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Eco-Friendly Agent Based Advanced Traffic Management Techniques in a Connected Vehicle Environment

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Eco-Friendly Agent Based Advanced Traffic Management Techniques in a Connected Vehicle Environment

A Dissertation submitted in partial satisfaction of the requirements for the degree of

Doctor of Philosophy

in

Electrical Engineering

by

Qiu Jin

August 2015

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I dedicate this dissertation to them.
ABSTRACT OF THE DISSERTATION

Eco-Friendly Agent Based Advanced Traffic Management Techniques in a Connected Vehicle Environment

by

Qiu Jin

Doctor of Philosophy, Graduate Program in Electrical Engineering
University of California, Riverside, August 2015
Dr. Matthew Barth, Chairperson

Transportation is responsible for one third of greenhouse gases (GHG), as well as a major source of other pollutants including hydrocarbons (HC), carbon monoxide (CO), and nitrogen oxides (NOx). Existing transportation systems are facing numerous issues resulting from the increased travel demands and limited capacities of roadway infrastructure. As wireless communication advances, agent-based techniques provide a new perspective to advanced traffic management systems. In both urban arterial and highway networks, vehicles and road infrastructure interact with each other as individual intelligent agents in an integrated environment, which can significantly improve the overall traffic performance in terms of safety, mobility and environmental sustainability, due to knowledge sharing and system-wide decision-making. In this dissertation, we propose a variety of environmentally-friendly agent-based advanced traffic management technologies in a connected vehicle environment.

For agent-based arterial traffic management, we developed an agent-based hierarchical structure for signal-less intersection management system. From the perspective of IMAs, they receive probe vehicle data from VAs, dynamically schedule
VAs’ arrival times (by potentially grouping VAs in platoons), reserve intersection time-space occupancies for VAs, and communicate arrival time advices back to VAs. Furthermore, an optimal lane selection algorithm for agent-based traffic management system is developed, which could provide guidance on determining optimal target lanes for individual vehicle agent in order to better regulate traffic flow, thus achieving a system-wide optimal solution in terms of maintaining desired traffic speeds.

On the other hand, vehicle agents use advices to plan their trajectories in order to further minimize energy consumption and pollutant emissions. Firstly, an Eco-Approach and Departure algorithm is introduced and field test has been conducted in Turner Fairbank Highway Research Center on automated vehicle. Secondly, a power-based approach is used to develop an optimal vehicle longitudinal control algorithm for individual vehicles by considering vehicle dynamics (e.g., engine efficiency map), roadway grade and other constraints (e.g., traffic signal status).

For freeway traffic management, a driving simulator study is conducted with truck drivers to evaluate the energy and emissions benefits as well as study the behavioral impact eco-driving may have on truck drivers.
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1. INTRODUCTION

1.1. MOTIVATION

1.1.1. Energy and Emission Impacts of Road Transportation

In the United States, the transportation sector has contributed significantly to air pollution and petroleum-based fuel consumption (including gasoline and diesel), comprising approximately 30% of the total energy consumption [3]. More than one quarter of total U.S. greenhouse gas emissions (GHG) come from roadway transportation, making transportation the second largest source of GHG emissions in the United States after the electric power sector (shown in figure 1-1) [4].

![GHG Emissions by Economic Sector](image)

**Figure 1-1. Greenhouse Gas Emissions by Economic Sector**

In 2013, of various transportation modes, light vehicles (including passenger cars and light-duty trucks) and medium/heavy-duty trucks consumed approximately 81% of the entire energy in the United States (shown in Figure 1-2) [5].
In order to reduce energy use and emissions caused by transportation sector, researchers are pushing for more promising options, such as more efficient vehicles and use of alternative fuels. However, although alternative energy sources (e.g., hydrogen fuel cell and ethanol flexible-fuel) and hybrid/electric vehicle technologies have shown great potential of significant energy savings and emission reduction, in the near term, conventional petroleum-based vehicles with internal combustion engine (ICE) cannot be completely replaced overnight due to the challenges related to cost, accessibility, and availability [6]. Meanwhile, as the traffic demand is growing much faster than the roadway capacity, the traffic congestion has gotten progressively worse, despite the push forward alternative modes of transportation and new energy.

1.1.2. Connected Vehicle Environment

Connected vehicle research has increased significantly in recent years. Coupled with other technologies such as smart sensors and on-board computer processing, connected
vehicles can carry out tasks such as identifying hazards on the roadway, provide warning signals to drivers, and share the information with others over communication networks.

To support numerous safety, mobility, and environmental applications, the vehicle communication network environment is typically considered in two ways: 1) having very high-speed transactions among vehicles (vehicle-to-vehicle or V2V), and 2) having communications between vehicles and the infrastructure (V2I and or I2V). V2V applications rely on sharing information between vehicles such as safety warnings and traffic information. V2I/I2V applications typically have roadside units (RSU) and vehicles as the communicating nodes. Connected vehicle mobility applications provide a connected, data-rich travel environment. As shown in Figure 1-3, these communication techniques could be able to support driver advisories, driver warnings, and vehicle and/or infrastructure controls, by capturing real-time data from equipment located on-board vehicles (automobiles, trucks, and buses) and within the transportation infrastructure. The data are transmitted wirelessly and are used by transportation managers in a wide range of dynamic, multi-modal applications to manage the transportation system for optimum performance. As part of this, connected vehicle environmental applications both generate and capture environmentally relevant real-time transportation data and use this data to support and facilitate green transportation choices, thus reducing the environmental impacts of each trip.
Already, a number of applications are starting to use “probe” data from connected vehicles to modify traffic control strategies and improve overall traffic performance. Vehicles that are used as probes can provide a variety of data, including vehicle attributes (e.g., position, velocity, etc.) and other traffic or roadway information (e.g., slick roads, etc.). Examples include priority traffic signal control [7] based on heuristic algorithms that have reduced average bus delay by 50% without negative impacts on other vehicles given a signal plan and a collection of priority request arrival times from probe data. H. Rim [8] proposed a methodology for estimating lane-level travel times under a V2I environment. Individual vehicle speeds and positions at every second were used as the inputs of the proposed methodology, and the survey showed that less than 10% mean absolute percentage error (MAPE) was achievable with 20% penetration rate. R. Oertel and P. Wagner [9] used a new approach to control traffic signals at isolated intersections.
by capturing vehicles’ delay times and using them to adjust the green times. This delay-based control outperformed the other two traditional control schemes given a penetration rate above 10%.

1.1.3. **Advanced Traffic Management System (ATMS) in ITS**

Advanced Traffic Management Systems (ATMS) [2] have been studied extensively for the last decade and a large variety of algorithms have been developed. These systems typically seek solutions to traffic congestion problems occurring on urban highways and local streets through the deployment of state-of-the-art sensing, communications, and data processing techniques. Problems considered mainly focus on congestion associated with different traffic patterns. To address these traffic needs, ATMS attempt to take advantage of available traffic information provided by infrastructure-based sensors (e.g., embedded loop detectors, radar, video cameras) and vehicle sensors that are coupled with on-board V2V and/or V2I communications. Real-time management solutions are being developed to adjust to dynamically changing traffic conditions, enabled by wireless communications.

1.1.4. **Eco-Driving Technologies**

A number of studies have been conducted to develop intelligent transportation systems (ITS) applications specifically for saving energy and reducing emissions. Previous studies indicate that eco-driving, or so-called “green” driving, with smooth vehicle speed profiles exhibits non-trivial potential to improve vehicle operations as well as the ability to achieve significant gains in energy efficiency [10]. However, in most of the existing studies, fuel savings and emissions reduction are considered to be just by-products of
smooth vehicle speed profiles when optimizing other criteria, such as minimizing the travel time or number of vehicle stops, other than directly minimizing the fuel consumption. A few studies (e.g., [11, 12]) have developed specific power-based vehicle longitudinal control algorithms that are optimized to minimize fuel, however they rely on Environmental Protection Agency (EPA) city and highway fuel economy ratings in addition to publicly available vehicle parameters, without taking into account the individual vehicle’s engine operation efficiency which may vary from vehicle-to-vehicle.

1.1.5. Agent-Based Systems

With the rapid growth in size and complexity of modern systems such as traffic networks, the development of intelligent and adaptive approaches to system management (including such functions as routing, congestion control, traffic/load management, etc.) has assumed considerable theoretical as well as practical significance.

Intelligent Agents can be described as autonomous computational systems that inhabit dynamic, not necessarily fully predictable environments. An agent is "autonomous" to some degree in that it can decide for itself how to relate data to commands in its efforts to achieve goals, satisfy motivations, etc. Multi Agent Systems can be characterized by the interaction of many agents trying to solve a variety of problems in a co-operative fashion [13].

Urban Advanced Traffic Management System requires intelligent agents of many types, and an agent-based ATMS should be capable of calculating and optimizing control strategies, as well have knowledge about the intersection(s) and freeway(s). The design of an agent-based traffic management system requires flexible autonomy. Meaning that
agents will sometimes be required to work autonomously, but will often be influenced and commanded by others. Sometime agents need to sacrifice some performance for the purpose of co-operative behavior caused by appointment of an authority agent or self-control of intelligent traffic management agent.

1.2. Problem Statement

As wireless communication advances, agent-based system technique provides a new perspective to advanced traffic management and has received increased attention from researchers and engineers in the field of transportation since the late 1990s. In both urban arterial and highway networks, vehicles and intersections interact with each other as individual intelligent agents in an integrated environment (called multi-agent system), which can significantly improve the overall traffic performance in terms of safety, mobility and environmental sustainability, due to knowledge sharing and system-wide decision-making. In this dissertation, we propose a variety of agent-based advanced traffic management technologies in a connected vehicle environment.

1.3. Contributions of the Dissertation

The primary objective of this dissertation is to develop agent-based advanced traffic management technologies for both arterial and freeway networks, in order to improve traffic congestion and reduce fuel consumption and pollutant emissions. The dissertation has several major contributions as listed below:

• A unique agent-based hierarchy structure of advanced intersection management system has been developed. Vehicles and roadside infrastructure are modeled as intelligent agents that are capable of flexible autonomous action in order to meet
its design objectives. A vehicle platooning algorithm and an optimal arrival scheduling algorithm have been designed to further reduce system communication loads and achieve a system-wide optimal traffic management solution.

- A real-time optimal lane-selection algorithm has been developed for agent-based traffic management in a connected vehicle environment. This algorithm can provide guidance on determining optimal target lanes for individual vehicle agent in order to better regulate traffic flow, at same time achieving a system-wide optimal solution in terms of maintaining desired traffic speeds. Moreover, the proposed algorithm can also be applied to both advanced driving assistance systems (ADAS) and automated vehicles.

- Two innovative vehicle longitudinal control algorithms have been designed for Eco Adaptive Cruise Control (Eco-ACC) system for traffic signal controlled intersections. Real-time traffic signal phasing and timing (SPaT) information and traffic condition are required to provide an “Eco-Friendly” speed trajectory for both human drivers and automated vehicles. For the eco-approach and departure algorithm, a fully integrated system prototype that incorporates the eco-driving algorithm with a vehicle that is equipped with visual display, communication, controller, processing, and positioning components has been created. Field-testing and demonstration of this system prototype have been conducted at the Turner-Fairbank Highway Research Center.
• A power-based optimal vehicle longitudinal control algorithm for individual vehicles with specific characteristics (e.g., engine type) has been developed in order to maximize fuel economy under a variety of traffic conditions. Tightly coupled road grade and individual vehicle’s engine operation efficiency has been taken into account to calculate vehicle speed profile in order to minimize the energy consumption and fuel use.

• A driving simulator study was conducted with truck drivers to evaluate heavy-truck dynamic eco-driving technology in advance freeway traffic management, as well as study the behavioral impact eco-driving may have on truck drivers. In terms of fuel consumption and emissions, the dynamic eco-feedback technology could assist drivers reduce the fuel usage and CO₂ emissions by as much as 9%.

1.4. Organization of the Dissertation

The dissertation is organized as follows: Chapter 2 reviews background and related work, including classifications of advanced traffic management systems, vehicle communications and applications in ATMS, a variety of traffic simulators and communications simulator, as well as several emission modes used to evaluated system performance in this dissertation. In Chapter 3, we focus on the agent-based advanced intersection management system in a connected vehicle environment. First of all roadway objects are modeled as different intelligent agents and the system hierarchy structure is introduced. Then a multi-agent based reservation system is established, followed by applying a vehicle platooning algorithm and an optimal vehicle arrival scheduling algorithm based on the real-time connected vehicle information. Chapter 4 describes the
real-time optimal lane-selection approach, which could provide guidance on determining optimal target lanes for individual vehicle agent in order to better regulate traffic flow based on traffic condition and vehicle desired travel speed. In Chapter 5, two types of vehicle longitudinal control strategies are introduced for an Eco-ACC system. Field-testing is conducted and some analytical results are also given. Chapter 6 describes a dynamic eco-driving algorithm for advanced freeway traffic management, followed by a driving simulation study conducted with truck drivers to evaluate heavy-truck dynamic eco-driving technology as well as study the behavioral impact eco-driving may have on truck drivers. We conclude the dissertation and describe potential future work in Chapter 7.
2. LITERATURE REVIEW

2.1. Review of Advanced Traffic Management Systems

2.1.1. Existing Advanced Traffic Management Systems

To reduce vehicle emissions and fuel consumption, Intelligent Transportation System has generated a wide variety of techniques and applications to reduce traffic congestion, improve roadway safety, and smooth traffic flow. As an example, Advanced Traffic Management Systems have been identified as one ITS area that can significantly reduce these problems [2].

Despite large differences in approach and scope, existing ATMS can be classified as “off-line” systems and “on-line” systems [14]. Most “off-line” systems use fixed time timing plans based on historical data. These plans are typically implemented by time of day (TOD), e.g., morning, midday and afternoon peak periods. However, fixed time plan cannot deal with the variability of the traffic patterns throughout the day, and they become outdated because of the traffic growth and changes in traffic pattern. The other “off-line” control systems improve the strategies by utilizing spare green time in signal cycle in every phase. These systems select their timing plan based on volume and occupancy data collected from system detectors located in key locations of the network. As a result, they can reduce the total delay time in the intersection by responding to cycle-by-cycle fluctuations in traffic flow [15, 16].

“On-line” control systems update their timing plans based on real-time information gained from detectors located in each approach of the intersection. They fall
into two major categories: traffic responsive or timing plans update (e.g., SCATS [17, 18, 19] and SCOOT [20, 21, 22]) and adaptive control policies (e.g., OPAC [23, 24] and RHODES [25, 26]) that can optimize the timing continuously at each intersection over a short time interval.

To evaluate those ATMS, most of the field studies uses “before” and “after” measurements of trip traffic time, intersection delays, number of vehicle stops and total pollutant emissions and fuel consumption to quantify the improvements.

The Transport and Road Research Laboratory (TRRL) in Great Britain developed SCOOT (Split, Cycle and Offset Optimization Technique) [27, 28] beginning in 1973, and by 1979 implemented it on a full-scale trial in Glasgow. Based on detector measurements upstream of the intersection, the SCOOT traffic model computes the cyclic flow profile for every traffic link every four seconds and contains provisions for weighting capabilities in the signal optimizers to give preference to specific links or routes. Five cities took part in assessment of SCOOT. These results show overall a reduction in delay of about 12% compared with good fixed time plans. The Roads and Traffic Authority (RTA) of New South Wales, Australia, developed SCATS (Sydney Co-ordinate Traffic Control System). It adjusts signal timing in response to variations in traffic demand and system capacity, using information from vehicle detectors, located in each lane immediately in advance of the stop line. SCATS uses two levels of control: strategic and tactical. Strategic control determines suitable signal timings for the areas and sub-areas based on average prevailing traffic conditions [29]. Tactical control refers to control at the individual interaction level. Several studies have been performed to
measure the effectiveness of SCATS. Abdel-Rahim [30] found the following results in Oakland County, Michigan. The results indicated travel time decreased 8.6% in the morning peak direction of travel and 7% in the evening peak direction of travel. Off peak and non-peak direction travel times were also improved, decreasing 6.6 to 31.8%. A study by the City of Troy, Michigan [31], found 20% reduction in stopped vehicle delay. And although no significant decrease in the number of accidents, the percentage of incapacitating crashes reduced from 9% to 4%. The RHODES [32] architecture is based on decomposing the control-estimation problem into three hierarchical levels: (1) intersection control; (2) network control; and (3) network loading. At the lowest level, intersection control, traffic flow predictions and signal phase and duration decisions are made based on observed vehicle flows, coordination constraints, flow predictions and operational constraints that are typically established by the traffic engineer. At the middle level, the network control level, predictions of platoon flows are used to establish coordination constraints for each intersection in the network. These decisions are made periodically at an approximate interval of 200-300 seconds depending on the network characteristics. At the highest level, the network loading level predicts the general travel demand over longer periods of time, typically one hour. These demands can be used proactively to determine future platoon sizes at or near the control boundaries. OPAC (Optimized Policies for Adaptive Control) [24] is a set of algorithms that calculate signal timings to minimize a performance function of stops and delays. It implements a “rolling horizon” strategy to make use of flow data that are readily available from existing detection equipment without degrading the performance of the optimization procedure.
ACS Lite (Adaptive Control Software Lite) is a low cost system, which samples traffic data as it happens in order to dynamically, adjusts offsets and splits to improve signal timing [33]. ACS Lite has shown 5-25% improvement in arterial travel times, significant reduction in stops, and between 5% and 50% improvement in delays at side streets and left turns, over standard coordinated arterials [33].

2.1.2. Agent-based Advanced Traffic Management Systems

Agent-based system techniques provide a new perspective to advanced traffic management and has received increased attention from researchers and engineers in the field of transportation since the late 1990s [34]. In urban arterial networks, vehicles and intersections interact with each other as individual intelligent agents in an integrated environment (called multi-agent system), which can significantly improve the overall traffic performance in terms of safety, mobility and environmental sustainability, due to knowledge sharing and system-wide decision-making. Researchers have designed a variety of MAS to solve traffic congestion problems, some of which have already been effectively applied to traffic controls in real world by improving efficiency, strengthening robustness, increasing scalability and reducing costs.

At the heart of all agent-based transportation systems is a wireless network environment connecting different agents together. The U.S. Department of Transportation’s Connected Vehicle (CV) initiative (which was initially known as Vehicle Infrastructure Integration and later as IntelliDrive) employs state-of-the-art technologies, including wireless communications (e.g., dedicated short range communication or DSRC), GPS receivers, and advanced sensors to set up an integrated
connected traffic network which can be accessed by both vehicles and infrastructure. This enables the development of more efficient traffic management strategies for arterial networks, such as multi-agent intersection management systems [35, 36].

Many researches have explored the use of MAS for cooperative urban traffic networks. Desai et al. [37] reviewed existing congestion management techniques and comprehensively surveyed advantages of existing MAS in the realm of intelligent transportation systems. Different multi-agent technologies were classified and their suitability in congestion management was discussed. Wu [38] proposed an urban traffic MAS to manage the gradual congestion of a traffic network, where a fuzzy control strategy was developed for the intersection agent. The simulation study showed that the proposed control resulted in better traffic performance than either fixed-time or actuated signal control. In a large-scale traffic network, multi-agent techniques could also coordinate the individual traffic control instruments by modeling various traffic control measures as intelligent agents. Katwijk et al. [39] developed an integrated block-based look-ahead traffic-adaptive control algorithm with the multi-agent coordination approach and illustrated the benefits of the improved algorithm for an arterial case in simulation.

Most recently, Autonomous Intersection Management (AIM) [35, 40] system has increased interest to transportation researchers. The goal of the system is to create a scalable, safe, and efficient multi-agent framework for managing autonomous vehicles at intersections. This system proposed a novel multi-agent intersection control mechanism in which autonomous driver agents “call ahead” and request space-time occupancy in the intersection. A FCFS (First Come, First Serve) algorithm was developed and the
associated communication protocol was designed for driver agents and the intersection manager. Compared with a conventional optimized signal-timing plan, the multi-agent intersection control showed an improvement in average vehicle delay by at least 50% [41]. However, there are some drawbacks in this system: 1) Based on a simple FCFS algorithm, vehicles gain and lose reservation frequently. 2) Lack of V2V communication between vehicle agents and 3) No energy-oriented vehicle trajectory planning is designed. 4) System may break down after a period of time because of intersection capacity; it will give rise to traffic flow problems. 5) Centralized System controller will break down if overloaded.

2.2. Review of Vehicle Communications and Applications in ATMS

2.2.1. Connected Vehicle Applications

As wireless communication techniques continue to advance, a connected-vehicles-based ATMS has gained significant research interest due to its high potential. Connected vehicle research uses leading edge technologies — smart sensors, advanced wireless communications, on-board computer processing, and others to identify hazards on the roadway, provide warning signals to drivers and share the information with others over communication networks.

One of the cores of connected vehicle research is a so-called vehicular communication network environment supporting very high speed transactions among vehicles (V2V), and between vehicles and infrastructure (V2I/I2V) or hand held devices (V2D) to enable numerous safety and mobility applications. Vehicular Communication networks are an
emerging type of networks in which vehicles and roadside units (RSU) are the communicating nodes; sharing information with one another, such as safety warnings and traffic information. As a cooperative approach, the goal of applying vehicular communication networks is to become more effective in avoiding accidents and mitigating traffic congestions than an isolated vehicle without any information from others. Applications using vehicle-to-vehicle (V2V) and/or vehicle-infrastructure (V2I/I2V) communications have the potential to provide valuable dynamic traffic information for an ATMS to facilitate the development of more efficient management strategies. Some of the applications include: 1) warnings on entering intersections, 2) lane change warnings [42], 3) variable speed limits [43], 4) adaptive traffic lights [44, 25], 5) automated traffic intersection control [45], and 6) cooperative adaptive cruise control.

A number of studies have used probe data from connected vehicles technology [46] to modify traffic control strategies and improve the performance of ATMS. Probe data are comprised of vehicle attribute and sensor data collected and sent from a vehicle OBU (On-Board Unit) to a local RSU. This data contains real-time road, weather, and traffic conditions information. The post-processed data is used to advise vehicles approaching the intersections and suggest appropriate manipulation. A heuristic algorithm for priority traffic signal control [7] has reduced average bus delay by 50% without negative impacts on other vehicles given a signal plan and a collection of priority request arrival times from probe data. When an incident occurs on the road, drivers need to obtain travel time information that will use the distance from the current location to the incident and recognize that their future plans are controllable. Him [47] has proposed a
methodology for estimating lane-level travel times under a V2I environment. Individual vehicle speeds and positions at every second were used as the inputs of the proposed methodology, and the survey showed that less than 10% mean absolute percentage error (MAPE) was achievable with 20% penetration rate. R. Oertel and P. Wagner [9] used a new approach to control traffic signals at isolate intersections by capturing vehicles’ delay times and using them to adjust the green times. A queue clearing policy was applied: within the bound of the minimum and maximum green time, a running green phase is terminated as soon as the accumulated delay on an approach is dissolved. This delay-based control outperformed the other two traditional control schemes given a penetration rate above 10%.

2.2.2. Applications for the Environment: Real-time Information Synthesis (AERIS)

As part of the connected vehicle research effort, the U.S. DOT Intelligent Transportation Systems Joint Program Office (JPO) initiated the Applications for the Environment: Real-Time Information Synthesis (AERIS) research program to generate and/or acquire environmentally relevant real-time transportation data to create actionable information to support and facilitate “green” transportation choices by transportation system users and operators. Employing a multi-modal approach, the AERIS Research Program aims to encourage the development of technologies and applications that support a more sustainable relationship between transportation and the environment chiefly through fuel use reductions and resulting emissions reductions [48].

The AERIS program is investigating five operational scenarios or bundles of connected vehicle applications, including: Eco-Signal Operations, Eco-Lanes, Low Emissions
Zones, Eco-Traveler Information, and Eco-Integrated Corridor Management. Each Operational Scenario encompasses a set of applications, which individually achieve environmental benefits. AERIS applications are designed to work in a connected vehicle environment or a setting where vehicles and infrastructure communicate among themselves and with each other to transmit information that can be used for various purposes. Such an exchange of information opens up tremendous opportunities to derive a variety of benefits, such as reduction of vehicle collisions and reduction of travel times and delays, as well as a reduction in fuel consumption and emissions.

The Eco-Signal Operations Operational Scenario includes the use of connected vehicle technologies to decrease fuel consumption and decrease GHGs and criteria air pollutant emissions on arterials by reducing idling, reducing the number of stops, reducing unnecessary accelerations and decelerations, and improving traffic flow at signalized intersections. As the AERIS Program defined Eco-Signal Operations, it initially envisioned four applications [49]: (1) Eco-Traffic Signal Timing, (2) Eco-Traffic Signal Priority, (3) Eco-Approach and Departure at Signalized Intersections, and (4) Connected Eco-Driving.

2.3. Review of ITS Simulation Approaches

2.3.1. Traffic Simulators

A number of simulation software packages have been developed for modeling advanced surface street networks. SimTraffic [50] is a software package originally developed for modeling and optimizing traffic signal timings and provides a Windows-
based, easy-to-use solution for single intersection capacity analysis and signal timing optimization. CORSIM [51] is a comprehensive traffic simulation package developed to model surface streets, freeway systems, and combined networks having simple or complex control conditions. The strengths of the model lie in its ability to simulate a wide variety of traffic conditions from signalized arterial corridors and freeway corridors to stop controlled intersections. PARAMICS [52] and VISSIM [53] are two-part (surface street and freeway) microscopic traffic simulation tools designed to simulate both urban arterial and highway networks. However, these traffic simulators have less ability to work with network simulator when wireless communications is added into traffic control simulation.

SUMO (Simulation of Urban Mobility) [54] is a highly portable and microscopic road traffic simulation package developed by employees of the Institute of Transportation Systems at the German Aerospace Center.

2.3.2. Vehicular Network Simulation Framework

With SUMO, the advance traffic control can be implemented in Veins (Vehicles in Network Simulation) [55], which is an Inter-Vehicular Communication (IVC) simulation framework composed of an event-based network simulator (e.g., OMNeT++, NS2, NS3 [56]) and a microscopic traffic simulation model (e.g., SUMO) through a Traffic Control Interface, which is called TraCI. OMNeT++ [57] is an extensible, modular, component-based C++ simulation library and framework, primarily for building network simulators. In my future research, OMNeT++ will be used to build an ad-hoc network. Figure 2-1 shows the framework of advanced traffic control simulation.
2.3.3. Driving Simulators

Driving simulators can be used as a cost-effective way to measure the potential effects of eco-driving on both light-duty vehicles and heavy-duty trucks and it provides an environment that is both safe and replicable. The driving simulator used in this dissertation is a quarter-cab National Advanced Driving Simulator (NADS) Minisim™ developed by researchers at University of Iowa [58]. The NADS Minisim™ simulator is a PC-based sophisticated simulator system and can be customized to meet the client’s specific needs. The MinisimTM can also be configured to have single or multiple displays, high-quality steering wheel and pedals built into the cab to the user’s specifications [59] As shown in Figure 2-2, the simulator’s visuals are displayed on three 42” flatscreen monitors and an LCD screen for the instrument panel. The simulator
conveys sound through a 2.1 audio system and the participants use an adjustable steering wheel, gas and brake pedals, and gear shifter (8 gears) for input.

![Minisim™ driving simulator from the National Advanced Driving Simulator Center](image)

**Figure 2-2. Minisim™ driving simulator from the National Advanced Driving Simulator Center**

### 2.4. Review of Emission Models

Vehicle emission estimation models [60] play a critical role for regional planning and development of emission control strategies and three emission models are introduced below.

