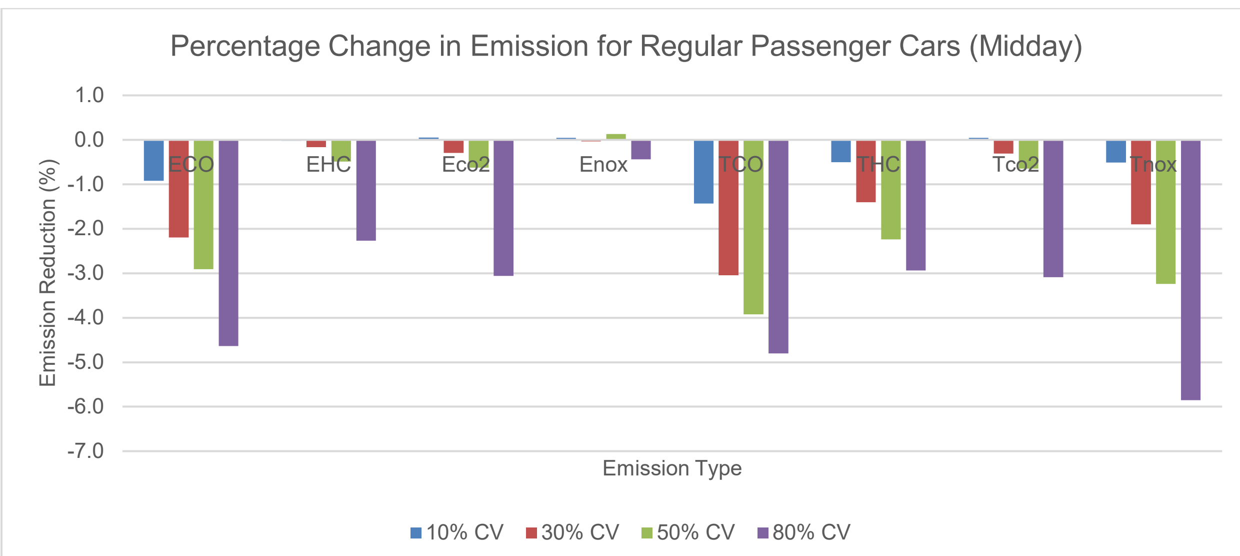
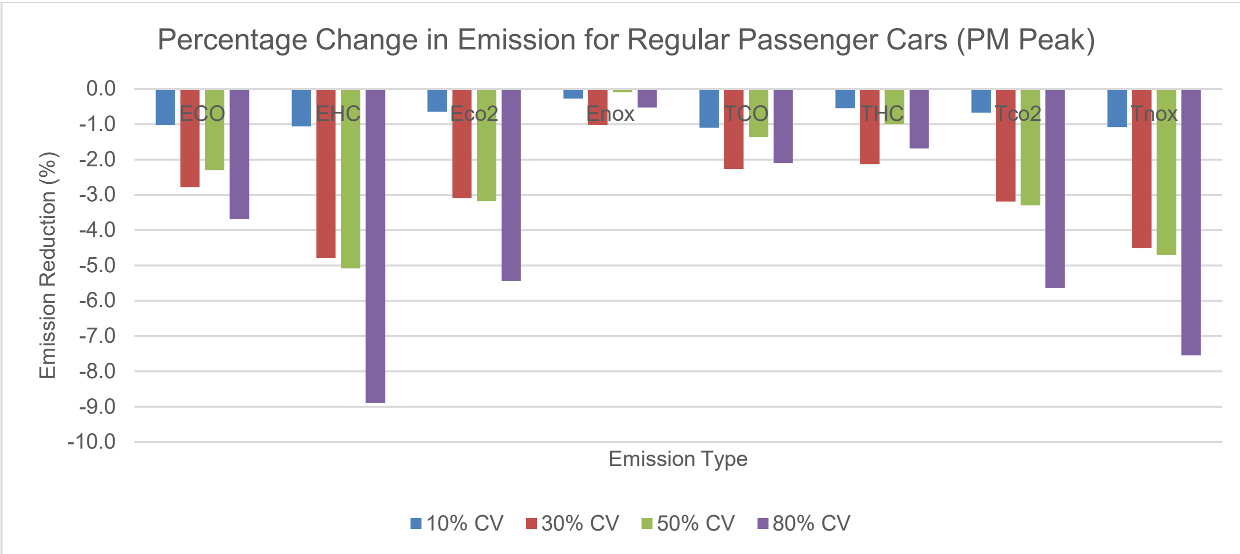
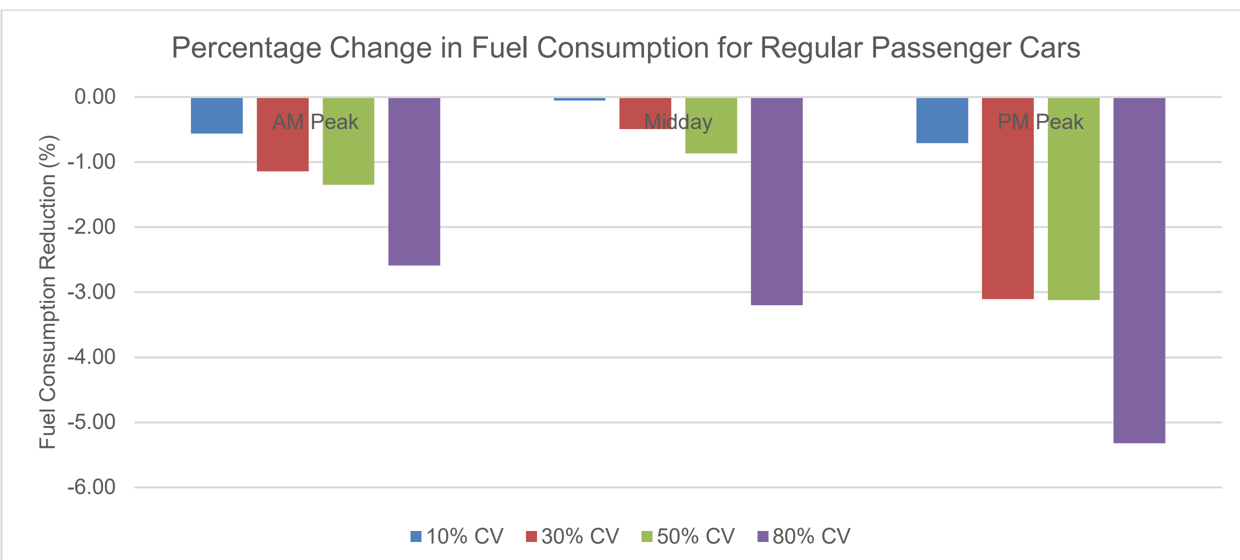