#### 2.4.1. MOVES (Motor Vehicle Emission Simulator)

EPA’s Motor Vehicle Emission Simulator (MOVES) [61] provides a modeling framework, which can be applied from very fine scales (e.g., intersections) to national-scale inventories for generating estimates of precursor, criteria, greenhouse, and toxic pollutants from on and off-road mobile sources. MOVES incorporates the concept of vehicle specific power (VSP) and characterizes vehicle activities according to VSP and speed. VSP is defined as the instantaneous power per unit mass of the vehicle, and many studies have found methods based on VSP more accurate to estimate vehicle fuel consumption and emissions.
2.4.2. **CMEM (Comprehensive Modal Emission Model)**

The CMEM [62] model estimates instantaneous vehicle emission rates using either vehicle engine or vehicle speed/acceleration data. One of the most important features of CMEM is that it uses a physical, power-demand approach based on a parameterized analytical representation of fuel consumption and emissions production. In this model, the entire fuel consumption and emissions process is broken down into components that correspond to physical phenomena associated with vehicle operation and emissions production. The required inputs for CMEM include vehicle activity (second-by-second speed trace, at a minimum) and fleet composition of traffic being modeled.

2.4.3. **HBEFA**

The Handbook Emission Factors for Road Transport (HBEFA) embedded in SUMO is a Microsoft access database application providing emission factors, i.e. the specific emissions in g/km, for all current road vehicle categories (passenger cars, light duty vehicles, heavy duty vehicles, buses, and motorcycles) [63]. Emission factors are provided for all regulated and the most important non-regulated air pollutants as well as for fuel consumption and CO₂. HBEFA is used to estimate road transport emissions on different spatial aggregation levels from national to street level.
3. MULTI-AGENT BASED ADVANCED INTERSECTION MANAGEMENT USING CONNECTED VEHICLE APPROACHES

In this chapter, we first present the platform of multi-agent based advanced intersection management using connected vehicle approaches including the system platform architecture and meta-model, followed by detailed control strategies descriptions. Then we evaluate the system performance of the proposed advanced traffic management system compared to existing traffic signal controlled strategies. We elaborate on system performance (e.g. traffic mobility, emissions and energy consumption and communication load) and show how the agent-based traffic management could result in a better real-time scalable platform for urban traffic flow modeling and control, due to better predictability, coordination, and cooperation.

3.1. Modeling Intelligent Agents

As noted earlier, an agent is defined here as an entity having some degree autonomy in action on its own as well as needing to interact with other agents in multi-agent system. This distinction provides guidance for us to identify the agents in an urban traffic management system. We defined three types agents that work in the different layers of the system:

- Vehicle Agents (VA or Mobile Agents): Since human beings regularly make extremely complex decisions in a traffic network filled with uncertainty, learning and modeling human performance is often a complex and error-prone task. In this
dissertation, by integrating advanced technologies in half or fully automated vehicles, such as digital maps, GPS, in-vehicle computers, and DSRC devices, an intelligent agent could be implanted in vehicle and represent the aims of human drivers.

- Intersection Management Agents (IMA or stationary Agents): are located in the intersection roadside infrastructure such as traffic signal controller, which also equipped with wireless communication devices, to monitor traffic condition, accept vehicle agents commands, delegate tasks and provide different control solutions to lower layer agents, such as vehicle agents.

Different levels of intelligence and behavior are associated with the two different types of agents. Vehicle agents are automated/autonomous, cooperative. IMA agents are autonomous, cooperative, and learning. Here “learning” refers to the learning from past traffic condition and providing further control strategies. “Reactive” means both VA and IMA could react to changes to in the environment or the messages from other agents. The Figure 3-1 shows the basic characteristics of vehicle and IMA agents.

Figure 3-1. Basic Characteristics of VA and IMA Agents

In order to work cooperatively, vehicle agents may form coalitions (platoons) that bond dissimilar agents into harmonious decision groups. Multistage reorganization and
coordination protocols that can efficiently maintain the stability of these platoons are required. Each vehicle agent has its individual goals, but also interact within a coalition through distributed cooperation models.

3.2. Agent-based System Architecture

Based on the characteristics of VA and IMA agents, a hierarchical architecture with three layers (coordination/cooperation layer, traffic control layer, management layer) is established for an intersection traffic management system and depicted in Figure 3-2. This proposed system has competing control strategies to handle same or different tasks in a more flexible way. All this needs yield some kind of coordination, selection, cooperation and evaluation. In the cooperation layer, agents share their own driving information and traffic information within a global or local area using wireless networking technologies. Then traffic control layer is built upon the coordination layer to provide agents with a variety of traffic control strategies. After that, since there may be a number of individual tasks in each control strategy, in the management layer, suitable agents will be determined to take care of different situations, such as forming a centralized platoon with a leader vehicle agent controlling other followers, or optimizing vehicle agents arrival time on the IMA agent side.
In this chapter, three urban traffic control strategies for ATMS are introduced in an agent-based manner, and will be achieved and evaluated using the proposed system architecture. Moreover, these three control strategies could be applied to ATMS as a signal layer or multi-layer according to the present traffic condition as shown in Figure 3-3.

Figure 3-2. Agent-based System Architecture

Figure 3-3. Three Traffic Control Strategies in Agent-based ATMS
3.3. Kernel Control Layer (Dynamic Reservation System)

3.3.1. Problem Statement

The kernel control layer throughout the proposed agent-based ATMS is a Dynamic Reservation System. As mentioned earlier, in our design, the ATM system consists of two components: Vehicle Agents (VA) and an Intersection Management Agent (IMA). In order to maximize traffic throughput and to better utilize the capacity of the intersection, the IMA needs to manage the space-time occupancies based on vehicle dynamics. Figure 3-4 and Figure 3-5 gives the time-space occupancies for example vehicles coming from one direction in one lane, and time-space occupancies of two-direction intersection. The total time-space is divided into n x n grids. To avoid collisions, only one vehicle can occupy one grid. Once Vehicle A, B, and C decide their trajectories, some grid cells (e.g., the yellow, green and purple Figure 3-4) have already been reserved based on their future dynamics. Also, the time slots (s1 (t1, t2), s2 (t3, t4), s3 (t5, t6)) represent the occupancies when vehicles travel through the intersection. In the multi-direction case, all approaching vehicles from all approaches should share the time-space occupancies of the intersection sharing area. Rectangle solid grids located at the intersection would represent the time-space occupancy for each vehicle. As we can see from this diagram, the capacity of the intersection is limited. The key to improving the traffic throughput is equivalent to maximizing the total time-space occupancies. For this traffic control strategy, we focus on maximizing the time-space occupancies in the intersection cross-area. To achieve this goal, the two types of agents need to have real-time communications and work collaboratively. On one hand, the IMA needs to arrange the vehicle’s arrival times in
order to maximize the reservation number; on the other hand, each VA has to preplan its own trajectory to avoid collisions and to arrive at the intersection with its predetermined arrival dynamics.

Figure 3-4. Road Time-Space Occupancies for Vehicles in one direction
As mentioned in the first section, due to different control objectives (safety, mobility, and environment), the management mechanisms for vehicle agents are developed separately according to their locations in the intersection. The proposed control strategy is designed primarily to address problems when vehicles are approaching the intersection and driving through the intersection.

### 3.3.2. System Assumptions

Several assumptions were made in the management mechanism:

- Each VA should be a fully controllable agent.
- All the agents are equipped with (V2I/I2V) wireless communication devices.
- Each VA can get its preceding vehicle’s dynamic information (speed, position).
- Each VA can get its own dynamic information (speed, acceleration, turning angle, position, road map, and etc.) from its on-boarding devices (OBD).
• No message drops in communications and unlimited communications capacity.

• A VA cannot enter the intersection without a reservation.

3.3.3. Dynamic Reservation System

In order to enter the intersection, each VA will keep sending reservation requests to the IMA until it obtains one. According to a vehicle’s arrival lane, turning intention and priority, three levels of policies are required to be followed when making reservations:

Level 1. Priority-based Policy: Request with higher priority will be processed first. The request message received by IMA can be classified as: Request message and Cancel-and-Reapply (CnR) message. Request message is used for the VA who doesn’t have a reservation in current status, and whose priority is set to 0. CnR is designed for the VA who needs to reapply a reservation immediately after its current reservation is canceled, and its priority is set to 1.

Level 2. Within-Lane-based Policy: If messages have the same priority, vehicle arrival lane and position will be examined. If any of the VAs that are traveling ahead of the request VA along the same lane has not obtained a reservation, then the request will be rejected. IMA then sends a reservation-rejected message to the VA.

Level 3. First come, first serve (FCFS) Policy: If messages have the same priority but different arrival lane and turning intention, the IMA will serve the earlier message.

After deciding which messages will be processed, the IMA will check its current Reservation Table, and find any available slots for requesting VAs to reserve a space-time occupancy cell.

Figure 3-6 illustrates the system architecture of the reservation-based ATMS.
3.3.4. Multi-Agent Behavior Design

In this advanced traffic management system, in order to guarantee that agents can operate without any collision, vehicle agents and intersection management agents need to follow a set of separate behaviors. Figure 3-7 and Figure 3-8 show the flowchart of those two types of actions. The MAS mode and Default mode in the flowcharts are vehicle motion planning modes that are describe in Section 3.3.4.
Figure 3-7. Vehicle agent actions

Figure 3-8. Intersection Management Agent Actions
3.3.5. Vehicle Agent Motion Planning

One of the keys to reduce traffic congestion and pollutant emission is to prevent vehicles from unnecessary stops before entering the intersection. The three-level reservation policy, by itself, reduces vehicles stop-and-go actions and therefore allows vehicles entering the intersection at a relatively high speed most of the time. Although this policy will be effective in this regard, there is still some room for further improvement on the vehicle itself. Therefore, it is crucial to carry out appropriate vehicle motion planning before it enters the intersection. A cooperative approach between VAs and the IMA may provide appropriate motion estimations.

In this section, four motion-planning modes are designed according to different status of vehicles: 1) Krauss Car-Following Mode [64], 2) Default Mode (arrival at maximum speed and shortest time), 3) SDMAS Mode (fixed arrival time and maximum arrival speed), and 4) Green-Driving Mode (minimizing emissions). The Krauss Car-Following Mode (KCFM) will govern all the vehicles whenever and wherever they are. If not holding a reservation and attempting to enter intersection later, a vehicle should use the default mode to make sure it can reach the intersection at a higher speed within a shortest time. Upon receiving Request-Accepted message, a VA is guaranteed to get a reservation. Therefore, it can select either the Shortest Duration and Maximum Arrival Speed (SDMAS) Mode or the Green-Driving Mode due to different concerns. These four motion-planning modes are described in detail below.
A. Krauss Car-Following Mode (KCFM)

Despite large difference in approach and scope, existing car-following models can be classified as: Deterministic Stimulus-Response Models, Safety Distance Car-following Models, Optimal Velocity Car-following Models, Cellular Automata Models, Psychophysical Car-following Models and Fuzzy-logic Car-following Models [ref]. The KCFM is based on safety distance and it is also used in our traffic simulator. The velocity updating rules is given as:

\[
v_n^{safe}(t) = v_{n-1}(t) + \frac{d_n(t) - d_{des}(t)}{\tau_b + \tau}
\]
(eq. 3.1)

\[
v_n^{des}(t + \Delta t) = \min[v_n^{max}, v(t) + a\Delta t, v_n^{safe}(t)]
\]
(eq. 3.2)

\[
v_n(t + \Delta t) = \max[0, v_n^{des}(t + \Delta t) - \eta]
\]
(eq. 3.3)

where \( d_n(t) \) is the actual gap distance for vehicle n; \( d_{des}(t) \) is the desired gap distance; \( \Delta t \) is updating interval; \( \tau \) is driver reaction time, here \( \tau = 0 \) because of autonomous vehicles; time scale \( \tau_b \) is defined as \( (v_n + v_{n-1})/2b \), \( b \) is the maximum deceleration rate, \( a \) is maximum acceleration rate; \( \eta \) is stochastic perturbation which is assumed to be \( \delta \) correlated in time [64].

B. Default Mode

For most of the time during travelling, a vehicle agent will not hold any reservation, even when it enters the intersection communication network. However, to enhance traffic flow and reduce total wasted time, vehicles still need to be piloted in a certain mode.
Under these considerations, the default motion mode is defined as the one when a vehicle needs to arrive at the intersection in the shortest time. At each moment, a vehicle will figure out its trajectory to the intersection based on its current velocity, safe call-following speed, and road speed. Also, two scenarios need to be considered according to vehicle’s current position. First, current position is greater than $D_{lim\, it}$. In this case, VA can preplan its trajectory without any deceleration, so that it can reach the intersection within a shorter duration and at a higher speed. Second, current position is smaller than $D_{lim\, it}$. Then VA needs to plan its trajectory with both accelerating and decelerating movement, considering that VA should have capability to stop before stop line if without holding a reservation. $D_{lim\, it}$ Is defined as the longest distance that a vehicle can travel at a current speed $V_{max}$ and a constant deceleration as $a_{min}$. We can illustrate how the estimation procedure works using a time-velocity diagram as shown in Figure 3-9. In this figure, $V_c$ is the current speed of VA, $t_0$ is current time, $D$ is the distance between VA and IMA, $V_{max}$ is the roadway speed limit, $V_{end}$ is the arrival speed at intersection, $a_{max}$ is the maximum acceleration, and $a_{min}$ is the maximum deceleration.
From the Figure above, we can see that function $V(t)$ needs to satisfy the following constrains, which guarantee that the planned vehicle trajectory is feasible.

1. $v(t_0) = V_c$  
   (eq. 3.4)

2. $0 < V(t) < V_{\text{max}}$, when $t_0 < t < t_{\text{end}}$  
   (eq. 3.5)

3. $\int_{t_0}^{t_{\text{end}}} v(t) dt = D$  
   (eq. 3.6)

4. $t = V_c - a_{\text{min}} t, V_c t - 0.5 a_{\text{min}} t^2 < D$  
   (eq. 3.7)
We use these constraints to minimize the arrival time by setting an appropriate acceleration speed at every time step moment for vehicles. In these diagrams, it should be noted that for simplicity, piecewise linear function is designed used to satisfy those constrain construct the speed profile. In case 1, the distance between a vehicle and intersection is long enough for the vehicle to accelerate to the roadway speed limit. Therefore, to make $t_{end}$ as small as possible, the vehicle will choose the maximum acceleration to reach the maximum speed and then keep this speed until it arrives at the intersection. In case 2, a vehicle cannot accelerate to the road limit speed even using the maximum acceleration because the distance is too small. Thus, the vehicle still has to accelerate to a high speed using $a_{\text{max}}$ to shorten the arrival time. In case 3, the current distance is less than $D_{\text{limit}}$, but there still has room to increase speed to a higher value. Consequently, the vehicle will accelerate at first and keep an eye on the distance. Once the distance is too close to make any acceleration behavior, it will decelerate immediately to ensure stop before the stop line. In view of the shortest arrival time and highest arrival speed at the intersection, in all these cases, the vehicle’s acceleration rate need to be $a_{\text{max}}$, $a_{\text{min}}$ or 0. Due to the assumption that the maximum or minimum acceleration is independent of vehicle state, piecewise linear speed profile always provides the smallest tend and largest $V_{\text{end}}$. Based on the default mode, a VA can figure out its estimated earliest arrival time and arrival speed at each time step, and also report this information to IMA when it requests for a reservation.

\begin{equation}
\begin{aligned}
    a_{\text{min}} < \frac{dV(t)}{dt} < 0 & \quad \text{or} \quad 0 < \frac{dV(t)}{dt} < a_{\text{max}} \\
\end{aligned}
\end{equation}
C. Shortest Duration and Maximum Arrival Speed (SDMAS) Mode

Once vehicle agent receives the Available Time Slots information from the IMA, it is guaranteed to have a place in intersection reservation queue. The VA needs to find out which time slot is the most suitable for arrival. Theoretically, all the time points in these time slots work, as long as they are behind the EEAT of VA. It is also required that vehicle should occupy a certain period of time in the intersection for safety reason. But the length of this slot may vary depending on the VA’s arrival speed. In some cases, this slot is longer than one or more time slots available by IMA, and the VA drops these slots consequently. From the available slots, the VA chooses the one with the earliest start time and acceptable length, and then preplans its arrival time $T_{arr}$.

The trajectory planning is similar to what was done in the default mode. The difference is, in the previous mode, the arrival time is not fixed, and we attempt to find out the minimum value. In the SDMAS mode, we need to construct the trajectory with a given ending time and maximize the arrival speed at the same time. Figure 3-10 shows the time-velocity diagram that is used by a vehicle to plan its trajectory with a given arrival time.
After choosing a target time slot, a vehicle uses the start time point as its trajectory’s ending time, \( t_{end} \). Then VA makes an acceleration/or deceleration decision based on \( V_{avg} \), which is defined as a constant velocity that vehicle applies to reach the distance \( D \) at \( t_{end} \),

\[
V_{avg} = \frac{D}{t_{end}}.
\]

(1) If \( V_c < V_{avg} \), VA plans an acceleration motion. In case 1, vehicle can accelerate to road limit speed \( V_{max} \) with an appropriate acceleration \( a \), which can be calculated from eq. 3.9, eq. 3.10 and eq. 3.11.

Figure 3-10. Time-Velocity diagrams for estimation of arrival time and arrival speed using SDMAS mode.
(2) In case 2, the distance is too small for vehicle to accelerate to $V_{\text{max}}$, so vehicle keeps a constant acceleration $a$ until it reaches the intersection, and $a$ can be figured out from the equations below.

\[
\begin{cases}
V(t) = V_c + at, & 0 < t < t_1 \\
V(t) = V(t_1) = V_{\text{max}}, & t_1 < t < t_{\text{end}}
\end{cases}
\quad (eq.3.9)
\]

\[
\int_{t_0}^{t_{\text{end}}} V(t) \, dt = D
\quad (eq.3.11)
\]

(3) If $V_c > V_{\text{arg}}$, VA makes a deceleration decision. It is shown in case 3, the whole trajectory is divided into two segments; in the first part, the vehicle applies a constant deceleration, while in the second part, the vehicle moves at a constant speed. This trajectory can be presented as follows.

\[
\begin{cases}
V(t) = V_c + at, & 0 < t < t_{\text{end}} \\
\int_{t_0}^{t_{\text{end}}} V(t) \, dt = D
\end{cases}
\quad (eq.3.12)
\]

\[
V(t) = V(t_1), & t_1 < t < t_{\text{end}}
\quad (eq.3.13)
\]

\[
\begin{cases}
V(t) = V_c + at, & 0 < t < t_1, a < 0 \\
V(t) = V(t_1), & t_1 < t < t_{\text{end}}
\end{cases}
\quad (eq.3.14)
\]

\[
\int_{t_0}^{t_{\text{end}}} V(t) \, dt = D
\quad (eq.3.15)
\]

It should be noted that in order to maximize $V_{\text{end}}$, $a$ has to be as large as possible. This can also be seen from the case 3 diagram. Blue trajectory with larger acceleration has a higher arrival speed than the green one. So we choose the maximum deceleration speed $a_{\text{min}}$.

(4) If $V_c = V_{\text{arg}}$, vehicle will keep a constant speed.

After $V_{\text{end}}$ is determined by previous methods, VA uses intersection map to simulate its trajectory in the intersection in order to get its departure time $t_{\text{dep}}$. If the slot $(t_{\text{end}}, t_{\text{dep}})$
can be fitted in the selected time slot, VA sends it to IMA and adjusts its motion based on this preplanned trajectory. Otherwise, it will redo the trajectory planning using the next earliest time slot.

D. Green-Driving Mode

As traffic issues give rise to increasing environmental problems, some Eco-Friendly strategies are taking into account in finding new solutions. Two dynamic vehicle longitudinal speed-planning algorithms on signalized corridors for minimizing fuel consumption and emission are proposed later in chapter five. Those eco-driving algorithms allow vehicle to choose a less pollutant emission trajectory given a fixed arrival time, which could also be applied to proposed system.

3.3.6. Simulation and Analysis

A. Simulation Setup

A virtual advanced traffic management for connected vehicle using multi-agent approach was created in SUMO, and the performance of this system was evaluated for varying amounts of traffic. Additionally, we compared these to the results from standard traffic lights in terms of improving traffic flow and reducing emissions.

For each experiment, the general simulation setup is:

- *An isolated intersection with one lane in each direction*
- *Lane length: each lane is 500 meters (from vehicle initial point to the center of the intersection)*
- *Speed limit for all lanes is 17.8166 m/s (40 miles per hour)*
• **Maximum acceleration:** 2.5 m/s²
• **Minimum acceleration:** -2.5 m/s²
• **Vehicle type:** light duty car
• **Vehicle length:** 2.5 meters
• **Vehicle safety gap:** 2.5 meters
• **Only one vehicle is allowed in intersection cross area at a time**
• **Each simulation time step:** 0.1 seconds
• **Total simulating steps:** 10000 steps

Note that the estimated communication range is 300 meters. We considered vehicles spawned from two directions (West-to-East bound and North-to-South bound) with various traffic volumes. For both directions, vehicle initial speed is set to be 0 m/s and traffic volume varies from 54 to 1227 vehicles spawned in 1000 seconds.

Two intersection control strategies have been tested for each experiment: 1) Reservation-based advanced traffic management using multi-agent approaches and connected vehicle strategies; and 2) Fixed timing signal: total cycle is 70 seconds, with green phase 30 seconds, yellow phase 4 seconds, and red clear for all roads 1 second.

**B. Travel Time Analysis**

The reservation-based advanced traffic management (ATM) approach significantly outperformed traditional signals in both set of experiments conducted with a view to reduce overall travel time and average travel time. As we can see from Table 3-1, the reduction percentage of vehicle (from both directions) average travel time ranges from
45.82% to 87% when traffic volume varies between 54 vehicles to 1227 vehicles spawned in 1000 seconds. As illustrated from the table, when traffic gets more congested, ATM approaches can more efficiently use the roadway occupancies compared to traditional signal control method.

<table>
<thead>
<tr>
<th>Vehicles Spawned Probability (Uniform Distribution U (0,1))</th>
<th>Vehicles Spawned Volume within 1000 seconds</th>
<th>Average Travel duration Using Traditional Signal Control (s)</th>
<th>Average Travel duration using ATM approach (s)</th>
<th>Reduction Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>56</td>
<td>114.59</td>
<td>62.09</td>
<td>45.82%</td>
</tr>
<tr>
<td>0.3</td>
<td>598</td>
<td>168.39</td>
<td>61.05</td>
<td>63.74%</td>
</tr>
<tr>
<td>0.5</td>
<td>814</td>
<td>430.93</td>
<td>61.10</td>
<td>85.82%</td>
</tr>
<tr>
<td>0.7</td>
<td>1227</td>
<td>480.59</td>
<td>61.07</td>
<td>87.29%</td>
</tr>
</tbody>
</table>

C. Emissions and Fuel Consumption Analysis

In order to evaluate emissions and fuel consumption, we used the emission model based on HBEFA (the Handbook of Emission Factors for Road Transport) integrated in SUMO. The objective of the emission analysis is to observe the variations of the evaluation metrics under different traffic conditions.

The evaluation metrics are emissions of CO\(_2\), CO, HC, NOx and fuel consumption. Cumulative emissions of the four pollutants and energy consumption for all vehicles were obtained from the emission evaluation of the simulation runs. As shown in the results, both emissions and fuel consumption are significantly reduced under advanced traffic control. The percentage of reduction for ATM control system ranges from 41% to 71% for CO, 65% to 75% for CO\(_2\), 55% to 78% for HC, 63% to 74% for NOx, and 65% to 75%
for fuel consumption in two-direction traffic flow scenario when traffic volume varies from 54 to 1227 vehicles spawned in 1000 seconds. Figure 3-11 shows fuel consumption reduction, CO₂ (major part of greenhouse gas emissions) reduction as well as other pollutant emissions reductions in a range of traffic volumes in two-direction traffic scenario.

![Figure 3-11. CO₂ reduction for a range of traffic volume in the two-direction traffic scenario](image)

It is shown that the reservation-based ATM approaches are able to significantly reduce vehicle emissions, as well as fuel consumption. On one hand, ATM approaches reduce average vehicle travel time, and thus the total vehicle emissions and fuel consumption are reduced; on the other hand, overall traffic flow is smoother with an advanced, real-time, and dynamic management, so that vehicles’ unnecessary behaviors (such as stop-and-go) decreases, which also leads to a less vehicle emissions and fuel consumption.
3.4. Platoon-based Control Layer

3.4.1. Problem Statement

Grouping vehicles into platoons is one way to increase roadway capacity, and V2V communication can facilitate this strategy for better traffic management. In recent years, more and more transportation-related studies have integrated vehicle platooning with information on origin-destination, real-time traffic conditions, and vehicle dynamics to improve traffic control and management. Fernandes [65] presented a vehicle platooning method by maintaining desired inter-vehicle spacing in platoons and the simulation results from SUMO showed that this approach outperformed other vehicle platooning methods in terms of reducing travel time. Jean-Michel et al. [66] proposed a physics-inspired MAS to group vehicles into platoons. The vehicle platooning solution in this system was based on interaction (merging and splitting) model in which every vehicle interacted with its preceding vehicles. An intra-platoon information management strategy for dealing with safe and stable operation was proposed in [67]. The proposed system showed that using anticipatory information for both the platoon’s leader and followers had significant impacts on platoon stability. To address the issues of collaborative driving in urban traffic, Halle et al. [68] developed a hierarchical architecture with three layers (guidance layer, management layer and traffic control layer), which could be used for simulating a centralized platoon (with a leader vehicle agent controlling other followers) or a decentralized platoon (with all vehicle agents coordinating with one another).
3.4.2. System Architecture

Unlike the previous reservation-based kernel control layer, in this intermediate control layer, the IMA and VAs interact on a platoon basis rather than on an individual vehicle basis. The system architecture is illustrated in Figure 3-12.

![System architecture of the proposed MAS](image)

As can be observed from Figure 3-12, when a platoon enters into the vehicle-to-infrastructure (V2I) communication range, only the leader vehicle agent (LVA) of the platoon communicates with the IMA by sending the estimated earliest arrival time (EAT) and earliest clearance time (ECT) of the platoon, and receiving reservation confirmation (either approval or rejection). In any case, all the follower vehicle agents (FVAs) only interact with and follow the trajectories recommended by the LVA.
3.4.3. Multi-agent Behavior Design

A. VA Labeling and Relabeling

In the vehicle platooning control layer, all VAs that approach the intersection need to be labeled as either a LVA or a FVA. Figure 3-13 presents the labeling scheme, which is described as follows:

1) *Whenever a VA is released into the network, it will check whether there is a LVA within the V2V communication range.*

2) *If yes, the VA will join the existing platoon and be labeled as a FVA. Otherwise, it will become the LVA of a new platoon.*

3) *Outside the V2I communication range, if the LVA of a platoon catches up with the preceding platoon, then the LVA will join the preceding platoon and be relabeled as a FVA unless the length of the preceding platoon has reached a predetermined threshold. The subsequent FVA will then be relabeled as the LVA of the platoon. This relabeling will trigger down the subsequent FVAs until the predetermined maximum length of the preceding platoon is reached.*

B. LVA Actions

As the leader of a platoon, the LVA is responsible for communicating with the IMA and other FVAs within the platoon. The major functions of a LVA include:

1) *Communication with FVAs.* The LVA is required to communicate with its followers and collect these FVAs’ information, including their vehicle characteristics (e.g., maximum deceleration/acceleration, vehicle length) and their instantaneous
velocity and location. This information is useful for the LVA to monitor and estimate the formation and motion of the whole platoon.