Figure 33. Emission Effects on Regular Cars in Arcadia, CA (PM Peak/Adaptive TSCS)



Again, 30% and 50% penetration rates come close to fuel consumption rates for regular passenger cars regardless of the time of day.

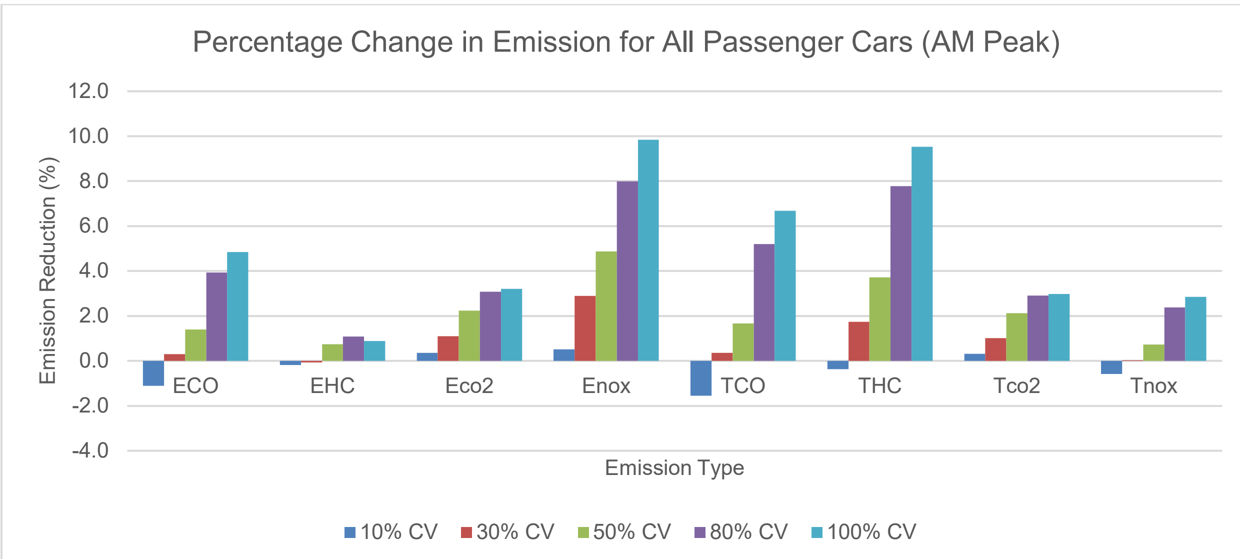
Figure 34. Fuel Consumption Effects on Regular Cars in Arcadia, CA (Adaptive TSCS)



7.5.2.3 Overall Effects on All Passenger Cars in Arcadia, CA

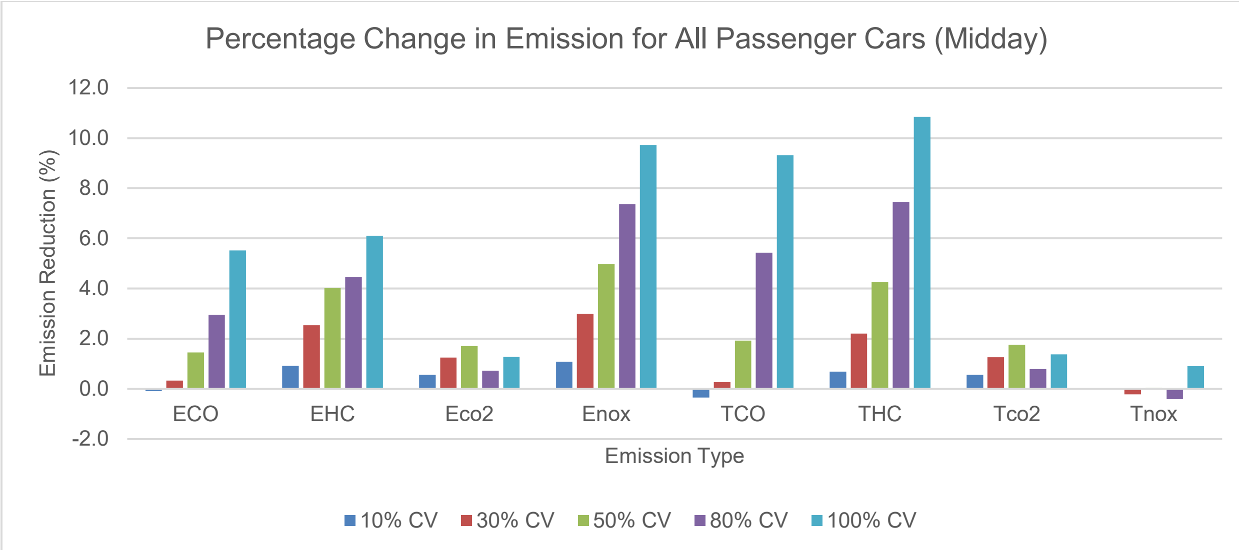
In case of overall (i.e., all passenger cars) performance, emissions in AM Peak have reduced when the CV penetration rate is 30% or higher. Reduction rate shows increasing trend with more sensitivity toward 50% to 80% penetration rate.

Figure 35. Overall Emission Effects in Arcadia, CA (AM Peak/Adaptive TSCS)



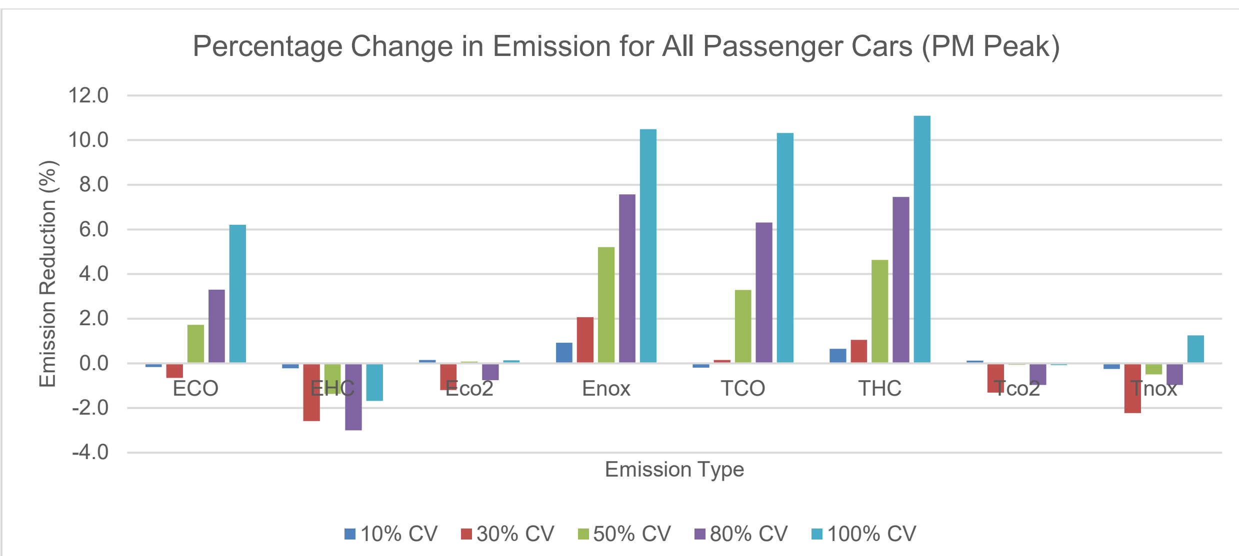
As with AM Peak, emissions in midday have reduced for all different emission types except tailpipe nitrogen oxides when the penetration rate is 30% or higher. However, 50% and 100% penetration rates show consistent reduction in emissions for all emission types.