2) Estimation of the platoon’s earliest arrival/clearance time (EAT/ECT). Once the LVA enters into the V2I communication range (set the time instance as \( t = 0 \) for simplicity), it will estimate the EAT/ECT of the platoon based on the information obtained from all FVAs through V2V communication. Then, the estimated EAT and ECT will be sent to the IMA to request a reservation.

As illustrated in Figure 3-14, for the \( i \)-th VA in a platoon, the earliest arrival time, \( t_i^{EA} \), can be derived as follows: For the acceleration portion, the acceleration time, \( t_i^{acc} \), and acceleration distance, \( d_i^{acc} \) are:

\[
    t_i^{acc} = \frac{v_{limit} - v_i^0}{a_i^{max}} \tag{1}
\]

\[
    d_i^{acc} = \frac{(v_{limit})^2 - (v_i^0)^2}{2 \cdot a_i^{max}} \tag{2}
\]
where $v_{\text{limit}}$ is the roadway speed limit; $v_i^0$ denotes the $i$-th VA’s speed at $t = 0$; and $a_{i}^{\text{max}}$ represents the maximum acceleration rate of the $i$-th VA. For the cruise portion, the cruise time, $t_i^{\text{cr}}$, and cruise distance, $d_i^{\text{cr}}$ are

$$t_i^{\text{cr}} = t_i^{\text{EA}} - t_i^{\text{acc}} \quad (3)$$
$$d_i^{\text{cr}} = v_{\text{limit}} \cdot t_i^{\text{cr}} \quad (4)$$

Note that

$$d_i^0 = d_i^{\text{acc}} + d_i^{\text{cr}} \quad (5)$$

Then, the $i$-th VA’s earliest arrival time is

$$t_i^{\text{EA}} = \frac{v_{\text{limit}} - v_i^0}{a_{i}^{\text{max}}} + \frac{1}{v_{\text{limit}}} \cdot \left[ d_i^0 - \frac{(v_{\text{limit}})^2 - (v_i^0)^2}{2 \cdot a_{i}^{\text{max}}} \right] \quad (6)$$

where $d_i^0$ is the distance between the front bumper of $i$-th VA and the stop bar of intersection at time $t = 0$.

It is noted that a platoon’s EAT depends on the performance of the critical vehicle agent within the platoon. Therefore, a platoon’s EAT is

$$t_{\text{pit}}^{\text{EA}} = \max_i \left\{ t_i^{\text{EA}} - \sum_{j=1}^{i-1} h_j^{\text{trg}} \right\} \quad (7)$$

where $h_j^{\text{trg}}$ is the target headway (front bumper to front bumper between the $j$-th and $(j+1)$-th VA. Similarly, the ECT of the platoon is

$$t_{\text{pit}}^{\text{EC}} = \max_i \left\{ t_i^{\text{EA}} + \sum_{j=1}^{n-1} h_j^{\text{trg}} + t_n^{\text{ctr}} \right\} \quad (8)$$

Where $t_n^{\text{ctr}}$ is the clearance time of the $n$-th VA (i.e., the last VA of the platoon) that depends on the VA’s speed, length and intersection’s geometry.
3) **Communication with IMA.** After the LVA estimates the platoon’s EAT/ECT, it will report the estimates to the IMA through V2I communication to request a reservation for the platoon’s occupancy in the intersection crossing area. The IMA will respond to such request by either confirming the reservation or rejecting the request accompanying with recommended reservation. Then, the LVA will confirm the recommended reservation and start planning its trajectory.

4) **Trajectory planning.** After the platoon’s arrival time and clearance time have been confirmed and reserved by the IMA, the LVA will design its trajectory to meet the requirements (e.g., reservation, safety gap). The trajectory planning method used in this paper is similar to [4], to which interested readers may refer for more details. It is noted that to reduce the platoon’s occupancy time within the intersection crossing area, the platoon’s speed (including LVA and FVAs) is designed to be $v^{\text{limit}}$ when it traverses the intersection.

Figure 3-15 depicts a detailed flow chart of how a LVA interacts with the IMA and its followers.
C. FVA Actions

The FVAs are required to communicate with the LVA to share their vehicle characteristics and dynamic information. At the same time, any FVA needs to communicate with its preceding vehicle to always maintain a safe gap in between. In the proposed system, when a platoon is outside the V2I communication range, all FVAs adjust their speeds to form a compact platoon (i.e., keeping the minimum safe gap between VAs) as soon as possible. When the platoon enters the V2I communication range, all VAs adjust their speeds to meet the requirements of the reservation. It is further assumed that a VA’s speed cannot exceed $v^{\text{limit}}$ at any time. Thus, the $i$-th FVA’s speed at time step $k$ is

$$v_{FVA_i}(k) = \min\{v_{FVA_i}(k - 1) + a_{FVA_i}^{\max}, v^{\text{limit}}, v^{ef}\}$$  \hspace{1cm} (9)
where $v^{cf}$ represents the speed constrained by the car-following logic (i.e., maintaining a safe gap with the preceding VA).

D. IMA Actions

After receiving a reservation request from a LVA, the IMA will check its latest reservation table for availability of the requested occupancy time. If the requested slots are available, then IMA will send a confirmation message to the LVA and update the reservation table. Otherwise, the IMA will counter back the LVA’s reservation request with recommendation on the platoon’s arrival/clearance time, and wait for the confirmation from the LVA. It is noted that the First-Come-First-Served (FCFS) rule applies when the IMA processes conflicting reservations.

3.4.4. Simulation and Analysis

To evaluate the effectiveness of the proposed platoon-based (PB) multi-agent intersection management system, an isolated intersection with automated vehicles (using connected vehicles technology) was coded in SUMO simulation environment. Based on the simulation results, we compared the proposed system with the traffic light control (TLC) system and the non-platoon-based (NPB) multi-agent intersection management system in terms of average travel time, fuel consumption, pollutant emissions (calculated using CMEM emission model) and the system’s communication load.

A. Simulation Setup

The general simulation setup is as follows:

- The intersection has two approach (Westbound and Northbound) with one lane
in each direction;

- Each approach is 1,000 meters long (from the vehicle release point to the center of the intersection);
- V2V communication range is 150 meters;
- V2I communication range is 500 meters;
- Speed limit for all lanes is 20 m/s;
- All vehicles are light-duty vehicles;
- Vehicle length is 2.5 meters and the safe clearance distance when stalled is 2.5 meters;
- Maximum acceleration and deceleration rates are 2.5 m/s² and -2.5 m/s², respectively;
- Vehicles are generated with a Poisson distribution;
- Vehicle initial speed is 15 m/s;
- Simulation time step is 0.1 seconds and the total number of steps is 10,000;
- Three traffic volumes (1,080veh/hr, 1,800veh/hr and 2,880 veh/hr) were examined.

Three different intersection management systems were tested: 1) Traditional fixed-time traffic light control system (TLC) 2) non-platoon-based multi-agent system (NPB); and 3) platoon-based multi-agent system (PB). The last two systems were simulated in a signal-less environment. For the fixed-time signal control system, the cycle length is 70 seconds, with 30 seconds of green phase, 4 seconds of yellow phase, and 1 second of all red. In the non-platoon-based system, vehicles’ status and behaviors are agnostic to each other as
there is no V2C communication. The individual VAs independently communicates with the IMA and request intersection crossing time-space reservation when they are within the V2I/I2V communication range.

In the platoon-based system, the different VAs play different roles according to the communication capability. FVAs follow closely behind LVAs to form platoons. The IMA communicates only with the LVAs and reserve time-space occupancies for vehicle platoons instead of individual vehicles.

**B. Travel Time Results**

As shown in Figure 3-16 and Table 3-2, under different traffic volumes, the platoon-based multi-agent intersection management system can reduce the average travel time by 12 to 30% and 4% to 8% compared with the traffic light control system and the non-platoon-based system, respectively. Further investigation of the individual travel time data reveals that unlike the traffic signal control system or the non-platoon-based system, vehicle headway can be effectively reduced by forming platoons, which increases the intersection capacity. In the traffic light control system, as the traffic volume increases, the intersection delay becomes larger.

![Figure 3-16. Average travel time for three traffic management systems](image-url)
Table 3-2. Comparison results on average travel time reduction

<table>
<thead>
<tr>
<th>Traffic Volume</th>
<th>1,080(veh/hr)</th>
<th>1,800(veh/hr)</th>
<th>2,880(veh/hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>TLC</td>
<td>11.6%</td>
<td>22.5%</td>
<td>30.0%</td>
</tr>
<tr>
<td>NPB</td>
<td>4.0%</td>
<td>6.0%</td>
<td>8.3%</td>
</tr>
</tbody>
</table>

C. Fuel Consumption and Emission Results

Table 3-3 summarizes the fuel consumption and CO₂ emission results of the platoon-based system compared to the traffic light control and the non-platoon-based systems. According to the table, both multi-agent intersection management systems outperform the traffic light control system in terms of fuel savings and emission reductions by more than 10% under different traffic volumes. In comparison with the non-platoon-based system, the platoon-based system may result in slightly higher fuel consumption and CO₂ emissions due to the formation of platoons.

Table 3-3. Relative reduction of fuel consumption and CO₂ emissions

<table>
<thead>
<tr>
<th>Traffic Volume</th>
<th>1,080(veh/hr)</th>
<th>1,800(veh/hr)</th>
<th>2,880(veh/hr)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fuel consumption</td>
<td>TLC</td>
<td>11.2%</td>
<td>17.3%</td>
</tr>
<tr>
<td>CO₂ emissions</td>
<td>NPB</td>
<td>0.6%</td>
<td>-5.7%</td>
</tr>
</tbody>
</table>

D. IMA Communication Load Results

In general, the bandwidth of a communication channel is limited. Increasing usage of the bandwidth may result in higher system operation costs. In addition, if the amount of transmitted data is beyond a system’s communication capacity, then it will result in loss of data packets and degraded system performance. One of the major benefits of the
proposed platoon-based system is the reduction in communication load of the IMA by distributing tasks to sub-components (i.e., platoons) in the system.

Here, we evaluated the IMA communication load in terms of the number of vehicles that are communicating with the IMA simultaneously at each time step. Because no vehicle communication is required in the traffic light control system, we only compared the platoon-based system with the non-platoon-based system. Figure 3-17 illustrates the results when traffic volume is 1,080 veh/hr, where much fewer vehicles are communicating with the IMA at each time step in the platooned-based system due to the system’s architecture that only LVAs are able to communicate with the IMA. When the traffic gets more congested (e.g., 2,880 veh/hr), the platoon-based system can significantly reduce the IMA communication load by as much as 90%, as shown in Table 3-4. Note that the communication load of the platoon-based system will not significantly increase with the growth of traffic volume, which indicates that it is more robust in terms of communication performance.

![Figure 3-17. IMA communication load comparison](image-url)
### Table 3-4. Comparison results on IMA communication load

<table>
<thead>
<tr>
<th>Statistics</th>
<th>Strategy</th>
<th>Traffic Volume</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Traffic Volume</td>
<td></td>
</tr>
<tr>
<td></td>
<td>1080(veh/hr)</td>
<td>1800(veh/hr)</td>
</tr>
<tr>
<td>Maximum (veh/sec)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NPB</td>
<td>22</td>
<td>29</td>
</tr>
<tr>
<td>PB</td>
<td>6</td>
<td>6</td>
</tr>
<tr>
<td>Reduction</td>
<td>72%</td>
<td>79%</td>
</tr>
<tr>
<td>Average (veh/sec)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NPB</td>
<td>14</td>
<td>19</td>
</tr>
<tr>
<td>PB</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>Reduction</td>
<td>71%</td>
<td>84%</td>
</tr>
<tr>
<td>STDEV</td>
<td></td>
<td></td>
</tr>
<tr>
<td>NPB</td>
<td>7.19</td>
<td>8.52</td>
</tr>
<tr>
<td>PB</td>
<td>1.75</td>
<td>1.17</td>
</tr>
<tr>
<td>Reduction</td>
<td>75%</td>
<td>86%</td>
</tr>
</tbody>
</table>

3.5. Vehicle Agent Arrival/Departure Scheduling Control Layer

3.5.1. Problem Statement

As mentioned in both reservation-based and platoon-based control layers, the agent-based intersection management system processes requests and clears VAs at the intersection primarily based on a first-in-first-out (FIFO) policy. This does not necessarily achieve system-wide benefits such as reduction of average trip time. For example, a VA may postpone its arrival (e.g. with smooth deceleration and acceleration) at the intersection and let a platoon of VAs along the conflicting approach pass through the intersection first to reduce the average trip times or fuel consumption. In the following, we will present the modified system with optimal scheduling on VAs’ departure times.

3.5.2. Agent-based System Architecture

To better schedule VAs departure times rather than simply apply the first-in-first-out (FIFO) rule at the intersection, multiple vehicle agents’ (VAs) dynamic information, such as entrance times and speed within the controlled region, should be taken into account.
Similar to the existing intersection management system mentioned in section III, each VA will keep communicating with the intersection management agent (IMA) as well as reporting their dynamics in real-time. However, unlike the previous system, a batch of requests will be processed at one time. Since each request contains the requested VA’s current status (e.g., position, velocity, and intended turning), it is possible for the IMA to schedule the arrival or departure time of requested VA at the intersection in an optimal way. In the following discussion, we will focus on scheduling VA’s departure time, i.e., when the VA leaves the intersection cross area (see Figure 3-18).

In this study, our major goal of departure time scheduling is to minimize the total travel times for all VAs (or equivalently, the average VA’s travel time). Assuming that all VAs are fully controlled and both VAs and IMA have equipped with vehicle-to-infrastructure (V2I) and infrastructure-to-vehicle (I2V) communication devices to exchange real-time information between each other, we can modify the system architecture as shown in Figure 3-19. On the one hand, the IMA will re-order the departure sequence for each VA following some constraints, such as no over-taking along the same lane or no departure before the earliest possible time, and send the scheduled departure information to each VA of interest. On the other hand, the VA will update its trajectory, take the responsibility to follow the planned trajectory and clear the intersection on time, upon receiving the information from the IMA.
3.5.3. Multi-Agent Behavior Design

A. Ideal Arrival Scheduling for Vehicle Agents

In the ideal case, with more advanced information from the state-of-the-practice communication technologies, such as cellular-based network, it is possible for the IMA to obtain estimated entrance times and dynamics of VAs within the controlled region (e.g., 500 meters before and after the intersection). Thus, the IMA is capable of scheduling all the VAs’ departure times based on those information and safety constraints to minimize...
the total travel times for all VA’s. In other words, all VAs’ information will contribute to
the decision making at the same time and the optimization will be conducted once for all.
As a consequence, all VAs will receive their own static scheduled departure times and
plan their subsequent trajectories accordingly.

B. Problem Formulation

As illustrated in Figure 3-20, we can formulate the optimal scheduling into a 0-1 binary
linear programming problem and solve it by using IBM ILOG CPLEX Optimization
Studio ver. 12.4 [69], an efficient optimization solver. For simplicity of explanation, we
further assume that, without loss of generality, there are only two conflicting approaches
(Westbound and Northbound) at the intersection and each direction has only one lane.
Therefore, the optimization problem can be formulated as follows:

1) Objective function: To minimize the total travel times for all VAs, i.e.,

\[ \text{Min } \left( \sum_{i=1}^{n_1} (t_{i,w}^D - t_{i,w}^E) + \sum_{j=1}^{n_2} (t_{j,n}^P - t_{j,n}^E) \right) \]

where \( n_1 \) and \( n_2 \) are the total number of VAs traveling Westbound and Northbound,
respectively. \( t_{i,w}^E \) and \( t_{i,w}^D \) are the entrance time (within the controlled region) and
departure time at the intersection, respectively, for the $i$-th VA along the Westbound lane; while $t_{i,n}^E$ and $t_{i,n}^D$ are the counterparts for the $j$-th VA traveling Northbound.

2) Known variables and decision variables: VAs’ entrance times, $t_{i,w}^E$’s and $t_{j,n}^E$’s are given but the departure times, $t_{i,w}^D$’s and $t_{j,n}^D$’s at the intersections are decision variables.

3) Constraints: These constraints are safety-related or based on a set of assumptions that govern the modified intersection management system.

- Each VA has a unilateral range for its departure time at the intersection, i.e.,
  \[ t_{i}^D \in \left[ t_{i}^E + \Delta t_i, +\infty \right), \quad \forall i \]
  where $\Delta t_i$ is the shortest travel time for the $i$-th VA, which may depend on the distance to intersection, roadway speed limit, VA’s dynamics and etc.

- If $t_{i}^E < t_{j}^E$, then $t_{i}^D < t_{j}^D$, for any $i$-th and $j$-th VA traveling along the same lane. In other word, overtaking is not allowed along the same lane in the proposed system.

- For safety, the time gap between two consecutive VAs along the same lane should exceed a certain threshold:
  \[ t_{i+1}^D - t_{i}^D \in [\Delta T_1, +\infty), \quad \forall i \]
  where $\Delta T_1$ is the smallest acceptable time gap along the same lane.

- The time gaps between two consecutive VAs along different approaches should be no less than another threshold:
  \[ |t_{i,w}^D - t_{j,n}^D| \in [\Delta T_2, +\infty), \]
  for any $i$-th and $j$-th VAs which leave the intersection consecutively along different approaches. Obviously, $\Delta T_2 > \Delta T_1$, which motivates the scheduling of departure
times along different directions in this paper. In addition, the values of $\Delta T_1$ and
$\Delta T_1$ may depend on very specific conditions in the system.

4) *Notes*: To mathematically interpret some of the aforementioned constraints, additional 0-1 binary variables have been introduced, and the Big M method was used to solve the optimization problems.

*C. Trajectory Planning*

Upon receiving the optimal scheduled departure time, the VA will plan an appropriate trajectory in order to assure its leaving at the advisory time. To achieve different performances, such as minimizing travel time, number of stops, and trip fuel consumption, different trajectories should be designed accordingly. Similar to reservation-based control layer, we plan each VA’s trajectory in this control layer using a piece-wise linear function, but further require to minimize the passage time through the intersection cross-area. In other words, each VA will pass the intersection at the maximum speed.

*D. Discussion on Dynamic Scheduling*

The ideal scheduling described above may not be realistic in some cases, where the communication range is limited, such as using the DSRC technology. Therefore, it is impossible for the IMA to obtain or estimate all VAs’ entrance times and conduct the optimal scheduling once for all. One heuristic solution is to use dynamic (real-time) scheduling based on the most up-to-date available traffic information and VAs’ dynamics. At each time step, the IMA will screen through all the VAs approaching the intersection
and fall between the communicable region and decision-making region (see Figure 3-18), and keep updating their information. Whenever one or more VA(s) just enter the decision-making region (which is much closer to the intersection than the communication region), then the IMA will re-run the optimization based on the most updated input knowledge and re-schedule the departure times for all the involved VAs. For those VAs which have entered the decision-making region, there is no need to include them in the dynamic scheduling and update their departure times, since these VAs may be too close to the stop line to change the trajectory in a flexible way.

3.5.4. Simulation and Analysis

To evaluate the performance of the modified multi-agent intersection management system with optimal scheduling, an isolated intersection with autonomous vehicles (using connected vehicles technology) has been coded in SUMO simulation environment. In addition, we compared the results with existing first-in-first-out (FIFO) reservation-based intersection management system in terms of average travel time, travel time reliability, fuel consumption and pollutant emissions.

A. Simulation Setup

The general simulation setup is as follows:

- *The intersection has two approach (Westbound and Northbound) with one lane in each direction;*
- *Each arm is 500 meters long (from vehicle initial point to the center of the intersection), which is also the communication range;*
- *Speed limit for all lanes is 20 m/s;*
• Vehicular flow is homogeneous and all vehicles are light-duty;
• Vehicle length is 2.5 meters and the safety distance when stalled is 2.5 meters;
• Maximum acceleration and deceleration rates are 2.5 m/s\(^2\) and -2.5 m/s\(^2\), respectively;
• Vehicles are generated by the Poisson distribution with the rate of 1 vehicle every 3 seconds;
• Vehicle initial speed is 15 m/s;
• Simulation time step is 0.1 seconds and the total number of steps is 10,000;
• \(\Delta T_1\) is 0.125 second and \(\Delta T_2\) is 0.6 second (these values are specific to this study case).

Two multi-agent intersection management systems have been tested: 1) FIFO-based ATMS; and 2) optimal scheduling based ATMS. Both these systems were simulated in a signal-less intersection.

B. Travel Time Analysis

As can be observed from Figure 3-21(a) and 3-21(b), the optimal scheduling based multi-agent intersection management system can reduce the average travel time by around 1.42\% (1.62\% for the Westbound trip and 1.22\% for the Northbound one), compared with the FIFO-based system. Further investigation of individual travel time sample reveals that unlike the FIFO based system, some VAs have to sacrifice their own interest by decelerating en-route to gain a global benefit in the optimal scheduling based system. Table 3-5 presents the results on variability of travel time. It can be seen that the
optimal scheduling based system can significantly improve the travel time reliability by as much as around 60%.

Figure 3-21. (a) Average Travel Time for Two Traffic Management Systems; (b) Relative Reduction in Average Travel Time

<table>
<thead>
<tr>
<th></th>
<th>FIFO-based (sec)</th>
<th>Optimal scheduling based (sec)</th>
<th>Relative improvement (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Westbound</td>
<td>0.49</td>
<td>0.20</td>
<td>59%</td>
</tr>
<tr>
<td>Northbound</td>
<td>0.50</td>
<td>0.22</td>
<td>56%</td>
</tr>
</tbody>
</table>

C. Fuel Consumption and Emission Analysis

The system environmental impacts evaluation metrics include emissions of CO₂, CO, HC, NOx and fuel consumption. Cumulative emissions of each type of pollutants and energy consumption for all vehicles were obtained from the simulation runs. The results have shown that trivial improvements (around 0.03%) for both CO₂ emissions and fuel consumption can be achieved using the optimal scheduling based system. When comparing to the FIFO-based system, no clear change can be witnessed for the emissions of other criteria pollutants. A potential explanation is that the modified system was designed to minimize the total travel times rather than optimize the fuel economy. A heuristic piece-wise linear function was used without digging into the microscopic level of the trajectory planning which has much impacts on the fuel consumption and pollutant
emissions. Optimization of VA’s trajectories can be a future topic and included in the frameworks of the proposed system.

3.6. Comprehensive Simulation Results and Analysis

This section presents a comprehensive simulation experiment showing how different traffic control strategies affect the performance of a typical multi-lane intersection. In this experiment, this intersection uses fixed-timing traffic signal control, adaptive traffic signal control, or proposed agent-based advanced traffic management strategies. The results demonstrate that proposed agent-based system outperform other traffic control strategies by improving total system performance in terms of increasing the throughput as well as improving the fuel consumptions and emissions. It also illustrates well how the proposed agent-based ATMS framework could be practically used in this sort of experiments.

3.6.1. Simulation Network

This experiment uses SUMO to simulate 20 minutes of traffic on the intersection of University Avenue and Chicago Avenue in Riverside, California, which is illustrated in Figure 3-22.
In order to be able to run tests, we firstly needed to obtain a map of the intersection, compatible with SUMO. The SUMO module Netconvert offers a way to import digital road networks from various sources (such as VISUM or OpenStreetMap) and creates networks usable by the other SUMO modules. The SUMO scenario of this two-lane intersection is converted from OpenStreetMap (OSM) \[115\] data, which offers high quality traffic network data in urban areas. In both OSM and converted SUMO scenario, traffic lights and lane information have been mapped in great details, see figure 3-23.
3.6.2. Simulation Setups

The general simulation setup is as follows:

- The intersection has four approach (Westbound, Northbound, Eastbound and Southbound) with two lanes in each direction;
- Each arm is 1,110 meters long (from the vehicle release point to the center of the intersection);
- In this approach, right-turn lane and through-lane are on the right-most-lane; left-turn lane is on the left-most-lane (illustrated in Figure 3-24);
- V2V communication range is 150 meters;
- V2I communication range is 500 meters;
- Speed limit for all lanes is 17.88 m/s;
- All vehicles are light-duty vehicles;
- Vehicle length is 2.5 meters and the safe clearance distance when stalled is 2.5 meters;
• Maximum acceleration and deceleration rates are 2.5 m/s² and -2.5 m/s², respectively;
• Vehicles are generated with a Poisson distribution;
• Vehicle initial speed is 12 m/s;
• Simulation time step is 0.1 seconds and the total number of steps is 10,000;
• Traffic volume for entire intersection is 7488 vehicles per hour, 50% of which is through traffic. Right-turn and left-turn vehicles each account for 25% of all vehicles.

Figure 3-24. Intersection Traffic Maneuvers

3.6.3. Comparison traffic control strategies

A. Fixed-timing traffic light system (F-TLS)

For the purpose of comparing the proposed ATMS with conventional traffic control strategies, a conventional traffic light controlled intersection is programmed. This fixed
Timing signal light is defined as a traffic controller has a semaphore plan, which is characterized by a sequence of phases.

Each phase has a duration and a color scheme (green, yellow, flashing yellow and/or red), whose values correspond to every possible maneuver at the intersection. The execution of the phases sequence is called a cycle and has a period equal to the sum of the durations of the phases. In Figure 3-24 the intersection has 12 possible maneuvers, indicated by the arrows, which means that each phase has to specify a color for each maneuver. The phase number guides the sequence of phases, and after the end of the phase, a 120-second cycle duration is completed, following again phase 1. For each maneuver the traffic light may show the green color with symbol G, yellow with symbol y, flashing yellow with symbol g and red with symbol r. Figure 3-25 shows the sequence of phases and an example of phase 1.

<table>
<thead>
<tr>
<th>Phase</th>
<th>0</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>Duration(s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>G</td>
<td>G</td>
<td>g</td>
<td>g</td>
<td>r</td>
<td>r</td>
<td>G</td>
<td>G</td>
<td>g</td>
<td>g</td>
<td>r</td>
<td>r</td>
<td>31</td>
</tr>
<tr>
<td>2</td>
<td>y</td>
<td>y</td>
<td>g</td>
<td>g</td>
<td>r</td>
<td>r</td>
<td>y</td>
<td>y</td>
<td>g</td>
<td>g</td>
<td>r</td>
<td>r</td>
<td>9</td>
</tr>
<tr>
<td>3</td>
<td>r</td>
<td>r</td>
<td>G</td>
<td>r</td>
<td>r</td>
<td>r</td>
<td>G</td>
<td>r</td>
<td>r</td>
<td>r</td>
<td>G</td>
<td>r</td>
<td>6</td>
</tr>
<tr>
<td>4</td>
<td>r</td>
<td>r</td>
<td>y</td>
<td>r</td>
<td>r</td>
<td>r</td>
<td>y</td>
<td>r</td>
<td>r</td>
<td>r</td>
<td>y</td>
<td>r</td>
<td>9</td>
</tr>
<tr>
<td>5</td>
<td>r</td>
<td>r</td>
<td>r</td>
<td>G</td>
<td>G</td>
<td>g</td>
<td>r</td>
<td>r</td>
<td>G</td>
<td>G</td>
<td>g</td>
<td>31</td>
<td></td>
</tr>
<tr>
<td>6</td>
<td>r</td>
<td>r</td>
<td>r</td>
<td>y</td>
<td>y</td>
<td>g</td>
<td>r</td>
<td>r</td>
<td>y</td>
<td>y</td>
<td>g</td>
<td>9</td>
<td></td>
</tr>
<tr>
<td>7</td>
<td>r</td>
<td>r</td>
<td>r</td>
<td>r</td>
<td>r</td>
<td>G</td>
<td>r</td>
<td>r</td>
<td>r</td>
<td>r</td>
<td>G</td>
<td>6</td>
<td></td>
</tr>
<tr>
<td>8</td>
<td>r</td>
<td>r</td>
<td>r</td>
<td>r</td>
<td>y</td>
<td>r</td>
<td>r</td>
<td>r</td>
<td>r</td>
<td>r</td>
<td>y</td>
<td>9</td>
<td></td>
</tr>
</tbody>
</table>

(a)
B. Adaptive traffic light system (A-TLS)

Another traffic signal control simulated in this network is a simply implemented adaptive traffic signal control. This control strategy adjusts the timing of red, yellow and green lights to accommodate changing traffic patterns, which could better ease traffic congestion than conventional fixed-timing signal control. To get the real-time traffic data, 4 inductive loop detectors (D1, D2, D3 and D4) are placed near the stop bar (20 meters) at each approaching lane, illustrated in Figure 3-26. In this simulation, signal controller will only adjust the phase duration based on the through-traffic. The minimal green phase duration of through-traffic is 21 seconds and the maximal duration is 31 seconds. At the end of 21 seconds of the green phase, if no vehicle is detected stopping at the loop detector on the conflicting approaches, than the green phase could be expended by
another 3 seconds. Note that the total duration would not exceed the maximal 31-second duration.

Figure 3-26. Intersection with Inductive loop detectors

C. Agent-Based ATMS

To evaluate the performance of the proposed agent-based ATMS, we coded a communicable roadside agent and vehicle agents in SUMO. Each vehicle was modeled as point agent with a simple acceleration-based dynamic model. Each agent has a behavior governing it, responsible for obeying intersection policies and avoiding collisions. Two agent-based traffic control strategies, reservation-based ATMS without platooning (NPB-ATMS) and platoon-based ATMS (PB-ATMS), are evaluated and compared to the other two signalized traffic control strategies. Vehicles are spawn at an initial speed at 12 m/s.
A piece-wise linear speed profile will be used to generate vehicle’s approaching trajectory when vehicle obtains a reservation.

3.6.4. Comprehensive Simulation Results and Analysis

A. $CO_2$ Emission and Energy Consumption Analysis

In order to evaluate the impact different traffic control strategies may have on system performance in terms of emissions and fuel consumption, second-by-second vehicles’ speed profiles were collected from SUMO simulation and MOVES emission model were adopted to calculate the $CO_2$ emission and energy consumption. And herein we assume vehicles simulated in this experiment are light-duty vehicle (with vehicle type ID=21 in MOVES). Corresponding second-by-second vehicle-specific power values that indicate vehicle emission levels were calculated based on vehicle speed and acceleration profiles, and emission rates by vehicle operating mode (OpMode) for each vehicle were generated. These emission rates are then applied to the vehicle OpMode distributions to estimate emissions for the scenario simulated. Figure 3-27 illustrates the procedure to estimate emissions and energy consumption by using MOVES.

![Figure 3-27](image-url)

Figure 3-27. Procedure to estimate emissions and energy consumption by using MOVES.
Figure 3-28 shows fuel consumption and CO₂ (major part of greenhouse gas emissions) emission results by applying four different control strategies on the proposed intersection.

![Average Energy Consumption](image1)

![Average CO₂ Emission](image2)

Figure 3-28. Average energy consumption (a) and average CO₂ emission (b) for four traffic management systems.

Table 3-6 and Table 3-7 illustrate the relative reductions on energy consumption and CO₂ emission between every two traffic management systems. It can be seen from the table that, compared to conventional fixed-timing traffic light system, both non-platoon based ATMS and platoon-based ATMS significantly reduced the energy consumption and CO₂ emission by around 37.3% and 35.4% respectively. Although adaptive traffic light system offers more a lot more control flexibility and reduced both energy consumption and CO₂ emission by 6.7% comparing to fixed-timing traffic light system, the PB-ATMS and NPB-ATMS could even outperform the adaptive traffic light system by improving the energy use and CO₂ emission by 32.8% and 30.8% respectively. In comparison with the non-platoon-based ATMS, the platoon-based ATMS may result in slightly (around 3.0%) higher energy consumption and CO₂ emissions due to the formation of platoons.
Table 3-6. Relative Average Energy Consumption Reduction Between Each Two Traffic Management Systems

<table>
<thead>
<tr>
<th>%</th>
<th>F-TLS</th>
<th>A-TLS</th>
<th>NPB-ATMS</th>
<th>PB-ATMS</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-TLS</td>
<td>-</td>
<td>-7.22</td>
<td>-59.6</td>
<td>-55.06</td>
</tr>
<tr>
<td>A-TLS</td>
<td>6.73</td>
<td>-</td>
<td>-48.85</td>
<td>-44.62</td>
</tr>
<tr>
<td>NPB-ATMS</td>
<td>37.34</td>
<td>32.82</td>
<td>-</td>
<td>2.82</td>
</tr>
<tr>
<td>PB-ATMS</td>
<td>35.51</td>
<td>30.85</td>
<td>-2.93</td>
<td>-</td>
</tr>
</tbody>
</table>

Table 3-7. Relative Average CO₂ Emission Reduction Between Each Two Traffic Management Systems

<table>
<thead>
<tr>
<th>%</th>
<th>F-TLS</th>
<th>A-TLS</th>
<th>NPB-ATMS</th>
<th>PB-ATMS</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-TLS</td>
<td>-</td>
<td>-7.15</td>
<td>-59.49</td>
<td>-54.83</td>
</tr>
<tr>
<td>A-TLS</td>
<td>6.67</td>
<td>-</td>
<td>-48.84</td>
<td>-44.49</td>
</tr>
<tr>
<td>NPB-ATMS</td>
<td>37.3</td>
<td>32.81</td>
<td>-</td>
<td>2.92</td>
</tr>
<tr>
<td>PB-ATMS</td>
<td>35.41</td>
<td>30.79</td>
<td>-3.01</td>
<td>-</td>
</tr>
</tbody>
</table>

B. Other Criteria Pollutant Emissions Analysis

Besides the fuel consumption and CO₂ emission analysis, we also observed the performance of different traffic management systems in terms of criteria pollutant emissions, such as NOx, PM2.5, CO and HC. Table 3-8 summarizes the results of average pollutant emissions by utilizing MOVES emission model as well. In table 3-9, we have compared the emissions reductions between two proposed ATMS and two conventional traffic light systems. As shown in the results, when compared to the two conventional traffic light systems, both non-platoon-based ATMS and platoon-based ATMS could gain significant reductions on the major pollutant emissions ranging from 25% to 35%.

Table 3-8. Average Criteria Pollutant Emissions (CO, HC, NOx, PM2.5)

<table>
<thead>
<tr>
<th></th>
<th>CO (g)</th>
<th>HC (g)</th>
<th>NOx (g)</th>
<th>PM2.5_Elg (g)</th>
<th>PM2.5_org (g)</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-TLS</td>
<td>6.33E+00</td>
<td>5.22E-02</td>
<td>1.74E-01</td>
<td>6.83E-03</td>
<td>3.13E-02</td>
</tr>
<tr>
<td>A-TLS</td>
<td>6.20E+00</td>
<td>4.99E-02</td>
<td>1.71E-01</td>
<td>6.43E-03</td>
<td>2.95E-02</td>
</tr>
<tr>
<td>NPB-ATMS</td>
<td>4.59E+00</td>
<td>3.51E-02</td>
<td>1.29E-01</td>
<td>4.44E-03</td>
<td>2.04E-02</td>
</tr>
<tr>
<td>PB-ATMS</td>
<td>4.62E+00</td>
<td>3.57E-02</td>
<td>1.28E-01</td>
<td>4.45E-03</td>
<td>2.04E-02</td>
</tr>
</tbody>
</table>
Table 3-9. Relative Reduction on Criteria Pollutant Emissions (CO, HC, NOx, PM2.5)

<table>
<thead>
<tr>
<th></th>
<th>CO</th>
<th>HC</th>
<th>NOx</th>
<th>PM2.5_Elg</th>
<th>PM2.5_org</th>
</tr>
</thead>
<tbody>
<tr>
<td>NPB-ATMS vs. F-TLS</td>
<td>27.48</td>
<td>32.75</td>
<td>25.86</td>
<td>34.99</td>
<td>34.82</td>
</tr>
<tr>
<td>PB-ATMS vs. F-TLS</td>
<td>27.01</td>
<td>29.65</td>
<td>26.43</td>
<td>30.94</td>
<td>34.82</td>
</tr>
<tr>
<td>NPB-ATMS vs. A-TLS</td>
<td>25.96</td>
<td>31.65</td>
<td>24.56</td>
<td>34.83</td>
<td>30.84</td>
</tr>
<tr>
<td>PB-ATMS vs. A-TLS</td>
<td>25.48</td>
<td>28.45</td>
<td>25.14</td>
<td>30.79</td>
<td>30.84</td>
</tr>
</tbody>
</table>

C. Travel Time Analysis

The proposed advanced traffic management system could significantly outperformed traditional traffic light system in the simulation study conducted with a view to reduce overall travel time and average travel time, which is illustrated in Figure 3-29. As we can see from Table 3-10, the reduction percentage of vehicle average travel time in both non-platoon-based ATMS and platoon based ATMS are approximately 48.42% and 44.56% when compared to fixed-timing traffic light system and adaptive traffic light system, resulting from much efficiently utilizing roadway space and therefore largely shortened idling time. As illustrated from the table, when traffic gets more congested, ATM approaches can more efficiently use the roadway occupancies compared to traditional signal control method.

Figure 3-29. Average Travel Time for four traffic management systems
Further investigation of the individual travel time data reveals that unlike non-platoon-based system, reserving time spacing for one platoon (or multiple vehicles at a time) may sometimes lead to negative impact on other platoons which are on the conflicting approaches by adding same amount of idling time to all the vehicles in those platoons.

### D. IMA Communication Load Results

In general, the bandwidth of a communication channel is limited. Increasing usage of the bandwidth may result in higher system operation costs. In addition, if the amount of transmitted data is beyond a system’s communication capacity, then it will result in loss of data packets and degraded system performance. One of the major benefits of the platoon-based ATMS is the reduction in communication load of the IMA by distributing tasks to sub-components (i.e., platoons) in the system.

Here, we evaluated the IMA communication load in terms of the number of vehicles that are communicating with the IMA simultaneously at each time step. Because no vehicle communication is required in the traffic light control system, we only compared the platoon-based system with the non-platoon-based system. Table 3-11 illustrates the results that much fewer vehicles are communicating with the IMA at each time step in the platoon-based system due to the system’s architecture that only LVAs are able to communicate with the IMA. The platoon-based system can significantly reduce the

---

**Table 3-10. Vehicle Average Travel Time Reduction Between Each Two Traffic Management Systems**

<table>
<thead>
<tr>
<th></th>
<th>F-TLS</th>
<th>A-TLS</th>
<th>NPB-ATMS</th>
<th>PB-ATMS</th>
</tr>
</thead>
<tbody>
<tr>
<td>F-TLS</td>
<td></td>
<td>-12.64</td>
<td>-93.87</td>
<td>-80.37</td>
</tr>
<tr>
<td>A-TLS</td>
<td>11.22</td>
<td></td>
<td>-72.1</td>
<td>-60.12</td>
</tr>
<tr>
<td>NPB-ATMS</td>
<td>48.42</td>
<td>41.89</td>
<td></td>
<td>6.96</td>
</tr>
<tr>
<td>PB-ATMS</td>
<td>44.56</td>
<td>37.54</td>
<td>-7.48</td>
<td></td>
</tr>
</tbody>
</table>
IMA communication load by as much as 68.18% as shown in Table 3-11. The table also shows the possibility of improving the robustness and stability of the IMA system with a variation reduction on communication load of approximately 66.71% in platoon-based ATMS.

<table>
<thead>
<tr>
<th>Statistics (veh/sec)</th>
<th>Strategy</th>
<th>IMA communication load</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximum</td>
<td>NPB</td>
<td>66</td>
</tr>
<tr>
<td></td>
<td>PB</td>
<td>21</td>
</tr>
<tr>
<td>Reduction</td>
<td></td>
<td>68.18%</td>
</tr>
<tr>
<td>Average</td>
<td>NPB</td>
<td>30.87</td>
</tr>
<tr>
<td></td>
<td>PB</td>
<td>11.81</td>
</tr>
<tr>
<td>Reduction</td>
<td></td>
<td>61.74%</td>
</tr>
<tr>
<td>STDEV</td>
<td>NPB</td>
<td>21.69</td>
</tr>
<tr>
<td></td>
<td>PB</td>
<td>7.22</td>
</tr>
<tr>
<td>Reduction</td>
<td></td>
<td>66.71%</td>
</tr>
</tbody>
</table>

### 3.6.5. Summary

An advanced traffic management for connected vehicle using multi-agent approach is described in this chapter. Based on this system, a multi-layer reservation policy is proposed and interactions between vehicle agents and intersection management agent are detailed presented. Also, a related vehicle motion planning based on these policies is proposed in this report. All of these approaches for advanced traffic management are to make the traffic flow even more smoothly and significantly reduce necessary idling time. Then simulation results also show that advanced traffic management has a great advantage on reducing vehicle emissions, as well as the fuel consumption.

In addition, a platoon-based multi-agent intersection management system where vehicle agents can proactively group into platoons through V2V communication and
traverse intersections using the platoon-based reservation scheme through V2I communication. This simulation study has illustrated promising results in improving mobility and environmental sustainability, compared with conventional traffic signal control strategy. Unlike the non-platoon-based intersection management system, the proposed platoon-based system can significantly reduce the IMA communication loads and is much more robust against the variation of traffic volumes.

A multi-agent based optimal scheduling approach is also developed for ATMS. Unlike those systems with first-in-first-out (FIFO) assumption, the proposed system may schedule the vehicle agents’ (VAs) departure time at intersection to obtain a global benefit. Simulation study has illustrated the promising results in both mobility and reliability. No clear benefits can be observed on the sustainability, compared with the FIFO-based system.

As a future step, the dynamic scheduling management system should be integrated into the proposed system to address more realistic scenarios. To better evaluate the performance of our proposed system, different traffic conditions, such as volume-to-capacity ratio, and different traffic pattern or arrival distribution, will be tested and analyzed in the future.
4. AGENT-BASED VEHICLE OPTIMAL LANE SELECTION IN ATMS

4.1. Problem Statement

Limited roadway capacities along with ever-increasing travel demand continue to pose challenges to researchers and engineers on how to manage the traffic system more efficiently in terms of mitigating congestion. A significant amount of research effort focuses on improving traffic flows at congested roadway locations by coordinating traffic control devices, such as ramp meters (for freeways) and traffic signals (for arterials). These traffic management strategies, however, typically assume little knowledge and control on microscopic driving maneuvers, e.g., lane changes, which can affect the operational effectiveness of the roadway system. Previous studies also indicate that well-coordinated lane changes exhibit a non-trivial potential to minimize shockwave impacts, increase roadway throughput, maintain desired speeds and ensure driving comfort [70].

As a key procedural element of lane change driving behavior, lane selection has been widely studied for years to achieve a better understanding of traffic systems in the real world. Typically, lane selection without external guidance can be classified as either discretionary or mandatory [71], where discretionary lane selection is performed to improve the current driving conditions, while mandatory lane selection is performed when the vehicle has to leave its current lane due to unavoidable constraints, such as lane drops or exiting the roadway. It turns out that discretionary lane selection (and the resultant lane changes) may be disruptive to traffic flow by creating moving bottlenecks
under congested traffic conditions [72], thus impairing the operational performance of the entire traffic system. This results from both individual desires and the lack of system-wide traffic information for better decision making.

In ATMS, with the capabilities to share information through wireless communication among vehicles (vehicle-to-vehicle, V2V) as well as between vehicles and infrastructure (V2I/I2V), connected vehicle technology may provide a well-defined platform for developing cooperative lane selectionchanging to improve traffic operation. Based on the CV technology, this chapter presents a real-time lane selection algorithm, which can provide guidance on determining optimal target lanes for individual vehicles in order to better regulate traffic flow, thus achieving a system-wide optimal solution in terms of maintaining desired traffic speeds. It is noted that the proposed algorithm can be applied to both advanced driving assistance systems (ADAS) and automated vehicles.

4.1.1. Traffic Flow Impacts Due to Potential Vehicle Conflicts

Assume that a number of vehicles are traveling along a multi-lane highway segment and each of them has its own desired speed. Potential conflicts may occur if all vehicles want to maintain their own desired speeds that usually are not homogenous. Previous studies show that such potential vehicle conflicts could interrupt traffic flows and, even worse, lead to accidents [73]. To avoid these conflicts, vehicles may either change speeds or lanes. However, aggressive driving, such as hard braking and cutting into small gaps, could have disproportionate impacts on the upstream traffic flow along the involved lanes, resulting in degradation of system performance in terms of safety, mobility, environmental sustainability and reliability. Figure 4-1 illustrates two example scenarios
(slowing-down and cutting-in) where potential conflicts of preceding vehicles may unfavorably influence the upstream vehicles E and F, respectively. Please note that the numbers indicate the desired speed of the individual vehicles.

![Figure 4-1. Conceptual example of (a) slowing down vehicle and (b) cutting-in vehicle due to potential vehicle conflicts](image)

### 4.1.2. Lane Selection and Lane Changing

One of the earliest lane selection models can be found in Gipps [74], which has already been implemented in several micro-simulation modeling tools, e.g., CORSIM [75]. Since then, numerous studies [76, 77] on lane change (including lane selection) have attached importance to the modeling of driver behavior without external guidance from advanced driving assistance systems (ADAS). For example, the Freeway Lane Selection (FLS) algorithm introduced by the FHWA’s Next Generation SIMulation (NGSIM) program [78] has incorporated the “target lane” concept, which facilitates the modeling of lane change behavior along freeway segments. To determine the best target lane, the FLS algorithm will assign an individual “score” to each lane based on a variety of parameters, such as the distance to the upcoming exit and average vehicle speed in each lane, and choose the lane with the highest score. Then, the vehicle will complete a lane change to the target lane if both the lead gap and the lag gap are acceptable. However, it is noted
that such an algorithm assumes only the availability of localized traffic conditions that can be perceived by the driver. As sensor technologies within ADAS advances, new features such as blind spot detection (BSD) have been commercialized to provide the driver guidance (not) to change lanes. However, the majority of this technology is purposefully developed for safety only [79]. Recently, the concept of predictive lane changing, particularly in the framework of automated driving, has been attracting increased attention [80]. Such strategies aim at optimizing the lane changing maneuvers of individual vehicles in terms of user-defined performance measures (e.g., travel time), without considering the impacts on other vehicles. With progress in vehicular communication technologies, Ralf and Paul [81] designed a cooperative driving system, which enabled the vehicle to automatically handle typical freeway lane-changing by taking into account the future intentions of surrounding vehicles in a more “win-win” manner. More recently, Kishore [82] proposed an intelligent lane-changing advisory system (ices) based on vehicle-to-vehicle (V2V) and infrastructure-to-vehicle (I2V) communication. Such advisory systems can guide the driver to select better target lane under prevailing traffic conditions, in order to improve driving performance (e.g., reducing travel time) of the subject vehicle. Just like other existing ADAS, it might gain the benefit at the expense of other vehicles, thus only achieving sub-optimal, or even worse, degraded operational performance of the entire traffic system. In a new proposed method described below, we aim to optimize lane changes from a systems perspective.
4.2. Agent-based Real-time Optimal Lane Selection

As pointed out in the previous sections, well-coordinated lane changes can help maintain desired speeds, minimize shockwave impacts, and thus improve traffic system performance. However, if the real-time traffic information cannot be well shared, then the lane selection decision made by individual driver may not achieve the system-wide optimality, or may even deteriorate the system performance. Thanks to the connected vehicle technology, we are able to develop an improved lane selection algorithm as described in the following, to minimize potential vehicle conflicts of the entire traffic flow.

The basic idea of this algorithm is to determine the optimal target lane for each vehicle based on its current location, speed, lane index and desired speed, in order to avoid subsequent hard brakes or lane changes forced by slow vehicles or lane drops.

4.2.1. Agent Definition

As shown in Figure 4-2, the proposed real-time optimal lane selection system consists of two components: a lane selection agent (LSA) and vehicle agents (VAs). The LSA, which may be a roadside unit, is capable of communicating with involved vehicles within a certain range (orange vehicles within the shadowed region in Figure 4-3) to access their real-time information, including the locations, speeds, lanes and desired driving speeds. The desired driving speed may be specified by the driver at the start of a trip, or inferred from the historical speed profile. Based on such information, the LSA can estimate the associated exiting speeds and provide drivers advice on target lanes.
4.2.2. Agent-base System Architecture

The proposed lane selection optimization algorithm in an agent-based ATMS can be divided into three steps:

1) Data collection: In this stage, the lane selection agent collects real-time information of vehicles (orange vehicles in Figure 4-3) within the infrastructure-to-vehicle (I2V) and vehicle-to-infrastructure (V2I) communication range. Before a vehicle leaves the communication range or its target lane has been optimized, the vehicle needs to update its states whenever they change.

2) Optimal target lane determination: An optimization for target lane selection is performed by using the information from Step 1). The problem formulation is detailed in the following section. It is noted that for real-time implementation, we apply the variable sliding window technique [83] to the optimization, which enables the optimization to be triggered once all the vehicles that have been optimized in the previous run leave the I2V communication range.

3) Lane changing implementation: After the target lane is selected, each vehicle (blue vehicles in Figure 4-3) will perform its lane change accordingly.
4.2.3. Problem Formulation

As described earlier, our goal is to determine a target lane for each vehicle agent by using CV technology, in order to achieve system-wide benefits for the entire traffic network. We model the optimal target lane selection as a multiple identical machines (the \(i\)-th machine represents the \(i\)-th lane) scheduling problem, where the objective is to minimize the overall number of conflicting jobs (i.e., VAs traveling through the segment).

If we further define

\[
y_{i,j,k} = \begin{cases} 
1, & \text{\textit{i – th VA is assigned to lane } j \text{ in } k \text{ – th place}} \\
0, & \text{otherwise} 
\end{cases}
\]

then the optimization problem can be formulated as follows:
\[
\min \sum_{j \in L} \sum_{k \in K} \text{sign} \left( \max \left( 0, \sum_{i \in I} t_i^{\text{act.out}} \cdot y_{i,j,k-1} - \sum_{i \in I} t_i^{\text{act.out}} \cdot y_{i,j,k} \right) \right)
\]

s.t.
\[
\begin{align*}
\sum_{j \in L} \sum_{k \in K} y_{i,j,k} &= 1 \quad \forall i \in I \quad (2) \\
\sum_{i \in I} y_{i,j,k} &\leq 1 \quad \forall j \in L, k \in K \quad (3) \\
\sum_{i \in I} \sum_{k \in K} t_i^{\text{in}} \cdot y_{i,j,k} - \sum_{i \in I} \sum_{k \in K} t_i^{\text{in}} \cdot y_{i,j,k-1} &\geq 0 \quad \forall j \in L \quad (4) \\
t_i^{\text{des.out}} &= d / v_i^{\text{des}} + t_i^{\text{in}} \quad \forall i \in I \quad (5) \\
\sum_{i \in I} \sum_{k \in K} t_i^{\text{act.out}} \cdot y_{i,j,k} &\leq \sum_{i \in I} \sum_{k \in K} t_i^{\text{des.out}} \cdot y_{i,j,k} \forall j \in L \quad (6)
\end{align*}
\]

\[
\begin{align*}
\sum_{i \in I} \sum_{k \in K} t_i^{\text{act.out}} \cdot y_{i,j,k} &= \sum_{i \in I} \sum_{k \in K} t_i^{\text{act.out}} \cdot y_{i,j,k-1} + \Delta T \quad \forall j \in L \quad (7) \\
\sum_{i \in I} t_i^{\text{act.out}} \cdot y_{i,j,1} &= \sum_{i \in I} t_i^{\text{des.out}} \cdot y_{i,j,1} \quad \forall j \in L \quad (8)
\end{align*}
\]

where, \(I, L\) and \(K\) represent the set of VAs, lanes and placements, respectively. \(t_i^{\text{in}}\) and \(t_i^{\text{act.out}}\) denote the entrance and exit times of the \(i\)-th VA. \(t_i^{\text{des.out}}\) is the desired exit time of the \(i\)-th VA under the mean desired speed, \(v_i^{\text{des}}\). \(d\) represents the length of the roadway segment, while \(\Delta T\) represents the minimum time gap of two consecutive VAs.

In the above mathematical formulation, Eq. (1) will be minimized if the desired exit time of each VA is (at least \(\Delta T\)) later than its preceding VA and the objective function is zero. However, due to the differences in entrance times and in desired speeds, there would be more or less potential conflicts that may render a non-zero value of the objective function. Eq. (2) through Eq. (8) governs the system dynamics and cast constraints on the placement of consecutive VAs. For example, Eq. (2) guarantees that each VA will only show up once on all placements across all lanes, while Eq. (7) ensures the consistency of placement, i.e., any vehicle cannot exit the roadway segment earlier than its predecessor along the same lane. It is noted that a CPLEX Python API was coded in the study to conduct the real-time optimization.
4.3. Simulation Results and Analysis

4.3.1. Assumptions

To evaluate the performance of the proposed real-time optimal lane selection algorithm under different congestion levels, we coded a three-lane highway segment with a communicable roadside lane selection agent and vehicle agents (using connected vehicle technology) in SUMO. The lane selection agent collected real-time information of vehicle agents on this highway segment that were within the V2I/I2V communication range, and determined an optimal target lane for each vehicle after which the vehicles performed lane changes accordingly. It should be noted that since the lane changing module of SUMO was used, it could not be guaranteed that all the vehicles had reached their target lanes upon the completion of the simulation. The simulation results in terms of average travel time, fuel consumption and emissions were compared with those for a standard three-lane highway segment without an implementation of the proposed lane selection algorithm.

4.3.2. Simulation Setup

The simulation network was set up in SUMO as follows:

- *The highway segment is 2000 meters long;*
- *Speed limit for all lanes is 50 mph;*
- *Vehicular flow is homogeneous and all vehicles are light-duty vehicles;*
- *Vehicle length is 2.5 meters and the safety distance when stalled is 2.5 meters;*
- *Maximum acceleration and deceleration rates are 2.5 m/s$^2$ and -2.5 m/s$^2$, respectively;*
• Vehicles are generated by a Poisson distribution;

• Simulation time step is 0.1 seconds and the total number of steps is 10,000;

• No on- and off- ramp is considered;

• Two scenarios were evaluated: 1) Optimal Lane Selection (OLS) based scenario; and 2) Non-Lane Selection (NLS) based scenario;

• For each of the OLS-based and NLS-based scenarios, we ran the simulation at five different congestion levels represented by volume to capacity ratio (V/C): 0.5, 0.6, 0.7, 0.8, and 0.95.

• For the OLS based scenario, The V2I/I2V communication range is 300 meters. The minimum update window between two optimizations is 10 seconds.

• For the NLS based scenario, no control strategy is applied to lane change maneuver. While for the OLS based scenario, vehicles change lane based their optimal target lane information.

• The desired speed of each vehicle, $v_i^{des}$, is sampled from a Gaussian distribution with the mean of roadway speed limit (i.e., 50 mph) and a predefined standard deviation, $\sigma$ (we selected 2.5 mph in this study).