Figure 36. Overall Emission Effects in Arcadia, CA (Midday/Adaptive TSCS)



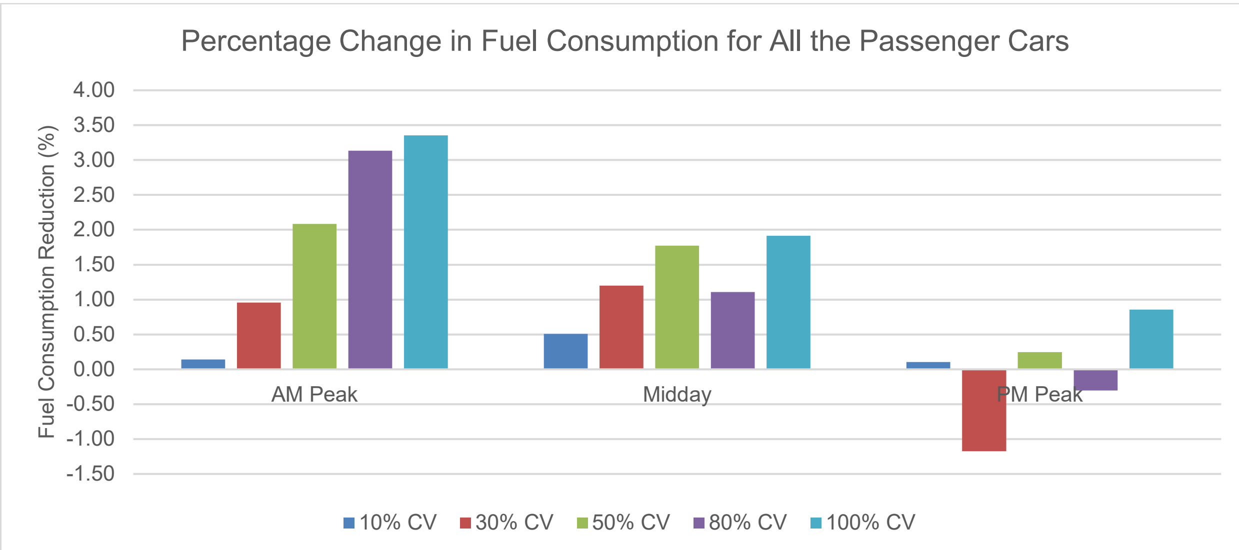
Like the conventional traffic signal control system, the output from PM Peak shows some turbulences such as simultaneous rise and reduction in emission for different emission types in a particular penetration rate. However, 100% and 50% CV penetration rates show relatively better performances.

Figure 37. Overall Emission Effects in Arcadia, CA (PM Peak/Adaptive TSCS)



Overall, the output of all the three scenarios—AM Peak, Midday, and PM Peak—are consistent with the conventional traffic signal control system. Similar trend has been observed. However, instead of 80% CVs, 50% and 100% CVs in the fleet reduced fuel consumption in the adaptive system regardless of the time of day.

Figure 38. Overall Effects on Fuel Consumption Effects in Arcadia, CA (Adaptive TSCS)



Although 100% penetration rate helps reduce emission and fuel consumptions consistently regardless of the time of day, 80% penetration rate is still better for AM Peak, that is, normal flow conditions.

7.5.3 Conventional Signal Control System in Manhattan, NY

Above discussion clearly shows that the higher flow rate, that is, saturated or over-saturated flow results in unpredictable behavior of the eco-drive application. Moreover, sufficient gap between two adjacent intersections are required for the expected performance of an eco-drive application. Otherwise, vehicles won't be able to comply with the instructions of the algorithm. Most of the intersections in Arcadia are located at more than 500 ft. apart, which helps the vehicle to comply with the instructions and thus, save emission and fuel. However, Manhattan, NY has a grid network that consists of intersections 250 ft. apart, which significantly reduces the applicability of the algorithm. This issue coupled with the saturated flow condition is expected to hinder the benefits of the application for Manhattan study area. AM Peak, Midday, and PM Peak results are described in the following sections under three categories—connected passenger cars, regular passenger cars, and overall effects.

7.5.3.1 Effects on Connected Passenger Cars in Manhattan, NY

The eco-drive application shows neither consistent nor significant improvement for connected passenger cars when the application's strategies are adopted by the connected vehicles traveling in Manhattan, NY network.