• If there is no interaction with other vehicles (i.e., not under the influence of the car-following logic), the actual speed of a vehicle at each time step follows a Gaussian distribution with the mean of its desired speed, $v_i^{des}$, and a standard deviation, $\sigma_i$ (chosen as 0.4 mph).
4.3.3. Simulation Results and Analysis

A. Travel Time Comparison Results

For each congestion level in each scenario, we calculate the mean travel time of four simulation runs with different random seed numbers. The comparison results are summarized in Table 4-1. It can be observed that when the traffic volume is not so high, e.g., V/C = 0.5, there is trivial reduction in the mean travel time. This may be because the gaps between vehicles are large so unregulated lane changes have little impact on the traffic flow. As the congestion level increases, the benefit from the proposed optimal lane selection algorithm also increases. When V/C = 0.7, the mean travel time of the OLS based is about 4% lower than that of the NLS based. However, if the segment becomes heavily congested (say, V/C = 0.95), then the relative improvement in the mean travel time drops. A potential explanation is that there is less room for the VAs to conduct lane changes to their desired target lanes when the traffic volume is very high.

Table 4-1. Comparison results on mean travel times (in second) between two scenarios: NLS based vs. OLS based

<table>
<thead>
<tr>
<th>V/C</th>
<th>Scenarios</th>
<th>% Improvement</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>NLS Based</td>
<td>OLS Based</td>
</tr>
<tr>
<td>0.5</td>
<td>113.0</td>
<td>112.4</td>
</tr>
<tr>
<td>0.6</td>
<td>113.2</td>
<td>110.7</td>
</tr>
<tr>
<td>0.7</td>
<td>114.1</td>
<td>109.8</td>
</tr>
<tr>
<td>0.8</td>
<td>114.3</td>
<td>110.5</td>
</tr>
<tr>
<td>0.95</td>
<td>118.4</td>
<td>115.3</td>
</tr>
</tbody>
</table>

To verify whether the improvement is statistically significant, a two-sample t-test was performed on the case of V/C = 0.7. We conducted 20 runs with different seed numbers for each of the NLS based and OLS based scenarios and calculated the mean and standard deviation of the average travel time, respectively. It was found that if the
proposed optimal lane selection algorithm is applied, then the average travel time is statistically smaller than the baseline (NLS based scenario) at the significance level of 5%, where p-value is 4.0e-05.

B. Energy Consumption and Emissions Analysis

Besides the travel time analysis, we also evaluated the benefits of the proposed lane selection algorithm in terms of reductions in energy consumption and emissions of criteria pollutants, such as CO, HC, NOx and PM2.5.

Figure 4-4 summarizes all these results for the different congestion levels. As shown in the figure, when traffic congestion is low, such as V/C = 0.5 and 0.6, the reductions in energy consumption and CO$_2$ emissions are trivial while the reductions in other pollutant emissions are in the order of up to 4%. When V/C = 0.7, the maximum reductions in energy consumption and emissions are achieved. The energy consumption and CO$_2$ emissions are reduced by around 2.2%, while other criteria pollutants emissions are reduced by more than 15%. However, as the traffic becomes more and more congested, those reductions become smaller potentially due to the limited room for better-coordinated lane changes.

Similar to the travel time analysis, we also conducted a two-sample t-test on the energy consumption between the NLS based and the OLS based scenarios (V/C = 0.7), each of which was run with 20 different random seed numbers. The results show that the average energy consumption is significantly reduced (at 5% significance level) due to the implementation of the proposed lane selection algorithm.
C. Statistics on Number of Lane Changes

The proposed algorithm aims to provide advice on the optimal (in terms of the system-wide benefits) target lanes for involved VAs, rather than forcing them to change to the desired target lane. Whether or not each VA can successfully change to its optimal target lane also depends on how the lane-changing module in SUMO works. To obtain further insight into the performance of the OLS algorithm and get better understanding on the simulation results, we compared the number of lane changes between the two scenarios. The results are presented in Table 4-2. It is noted that the number of lane changes is defined as the number of lane-changing maneuvers to the adjacent lane. For example, if a VA changes from lane 1 to lane 3 as guided by output of the OLS algorithm, then the number of lane changes is two.
<table>
<thead>
<tr>
<th>V/C</th>
<th>NLS Based</th>
<th>OLS Based</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Valid^a</td>
<td>Total</td>
</tr>
<tr>
<td>0.5</td>
<td>82</td>
<td>182</td>
</tr>
<tr>
<td>0.6</td>
<td>92</td>
<td>225</td>
</tr>
<tr>
<td>0.7</td>
<td>108</td>
<td>244</td>
</tr>
<tr>
<td>0.8</td>
<td>110</td>
<td>269</td>
</tr>
<tr>
<td>0.95</td>
<td>124</td>
<td>294</td>
</tr>
</tbody>
</table>

^a represents those lane changes completed at the desired target lanes  
^b valid lane change rate: # of valid lane change / # of total

It can be seen from Table 4-2 that as the volume to capacity ratio increases, the total number of lane changes without the application of optimal lane selection algorithm continues to grow, accompanied (almost linearly) by the number of valid lane changes. However, the total number of lane changes (and valid lane changes as well) under OLS based scenarios reaches the peak when V/C = 0.7. This may be reconciled by the increase in traffic demand and decrease in the available room for lane changes to the desired target lanes. In addition, the valid lane change rates in OLS-based scenarios are much higher than the NLS-based scenarios under different congestion levels.

4.3.4. Discussion

In this study, we only explore the optimal lane selection algorithm that can minimize the number of potential vehicle conflicts. However, other objective functions could be used. For example, if the goal is to minimize the total travel time (i.e., overall job processing time), we can simply replace Eq. (1) with

$$\min \sum_{l \in L} \sum_{j \in L} \sum_{k \in K} (t_{l}^{act, out} - t_{l}^{in}) \cdot y_{l,j,k} \quad (9),$$

without increasing the computational complexity compared to the original mathematical optimization problem.
On the other hand, we do not consider any constraints on the target lane of each vehicle agent. For instance, in some cases, certain type of VAs may have to choose a subset of lanes as their target lanes, due to the movement requirement at an intersection or leaving a freeway via the off-ramp. A simple way to include these cases is to modify Eq. (2) to

\[
\sum_{j \in L_i} \sum_{k \in K} y_{i,j,k} = 1 \quad \forall i \in I (10)
\]

where \( L_i \) is the customized set for the \( i \)-th VA to accommodate its constraints on the target lanes.

In addition, the proposed mathematical optimization problem does not explicitly utilize the entrance lane index information, which may be useful to constrain the number of lane changes or even minimize the occurrence of lane-changing maneuvers. In such case, an external input variable related to the entrance lane has to be defined for each VA in the problem formulation.

4.3.5. Summary

In this chapter, we propose a real-time optimal lane selection algorithm in order to minimize the potential vehicle conflicts and to maintain the desired speed of each vehicle agent. All the required input information can be readily obtained through the connected vehicle technology. After formulating the problem into an integer-programming problem, we solved the optimization by using CPLEX Python APIs, which works with the microscopic traffic simulation model in parallel. The simulation results indicate that the proposed algorithm cannot only shorten the system-wide travel times and lower energy consumption, but also significantly reduce the emissions of criteria pollutants.
In the future, more experiments of the proposed algorithm or its extension will be conducted for further validation. Another potential topic for future work would be to incorporate this algorithm into the modeling of lane changing behavior to achieve desired performance in a more cooperative way.
5. Dynamic Trajectory Planning at Signalized Intersection Using a Connected Vehicle Approach in ATMS

5.1. Problem Statement

Adaptive Cruise Control systems have emerged in recent years to automatically adjust the vehicle speed to maintain a safe distance from preceding vehicles, based on information from on-board sensors. As a key procedural element of ACC, the vehicle’s longitudinal control is a non-trivial problem, especially in the complicated real-world environment (e.g., interacting with other vehicles and control infrastructure). ACC has attracted increasing interest from researchers and engineers due to rapid advances in sensing and control technologies. In particular, due to the increased concerns about energy independence and security as well as public interest in reducing our overall carbon footprint, Eco-Adaptive Cruise Control (Eco-ACC) systems have emerged, extending the capability of ACC by minimizing the in-route energy consumption and emissions.

A number of recent studies have been conducted to design vehicle longitudinal control in a fuel-efficient manner. Based on a modified Newell’s car-following model, [87] developed a “green” longitudinal control algorithm for freeway driving, aiming at reducing the number and severity of acceleration and deceleration maneuvers rather than minimizing fuel consumption and emissions directly. Taking advantage of signal phase and timing (SPaT) information and considering the queue discharging process, Chen et al. [88] proposed an Eco-ACC algorithm for a vehicle approaching and leaving a signalized intersection.
intersection to minimize a linear combination of emissions and travel time, without taking into account roadway grade information. Park et al. [89] developed a predictive eco-cruise control system (for freeway driving) that uses roadway topographic information and a user-defined target speed range as inputs to calculate an optimal vehicle speed (limit) profile for fuel savings. Themann et al. [90] expanded conventional ACC functionalities by maximizing energy efficiency with respect to the choices of 11 driving strategies such as “coasting in neutral” and “fuel cut-off”, which were developed to represent possible states of longitudinal dynamics variables (e.g., driving speed and acceleration status per route segment). Wang et al. [91] put forward a modeling framework for Eco-ACC system by applying a penalty cost when the vehicle deviates from fuel-efficient or environment-friendly speeds, which was determined based on the carbon dioxide (CO₂) emission model developed by Barth and Boriboonsomsin [84]. However, the lack of consideration of other information (e.g., traffic, road grade, position and speed of the preceding vehicles) restricts the applicability of such an eco-cruise control algorithm.

This chapter introduces two dynamic vehicle trajectory planning algorithms using connected vehicle technologies, which could be also applied to ATMS. The first algorithm is Eco-Approach and Departure Algorithm which originally designed to address the problem that how a vehicle can pass a signalized intersection with the minimal fuel consumption and emissions. In order to demonstrate the effectiveness of the eco-approach and departure technology, a number of field experiments were carried out
in real world at various locations with human driven vehicles as well as automated vehicles.

When most existing longitudinal control algorithms developing, fuel savings and emissions reduction are considered to be just by-products of smooth vehicle speed profiles when optimizing other criteria, such as minimizing the travel time or number of vehicle stops, other than directly minimizing the fuel consumption. In the second part of this chapter, an optimal vehicle longitudinal control algorithm is introduced, which is aiming at maximizing fuel economy under a variety of traffic conditions, with taking into account the individual vehicle’s engine operation efficiency which may vary from vehicle-to-vehicle, followed by an extensive comparative evaluation of the proposed algorithm against some existing Eco-ACC algorithms.

5.2. Eco-Approach and Departure Algorithm

5.2.1. Assumptions

It is noted that EAD algorithm herein was developed under the following assumptions, although another more complex version is underway.

- The traffic signal control is fixed-timing. In other words, the signal phase and timing (SPaT) in the future is perfectly known and deterministic;
- The algorithm is designed for an isolated vehicle (i.e., assuming without any interaction by other traffic). The preceding vehicle information is not used (i.e., the car-following logic does not take effect);
• The roadway grade information is not taken into consideration. A flat territory is assumed;

• The algorithm is designed for a generic car model, explicitly considering the constraints on maximum acceleration/deceleration and jerk. No detailed information on a specific vehicle (e.g., vehicle type and engine dynamics) is fed into the algorithm.

5.2.2. Background and Problem Statement

In order to design Eco-Friendly vehicle driving trajectory, the relationship between fuel consumption/emissions and vehicle velocity has to be studied extensively at a microscopic, physical level [84]. In general, the fuel consumption versus average cruise speed generalized functional relationship in shown in Figure 5-1.

![Figure 5-1. Fuel consumption versus average cruise speed generalized functional relationship [84]](image_url)
At lower speeds, vehicles are spending a greater time, which results in high fuel/distance value. At higher speeds, more fuel is required to overcome aerodynamic resistance; therefore the energy use and emissions are higher. In between these extreme speeds, the fuel consumption and emissions are relatively minimal. For signalized arterials, driving scenarios can be categorized into four groups as shown in Figure 5-2:

- Scenario 1: vehicle 1 cruises through the intersection with constant speed (green line);
- Scenario 2: vehicle 2 speeds up to pass the intersection and then gets back to initial speed after the intersection (blue line);
- Scenario 3: vehicle 3 slows down and stop at the intersection (red line);
- Scenario 4: vehicle 4 slows down gently and passes the intersection with a slow speed, and then speeds up to its initial speed (yellow line).

![Figure 5-2. Illustration of different vehicle trajectories approaching an intersection [85]](image)

The cruising scenario uses least fuel since no unnecessary acceleration or deceleration is needed. Scenario 2 and 4 both consume more fuel then scenario 1 since there are slight acceleration and deceleration. Scenario 3 uses the most amount of fuel as it decelerates to a full stop, idles for certain time, and accelerates to high speed. Therefore, if vehicle can
keep current speed (or cruising speed) to pass the intersection with green phase, it needs
to properly adjust its speeds in advance in order to save fuel.

5.2.3. Algorithm Description [85]

A. Algorithm Diagrams

The block diagram of the vehicle trajectory-planning algorithm (VTPA) is shown in
Figure 5-3. The control logic for the velocity planner requires several input parameters:

![Figure 5-3. Block diagram of the vehicle trajectory planning algorithm (VTPA).]

where,

- SPaT: Signal phase and timing information;
- MAP: Geometric information of test intersection and route;
- $a_{max}$: Maximum acceleration due to mechanical constraints;
- $jerk_{max}$: Maximum jerk due to drivers’ comfort.

Figure 5-4 represents the top-level diagram of the VTPA, where the available effective
green window, $\Gamma$, is calculated as follows (current time is “0” without loss of generality):
\( \Gamma = \{[0, g_1^i) \cup [g_{s}^i, g_e^i), \text{ if current phase is } "Green" \} \) \n\[ [g_{s}^i, g_e^i), \text{ if current phase is } "Red" \]

where \( g_{s}^i \) and \( g_e^i \) represent the start and end of the \( i \)-th green window, respectively.

The Level-two diagram (i.e., the “decision tree”) is illustrated in Figure 5-5 as follows, where there are two major components: 1) scenario identifier; and 2) trajectory generator. Figure 5-6 (i.e., Level-three diagram) presents more detailed building blocks for each component.
In order to stay within the target range of velocity \(0 \leq v_t \leq v^{\text{limit}}\), or to achieve a velocity so the vehicle can reach the intersection at a specific time, the vehicle will be able to accelerate or decelerate to certain target velocity within a specific time window. There are an infinite number of ways to accelerate or decelerate from one speed to another. Several trajectory planning algorithms have been suggested in the literature, including constant acceleration/deceleration rates, linear-acceleration/deceleration rates,
and constant power rates. In this design, we use a trigonometric acceleration/deceleration profile originally designed by Xia et al. [85], which could minimizes fuel consumption/emissions and is still comfortable to the passengers (i.e., constrained by the maximum jerk) as shown in Figure 5-7.

![Figure 5-7](image)

Figure 5-7. Acceleration (left) and deceleration (right) profiles for reaching a specific location at a specific time [85]

The family of trigonometric velocity profiles which guarantees the smoothness of trajectories is given by:

\[
\begin{align*}
&\begin{cases}
    v_h - v_d \cos(mt) & t \in [0, \frac{\pi}{2m}) \\
    v_h - v_d \frac{m}{n} \cos n\left(t - \frac{\pi}{2m} + \frac{\pi}{2n}\right) & t \in \left[\frac{\pi}{2m}, \frac{\pi}{2m} + \frac{\pi}{2n}\right) \\
    v_h + v_d \frac{m}{n} & t \in \left[\frac{\pi}{2n} + \frac{\pi}{2m}, \frac{\pi}{2m}\right]
\end{cases}
\end{align*}
\]

where \(d_0\) is the distance to intersection; \(v_c\) is the current velocity; \(v_h\) is the referenced velocity; and \(v_d\) is defined such that \(v_d = v_h - v_c\). The three regions in above equations are divided by \(\pi/2m\) and \((\pi/2m + \pi/2n)\), which are \(t_1\) and \(t_2\) in Figure 5-7 and Figure 5-8, respectively. The parameters \(m\) and \(n\) define the family of velocity profiles. Different values of \((m, n)\) correspond to different velocity profiles. Parameter \(m\) controls the rate of change of acceleration/deceleration in region A and parameter \(n\)
controls the rate of change of acceleration/deceleration in region B of in Figure 5-7 and Figure 5-8. Given a value of \( m \), the choice of \( n \) will depend on the requirement that the vehicle has to reach the intersection at a specific time.

**B. Scenario Identifier**

As shown in the Level-three diagram (Figure 5-6), this component is to determine into which scenario the target vehicle trajectory should be categorized, based on the system parameters (such as velocity, SPaT, distance to intersection and other constraints) at current time. For example, if the subject vehicle can cruise at the current velocity and pass the intersection at green, then the trajectory is categorized into Scenario 1 (cruise). The cruise time, \( t^{cr} \), is given as

\[
t^{cr} = \frac{d}{v_c}
\]

If Scenario 1 is not guaranteed, then the earliest time to arrival, \( t^e \), will be calculated to determine whether the trajectory satisfies the condition of Scenario 2 (accelerate to pass). More specifically,

\[
t^e = \frac{d - v_c \cdot \frac{\pi}{2m}}{v_{limit}} + \frac{\pi}{2m} \quad \text{and} \quad m = \min \left\{ \frac{2 \cdot a_{max}}{v_{limit} - v_c}, \frac{\sqrt{2 \cdot \text{jerk}_{max}}}{v_{limit} - v_c} \right\}
\]

where, \( v_{limit} \) represents the upper limit (hard constraint) of the target velocity due to the subject vehicle’s ability or roadway enforcement. \( a_{max} \) and \( \text{jerk}_{max} \) are the maximum acceleration and jerk, respectively, whose values can be chosen as recommended in [86].

If the subject vehicle is determined to be not able to pass the intersection by acceleration, then the trajectory will fall into either Scenario 3 (decelerate to a full stop) or Scenario 4 (decelerate-then-acceleration without any stop), depending on the latest
time to arrival without any stop, $t^l$. In addition, 

$$t^l = \frac{d_0 - v_c}{v_{\text{coast}}} \frac{\pi}{2m} + \frac{\pi}{2m}$$

and

$$m = \min \left\{ \frac{2a_{\text{max}}}{v_{\text{coast}}}, \sqrt{\frac{2\text{jerk}_{\text{max}}}{v_{\text{coast}}} - v_{\text{coast}}} \right\}$$

where $v_{\text{coast}}$ denotes the coasting speed (e.g., 5 mph).

C. Trajectory Generator

This component is to determine the actual time to arrival, $t^{\text{arr}}$ (or time to leaving the stop-bar in Scenario 3), and the target vehicle trajectory for each scenario as shown in Figure 5-6. More specifically, for Scenario 1, the target velocity, $v_t$, is simply the current velocity, $v_c$.

For Scenario 2, the target velocity, $v_t = f(v_c, v_h)$, where

$$f(v_c, v_h) = \begin{cases} 
  v_h - (v_h - v_c) \cdot \cos (mt) & t \in \left[0, \frac{\pi}{2m}\right] \\
  v_h - (v_h - v_c) \cdot \frac{m}{n} \cdot \cos \left[ n \cdot \left( t - \frac{\pi}{2m} + \frac{\pi}{2n} \right) \right] & t \in \left[\frac{\pi}{2m}, \frac{\pi}{2m} + \frac{\pi}{2n}\right] \\
  v_h + (v_h - v_c) \cdot \frac{m}{n} & t \in \left[\frac{\pi}{2m} + \frac{\pi}{2n}, \frac{d_0}{v_h} + \frac{\pi}{2n}\right] \\
  v_h - (v_h - v_c) \cdot \frac{m}{n} \cdot \cos \left[ n \cdot \left( t - \frac{d_0}{v_h} + \frac{\pi}{n} \right) \right] & t \in \left[\frac{d_0}{v_h} + \frac{\pi}{2n}, \frac{d_0}{v_h} + \frac{\pi}{2n} + \frac{\pi}{2n}\right] \\
  v_h - (v_h - v_c) \cdot \cos \left[ m \cdot \left( t - \frac{d_0}{v_h} - \frac{\pi}{2m} - \frac{\pi}{2n} \right) \right] & t \in \left[\frac{d_0}{v_h} + \frac{\pi}{2n}, \frac{d_0}{v_h} + \frac{\pi}{2n} + \frac{\pi}{2n}\right] \\
  v_c & t \in \left[\frac{d_0}{v_h} + \frac{\pi}{2n} + \frac{\pi}{2n}, +\infty\right]
\end{cases}$$

and $m (>0)$ is chosen as the maximum that satisfies:
\[
\begin{aligned}
&\left\{ m \cdot \left[ m \left( \frac{d_0 m}{v_h} - \frac{\pi}{2} \right) + \sqrt{m^2 \left( \frac{d_0 m}{v_h} - \frac{\pi}{2} \right)^2 - 4m^2 \left( \frac{\pi}{2} - 1 \right)} \right] \cdot (v_h - v_c) \leq 2 \text{jerk}_{\text{max}} \right. \\
&\quad \left. m \geq \frac{v_h}{d_0} \left( 2 \sqrt{\frac{\pi}{2} - 1} + \frac{\pi}{2} \right) \text{ or } 0 < m \leq \frac{v_h}{d_0} \left( \frac{\pi}{2} - 2 \sqrt{\frac{\pi}{2} - 1} \right) \right. \\
&\quad \left. \text{and} \quad n = \frac{1}{2} \cdot \left[ m \left( \frac{d_0 m}{v_h} - \frac{\pi}{2} \right) + \sqrt{m^2 \left( \frac{d_0 m}{v_h} - \frac{\pi}{2} \right)^2 - 4m^2 \left( \frac{\pi}{2} - 1 \right)} \right] \right. \\
&\text{For Scenario 3, the target velocity, } v_t = g(v_c, v_h), \text{ where} \\
&g(v_c, v_h) \\
&\left\{ \begin{array}{ll}
&v_h - (v_h - v_c) \cdot \cos (mt) \\
&v_h - (v_h - v_c) \cdot m \cdot \cos \left[ n \cdot \left( t - \frac{\pi}{2m} + \frac{\pi}{2n} \right) \right] \\
&v_h + (v_h - v_c) \cdot \frac{m}{n} \\
&v_h - (v_h - v_c) \cdot m \cdot \cos \left[ n \cdot \left( t - \frac{g_s^2}{2n} + \frac{\pi}{n} \right) \right] \\
&v_h - (v_h - v_c) \cdot \cos \left[ m \cdot \left( t - \frac{g_s^2}{2m} - \frac{\pi}{2n} \right) \right] \\
&v_h - (v_h - v_c) \cdot \cos \left[ m \cdot \left( t - \frac{g_s^2}{2m} - \frac{\pi}{2n} \right) \right] \\
&v_c \\
&\end{array} \right. \\
&\text{and } m (>0) \text{ is chosen as the maximum that satisfies: } \left\{ \begin{array}{ll}
m \cdot (v_c - v_h) \leq a_{\text{max}} \\
m^2 \cdot (v_c - v_h) \leq \text{jerk}_{\text{max}} \end{array} \right. \text{ and} \\
&n = m. \\
&\text{For Scenario 4, the target velocity, } v_t = h(v_c, v_h), \text{ where} \\
&h(v_c, v_h) \\
\end{aligned}
\]
h(v_c, v_h)

\[ h(v_c, v_h) = \begin{cases} 
  v_h - (v_h - v_c) \cdot \cos (mt) & t \in [0, \frac{\pi}{2m}) \\
  v_h - (v_h - v_c) \cdot \frac{m}{n} \cdot \cos \left[n \cdot \left(t - \frac{\pi}{2m} + \frac{\pi}{2n}\right)\right] & t \in \left[\frac{\pi}{2m}, \frac{\pi}{2m} + \frac{\pi}{2n}\right) \\
  v_h + (v_h - v_c) \cdot \frac{m}{n} \cdot \cos \left[n \cdot \left(t - \frac{d_0}{v_h} + \frac{\pi}{2n}\right)\right] & t \in \left[\frac{\pi}{2m} + \frac{d_0}{v_h}, \frac{\pi}{2m} + \frac{d_0}{v_h} + \frac{\pi}{2n}\right) \\
  v_h - (v_h - v_c) \cdot \frac{m}{n} \cdot \cos \left[n \cdot \left(t - \frac{d_0}{v_h} + \frac{\pi}{2n}\right)\right] & t \in \left[\frac{d_0}{v_h} + \frac{\pi}{2n}, \frac{d_0}{v_h} + \frac{\pi}{2n} + \frac{\pi}{2n}\right) \\
  v_h - (v_h - v_c) \cdot \frac{m}{n} \cdot \cos \left[n \cdot \left(t - \frac{d_0}{v_h} + \frac{\pi}{2n}\right)\right] & t \in \left[\frac{d_0}{v_h} + \frac{\pi}{2n} + \frac{\pi}{2n}, +\infty\right) \\
  v_h - (v_h - v_c) \cdot \frac{m}{n} \cdot \cos \left[n \cdot \left(t - \frac{d_0}{v_h} + \frac{\pi}{2n}\right)\right] & t \in \left[\frac{d_0}{v_h} + \frac{\pi}{2n} + \frac{\pi}{2n} + \frac{\pi}{2n}\right) \\
  v_h - (v_h - v_c) \cdot \frac{m}{n} \cdot \cos \left[n \cdot \left(t - \frac{d_0}{v_h} + \frac{\pi}{2n}\right)\right] & t \in \left[\frac{d_0}{v_h} + \frac{\pi}{2n} + \frac{\pi}{2n} + \frac{\pi}{2n}\right)
\end{cases} \]

and m (>0) is chosen as the maximum that satisfies:

\[ m \cdot (v_c - v_h) \leq a_{\text{max}} \]
\[ m^2 \cdot (v_c - v_h) \leq \text{jerk}_{\text{max}} \]

\[ m \geq \frac{v_h}{d_0} \left(2 \sqrt{\frac{\pi}{2} - 1} + \frac{\pi}{2}\right) \quad \text{or} \quad 0 < m \leq \frac{v_h}{d_0} \left(\frac{\pi}{2} - 2 \sqrt{\frac{\pi}{2} - 1}\right) \]

and \( n = \frac{1}{2} \cdot m \left(\frac{d_0 m}{v_h} - \frac{\pi}{2}\right) + \sqrt{m^2 \left(\frac{d_0 m}{v_h} - \frac{\pi}{2}\right)^2 - 4m^2 \left(\frac{\pi}{2} - 1\right)} \)

5.2.4. Field Experiments

Preliminary field tests that were conducted in 2012 demonstrated reduced fuel consumption of up to eighteen percent, with a single laptop to run an application and a dashboard-mounted tablet to display the target speed to the driver [85]. Although the recommended speed profiles can be provided to the drivers through human-machine interfaces (HMIs) in real-time, however, the drivers may not be able to follow the recommended speed profiles closely. In that case, the effectiveness of the applications
might be degraded. These HMIs may even be distracting and detrimental to safety. Partial vehicle automation can be used to follow a recommended speed profile and play an important role to ensure that the benefits of these connected vehicle based applications are realized fully.

In this field experiments, the Eco-approach and Departure algorithm will be further evaluated using a vehicle that is equipped with full-range automated longitudinal control capabilities. The EAD algorithm based speed control application is design and carried out to provide a number of benefits: 1) Evaluate the performance of EAD algorithm 2) Creating automated driving protocol for future speed control applications, 3) Understand driving experience of human driver in both HMI driving and automated driving.

5.2.4.1. Test Site

The field test took place at the Turner-Fairbank Highway Research Center (TFHRC) in McLean, Virginia using the Saxton Lab Intelligent Intersection, which offers a sheltered traffic environment where the automated prototype can be tested with minimal safety risk and without disrupting live traffic operations. Figure 5-8 below provides an overview of the test site within the TFHRC campus. The figure identifies the test starting point where the vehicle will begin test runs from a stop and travel westbound towards the Intelligent Intersection and relevant traffic signal under automated control.
5.2.4.2. System Architecture

Figure 5-9 depicts the system architecture, as well as inputs and output through the system’s hardware components. On top of the base functionality of this vehicle, hardware, including a DSRC unit and an Advanced Positioning System that installed to provide input to an In-Vehicle Processor. The In-Vehicle Processor will run a Speed Control application that uses the EAD algorithm to calculate the vehicle’s target speed and acceleration, which will be sent to the vehicle’s automated longitudinal controls to be executed by the vehicle. Additionally, the on-board system could provide input and output capability to the Driver-Vehicle Interface, a tablet, which allows the driver to control the vehicle and view information during operation.
The data input required for the Speed Control application includes the following elements: 1) Signal Phase and Timing (SPaT) data, 2) Geometric Intersection Description (GID or “MAP”) data, 3) Current Position data, 4) Current Speed data, and 5) Mass Air Flow (for post-processing and analysis).

5.2.4.3. Test Vehicle Setup

Figure 5-10, shows the Ford 2010 Escape Hybrid that is instrumented for the Speed Control Application. The vehicle can be operated manually, consistent with the stock functionality of the Ford Escape Hybrid, or using the partially automated control subsystems.
In-vehicle equipment components include the DSRC After-market Safety Device (ASD), Positioning System, In-Vehicle Processing capability, and Ethernet interface, as pictured below in Figure 5-11. These components are connected by Ethernet to facilitate data exchange, which ultimately serves the Speed Control application and EAD algorithm to calculate the output target speed and acceleration. The ASD unit is installed in the vehicle to receive SPaT and MAP messages over DSRC at 10Hz and 1Hz, respectively. For this experiment, the ASD acts as middleware between the DSRC RSU and the In-Vehicle Processor, providing data from the roadside to the In-Vehicle Processor for use in the Speed Control application as an input to the Eco-Approach and Departure algorithm. A robust speed controller kit (By Wire XGV) [116] is equipped on the test vehicle to provide full-range Automated Longitudinal Control capabilities in both forward and reverse directions.
5.2.4.4. **Intersection Infrastructure Setup**

As depicted in Figure 5-12, the roadside infrastructure includes the Traffic Signal Controller, NTCIP to FHWA SPaT Translator (blackbox) and the DSRC Roadside Unit (RSU). Signal Phase and Timing (SPaT) data is generated by the Traffic Signal Controller and sent over Ethernet to the blackbox, which converts the data to a DSRC SPaT message and transmits it to the DSRC RSU. An Econolite ASC/3-2100 unit is installed in the cabinet at the Turner Fairbank Highway Research Center’s (TFHRC’s) Intelligent Intersection to provide fix-timing traffic signal control. For the experimentation at TFHRC, the traffic signal controller is set up for fixed timed signal phasing: 27-seconds green, 3-seconds yellow, followed by 30-seconds of red. The total cycle time is 60 seconds. As depicted in Figure, two radios are set-up in a Primary/Secondary configuration at the test intersection, where the RSU installed near the traffic signal controller (RSU A) will receive and broadcast the SPaT message from the blackbox at 10Hz and the RSU installed along the test roadway (RSU B) will receive and repeat the SPaT broadcast from RSU A, which will extend the effective range of around the bend in the test roadway.
5.2.4.5. **Driver-Vehicle Interface (DVI)**

The driver vehicle interface used in this experiment is a 7-inch rugged tablet powered by Android 4.0 with a daylight-readable display and all-weather dust and water resistant design. The DVI contents include Signal Phase and Timing Display, Motion Status Indicator (Motion Status Indicator).

5.2.4.6. **Field Test Approach**

The field experimentation was organized into three stages:

The first stage (Stage I) is the “manual-uninformed” driver stage, where a driver approaches and travels through the intersection in a normal fashion without guidance or automation, stopping as needed without any automated vehicle control. The vehicle’s fuel economy will be measured for a large number of driving trajectories (i.e., starting at different points in the signal timing cycle and at various operating speeds), establishing a baseline that can be used as a point of comparison for the Stage II and III experiments.

The second stage (State II) is the “manual-DVI” driver stage, where a driver approaches and travels through the intersection in a normal fashion but is provided an
enhanced dashboard which provides a speed range band overlaid onto a speedometer for
the driver to follow as guidance on how to approach and depart the intersection in an
environmentally friendly manner while obeying the traffic signal (see Figure 5-13) This
stage simply provides speed guidance to the driver and does not involve any automated
vehicle control.

Figure 5-13. Driver Vehicle Interface

The third stage (Stage III) is the “automated” driver stage, where the Automated
definition is responsible for longitudinal control of the vehicle allowing it to speed up or
slow down while the driver steers for lateral control and monitors the application on the
DVI (shown in Figure 5-14). In this stage, the vehicle automatically controls the brake
and throttle based on the output of the Eco-Approach and Departure (EAD) algorithm,
which calculates an Eco-Friendly velocity profile according to the DSRC SPaT messages and distance to the intersection.

![Diagram of traffic light](image)

Figure 5-14. Automated Driver Stage [116]

### 5.2.4.7. Data Collection

To order to cover aforementioned four driving scenarios, the field experimentation was designed to be comprehensive in that the test vehicle will approach the intersection at different timed intervals throughout the entire signal cycle (i.e., varying by 5-seconds in the 60 second cycle). Furthermore, the vehicle enters the intersection communicable area with a driving speed (operating speed) at 20mph. The overall vehicle fuel economy and CO₂ emissions will then be calculated and compared between the Stage I (manual-uninformed driver) experiments, Stage II (manual-DVI driver) experiments, and Stage III (automated) experiments.
In the State I and II experiments, the driver with no previous exposure to the application was asked to drive normally through the intersection to ensure naturalistic driving is captured with regard to the signal timing. In the Stage III experiments, the test vehicle was operated by a trained driver to maintain safety as a top priority when conducting test runs, meanwhile, the application will automatically control the vehicle.

In order to cover every possible driving scenario, a field study matrix was developed that varies the vehicle’s operating speed and signal timing start with respect to the overall cycle of the traffic signal (shown in Figure 5-15). This test matrix consists of the time in current phase in the signal cycle across the horizontal access as well as the current phase of the traffic signal. In this matrix, there are a total of $12 \times 3 = 36$ test cells for three driving scenarios.

<table>
<thead>
<tr>
<th>Current Phase</th>
<th>Green</th>
<th></th>
<th>Red</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time in Phase(s)</td>
<td>2</td>
<td>7</td>
<td>12</td>
</tr>
<tr>
<td>Uninformed</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>DVI</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Automated</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Figure 5-15. Field Study Matrix

5.2.4.8. Data Analyses

A. Fuel Consumption and Emissions Analysis

With the second-by-second (actual) speed trajectory data collected from each individual test run, the trip energy consumption, greenhouse gas (GHG) and criteria pollutant emissions (HC, NOx, and CO) are calculated by a microscopic
energy/emissions estimation model (CMEM). The CMEM model was calibrated particularly for the test vehicle, Ford Escape Hybrid 2012, which has engine size 2.5L and rated fuel economy at 22(on highway)/31 mpg (on arterial). Road grade was also calibrated based on the test route and applied in emission and energy calculation. However, it is envisioned that some estimation errors might occur due to the hybridization feature of the XGV’s powertrain and the intractability (in the current sense) of shutting down the electric path from the batteries.

Table 4-3 shows the relative reduction of fuel uses between DVI driving and uninformed driving (D vs. U), between automated driving and uninformed driving (A vs. U), as well as between automated driving and DVI driving (A vs. D). In addition, the most-right column shows the overall improvement in fuel economy. Similarly, Table 4-4 shows the relative changes of CO₂ emissions between the three test scenarios. In general, the automated driving with Eco-approach and departure algorithm could reduce CO₂ emission and lower fuel consumption by 22.2% compared to uninformed manual driving. When compared to manual-DVI driving, automated driving could have approximate 15.9% reduction on both fuel consumption and CO₂ emissions.

<table>
<thead>
<tr>
<th>Phase</th>
<th>Green (s)</th>
<th>2</th>
<th>7</th>
<th>12</th>
<th>17</th>
<th>22</th>
<th>27</th>
<th>Red (s)</th>
<th>2</th>
<th>7</th>
<th>12</th>
<th>17</th>
<th>22</th>
<th>27</th>
<th>On Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>D vs. U</td>
<td>11.8</td>
<td>11.7</td>
<td>25.0</td>
<td>37.8</td>
<td>18.3</td>
<td>21.7</td>
<td>-</td>
<td>13.5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A vs. U</td>
<td>0</td>
<td>5</td>
<td>7.59</td>
<td>5.20</td>
<td>7.56</td>
<td>12.05</td>
<td>8</td>
<td>0</td>
<td>4</td>
<td>1</td>
<td>0.55</td>
<td>3</td>
<td>7.34</td>
<td></td>
<td></td>
</tr>
<tr>
<td>A vs. D</td>
<td>4.67</td>
<td>7.55</td>
<td>35.2</td>
<td>20.9</td>
<td>32.6</td>
<td>47.9</td>
<td>-</td>
<td>26.4</td>
<td>20.0</td>
<td>22.8</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A vs. D</td>
<td>14.7</td>
<td>17.2</td>
<td>29.9</td>
<td>16.6</td>
<td>10.1</td>
<td>16.2</td>
<td>12.1</td>
<td>20.4</td>
<td>10.8</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4-3. Relative reduction of fuel use (in percentage)
Table 4-4. Relative reduction of CO$_2$ emission (in percentage)

<table>
<thead>
<tr>
<th>Phase</th>
<th>Gree n</th>
<th>Red</th>
<th>On Average</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time in Phase (s)</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>7</td>
<td>12</td>
</tr>
<tr>
<td>D vs. U</td>
<td>11.7</td>
<td>11.7</td>
<td>25.06</td>
</tr>
<tr>
<td>A vs. U</td>
<td>4.67</td>
<td>7.55</td>
<td>32.64</td>
</tr>
<tr>
<td>A vs. D</td>
<td>14.7</td>
<td>17.2</td>
<td>31.70</td>
</tr>
</tbody>
</table>

According to the collected second-by-second speed profile, each run can be categorized as one the aforementioned driving scenarios. In Table 4-5, each run is marked with a color presenting one of the driving scenarios.

Table 4-5. Normalized Fuel Consumption (gram per mile)

<table>
<thead>
<tr>
<th>Phase</th>
<th>Gree n</th>
<th>Red</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time in Phase (s)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>7</td>
</tr>
<tr>
<td>Uninformed (DVI)</td>
<td>57.61</td>
<td>60.69</td>
</tr>
<tr>
<td>DVI (D)</td>
<td>64.41</td>
<td>67.82</td>
</tr>
<tr>
<td>Automatic (A)</td>
<td>54.92</td>
<td>56.11</td>
</tr>
</tbody>
</table>

Aforementioned, scenario 3 is the most fuel consuming driving scenario since vehicle has to fully stop at intersection, spend extra idling time, and then accelerate to normal driving speed. It can be seen from Table 4-5, automated driving could significantly reduce the occurrence of the driving scenario 3 (pink cells) by closely following the EAD speed profile in order to pass intersection in green phase. Table 4-6 shows the fuel consumption savings between different driving scenarios. For test runs in scenario 1, 2 or
t shows that the Eco-Approach and Departure module has more benefits in fuel savings in both automated and DVI driving, owing to the less aggressive acceleration and deceleration profiles used when approaching and departing.

Table 4-6. Fuel Consumptions Reduction between different driving scenarios

<table>
<thead>
<tr>
<th>%</th>
<th>Scenario vs. Scenario</th>
<th>S1 vs. S1</th>
<th>S2 vs. S2</th>
<th>S2 vs. S3</th>
<th>S3 vs. S3</th>
<th>S4 vs. S3</th>
<th>S4 vs. S4</th>
</tr>
</thead>
<tbody>
<tr>
<td>D vs. U</td>
<td>0.91</td>
<td>-11.75</td>
<td>N/A</td>
<td>8.10</td>
<td>25.08</td>
<td>37.80</td>
<td></td>
</tr>
<tr>
<td>Model vs. A vs. U</td>
<td>14.03</td>
<td>7.55</td>
<td>35.25</td>
<td>N/A</td>
<td>26.40</td>
<td>47.92</td>
<td></td>
</tr>
<tr>
<td>Model vs. A vs. D</td>
<td>12.86</td>
<td>17.27</td>
<td>29.93</td>
<td>N/A</td>
<td>17.57</td>
<td>13.16</td>
<td></td>
</tr>
</tbody>
</table>

Table 4-7, 4-8 and 4-9 illustrate the relative reductions on other criteria pollutant emissions (HC, NOx, and CO) respectively.

Table 4-7. Relative Reductions (in percentage) of HC emission (normalized by distance)

<table>
<thead>
<tr>
<th>Phase</th>
<th>Time in Phase</th>
<th>Green</th>
<th>Red</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2s</td>
<td>7s</td>
<td>12s</td>
</tr>
<tr>
<td>D vs. N</td>
<td>+37.5</td>
<td>13.7</td>
<td>-</td>
</tr>
<tr>
<td>A vs. N</td>
<td>5.88</td>
<td>0.00</td>
<td>76.47</td>
</tr>
<tr>
<td>A vs. D</td>
<td>-6.67</td>
<td>-60.00</td>
<td>73.33</td>
</tr>
</tbody>
</table>

Table 4-8. Relative Reductions (in percentage) of CO emission (normalized by distance)

<table>
<thead>
<tr>
<th>Phase</th>
<th>Time in Phase</th>
<th>Green</th>
<th>Red</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2s</td>
<td>7s</td>
<td>12s</td>
</tr>
<tr>
<td>D vs. N</td>
<td>-60.25</td>
<td>94.10</td>
<td>1.64</td>
</tr>
<tr>
<td>A vs. N</td>
<td>20.50</td>
<td>26.04</td>
<td>22.66</td>
</tr>
<tr>
<td>A vs. D</td>
<td>50.39</td>
<td>61.36</td>
<td>21.38</td>
</tr>
</tbody>
</table>
Table 4-9. Relative Reductions of NOx emission (normalized by distance)

<table>
<thead>
<tr>
<th>%</th>
<th>Start at Green Phase at</th>
<th>Start at Red Phase at</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2s</td>
<td>7s</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D vs. N</td>
<td>- 62.7</td>
<td>17.7</td>
</tr>
<tr>
<td></td>
<td>16.2</td>
<td>31.2</td>
</tr>
<tr>
<td>A vs. N</td>
<td>8.57</td>
<td>8</td>
</tr>
<tr>
<td></td>
<td>48.5</td>
<td>16.3</td>
</tr>
<tr>
<td>A vs. D</td>
<td>42.86</td>
<td>7</td>
</tr>
</tbody>
</table>

B. Travel Time Analysis

In addition to evaluate the application performance in terms of fuel consumption and emissions, total travel time of each test run has been recorded and analyzed. Travel time results summarized in Figure 4-10 shows that, most of automated driving and DVI driving results in a slight penalty of averagely 3% for travel time. Some extreme case occurs when uninformed driving vehicle stops at very last second of the red phase in the uninformed driving (scenario 3), while it is able to pass the intersection at the first second of the green phase (scenario 2). Therefore, greater travel time reduction could be gained resulting from much less idling time.

Table 4-10. Relative Reductions of Travel Time (normalized by distance)

<table>
<thead>
<tr>
<th>%</th>
<th>Start at Green Phase at</th>
<th>Start at Red Phase at</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>2s</td>
<td>7s</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D vs. N</td>
<td>- 3.03</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>6.0</td>
<td>6.0</td>
</tr>
<tr>
<td>A vs. N</td>
<td>6.06</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>0.00</td>
<td>3.13</td>
</tr>
</tbody>
</table>

5.2.5. Summary

As part of the AERIS field study program, an eco-approach and departure application to traffic signals was extensively evaluated using several test vehicles and test sites to
determine potential fuel economy and emissions impacts. Three testing stages were carried out that included uninformed driving, manual-DVI driving and automated driving. The field test took place at the Turner-Fairbank Highway Research Center (TFHRC) in McLean, Virginia using the Saxton Lab Intelligent Intersection. The results show that on average, automated driving with EAD speed control outperform both manual-DVI driving and uninformed driving in terms of fuel economy and emissions. In general, the automated driving with Eco-approach and departure algorithm could reduce CO\textsubscript{2} emission and lower fuel consumption by 22.2\% compared to uninformed manual driving. When compared to manual-DVI driving, automated driving could have approximate 15.9\% reduction on both fuel consumption and CO\textsubscript{2} emissions, with a slight penalty of averagely 3\% for travel time.

5.3. Optimal Power-Based Dynamic Trajectory Planning

5.3.1. Problem Statement

In this section, a power-based approach was developed as an optimal vehicle longitudinal control algorithm for individual vehicles with specific characteristics (e.g., engine type) in order to maximize fuel economy under a variety of traffic conditions. In this approach, the system state at each time step is defined as a tetrad, including vehicle speed (v), acceleration (a), road grade (g), and engine efficiency (\eta\textsubscript{e}). Given the downstream traffic information (using connected vehicle technologies) and route elevation profiles, the second-by-second optimal system states can be obtained using mixed integer linear programming (MILP) techniques.
As mentioned before, Xia et al. [85] at the University of California, Riverside have developed a longitudinal control algorithm for arterial driving as part of the Eco-Approach and Departure at Signalized Intersections application. With the knowledge of Signal Phase and Timing (SPaT) of the upcoming intersection (via connected vehicle technologies) and the surrounding traffic conditions, a trigonometric speed profile (TSP) was designed to minimize tractive power requirement for the vehicle as well as to reduce the overall intersection delay.

Like many other Eco-ACC algorithms, such a TSP-based algorithm was developed for a generic vehicle model without considering the variability in road grade and vehicle characteristics (e.g., engine type). To address these limitations, we propose herein an optimal vehicle longitudinal control algorithm, which explicitly uses the brake specific fuel consumption (BSFC) numbers of the subject vehicle, roadway topographic information, and other traffic parameters (e.g., position of the preceding vehicle) to determine the optimal speed profile in terms of fuel economy. To evaluate the performance of the proposed Eco-ACC algorithm, field experiment data and simulation data from previous studies for both baseline (where no control is implemented) and the TSP-based cases are used for comparison. In the next subsection, we briefly present some background information about a vehicle’s powertrain to facilitate the problem formulation.

### 5.3.2. Vehicle Propulsion Powertrain for Gasoline Vehicles

For a conventional gasoline vehicle, Figure 5-16 depicts a diagram of a simplified powertrain and the corresponding energy flows.
The powertrain consists of the engine, transmission, final drive, and driven wheels. The instantaneous tractive power $P_t(v, a, g)$ required at the driven wheels can be calculated by Eq. (1), including any consumed power due to the rolling resistance ($F_f$), aerodynamic drag ($F_d$), grade resistance ($F_g$) and inertia force ($M \cdot \delta \cdot dv/dt$) [98-99].

$$P_t(v, a, g) = F_t \times v = \left( F_f + F_d + F_g + M \delta \frac{dv}{dt} \right) \times v$$  \hspace{1cm} (1)

where $v$, $a$, and $g$ are instantaneous vehicle speed, acceleration or deceleration rate, and road grade, respectively; $M$ represents the vehicle mass, while $\delta$ is a coefficient accounting for the effect of rotating and reciprocating parts.

As shown in Figure 5-15, given the tractive power at the driven wheels, the engine power, $P_e(v, a, g)$, can be written as

$$\dot{m} = \frac{P_e(v, a, g)}{\eta_e} = \left( \frac{P_t(v, a, g)}{\eta_t} + P_{acc} \right) / \eta_e$$  \hspace{1cm} (2)

where $P_e(v, a, g)$ represents the engine power; $\eta_e$ denotes the engine efficiency (or the inverse of BSFC number), pre-calculated by the optimal gear ratio with respect to different engine torque and engine speed (thus vehicle speed) values; $\eta_t$ is the total
transmission and final drive efficiency with the consideration of friction loss on transmission and final drive; and $P_{\text{acc}}$ is the power required from other accessories.

5.3.3. **Power-based Longitudinal Control Algorithm**

5.3.3.1. **System Architecture**

Vehicle trajectory planning is one of the critical tasks performed by ACC systems and automated vehicles. For the sake of fuel economy, power-based vehicle control is of particular interest. Figure 5-17 depicts a generic system architecture for vehicle longitudinal speed control where both exogenous (e.g., signal phase and timing, roadway grade, and downstream traffic conditions) and endogenous (e.g., engine dynamics and gear ratio) information are utilized to predict the system state (e.g., travel speed and arrival time). With consideration of other factors such as driving comfort (or jerk threshold) and engine power constraints, the longitudinal control system is able to regulate the subject vehicle’s second-by-second speed based on user-defined measures of effectiveness (MOEs), for example, total energy consumption. As a closed-loop control system, both real-time vehicle dynamics and exogenous information are monitored in order to update the predicted states and planned trajectory as necessary.
5.3.3.2. Problem Formulation

As aforementioned, the major goal of the proposed vehicle longitudinal control in this study is to minimize fuel (or energy) consumption for the entire trip, which is mainly determined by the propulsion power, a function of vehicle mass, speed, acceleration/deceleration, and roadway grade. The vehicle speed at any point in time is constrained by many factors, such as the maximum engine power, upcoming traffic signal status, and downstream traffic conditions. Therefore, the optimal power-based vehicle longitudinal control problem (in continuous form) is in essence a constrained nonlinear programming (CONLP), i.e.,
where \( f(\cdot) \) is the fuel consumption rate; \( T \) is the expected trip time; \( x(t) \) represents the real value decision vector (e.g., speed and gear ratio); \( u(t) \) denotes other time-varying variables, such as SPaT and the preceding vehicle’s speed; and \( p \) denotes the deterministic variables (e.g., network topology, fuel type, and the vehicle’s frontal area).

Notice that the optimization of the above generic formulation is quite challenging, therefore, we reformulate the problem into a 0-1 binary Mixed Integer Linear Programming (MILP) problem based on the following steps: First, we discretize the system states, i.e., the speed (e.g., 1 mph), acceleration/deceleration (e.g., 1 mph/sec), and road grade (e.g., 1%), balancing the data resolution against computational load. This discretization step is only applied to the feasible region constrained by the maximum power and data availability. Then, we estimate the fuel consumption rate (e.g., every 1 second) with respect to each discretized system state and construct a set of look-up tables of step-by-step fuel consumption. Although the calculation of fuel consumption rate involves a set of complex non-linear models of vehicle dynamics (e.g., engine efficiency, optimal gear ratio), this step can be executed offline to reduce the computational burden of the optimization. Therefore, the optimal power-based vehicle longitudinal control problem (i.e., Eq. (3) and (4)) is reduced to a 0-1 binary MILP, where the system state (i.e., speed, acceleration and road grade) at each time step is chosen to construct an
optimal transition trajectory in terms of fuel consumption along the entire trip (traced by the dashed-dotted line and red dots in Figure 5-18), while satisfying all exogenous and endogenous constraints. To incorporate the road grade information, the entire route is divided into multiple sections according to predefined grade levels (e.g., -1%, 0%, and 1%) and each section has a constant grade value irrespective of its length. Figure 5-19 illustrates how an example route is segmented.

Figure 5-18. State transition diagram.
Figure 5.19. (a) An example of a hypothetical segmented trip due to change in roadway grade; (b) Discretized road grade along the trip in (a).

More specifically, we define a 0-1 binary variable (i.e., decision variable) as

\[
y_{i,j,k,g} = \begin{cases} 
1, & \text{if Condition 1 is satisfied} \\
0, & \text{otherwise} 
\end{cases}
\]  

Condition 1: at the \( i \)-th time step the vehicle is traveling at the speed of \( j \)-th level and acceleration of \( k \)-th level within the \( g \)-th roadway section index (differentiated by road grade).

With the decision variable defined above, the optimal power-based vehicle longitudinal control problem can be reformulated as follows:

\[
\min \sum_{i=1}^{T} \sum_{j=1}^{V} \sum_{k=1}^{A} \sum_{g=1}^{G} y_{i,j,k,g} \times f_{j,k,g} 
\]

subject to the following endogenous and exogenous constraints:
(a) Endogenous Constraints:

(a.1) At each time step, only one state is selected:
\[
\sum_{j=1}^{V} \sum_{k=1}^{A} \sum_{g=1}^{G} y_{i,j,k,g} = 1, \quad \forall i \in T
\]  

(a.2) At each time step, the acceleration/deceleration is the speed difference between the current step and previous step:
\[
\begin{align*}
\sum_{j=1}^{V} \sum_{k=1}^{A} \sum_{g=1}^{G} y_{i,j,k,g} \times a_k &= \sum \sum \sum y_{i,j,k,g} \times v_j - \\
\sum_{j=1}^{V} \sum_{k=1}^{A} \sum_{g=1}^{G} y_{i-1,j,k,g} \times v_j, & \forall i \in T
\end{align*}
\]  

(a.3) The total travel distance should be no less than the trip distance, L:
\[
\sum_{i=1}^{T} \sum_{j=1}^{V} \sum_{k=1}^{A} \sum_{g=1}^{G} y_{i,j,k,g} \times v_j \geq L
\]  

(b) Exogenous Constraints:

(b.1) At each time step, the subject vehicle’s position is constrained by that of the preceding vehicle (due to keeping the safe-following distance):
\[
\sum_{i=1}^{T} \sum_{j=1}^{V} \sum_{k=1}^{A} \sum_{g=1}^{G} y_{i,j,k,g} \times v_j \leq p_i, \quad \forall i \in T
\]  

(b.2) At the location of some waypoint (e.g., the stop bar of a signalized intersection), W, as measured by the distance from the trip starting point, the subject vehicle is allowed to pass through it within certain time windows (i.e., green intervals):
\[
\begin{align*}
\text{If } & \sum_{i=1}^{T} \sum_{j=1}^{V} \sum_{k=1}^{A} \sum_{g=1}^{G} y_{i,j,k,g} \times v_j = W + \delta \\
\text{then } & \tau \in \Phi
\end{align*}
\]  

(c) Other Constraints:

(c.1) At each time step, current road grade and current position are consistent:
\[ \sum_{t=1}^{T} \sum_{j=1}^{V} \sum_{k=1}^{A} \sum_{g=1}^{G} y_{i,j,k,g} \times v_{j} \leq \]
\[ \sum_{j=1}^{V} \sum_{k=1}^{A} \sum_{g=1}^{G} v_{i,j,k,g} \times s_{g}, \quad \forall t \in T \]  \hspace{1cm} (12)

and
\[ \sum_{t=1}^{T} \sum_{j=1}^{V} \sum_{k=1}^{A} \sum_{g=1}^{G} y_{i,j,k,g} \times v_{j} \geq \]
\[ \sum_{j=1}^{V} \sum_{k=1}^{A} \sum_{g=1}^{G} v_{i,j,k,g} \times s_{g-1}, \quad \forall t \in T \]  \hspace{1cm} (13)

where, \( f_{i,j} \) is the discretized fuel consumption rate at different levels of speed and acceleration within different roadway sections; \( v, a, \) and \( g \) are the discretized levels for vehicle’s speed, acceleration, and road grade, respectively; \( V, A \) and \( G \) are the maximum number of levels of the corresponding state variables; \( \beta_{t} \) represents the upper limit of traveled distance by the \( t \)-th time step, deduced from General Motors’ car-following model [94]; \( \delta \) is a small number (e.g., 0.1); \( \Phi \) is the set of feasible time windows or green intervals; and \( S_{g} \) represents the distance between the end point of the \( g \)-th roadway section and the trip starting point. In this study, we use the IBM ILOG CPLEX Optimization Studio [69] to solve the above problem.