Table 9. Effects on CVs in Manhattan, NY (Conventional TSCS)

Time of Day	Penetration Rate of CV	Percentage Improvement in each Emission Type and Fuel Consumption								
		ECO	**EHC**	**Eco2**	**Enox**	**TCO**	**THC**	**Tco2**	**Tnox**	**Fuel**
AM Peak	10%	-0.95	-0.45	0.47	0.78	-1.42	0.12	0.42	-0.23	0.27
	30%	-1.79	-0.40	0.55	0.59	-2.46	-0.54	0.47	-0.60	0.23
	50%	-3.19	-0.65	0.03	-0.12	-4.35	-1.53	-0.03	-1.12	-0.38
	80%	-3.36	-0.85	-0.05	-0.15	-4.43	-1.29	-0.13	-1.58	-0.48
	100%	-3.19	-0.81	0.04	-0.18	-4.22	-1.09	-0.04	-1.38	-0.38
Midday	10%	1.41	-1.77	0.93	1.78	1.73	1.91	0.82	0.56	0.91
	30%	1.36	-1.08	1.38	2.13	1.80	2.25	1.24	0.77	1.30
	50%	-0.79	-1.81	0.81	1.10	-1.01	0.53	0.68	-0.07	0.52
	80%	-0.09	-1.75	0.92	1.26	-0.23	0.99	0.80	-0.13	0.70
	100%	-2.09	-2.09	0.43	0.42	-2.62	-0.44	0.29	-0.67	0.01
PM Peak	10%	-0.84	-2.30	0.45	0.65	-1.33	-0.90	0.35	-1.21	0.19
	30%	-1.56	-2.21	0.60	0.61	-2.12	0.17	0.47	-0.39	0.23
	50%	-1.47	-2.93	0.32	0.53	-1.81	-0.23	0.17	-1.05	-0.01
	80%	-2.23	-2.31	0.52	0.33	-2.92	-0.76	0.38	-1.06	0.07
	100%	-2.56	-2.72	0.20	0.01	-3.26	-0.79	0.06	-1.32	-0.25

7.5.3.2 Effects on Regular Passenger Cars in Manhattan, NY

Like connected cars, the eco-drive algorithm has no consistent or significant effect on regular passenger cars in Manhattan, NY.

Table 10. Effects on Regular Cars in Manhattan, NY (Conventional TSCS)

Time of Day	Penetration Rate of CV	Percentage Improvement in each Emission Type and Fuel Consumption								
		ECO	EHC	Eco2	Enox	TCO	THC	Tco2	Tnox	Fuel
AM Peak	10%	-0.24	-0.12	-0.21	-0.07	-0.16	0.04	-0.21	0.07	-0.21
	30%	0.28	0.09	-0.12	0.05	0.40	0.11	-0.10	-0.24	-0.06
	50%	-0.39	-0.10	-0.07	-0.03	-0.58	-0.48	-0.07	-0.45	-0.11
	80%	-0.52	-0.31	-0.06	-0.23	-0.65	-0.37	-0.07	-0.96	-0.12
Midday	10%	0.01	-0.03	0.14	0.08	-0.03	0.19	0.13	0.11	0.12
	30%	0.02	0.10	-0.09	0.06	0.22	0.19	-0.10	0.19	-0.07
	50%	-0.37	-0.29	-0.18	-0.17	-0.44	-0.37	-0.18	-0.31	-0.21
	80%	0.46	0.28	0.38	0.54	0.77	1.16	0.35	0.76	0.39
PM Peak	10%	-0.55	-0.24	-0.21	-0.28	-0.68	-0.51	-0.21	-0.32	-0.25
	30%	-0.51	-0.64	-0.17	-0.30	-0.55	-0.09	-0.20	-0.34	-0.23
	50%	0.07	-0.86	-0.44	-0.07	0.32	0.33	-0.46	-0.22	-0.39
	80%	0.06	-0.24	-0.14	-0.08	0.27	0.50	-0.16	0.06	-0.12

7.5.3.3 Overall Effects on All Passenger Cars in Manhattan, NY

Negligible as well as inconsistent effect has been observed in all passenger cars—regular and connected. However, with 10% less traffic than AM and PM Peak, Midday is seemingly inclined to the consistent but negligible improvement in most emission types and fuel consumption.

Table 11. Overall Effects on All Passenger Cars in Manhattan, NY (Conventional TSCS)