### 5.3.4. Performance Evaluation

To evaluate the performance of the proposed longitudinal control algorithm, we employ vehicle data collected from the field and estimate the vehicle speed profile using the proposed algorithm. Furthermore, we compare the results with those obtained from both the baseline (i.e., no control scenario, see [95]) and the TSP-based algorithm.
5.3.4.1. Data Collection and Description

The data used in this study were originally collected from test runs on Palmyrita Avenue in Riverside, California, for the field testing of the Eco-Approach application [95]. As shown in Figure 5-20, a portable traffic signal with an Econolite ASC/3-2100 controller was set up (along the roadside) in the middle of the study route to mimic a real-world intersection. The traffic signal controller was also connected to a separate computer which translated the controller’s outputs into SPaT messages (or blobs). These messages were then pushed to a road-side unit (RSU) which was mounted on the signal arm, and were broadcast via Dedicated Short Range Communication (DSRC) at 10 Hz. The elevation profile of the study route exhibits a consistent slope with the roadway grade of around -3.4% (downhill) along the traveling direction.

A 2008 Nissan Altima was used as the test-bed vehicle, which was set up as shown in Figure 5-21. An on-board unit (OBU) was equipped to receive SPaT messages from the RSU via DSRC. Such SPaT information along with vehicle speed data (from the OBD-II interface) as well as accurate position (from the GPS receiver) was fed into another computer to calculate the desired vehicle trajectories.

Based on this experimental setup, comparative field testing had been performed where the driver might or might not be informed by the “eco-speed” advice and approached the intersection at different times within the signal cycle and at a variety of driving speeds, (i.e., 30 mph, 35 mph, and 40 mph). The overall energy consumption and pollutant emissions were estimated from the second-by-second vehicle speed trajectories using the Motor Vehicle Emission Simulator or MOVES model developed by the United States
Environmental Protection Agency (USEPA). For the following comparative analysis, we selected a sample human-driven vehicle trajectory without the eco-speed advice as a baseline case and follow the procedure in [93] to simulate an artificial trajectory generated from the TSP-based algorithm. Another trajectory is also calculated by using the proposed algorithm.

Figure 5-20. Field study location and artificial intersection configuration in Riverside California (Palmyrita Ave, Riverside CA).

Figure 5-21. Configuration of the test-bed vehicle (a 2008 Nissan Altima).
5.3.4.2. Comparative Studies

In this study, one 477-meter arterial driving profile (252 meters upstream and 225 meters downstream) extracted from Palmyrita Avenue is analyzed with MATLAB simulation for the proposed power-based optimal longitudinal control algorithm. Its travel time and energy consumption (estimated by MOVES) are compared to the previous field test data of both the baseline case and the case simulated with the TSP-based algorithm. Both the entrance and departure speeds are 15.5 m/s, and the maximum acceleration and deceleration are 2.5 m/s2 and -4.5 m/s2, respectively. The green window is from 33 to 63 seconds after the start of the trip. The BSFC factors are adapted from the Autonomie powertrain simulation tool [96] developed by the Argonne National Laboratory (ANL). Several different scenarios were then carried out.

1) Scenario 1: Same Arrival Speed at the Intersection and Same Travel Time

In this scenario, we chose the same parameters, i.e., upstream and downstream travel time (33 seconds and 16 seconds, respectively) and vehicle arrival speed (6 m/s) at the stop bar, as in the TSP-based case. The speed trajectories are depicted in Figure 5-22. Notice that the trajectory by the proposed algorithm (i.e., the green solid line) has been smoothed using a moving average method [97] to mitigate the effect of the discretization.

![Figure 5-22. Vehicle speed profiles of different control strategies](image-url)
As can be observed in Figure 5-22, both the proposed and TSP-based cases exhibit less variable speed profiles than the one for the baseline case. In addition, the proposed algorithm makes the vehicle decelerate at a lower rate when approaching the intersection, compared to the TSP-based algorithm. Table 5-1 summarizes the energy consumption of the three cases. The results reveal that the power-based optimal longitudinal control algorithm, when compared to the baseline and TSP-based cases, can reduce energy consumption by around 14% and 4%, respectively.

2) Scenario 2: Different Arrival Speed at the Intersection but Same Travel Time

If the arrival speed constraint is relaxed, the proposed power-based algorithm exhibits better performance without a penalty on mobility (i.e., the travel time is intact). Figure 5-23 presents the speed trajectories where the arrival speeds range from 7 m/s to 13 m/s. The results of energy savings compared to both the baseline and TSP-based cases are shown in Table 5-2. According to the table, the energy consumption is minimized when the arrival speed is 11 m/s. The saving in energy is as much as around 8%, compared to the TSP-based algorithm. An interesting finding from the speed trajectories is that when the downstream travel time is fixed, the vehicle can potentially save more fuel or energy.
if it slowly accelerates to approach the intersection (and reach a relatively high arrival speed when the signal turns to green) rather than cruise at a low speed or even wait at the stop bar.

![Figure 5-23. Vehicle speed profiles with different arrival speed at the intersection.](image)

**TABLE 5-2. COMPARISON RESULTS ON ENERGY CONSUMPTION WITH DIFFERENT ARRIVAL SPEED**

<table>
<thead>
<tr>
<th>Arrival Speed at the Intersection (m/s)</th>
<th>v=7</th>
<th>v=9</th>
<th>v=11</th>
<th>v=13</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy consumption (KJ/mi)</td>
<td>1270.8</td>
<td>1268.2</td>
<td>1239.6</td>
<td>1268.9</td>
</tr>
<tr>
<td>Energy Savings vs. Baseline (%)</td>
<td>14.37%</td>
<td>14.55%</td>
<td>16.48%</td>
<td>14.51%</td>
</tr>
<tr>
<td>Energy Savings vs. TSP-based (%)</td>
<td>5.30%</td>
<td>5.49%</td>
<td>7.63%</td>
<td>5.45%</td>
</tr>
</tbody>
</table>

3) **Scenario 3: Same Arrival Speed at the Intersection but Different Travel Time**

As mentioned previously, the green time window is between 33 and 63 seconds after the start of the trip. With this constraint, different travel time combinations for the upstream and downstream portions are tested in the proposed longitudinal control algorithm. Three travel times--33, 34 and 35 seconds--are chosen for the upstream portion, while three others--16, 17, and 18 seconds--are chosen for the downstream part. In Figure 5-24, it can be seen that the travel time changes on the upstream portion do not
have much impact on the shapes of the speed profiles. However, for the downstream portion, when the travel time increases, the vehicle accelerates more smoothly. For further evaluation, we calculate the energy consumption using the MOVES model and compare the results to those of the TSP-based case. The results are presented in Table 5-3.

It is noted that the travel time has a trivial impact on the energy consumption for the upstream portion. This may be because of the small changes in energy consumption rates for the deceleration maneuvers at different speeds. A hypothesis is that the original 33-second travel time is long enough to complete an energy-efficient trip. However, for the downstream portion, a significant reduction in energy consumption can be observed when the travel time is longer. A hypothesis is that energy consumption is more sensitive to the acceleration maneuvers. For example, the downstream trip with a travel time of 16 sec (the shortest) has to speed up faster to reach the destination at the specified time and at the specified target speed of 15.5 m/s. Therefore, it requires more fuel and energy, compared to the other two cases (i.e., t=17 and t=18).

Figure 5-24. Vehicle speed profiles for upstream trip (upper) and downstream trip (lower) with different travel times.
4) Scenario 4: Different Arrival Speeds at the Intersection and Different Travel Time

If both the arrival speed and travel time (upstream and downstream) constraints are relaxed, the proposed power-based algorithm presents even higher potential for reducing energy consumption. Various combinations of arrival speed (7 m/s, 9 m/s, 11 m/s, and 13 m/s) and travel time (ranges from 33 to 37 sec for the upstream trip and from 15 to 19 sec for the downstream trip) are tested. Fig. 11 illustrates the variation of energy consumption with different travel times and arrival speeds. As shown in Figure 5-25 an optimal power-based trajectory with the travel times of 33 sec upstream and 15 sec downstream, and the arrival speed of 11 m/s presents a much smoother acceleration maneuver and higher departure speed in comparison with the other trajectories. In addition, the results reveal that such optimal power-based trajectory, when compared to the baseline and TSP-based cases, can reduce energy consumption by as much as around 18% and 10%, respectively (see Table 5-4).
Figure 5-25  Energy consumption with different travel times and arrival speeds

Table 5-4. Comparison results on energy consumption of three trajectory algorithms

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Energy Consumption (KJ/mi)</th>
<th>Energy Savings vs. Baseline</th>
<th>Energy Savings vs. TSP-Based</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>1484.2</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td>TSP-Based</td>
<td>1342.0</td>
<td>9.58%</td>
<td>--</td>
</tr>
<tr>
<td>Optimal Power-Based</td>
<td>1210.9</td>
<td>18.41%</td>
<td>9.76%</td>
</tr>
</tbody>
</table>

5) Scenario 5: Impact of Roadway Grade

One of the key features of our proposed power-based optimal longitudinal control algorithm is the consideration of roadway grade information. To evaluate the impact of roadway grade on energy consumption, we use a 250-meter generic freeway segment to test scenarios with different road grades: -6%, -3%, 0%, 3% and 6%, with the initial speed, final speed, and trip time being identical.
The second-by-second vehicle speed trajectories generated by the proposed power-based (algorithm (as plotted in Figure 5-26) are used to estimate energy consumption. It turns out that the energy consumption is monotonically increasing as the roadway grade grows. In addition, the relative difference in energy consumption can be as high as 170% when the roadway grade varies from -6% to 6% in our study (as shown in Table 5-5).

<table>
<thead>
<tr>
<th>Road Grades</th>
<th>-6%</th>
<th>-3%</th>
<th>0%</th>
<th>3%</th>
<th>6%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Energy consumption (KJ/mi)</td>
<td>537.0</td>
<td>618.8</td>
<td>782.9</td>
<td>981.1</td>
<td>1454.9</td>
</tr>
</tbody>
</table>

Figure 5-26. Vehicle speed profiles for different road grades

6) Scenario 6: Longitudinal Speed Profile Optimization with a Safe Headway Constraint

By adding more exogenous constraints (e.g., safe headway or car-following speed), the proposed longitudinal vehicle control algorithm can be extended to be adaptive to more complicated traffic environments. Figure 5-27 shows a modified longitudinal speed profile optimization scheme that takes into account the preceding vehicle information (e.g., speed and position). For on-line implementation, we may divide the entire trip into small time windows and employ the proposed power-based optimization over each time
window. Note that in the real world, the preceding vehicle information needs to be acquired and predicted before the optimization.

![Figure 5-27. Power-based longitudinal speed profile optimization with safety headway constraint.](image)

To validate the modified longitudinal control scheme, we program a 500-meter hypothetical roadway segment, assuming that the second-by-second speed profile of the preceding vehicle is predictable (following a hypothetical sinusoidal function as illustrated in Figure 5-28), and thus available for the optimization. Then, we use it to generate the optimal speed profile for the subject vehicle (also illustrated in Figure 5-28). Here, we also enforce the initial speed and the final speed of both speed profiles to be identical in order to keep the same energy level at the beginning and end of the trip. As shown in Figure 5-29, the subject vehicle could maintain a safe headway distance greater than the minimum threshold (5 meters) while generating an optimal longitudinal speed profile.
5.3.5. Summary

In this section, we propose a power-based optimal vehicle longitudinal control algorithm for an eco-ACC system that is customized to the vehicle’s specific characteristics (e.g., BSFC map and engine efficiency). We demonstrate its effectiveness in minimizing trip fuel consumption of a gasoline vehicle but the algorithm can also be adapted to work with diesel and alternative fuel vehicles (e.g., electric vehicles). In addition to endogenous information (e.g., engine dynamics and gear ratio), the proposed algorithm also takes into account exogenous information, including road grade, upcoming traffic signal status, and the preceding vehicle’s state in calculating an optimal speed profile that minimizes trip energy consumption.
Results from the numerical studies of the proposed algorithm show great promise. Compared to the existing TSP-based algorithm, the proposed algorithm can further reduce the energy consumption by about 4% in the scenario tested if the trip travel time and the arrival speed at the intersection are intact. If the arrival speed can be relaxed, greater energy savings (up to 8%) can be achieved without adversely affecting the travel time. If both arrival speed and travel time can be relaxed, the energy savings can be as much as 10%.

Since vehicle energy consumption is sensitive to road grade (e.g., it differs by 170% for road grade of -6% versus 6% in the example shown in this paper), the unique capability of the proposed algorithm to account for the impact of road grade is valuable.

As one area of future work, the real-time performance of the proposed algorithm should be evaluated and optimized. Then, the effectiveness of the algorithm should be validated in field operational tests.
6. DYNAMIC SPEED HARMONIZATION FOR HEAVY DUTY TRUCKS 
USING A CONNECTED VEHICLE APPROACH

6.1. Problem Statement

In the U.S., a significant portion of goods is transported by heavy-duty trucks. These trucks consume a large amount of fuel each year (close to 37 billion gallons of fuels according to FHWA [100], primarily due to their relatively low fuel economy and high annual mileage. In fact, fuel costs are one of the major cost components of total truck operations, accounting for roughly 1/3 of total operating costs and slightly smaller than labor costs [101]. Not only freight trucks consume a large amount of fuel, but they also produce a significant amount of greenhouse gas (GHG) emissions. Between 1990 and 2011, medium- and heavy-duty trucks, which were used mostly for freight movement, accounted for 22% of the U.S. GHG emissions from transportation sector or about 6% of the entire U.S. GHG emissions inventory. It is important to note that any measures that reduce fuel consumption will also reduce both criteria pollutant emissions (e.g., oxides of nitrogen and particulate matter) and greenhouse gas emissions (e.g., carbon dioxide); and thus, benefit the environment. Therefore, government agencies have been trying to develop and implement strategies to reduce fuel consumption and GHG emissions from these trucks as part of the effort to become energy independent and combat climate change.
One way of reducing fuel consumption and CO$_2$ emissions from trucking operations is to introduce “eco-driving” technology and behaviors to the truck operators [102]. Energy efficiency policy recommendations in support of the G8 plan of action in Paris). Eco-driving can be defined as fuel-efficient operation of a vehicle to achieve better fuel economy and lower tailpipe emissions while not compromising the safety of oneself and other road users [103]. Eco-driving is now being heavily promoted in several international projects. Japan is investigating eco-driving as part of their five-year “Energy ITS” research program [104]. Europe has a similar long-term research program in eco-driving called ECOSTAND [105]. The core of these eco-driving programs is to provide drivers with a variety of advice and feedback to reduce fuel consumption. The advice and feedback can be provided through various means including websites, classes or training, and in-vehicle driving feedback systems. The initial Eco-driving programs for light-duty vehicles in Europe and Asia have shown fuel economy improvements on the order of 5 to 15%.

To date, however, there have not been any significant studies addressing eco-driving for heavy-duty trucks. Because heavy-duty trucks play a very important role in goods movement while also having a significant impact on overall CO$_2$ emissions, it is critical that we also apply eco-driving techniques to trucks in order to better understand what potential fuel and CO$_2$ savings are possible. This proposed research is aimed at addressing this research problem.

For light duty vehicles, most of the eco-driving technology is aimed at smoothing velocity patterns: executing gentle accelerations, avoiding stop-and-go activity, and
choosing Eco-Friendly routes [107]. For trucks, however, the eco-driving approach will likely be different due to the fact that trucks typically have significantly lower power-to-weight ratios and many more gears (typically between 9 and 18) to constantly shift to match the speed and engine RPM. This implies that accelerations are more difficult to perform and road grade is an important factor.

In this study, CE-CERT investigators teamed with researchers from Cal State San Bernardino’s Leonard Transportation Center (LTC), with a focus on truck transport component. This proposed study is built upon UC Riverside’s previous research in dynamic eco-driving, where the drivers are given target speed advice when driving along the freeways. A driving simulator study is conducted with truck drivers to evaluate heavy-truck dynamic eco-driving technology, as well as studying the behavioral impact eco-driving may have on truck drivers.

Section 2 of this chapter reviews the proposed freeway-based dynamic eco-driving strategy, and the driving simulation being used in this study. Then, data sources, network setup and detailed testing procedures for the driving simulator study are described in Section 3, followed by the data analysis and the discussion of results in Section 4. Finally, Section 5 summarizes this paper with concluding remarks and future work.

6.2. Background

6.2.1. Truck Eco-Driving Technologies and Programs

Heavy-duty trucks are critical component of the U.S. goods movement system and consume a large amount of fuel and emit significant pollutant and greenhouse gas
emissions. The trucking industry is always looking for any measure to improve their operations and reduce fuel consumption, including improving how the truck is driven.

A variety of truck eco-driving programs have been tested or implemented in Europe, Asia, and North America. Even highly experienced truck drivers can boost their skills and enhance driving performance through driver training programs. A multi-media course, developed jointly by EPA and Natural Resources Canada, is claimed to enable many drivers to improve their fuel economy by 5 percent or more [108].

In the U.S., the combination of real-time feedback and focused training drives significant and immediate impact on overall fleet fuel consumption. In this study, by the end of the second month of the treatment period, the top 25% of drivers with the greatest improvement in fuel economy reduced fuel usage by an average of 22%, resulting in an annual average fuel savings of $12,553 per vehicle [109].

Experts in the freight industry agree that more than just eco-driving training is necessary to maintain efficient driving habits in the long term. One method for incentivizing eco-driving habits is reward schemes centered on bonuses for every mile per gallon (mpg) of increased fuel economy. Another method for motivating drivers to continue using eco-driving principles is the usage of on-board monitoring systems. These systems are able to record real-time information about brake usage, gear shifting, and fuel consumption and to remind drivers of eco-driving tips. As more freight companies adopt eco-driving as a means of reducing fuel costs and CO₂ emissions, other methods for ensuring long-term efficient driving behavior may need to be determined in order to maintain eco-driving benefits [110].
6.2.2. Freeway-based Dynamic Eco-Driving System

In 2009, University of California, Riverside has investigate the concept of dynamic eco driving, where advice is given in real-time to drivers changing traffic conditions in the vehicle’s vicinity [112]. This dynamic strategy takes advantage of real-time traffic sensing and telematics, allowing for a traffic management system to monitor traffic speed, density, and flow, and then communicates advice in real-time back to the vehicles (see Figure 6-1). Several different components interact together. This architecture takes advantage of the existing California Freeway Performance Measurement System (PeMS) [113]. The system consists of numerous embedded loop detectors on the major freeways in California, each reporting flow and occupancy and thus allowing average traffic speed to be computed. These data are collected through local Traffic Management Centers (TMCs), and then filtered, processed, and made accessible at 30-second intervals on the Internet via the PeMS server. The overall eco-driving strategy occurs primarily on a system server (potentially located at a traffic management center), where the PeMS data (e.g. average traffic speed on a link-by-link basis) are collected and processed. An algorithm determines an optimal “set” speed for an individual vehicle traveling on the network, based on the vehicle’s location, direction, and PeMS data in the vicinity. This suggested set speed is communicated to the instrumented vehicle via a wireless communications provider. We utilized instrumented vehicles that can also provide velocity trajectory data back to the system server for analysis. By providing dynamic advice to drivers, simulations showed approximately 10–20% in fuel savings and reduction of CO₂ emissions without a significant increase in travel time. Figure 6-2
illustrates the relationship of average traffic speed and optimal control speed, which was produced after analyzing a variety of traffic scenarios in both traffic simulation tool and real world experiments.

Figure 6-1. System architecture of dynamic eco-driving system [109]

Figure 6-2. relationship of average traffic speed and optimal control speed[109]
6.3. Driving Simulator Study

With trucks, driving simulators are really the only cost-effective way to measure potential effect of Eco-driving and it provides an environment that both safe and replicable. The driving simulator used in this study is a quarter-cab National Advanced Driving Simulator (NADS) Minisim™ developed by researchers at University of Iowa [58].

6.3.1. System Architecture

As shown in Figure 6-3, the Eco-Driver systems for heavy duty truck consists of (a) NADS Minisim™ truck driving simulator, (b) A data acquisition and process computer to collect drivers’ driving data and generate eco-driving feedbacks, and (c) a 7-inch automotive-grade monitor to serve as an artificial dashboard. In this architecture, the computer carriers out multiple tasks, including 1) collection traffic data to computer real-time average traffic speed, 2) Collection real-time driving data (e.g., speed and position) to calculate eco speed, as well as display the eco-feedback on the artificial dashboard. In Figure 6-4, a number of items are displayed in the artificial dashboard: 1) vehicle current speed (i.e., the speedometer), 2) the vehicle RPM (i.e., the tachometer), 3) an “advisory” speed as calculated from dynamic eco-driving algorithm, along with a green-zone moving along the edge of the speedometer.
6.3.2. Driving Scenario Development

6.3.2.1. Software Setup

Driving scenarios are built using two tools: TMT (Tile Mosaic Tool) and ISAT (Interactive Scenario Authoring Tool). TMT allows roadmaps to be built using a database of tiles. ISAT uses the roadmap built in TMT and on it places static and dynamic objects and coordinators. These objects include static, non-functional signs, obstacles and
pedestrians, as well as ADOs (Autonomous Dynamic Object) and DDOs (Dependent Dynamic Object). ADOs can be simply placed on a roadmap, and will drive autonomously while obeying preset controls, including lane deviation, maximum and minimum speed, acceleration, and gap between vehicles. DDOs require a designated path, and will not move unless given nodes to travel to on the roadmap. Coordinators serve to provide ways to control large groups of ADOs. DDOs are not affected by coordinators. Coordinators include traffic signals, global time triggers and road pads. Once the desired scenario has been built and the external driver has been given a spawn point on the roadmap, the scenario can be run by Minisim. Figure 6-5 depicted the system software setup.

Figure 6-5. System software setup
6.3.2.2. Real-World Traffic Representation

The Scenario used in the study is based upon a 6 mile segment of the 91E freeway located in District 12, Orange County, with consist of 20 vehicle detector stations (VDS) covering both HOV and mainline lanes (see Figure 6-6). The traffic data was collected from 3:00pm to 6:30pm on September 12th, 2012. The traffic data used in the study was obtained from the California’s Freeway Performance Measurement System (PeMS). PeMS receives real-time 30-seconds data measurement of traffic count and occupancy from each detector stations. Based on the traffic count and occupancy, the traffic speed is estimated using g-factor algorithm for single-loop detectors.

![Figure 6-6. Simulated road segment of 91 East Highway in Orange County, California](image)

TMT was used to build a roadmap that mimicked this segment of the 91E freeway. The segment was largely straight, with a slight curve at the segment’s beginning. To reproduce this, a curved freeway tile was linked to several miles of straight freeway tiles. Within ISAT, a variety of tools were used to make the scenario conform to the design of the experiment. 20 ADOs were placed on the roadmap, where the external driver was also
placed, with approximately 20 feet between each vehicle. Three types of coordinators are used: traffic source, road pad and global time. Several coordinators fires at the start of the simulation. A global time trigger is set to fire at global time of 0 seconds. When this trigger fires, messages are displayed, telling the external driver to “Start Engine” and “Drive”. The traffic source spawns vehicles from a set of 6 different vehicle types at random uniform times between 1.25 and 1.75 seconds. This creates a cloud of traffic surrounding the external driver. Using the traffic data from PEMS, road pads are placed along the roadmaps that control the speeds of ADOs, reproducing the speeds of recorded traffic on the 91E freeway. At the end of the 6 miles, the simulation closes.

6.3.3. Participants

Following UCR Human Research Review Board approval, participants were recruited through flyers sent by Cal State San Bernardino, ads placed on California Construction Trucking Association website and by word of mouth. They were compensated $100 upon completion of the one-hour study. All data were collected from September 4th through October 5th of 2014.

A total of 26 participants completed this research (23 male, 3 female). Participants ranged in age from 19 to 63 years (M = 44, SD = 12.36). All participants were required to have a valid driver’s license. 14 participants are professional truck drivers working for or owning trucking companies. The other 12 participants are trucking school graduates. The professional truck drivers’ years of driving experience ranged from 10 to 36 years, with an average of 20 years. None of the participants were familiar with any of the dynamic eco-driving system implemented on Minisim™ truck driving simulator.
6.3.4. Procedures

Once driving simulator is configured and programmed with the driving scenarios, Participants are randomly assigned to participate in either static Eco-driving experiment or dynamic Eco-driving experiment. The static Eco-driving experiment has three tasks: testing without training (task 1), testing after participants have been trained in eco-driving techniques (task 2) and testing with eco-driving feedbacks (task 3). The dynamic eco-driving experiment consists of two tasks: testing without training (task1), followed by testing with dynamic eco-driving feedbacks (task 3). This study address

Task 1: Driving Simulator Experimentation for Uninformed Drivers (Baseline-Driving)

Upon arrival to the study location, participants were given a consent form and intake before questionnaire to complete. Each participant then was introduced to the driving simulator. After getting used to its operation, the driver experienced the driving scenarios and was asked to drive in their normal fashion. While the testing was underway, real-time output parameters form the simulator was recorded, specifically, seconded-by-second velocity profiles, surrounding vehicle speeds, and simulated position along the programmed route. These data will be analyzed later to accurately determine fuel consumption and CO₂ emissions for all the driving that took place.

Task 2: Driving Simulator Experimentation after training for Informed Drivers (Eco-Driving)

After the initial uninformed driving has been carried out, the drivers in statics eco-driving group then underwent training by providing eco-driving technology brochure. Many of these eco-driving principles are outlined in a number of on-line training
programs, such as those found at http://www.ecodrivingusa.com. The general areas of training in driving operations are outlined in the eco-driving flowchart [114] shown in Figure 6-7. This basic training was modified and adapted for truck driving. After this training was carried out, then the truck driving participants used the driving simulators again, practicing their eco-driving skills. Data was collected for the same driving scenario tested in baseline drive, which will later be compared and analyzed.

**Task 3: Driving Simulator Experimentation with Eco-driving feedback for Informed Drivers (Extra Eco-Driving)**

After the static eco-driving experiments are complete, then the dynamic eco-driving strategies developed in Figure 6-2 were integrated into the driving simulators. These dynamic eco-driving strategies are more sophisticated than the static advice and take into account simulated traffic conditions. Based on knowing the traffic conditions at any point in time, the dynamic eco-driving speed advice was provided to the truck drivers on the speedometer on artificial dashboard, as is described in Figure 6-4. This speedometer not
only shows current speed, but also indicates a recommended driving speed both on the
dial with colors and digitally underneath. All participants then used the driving simulator,
practicing their dynamic eco-driving skills. In this task, the dynamic eco-driving
algorithm is activated and drivers were asked to follow the eco-speed advice as closely as
possible. Data will be collected for the same driving scenarios tested in Task 1 and 2.

6.3.5. Data Collection and Processing

Driving data is automatically recorded through Minisim™ DAQ (Data Acquisition)
tool. For more specific data acquisition, the route table is used. The route table specifies
exactly what data should be packed and sent by Minisim™. In order to extract the desired
data, the route table was modified to specify which variables Minisim™ should return. In
this study, OV (Object Vehicle) speed, OV position, OV engine RPM, OV lane
departures, ADO Names, ADO Velocities and message frame number were extracted.
This data is packed and sent to the data-acquisition and processing computer in 60Hz for
testing and calculating dynamic eco-driving speed. Meanwhile, Drivers’ second by
second speeds were recorded during each experiment. Afterwards, travel time and energy
consumption (estimated by MOVES) are compared based on previous test data of both
“uninformed” baseline case and “informed” cases.