Time of Day	Penetration Rate of CV	Percentage Improvement in each Emission Type and Fuel Consumption								
		ECO	EHC	Eco2	Enox	TCO	THC	Tco2	Tnox	Fuel
AM Peak	10%	-0.31	-0.15	-0.14	0.01	-0.28	0.05	-0.15	0.04	-0.16
	30%	-0.34	-0.06	0.08	0.21	-0.46	-0.09	0.07	-0.35	0.02
	50%	-1.77	-0.37	-0.02	-0.07	-2.43	-1.00	-0.05	-0.79	-0.25
	80%	-2.78	-0.74	-0.05	-0.17	-3.67	-1.10	-0.11	-1.46	-0.40
	100%	-3.19	-0.81	0.04	-0.18	-4.22	-1.09	-0.04	-1.38	-0.38
Midday	10%	0.14	-0.19	0.22	0.24	0.14	0.35	0.20	0.16	0.19
	30%	0.42	-0.25	0.35	0.68	0.69	0.81	0.30	0.36	0.34
	50%	-0.58	-1.05	0.32	0.47	-0.72	0.08	0.25	-0.19	0.15
	80%	0.03	-1.34	0.81	1.11	-0.02	1.02	0.71	0.05	0.64
	100%	-2.09	-2.09	0.43	0.42	-2.62	-0.44	0.29	-0.67	0.01
PM Peak	10%	-0.58	-0.45	-0.14	-0.18	-0.74	-0.55	-0.15	-0.41	-0.21
	30%	-0.82	-1.11	0.06	-0.03	-1.01	-0.01	0.00	-0.36	-0.09
	50%	-0.70	-1.89	-0.06	0.23	-0.75	0.05	-0.15	-0.63	-0.20
	80%	-1.76	-1.89	0.39	0.25	-2.27	-0.50	0.27	-0.83	0.03
	100%	-2.56	-2.72	0.20	0.01	-3.26	-0.79	0.06	-1.32	-0.25

7.5.4 Adaptive Signal Control System in Manhattan, NY

Fixed time traffic control system in Manhattan, NY has showed a minor change is emission and fuel consumption. Although the adaptive timing may partly contribute to the overall benefits in addition to eco-driving itself, significant improvement is highly unlikely for an adaptive traffic signal control system. As demonstrated in the previous section, AM Peak, Midday, and PM Peak results of the adaptive system are described in the following sections under three categories—connected passenger cars, regular passenger cars, and overall effects.

7.5.4.1 Effects on Connected Passenger Cars in Manhattan, NY

Like the connected passenger cars in the previous fixed-time traffic signal control system, performance of eco-drive application in the adaptive system is also inconsistent and insignificant.

Table 12. Effects on CVs in Manhattan, NY (Adaptive TSCS)

Time of Day	Penetration Rate of CV	Percentage Improvement in each Emission Type and Fuel								
		ECO	EHC	Eco2	Enox	TCO	THC	Tco2	Tnox	Fuel
AM Peak	10%	0.14	-0.83	0.29	0.75	-0.12	0.12	0.26	-0.92	0.23
	30%	-1.84	-0.53	0.43	0.52	-2.63	-0.63	0.37	-0.85	0.12
	50%	-2.47	-0.53	0.24	0.26	-3.44	-1.08	0.18	-1.00	-0.12
	80%	-3.57	-0.68	0.10	-0.16	-4.80	-1.65	0.03	-1.53	-0.37
	100%	-2.90	-0.81	0.03	-0.03	-3.88	-1.14	-0.04	-1.45	-0.36
Midday	10%	2.85	-2.15	0.48	2.29	3.70	2.18	0.40	0.56	0.73
	30%	0.26	-1.27	1.09	1.60	0.31	1.41	0.97	0.45	0.91
	50%	-1.03	-1.78	0.76	0.94	-1.30	0.37	0.62	-0.22	0.44
	80%	-0.57	-1.88	0.83	1.08	-0.72	0.52	0.69	-0.29	0.55
	100%	-1.33	-1.82	0.64	0.86	-1.70	0.19	0.51	-0.30	0.30
PM Peak	10%	-0.28	-2.66	0.39	0.80	-0.55	-0.13	0.29	-1.15	0.21
	30%	-1.53	-2.40	0.40	0.53	-1.96	0.09	0.27	-0.35	0.06
	50%	-1.48	-2.50	0.60	0.70	-1.95	-0.13	0.46	-0.78	0.23
	80%	-2.53	-2.52	0.33	0.08	-3.26	-1.24	0.19	-1.50	-0.14
	100%	-2.71	-2.85	-0.05	-0.05	-3.30	-0.84	-0.20	-1.22	-0.49

7.5.4.2 Effects on Regular Passenger Cars in Manhattan, NY

Like connected cars in both TSCSs and regular cars in fixed-time traffic signal control system, the eco-drive algorithm has insignificant effect on regular passenger cars in Manhattan, NY.

Table 13. Effects on Regular Cars in Manhattan, NY (Adaptive TSCS)

Time of Day	Penetration Rate of CV	Percentage Improvement in each Emission Type and Fuel								
		ECO	EHC	Eco2	Enox	TCO	THC	Tco2	Tnox	Fuel
AM Peak	10%	1.49	-0.58	-0.58	0.25	2.35	0.77	-0.57	0.11	-0.32
	30%	-0.57	0.01	-0.14	-0.22	-0.80	-0.30	-0.14	-0.35	-0.19
	50%	-1.24	-0.35	-0.27	-0.46	-1.62	-1.18	-0.28	-0.85	-0.39
	80%	-1.73	0.05	0.03	-0.66	-2.62	-1.53	0.03	-1.37	-0.18
Midday	10%	1.51	-0.18	-0.19	0.40	1.99	1.38	-0.17	0.28	0.05
	30%	-0.38	-0.03	-0.31	-0.29	-0.33	-0.11	-0.31	-0.17	-0.31
	50%	-0.22	0.04	-0.05	-0.06	-0.17	-0.21	-0.06	-0.15	-0.07
	80%	-0.97	-0.23	-0.01	-0.18	-1.22	-0.45	-0.03	-0.33	-0.15
PM Peak	10%	0.43	-0.20	-0.20	0.08	0.63	0.48	-0.19	0.06	-0.12
	30%	-0.72	-0.46	-0.15	-0.38	-0.86	-0.35	-0.17	-0.42	-0.24
	50%	-0.52	-0.52	-0.12	-0.19	-0.63	-0.08	-0.14	-0.12	-0.19
	80%	-0.53	-0.56	-0.22	-0.26	-0.49	0.06	-0.25	-0.41	-0.27

Overall Effects on All Passenger Cars in Manhattan, NY

Like fixed-time traffic signal control system, the effects of eco-drive algorithm are also inconsistent and negligible for all passenger cars—regular and connected. However, Midday is still seemingly inclined to the consistent but negligible improvement in most emission types and fuel consumption. Such a slight inclination prohibits the ability to draw a conclusion, but nevertheless, it opens a window for further investigation—an investigation that focuses on the effect of traffic volume on the eco-drive algorithm.

Table 14. Overall Effects on All Passenger Cars in Manhattan, NY (Adaptive TSCS)

Time of Day	Penetration Rate of CV	Percentage Improvement in each Emission Type and Fuel								
		ECO	EHC	Eco2	Enox	TCO	THC	Tco2	Tnox	Fuel
AM Peak	10%	1.36	-0.60	-0.49	0.30	2.11	0.70	-0.49	0.01	-0.27
	30%	-0.95	-0.15	0.03	0.00	-1.35	-0.40	0.01	-0.49	-0.10
	50%	-1.85	-0.44	-0.02	-0.11	-2.52	-1.13	-0.05	-0.93	-0.26
	80%	-3.19	-0.53	0.09	-0.26	-4.36	-1.63	0.03	-1.50	-0.33
	100%	-2.90	-0.81	0.03	-0.03	-3.88	-1.14	-0.04	-1.45	-0.36
Midday	10%	1.64	-0.37	-0.12	0.58	2.15	1.45	-0.11	0.30	0.11
	30%	-0.19	-0.40	0.11	0.27	-0.14	0.34	0.07	0.01	0.05
	50%	-0.62	-0.87	0.35	0.44	-0.73	0.08	0.28	-0.18	0.18
	80%	-0.65	-1.54	0.66	0.82	-0.82	0.32	0.54	-0.30	0.41
	100%	-1.33	-1.82	0.64	0.86	-1.70	0.19	0.51	-0.30	0.30
PM Peak	10%	0.36	-0.45	-0.14	0.15	0.51	0.42	-0.15	-0.06	-0.08
	30%	-0.96	-1.03	0.01	-0.11	-1.19	-0.22	-0.04	-0.40	-0.15
	50%	-1.00	-1.50	0.24	0.25	-1.29	-0.10	0.16	-0.45	0.02
	80%	-2.12	-2.12	0.22	0.01	-2.69	-0.97	0.10	-1.28	-0.16
	100%	-2.71	-2.85	-0.05	-0.05	-3.30	-0.84	-0.20	-1.22	-0.49

7.6 General Findings from Both Sites

Eco-driving under non-adaptive signals and adaptive signals both have the benefits of reduced emissions and fuel consumption. The less-than-perfect timing information from adaptive signals does not appear to compromise the effectiveness of eco-driving, though the adaptive timing may partly contribute to the overall benefits in addition to eco-driving itself.

Of the three scenarios of Arcadia, that is, morning peak hours (AM), midday hours, and evening peak hours (PM), network traffic volume during midday is 15% higher than that during morning peak hours, while network traffic volume during evening peak hours is 57% higher. For both non-adaptive signals and adaptive signals, eco-driving during morning peak hours is most beneficial in terms of fuel consumption savings. Clearly, the light traffic flow conditions permit vehicles more freedom to apply the optimal speed profiles as dictated by the eco-driving algorithm. When traffic is heavier, eco-driving may become moot as there is not much leeway for the algorithm to perform. Therefore, traffic density is a key factor that shapes the performance of eco-driving algorithm.

Vehicles that perform eco-driving impact those non-eco-driving vehicles in the same network and may cause the latter to resort to more speed fluctuations. The "smoothing" effect on the eco-driving vehicle speed profiles come from the leeway provided by those non-eco-driving ones. The results reveal that the benefits received by eco-driving vehicles depend on the co-existence of both eco-driving and non-eco-driving vehicles. When market penetration of eco-driving vehicles increases, the benefits for those eco-driving vehicles decrease. This seemingly counter-intuitive observation means the average benefit decreases for individual eco-driving vehicles as more vehicles adopt eco-driving, analogous to the economics theory that marginal benefit decreases as consumption increases. Overall, the fuel savings decrease gradually with the increase of CV penetration rate for all different times of day. In the PM Peak hours with the heaviest traffic, almost no fuel savings (< 1%) has been observed at 100% penetration. In a nutshell, connected vehicle penetration rate plays a significant role in the performance of eco-driving algorithm.

In Manhattan where traffic is highly oversaturated with shorter block distance, eco-driving provides negligible benefits for both non-adaptive and adaptive signals. During midday, adaptive signals appear to provide better results, possibly due to the additive benefits of adaptive timing and the lighter traffic during that period. Regardless of the accuracy of the signal timing information as provided by adaptive signals, eco-driving has no or insignificant effects on Manhattan central business district (CBD) traffic during morning or evening peak hours. This could be partly due to the low-vehicle speed limit in Manhattan CBD area (25 mph posted speed limit) with actual average speed typically lower than 10 mph. The low-average speed (< 10 mph) is not the most engine-friendly eco-driving speed, leaving no room for adjustments. The highly oversaturated traffic in the CBD area, very low average speed, as well as the densely spaced intersections (e.g., 250 ft.), contribute to the limited benefits of eco-driving in the City. Hence the results suggest that network and traffic flow characteristics, and even traffic flow regulations, are all relevant to the actual effectiveness of eco-driving. It should be stressed that New York City traffic network has various geometry types beyond the CBD grid. There are arterials, isolated intersections, and less-densely spaced grids that may be more suitable for eco-driving testing.

8 Conclusion

Utilizing a simulated connected vehicle environment, the network level impact of a new confidence-based robust eco-driving algorithm (taking into consideration the less-than-perfect SPaT information) is investigated using microscopic traffic simulation. The research demonstrates that the *bounded uncertainty* in SPaT introduced by a cyclic adaptive signal controller such as ACDSS, does not have a negative impact on the efficacy of the application. The study also reveals some significant underlying factors that influence the application's effectiveness, including traffic density, demand levels, distance between two adjacent signalized intersections, and penetration rate of connected vehicles.

The simulation results indicate that the new eco-driving algorithm is able to provide the benefits of fuel consumption savings and pollutant emission reductions with SPaT messages from both adaptive and conventional signals. Results of the Arcadia, CA study show significant fuel efficiency and emission reduction for AM Peak and Midday. The results also show some inconsistent improvement at the PM Peak when flow rate is nearly 1.6 times of the AM flow rate. Regardless of the accuracy of signal timing information, eco-driving has negligible network benefits when traffic becomes oversaturated such as that of the CBD area in New York City. This is because vehicles do not have much leeway to apply the needed eco-friendly speed profiles with the constraints from surrounding vehicles in high density traffic in densely spaced CBD intersections. It further emphasizes that the traffic-demand level is a key factor that should be taken into consideration while deciding the optimal speed profile.

Shorter distance between two adjacent intersections would leave the eco-driving application with no room for improvement. Results from the Manhattan test site show no noticeable improvement; this means it is necessary to consider the network topology while deciding the optimal speed profile. To be sure, the network impacts of eco-driving applications depend on network and local traffic flow characteristics, traffic regulations (e.g., speed limit), and market penetration of the application. Moreover, network benefits of eco-driving depend on the co-existence of both eco-driving vehicles and non-eco-driving vehicles, and 100% market penetration does not necessarily provide the best eco-driving benefit for individual vehicles.

In Arcadia, CA, simulation results show that the reduction in emission and fuel consumption are sensitive towards market penetration rate of connected vehicles. However, the relationship is non-linear while an “optimal” market penetration rate may be determined using a simulation approach. It is always advisable to consider the penetration rate in the decision-making process of promoting or adopting the eco-drive application.

This study provides insights regarding the impacts of traffic-flow characteristics, network topology, and penetration rate of connected vehicles. This may help in future research to decide when to activate the eco-drive application from a system-optimal perspective. This activation guidance could be broadcasted by a roadside unit (RSU).

This report investigates eco-driving for isolated intersections. Optimizing speed for multi-segment, instead of single segment, may provide better results in a network like Manhattan, NY where the intersections have short block distance. A future research subject may be to find out the effect of multi-segment optimization in different traffic networks, with a focus on the type of network with short segment similar to Manhattan. This may lead to a RSU-based eco-drive advisory application. Ultimately, a comprehensive eco-driving tool can be developed, potentially commercialized, and deployed to help increase fuel efficiency and decrease emissions in real life.

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