6.3.6. Pre- and Post- Experiment Questionnaires

Each driver completed questionnaires before and after each experiment in order to
capture the driver’s changes in driving behavior and fuel usage due to the eco-driving
feedback system. The before-survey was given to participants before they were
introduced to the eco-driving system. This survey asked questions concerning driver’s
existing driving practice, to set up a baseline to compare to the after-survey. At the end of 1-hour driving study, drivers were administered an after-survey to provide any changes on their driving behavior and opinion on the eco-driving feedback system.

6.4.Data Analysis and Results

To evaluate the impact eco-driving feedbacks may have on truck drivers, we compared the performances of Dynamic Eco-Driving with Eco-Driving and the baseline driving in terms of fuel consumption, pollutant emissions and travel times. Additionally, based upon the statistically analysis of the survey data, comparison of fuel savings by demographic groups are also presented.

6.4.1.Fuel Consumption and CO₂ Emission Analysis

A. Eco-Driving vs. Baseline Driving

As aforementioned, 13 drivers who assigned in static group have completed Eco-Driving (task 2) after provided eco-driving techniques brochure. For each driver, the speed profiles of the baseline driving and eco-driving were collected during the experiments and thus the fuel saving was calculated individually. The fuel and CO₂ savings over all drivers range from -2% to 9%, with a median of 2%. Figure 6-8 shows the number of drivers distributed over different fuel savings. Compared to their baseline driving, 54% of drivers reduced the fuel consumption by no greater than 2% in their Eco-driving. The results suggest that pre-training with eco-driving principles influenced some drivers’ behaviors, while it was ineffective for over half the participants.
Figure 6-8. Number of drivers by fuel savings (Eco driving vs. Baseline driving)

B. Extra Eco-Drivering vs. Baseline Driving

All 26 drivers (in both static and dynamic groups) experienced Extra Eco-Drivering experiment by following a recommendation speed while driving. Similarly, fuel consumption was calculated based on each driver’s speed profile in the Extra Eco-Drivering experiment and compared to the corresponding baseline driving. As it is shown in Figure 6-9, the overall results were significant. The fuel savings ranging from 0% to 9%, with a median of 4%, indicating that the eco-driving feedback device outperform the eco-driving training in terms of fuel consumption. Additionally, 70% of participants reduced the fuel consumption greater than 2% due to the feedback device. The other 30% had less fuel saving varying from 0% to 2%.
In order to clean the data for further analysis, each driver’s mpg for baseline driving was calculated from the CO₂ emissions. The diesel factor used in this study is from the calculations that vehicle manufactures use to measure fuel economy (EPA 2014). As can be seen from Figure 6-10, the baseline mpg and fuel savings in Extra Eco-driving experiments can be perceived as falling into a linear regression model, which indicates driver who conducts fuel-effective baseline driving would have less fuel saving in Extra Eco-driving experiments, even though the eco-feedback was provided.
For those drivers who have less 2% fuel savings in Extra Eco-driving experiments, the average mpg of their baseline driving is greater than 7.7 MPG, implying a very limited room to improve fuel consumption according to the linear model in Figure 6-10. Further regression on the fuel savings from the 70% of participants who reduced fuel more than 2% reveals that the relationship between fuel savings and numbers of drivers comes closely to a Gaussian distribution (M = 6%, SD = 0.024). Figure 6-11 shows overall Extra Eco-driving of all participants is more fuel effective, with an improvement on mpg from 7.48 MPG to 7.80 after the dynamic eco-driving device been applied.
Furthermore, driving behavior variation reduction for different drivers is another key focus. Drivers’ behaviors variation is undesirable because it creates numerous uncertainties in roadway transportation by slowing down the traffic due to poorly following the traffic or rear-ends collision caused by aggressive drivers. By measuring the variation on mpg for both baseline driving and Extra Eco-driving over all participants, it can be seen in Table 6-1, the difference between drivers is significantly reduced in Extra Eco-driving, with a variation reduction of approximately 52%. In addition, Table 6-2 also shows the mpg variation between two participants, one is with 30 years’ truck driving experience and the other is a graduate student in trucking school. The 99% variation reduction on mpg reflects the impact of the dynamic eco-driving feedback, which provides enough information to help less experienced truck drivers self-teach how to drive efficiently and consequently change driving behaviors.
**Table 6-1. MPG Variation Between Participants in Baseline and Extra-Eco Driving Experiments**

<table>
<thead>
<tr>
<th></th>
<th>STDEV</th>
<th>STDEV</th>
<th>Reduction vs. Baseline</th>
<th>VAR</th>
<th>Reduction vs. Baseline</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>0.0543</td>
<td></td>
<td></td>
<td>0.1577</td>
<td></td>
</tr>
<tr>
<td>Extra-Eco</td>
<td>0.0371</td>
<td>31.59%</td>
<td></td>
<td>0.1802</td>
<td>52.31%</td>
</tr>
</tbody>
</table>

**Table 6-2. MPG Variation Between Professional Truck Driver and Student Truck Driver**

<table>
<thead>
<tr>
<th></th>
<th>STDEV</th>
<th>STDEV</th>
<th>Reduction %</th>
<th>VAR</th>
<th>Reduction %</th>
</tr>
</thead>
<tbody>
<tr>
<td>Baseline</td>
<td>92.8431</td>
<td></td>
<td>8619.845</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Extra-Eco</td>
<td>7.8488</td>
<td>91.55%</td>
<td>61.605</td>
<td>99.29%</td>
<td></td>
</tr>
</tbody>
</table>

**C. Extra-Eco Driving vs. Eco-Driving**

Another issue this study aiming to address is how well eco-driving training helps drivers get fuel savings when using Extra Eco-driving device. Figure 6-12 presents the results of a paired difference test between extra eco-driving for the 13 drivers who only took extra-eco driving experiments (dynamic driving group) and the extra eco-driving for the other 13 drivers who drove both (static driving group). The graph shows number of drivers by different fuel savings for both groups. The figure illustrates a majority of participants in static driving group, exhibited a more decline of fuel usage in their extra-eco driving tests compared to the other group. Also, the overall static driving group saved more fuel during the extra eco-driving test with a median fuel saving of 6% compared to the 3% fuel saving of the dynamic driving group. This change is slight, but evident in the possibility of reducing more fuel consumption by providing eco-driving training prior to using eco-driving feedback.
6.4.2. Other Pollution Emissions Analysis

Besides the fuel consumption and CO₂ emission analysis, we also evaluated the benefits of the dynamic eco-driving feedback in terms of reductions in emissions of criteria pollutants, such as NOx, PM2.5, CO and HC. Figure 6-13 summarizes all these results for different emission pollutants. Emission pollutions of all 26 drivers’ extra-eco driving tests have been calculated based on the speed profiles using MOVES emission model, as well compared to the corresponding baseline driving results. As it shown in the Figure 6-13(a), over half (63%) participants improved the NOx by no less than 2%, while one third of them improved by 5% to 11%. A majority of participants (about 88%) participants achieved PM2.5 reduction of no less than 2%, with a median of 9% in Figure 6-13(b). Figure 6-13(c) illustrates more than 60% participants improved the CO emission by 2% to 11%. For the results of HC emission shown in Figure 6-13(d), only 4 drivers increased HC emission by only ~0%, while the others improved it by 2% to 13%.
Figure 6-13. Number of drivers by different pollution emissions (NOx, PM2.5, CO and HC)
6.4.3. Travel Time Analysis

In addition to information on fuel consumption and emissions, each participant’s total travel time of each driving test has been recorded and analyzed. As indicated above, some drivers exhibited change in behavior or improvement in fuel economy, while the degree to which behavioral changes influenced travel time is another critical indicator of the dynamic eco-driving feedback. Travel time results in Figure 6-14 shows that, during the extra-eco driving tests, around one third of participants took longer time to complete the 6 miles trip compared to their baseline records, while the remaining two third drivers were taking same or even less time. The result suggests that dynamic eco-driving feedback could assist drivers improve fuel economy without compromising too much travel time.

Figure 6-14. Number of drivers by travel time reduction
6.4.4. Comparison of Fuel Savings by Demographic Groups

Based on the before-and-after responses from all participants as collected through the surveys, we provide a review of savings by demographic groups. Note that here we mainly focus on fuel savings between extra-eco driving and baseline driving. It can be seen from Table 6-3, both the experienced professional truck drivers and student drivers present a fuel usage reduction of around 4% in their extra-eco driving tests using the in-vehicle dashboard displaying with driving feedback information. Interestingly, the student drivers reduced the fuel usage even slightly higher than the profession drivers. Through experimental observations, it is found the student drivers were more willing to accept the driving feedback technology and adjust their driving behavior, while it took longer time for the experienced truck drivers to alter their already-formed driving habits. Additionally, Table 6-4 also illustrates the female drivers exhibited higher fuel economy savings compared to male drivers.

<table>
<thead>
<tr>
<th>Count</th>
<th>Professional Truck Drivers</th>
<th>Student Truck Drivers</th>
</tr>
</thead>
<tbody>
<tr>
<td>%</td>
<td>54%</td>
<td>46%</td>
</tr>
<tr>
<td>Average fuel savings % (Extra-Eco vs. Eco)</td>
<td>4.02%</td>
<td>4.24%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Count</th>
<th>Male Drivers</th>
<th>Female Drivers</th>
</tr>
</thead>
<tbody>
<tr>
<td>%</td>
<td>88%</td>
<td>12%</td>
</tr>
<tr>
<td>Average fuel savings % (Extra-Eco vs. Eco)</td>
<td>3.65%</td>
<td>5.78%</td>
</tr>
</tbody>
</table>
6.4.5. Overall Driver Feedback

The survey captured the before-and-after stated responses from all participants, particularly their opinion upon the changes of driving behavior and fuel usage due to the eco-driving feedback technology. After-survey posted several questions regarding drivers’ statement on the eco-driving feedback system. More than two third (~77%) participants stated they changed their driving behavior due to the feedback device, while remaining 23% stated they did not. Regarding of the specific driving pattern altered, 69% of drivers stated they accelerated more slowly because of the driving feedback, 73% of drivers thought they braked more gradually in the extra-eco driving tests, 76% of drivers believed they drove at appropriate driving speed by following the driving feedback and a majority (~84%) of drivers stated they felt the driving feedback changed how they drove during the extra-eco driving test.

6.5. Summary

This study presents a work from a driving simulator study which investigated the energy and emission impacts of dynamic eco-driving technology on heavy-duty. The system was design to enable drivers to achieve fuel-effective driving through the provision of eco-driving feedback device. The results from the study suggest that the eco-driving can be improved by providing such advice.

In terms of fuel consumption and emissions, the dynamic eco-feedback technology assisted drivers reduce the fuel usage and CO₂ emissions averagely by 4%. The feedback device in combination with the eco-driving training has potential to further improve the fuel economy averagely by 6%. Furthermore, the drivers’ driving behavior variation can
also be significantly reduced using the eco-driving feedback device, which makes less traffic uncertainty associated with different drivers. Besides, the result of travel time analysis indicates dynamic eco-driving feedback could enhance the fuel economy without compromising too much travel time. Participants in this study were also taking before-and-after surveys during the tests to capture the change of their driving behavior and fuel usage. The data of the survey shows as much as 77% of drivers stated a significant driving behavior change due to the feedback system and a majority of participants believed the proposed technology could help them improve fuel usage when driving a heavy-duty truck.

However, the survey data also reveals more or less distraction from the eco-driving feedback on the artificial speedometer. Currently, the association between driver distractions and the feedback device is not well understood. However, an interesting finding observed from the study is most participants focused more on rpm on the tachometer other than the speedometer in order to keep the engine working at a fuel efficient speed during their normal baseline driving, which imply a modified tachometer with eco-driving feedback might further reduce the distraction on truck drivers.

Apart from the driver distraction, the results of study are also affected by various feathers, such as the willingness of drivers to accept this technology, the concentration level of drivers during the test, the ability of drivers to adapt the driving simulator. These issues need to be precisely considered and addressed in the further eco-driving study.
7. Conclusions and Future Work

This dissertation has presented a variety of Eco-Friendly agent-based advanced traffic management technologies in a connected vehicle environment. It involves the development of multi-agent based intersection traffic management prototype, agent-based lane selection technique, agent-based eco-driving algorithms (EAD and power-based) for arterial network, as well as the Dynamic eco-driving strategy for highway system. These proposed technologies have been evaluated in either traffic simulations, field tests or driving simulator study.

This chapter provides a brief summary of the dissertation, as well as the possible future work.

7.1. Conclusions

As wireless communication advances, agent-based system technique provides a new perspective to advanced traffic management and has received increased attention from researchers and engineers in the field of transportation. In both urban arterial and highway networks, vehicles and intersections interact with each other as individual intelligent agents in an integrated environment, which can significantly improve the overall traffic performance in terms of safety, mobility and environmental sustainability, due to knowledge sharing and system-wide decision-making.
In Chapter 3, for urban arterial traffic management, we examined the concept of advance traffic management system for connected vehicles using a multi-agent system approach, where both vehicle agents and intersection management agent can take advantage of real-time traffic information exchange, and developed a agent-based hierarchical structure for signal-less intersection management system. The proposed strategies have focused on developing hierarchical structure, analytical modeling, event scheduling and optimized algorithms that are effective for real-time traffic applications. One of the primary dynamic strategies is a “reservation-based” intersection management strategy which allows for an intersection management agent to receive vehicle data from vehicle agents, communicate advice in real-time back to the individual vehicles, and dynamically reserve intersection time-space occupancy for the vehicle agents. In parallel, the vehicle agents utilize this advice to preplan their trajectories and behavior in order to optimize the system-average travel time and reduce stop-and-go actions. The vehicle agents may also be clustered into platoons using connected vehicles technologies to further improve system performance and reduce system communication loads. As part of the system, an optimal scheduling model is proposed to determine the best access order to the intersection rather than following the FIFO assumption for all approaching vehicle agents based on their arrivals.

Based on the connected vehicle technology, Chapter 4 presents a real-time lane selection algorithm for agent-based traffic management system (for both urban arterial and highway networks), which can provide guidance on determining optimal
target lanes for individual vehicle agent in order to better regulate traffic flow, thus achieving a system-wide optimal solution in terms of maintaining desired traffic speeds. It is noted that the proposed algorithm can be applied to both advanced driving assistance systems and automated vehicles.

In Chapter 5, two kinds of dynamic longitudinal control algorithms have been developed and described. Firstly, we developed an algorithm for the “Eco-Approach and Departure” of a vehicle approaching a signalized intersection with fixed-timing signal control. This algorithm focuses on dynamic eco-driving on an arterial corridor with traffic control signals, where signal phase and timing (SPaT) information of traffic lights is provided to the vehicle as it drives down the corridor. Three types of field tests (uninformed driving, manual-DVI driving and automated driving) have been conducted in both Riverside and Turner Fairbank Highway Research Center on different vehicles (Nissan Altima and Ford Escape). Secondly, a power-based approach is used to develop an optimal vehicle longitudinal control algorithm for individual vehicles with specific characteristics (e.g., engine type) in order to maximize fuel economy under a variety of traffic conditions. In this approach, the system state at each time step is defined as a tetrad, including vehicle speed, acceleration, road grade, and engine efficiency. Given the downstream traffic information (using connected vehicle technologies) and route elevation profiles, the second-by-second optimal system states can be obtained using mixed integer linear programming (MILP) techniques. To evaluate the performance of the power-based longitudinal control algorithm, we employ vehicle data collected from the field and
estimate the vehicle speed profile using the proposed algorithm. Furthermore, we compare the results with those obtained from both the baseline (i.e., no control scenario) and the Eco-approach and departure algorithm.

In Chapter 6, a dynamic eco-driving algorithm has been introduced, where advice is given in real-time to drivers according to changing traffic conditions in the vehicle’s vicinity. This dynamic strategy takes advantage of real-time traffic sensing and telematics, allowing for a traffic management system to monitor traffic speed, density, and flow, and then communicates advice in real-time back to the vehicles. A driving simulator study is conducted with truck drivers to evaluate heavy-truck dynamic eco-driving technology, as well as study the behavioral impact eco-driving may have on truck drivers. In terms of fuel consumption and emissions, the dynamic eco-feedback technology could assist drivers reduce the fuel usage and CO₂ emissions by as much as 9%.

Taken together, the results in this dissertation demonstrate that advanced traffic management system, with intelligent vehicles and road traffic infrastructures, and dynamic network-wide information sharing based on connected vehicle technologies, can be used effectively to mitigate traffic congestion by making maximum use of road capacity, better regulating traffic flow in both macroscopic view (focusing on traffic bottleneck areas) and microscopic view (focusing on vehicle behaviors, e.g. lane changes and trajectory planning), and significantly reduce fuel consumption and pollutant emissions.
7.2. Selected Publications Resulting from This Research


7.3. Future Work

Thus far, the agent-based intersection traffic management system has been applied to isolated single-lane and multi-lane intersections, within limited time and regions. More data should be collected for a larger network. Traffic control strategies should be adjusted and better designed to network topologies. The ATMS prototype need to be designed to evaluated urban networks with multiple intersections.

This dissertation has explored an optimal lane selection algorithm that can minimize the number of potential vehicle conflicts. However, other objective functions (minimal travel time, minimal delay, or minimal fuel consumption) could be used. Another potential topic for future work would be to incorporate this algorithm into the modeling of lane changing behavior to achieve desired performance in a more cooperative way.

A power-based dynamic longitudinal speed control algorithm has been proposed. Simulation results are also given in this dissertation. In addition, an eco-driving application should be designed based on this proposed algorithm, and the performance of this eco-driving application should be evaluated with field test.

Finally, this dissertation presents a work from a driving simulator study which investigated the energy and emission impacts of dynamic eco-driving technology on heavy-duty. The system was design to enable drivers to achieve fuel-effective driving through the provision of eco-driving feedback device. However, the survey data also reveals more or less distraction from the eco-driving feedback on the artificial
speedometer. Currently, the association between driver distractions and the feedback device is not well understood. Apart from the driver distraction, the results of study are also affected by various feathers, such as the willingness of drivers to accept this technology, the concentration level of drivers during the test, the ability of drivers to adapt the driving simulator. These issues need to be precisely considered and addressed in the further eco-driving study.
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Appendix

A. ECO-Driving Technology and Behavior Research for Heavy-Duty Trucks

“Before” Survey

ECO-Driving Technology and Behavior Research for Heavy-Duty Trucks
“Before” Survey

Thank you for your participation. This is the first of two surveys you will take in this study. This survey will ask questions about your current driving practices and your knowledge about fuel-efficient driving techniques. The survey should take about 10-15 minutes to complete. You are not required to answer any question that you’d prefer not to answer. All responses are confidential and you may withdraw from the study at any time.

Please enter your participant ID. If you have forgotten it, please ask Research Staff for help.

Survey Questions

1. What is the make/model/year (if known) of the truck you drive?

2. Approximately how many miles per gallon do you get driving this truck on the highway?

3. In what city and state is your company?

4. How far is a typical trip with a single load?
   - □ 1 Less than 50 miles
   - □ 2 51-100 miles
   - □ 3 101-250 miles
   - □ 4 More than 250 miles

5. What type(s) of services do you perform? (check all that apply)
   - □ 1 Truckload
   - □ 2 Less-Than-Truckload
   - □ 3 Distribution and warehousing
   - □ 4 Parcel
   - □ 5 Freight forward
   - □ 6 Drayage
   - □ 7 Others (please specify)

6. Approximately how many miles a year do you drive a commercial truck?

7. What size is the fleet of your company?
   - □ 1 Small (1-5 trucks)
   - □ 2 Medium (6-25 trucks)
   - □ 3 Large (more than 25 trucks)

8. What is the average speed that you generally maintain on highway?
   - □ 1 45 mph or less
   - □ 2 50 mph
   - □ 3 55 mph
   - □ 4 60 mph
   - □ 5 65 mph
   - □ 6 70 mph
   - □ 7 75 mph
   - □ 8 80 mph
   - □ 9 85 mph or more

9. Has your company provided any training on how to improve fuel economy while driving?
   - □ 1 No (skip to Q10)
   - □ 2 Yes

   A. How often do you get training or feedback?
   - □ 1 Never
   - □ 2 Once every few years
   - □ 3 Every year
   - □ 4 Every 6 months
   - □ 5 Every 3 months or less
B. What measures have you been trained to take to improve fuel economy while at your company? (check all that apply)

☐ 1. Accelerate slowly  ☐ 2. Decelerate gradually
☐ 3. Use moderate highway driving speeds  ☐ 4. Platoon with other trucks on the highway
☐ 5. Use on-board anti-idling equipment (APUs)
☐ 6. Use truck stop electrification equipment
☐ 7. Other, please specify: ________________________________________________
☐ 8. None of these

C. Do you think these measures save fuel?


10. Do you think such training is or would be useful to you?


11. Do you do anything now to improve fuel economy? (please check all that apply)

☐ 1. Accelerate slowly  ☐ 2. Decelerate gradually
☐ 3. Use moderate highway driving speeds  ☐ 4. Platoon with other trucks on the highway
☐ 5. Use on-board anti-idling equipment (APUs)
☐ 6. Use truck stop electrification equipment
☐ 7. Other, please specify: ________________________________________________
☐ 8. None of these (Skip to Q12)

A. Which measure do you think saves the most fuel? (please select only one)

☐ 1. Accelerate slowly  ☐ 2. Decelerate gradually
☐ 3. Use moderate highway driving speeds  ☐ 4. Platoon with other trucks on the highway
☐ 5. Use on-board anti-idling equipment (APUs)
☐ 6. Use truck stop electrification equipment
☐ 7. Other, please specify: ________________________________________________

12. Do you manage or do maintenance on the truck you drive?

☐ 1. No, the company manages it (skip to Q13)  ☐ 2. Yes, I manage or do the maintenance myself

A. What sort of maintenance practices do you do?

☐ 1. Change Oil  ☐ 2. Change air filter  ☐ 3. Inflate tires
☐ 4. Other, please specify: ________________________________________________
☐ 5. Other, please specify: ________________________________________________
☐ 6. Other, please specify: ________________________________________________
B. Do you have any aerodynamic fittings on your tractor or trailer? □ 1 No (skip to Q13) □ 2 Yes

C. Where are these fittings located? (please check all that apply)
□ 1 On top of the tractor □ 2 Below trailer between the axles □ 3 At the back of the trailer
□ 4 Elsewhere, please explain: ____________________________________________________

13. Does your company provide any incentives to save fuel? □ 1 No (skip to Q14) □ 2 Yes

A. What incentives are you provided? ________________________________________________

14. Which of the following tool(s) do you use to provide driving directions? (check all that apply)
□ 1 None □ 2 Paper map □ 3 GPS system □ 4 Smart phone
□ 5 Other, please specify _________________________________________________________

15. How much would you be willing to pay for an in-vehicle device that improved your fuel economy by 3%?
□ 1 $0 □ 2 $1-$99 □ 3 $99-$199 □ 4 $200-$299 □ 5 $300 or more

16. How many years have you been a professional truck driver? ________________________

17. What is your gender? □ 1 Male □ 2 Female

18. What is your age? ____________________

19. We have a number of projects related to truck travel, technology, and parking. If you would be interested in participating in further research with us, please provide your email.

You would only be contacted regarding truck research and your email address will not be shared with another party. Giving us your email does not obligate you to participate in further studies, but it does allow us to contact you and give you the option.

There may or may not be compensation associated with additional research projects.

Email address (optional): ____________________________________________________________ (Please print clearly)
B. ECO-Driving Technology and Behavior Research for Heavy-Duty Trucks

“After” Survey

Thank you for your participation. This is the second and last survey you will take in this study. This survey will ask questions about your experience with the fuel-efficient driving feedback in the driving simulator. The survey should take about 10-15 minutes to complete. You are not required to answer any question that you’d prefer not to answer. All responses are confidential and you may withdraw from the study at any time.

Please enter your participant ID. If you have forgotten it, please ask Research Staff for help.

Survey Questions

1. How much knowledge did you have about fuel-efficient driving practices before participating in this study?
   □ 1 A lot □ 2 Some □ 3 A little □ 4 None

2. How often did you try to follow the recommended speed from the driving feedback during the second drive?
   □ 1 All the time □ 2 Most of the time □ 3 Sometime □ 4 Rarely □ 5 Never

3. How would you characterize the change in your fuel economy during the second drive?
   □ 1 Improved significantly □ 2 Improved moderately □ 3 Stayed the same (skip to Q3)
   □ 4 Worsened moderately □ 5 Worsened significantly

   A. How much would you say the change in your fuel economy during the second drive was due to the driving feedback?
      □ 1 A lot □ 2 Some □ 3 A little □ 4 None

4. About how often did you look at the driving feedback during the second drive?
   □ 1 All the time □ 2 Every 2-3 seconds □ 3 Every 10 seconds
   □ 4 Every 30 seconds □ 5 Once or twice □ 6 Never (skip to Q5)

   A. About how long did you look at the driving feedback each time?
      □ 1 Less than 1 second □ 2 1 second □ 3 2-3 seconds
      □ 4 5 seconds □ 5 10 seconds □ 6 More than 10 seconds

5. To what extent did you find the driving feedback to be a distraction from your driving?
   □ 1 A lot □ 2 Some □ 3 A little □ 4 None (skip to Q6)

   A. To what extent do you think that the distraction was significant enough to impair your driving?
      □ 1 A lot □ 2 Some □ 3 A little □ 4 None
6. Please state whether you Strongly Agree, Agree, Disagree or Strongly Disagree with the following statements during the second drive.

<table>
<thead>
<tr>
<th>Statement</th>
<th>Strongly Agree</th>
<th>Agree</th>
<th>Disagree</th>
<th>Strongly Disagree</th>
</tr>
</thead>
<tbody>
<tr>
<td>A. Because of the driving feedback, I accelerated more slowly.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>B. Because of the driving feedback, I braked more gradually.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>C. Because of the driving feedback, I drove at appropriate driving speeds.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>D. Overall, the driving feedback changed how I drove during the second drive.</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

If stating Strongly Agree or Agree in one of the above (otherwise, skip to Q7):

A. Do you think that these changes in your driving will persist without the driving feedback?
   - □ 1 Yes
   - □ 2 Probably
   - □ 3 Probably not
   - □ 4 No (skip to Q7)

B. How long do you think these changes in your driving will persist without the driving feedback?
   - □ 1 Less than 1 month
   - □ 2 1-3 months
   - □ 3 3-6 months
   - □ 4 More than 6 months

7. How efficiently, in terms of fuel consumption, do you think you will drive your truck in the future because of the participation in this study?
   - □ 1 Much more efficiently
   - □ 2 Somewhat more efficiently
   - □ 3 About the same
   - □ 4 Somewhat less efficiently
   - □ 5 Much less efficiently

8. Would you want to get a device that provides the driving feedback to use with your current truck?
   - □ 1 Yes
   - □ 2 Probably
   - □ 3 Probably not
   - □ 4 No

Please specify the reason(s):

________________________________________________________________________
________________________________________________________________________
________________________________________________________________________
________________________________________________________________________

9. How much will you be willing to pay for the device?

10. How often do you think you would use an in-vehicle dashboard display with driving feedback information if it came standard with your truck?
    - □ 1 All the time
    - □ 2 Most of the time
    - □ 3 Sometime
    - □ 4 Rarely
    - □ 5 Never
11. What driving feedback information do you want to have in your truck (check all that apply)?
   □ 1 Recommended driving speed (optimal driving speed based on traffic condition and road slope)
   □ 2 Aggressive acceleration warning (warning sign or sound when accelerating too fast)
   □ 3 Hard braking warning (warning sign or sound when braking too hard)
   □ 4 Excessive idling warning (warning sign or sound when idle too long)
   □ 5 Gear shifting indicator (light indicating an optimal point for shifting gear)
   □ 6 Real-time fuel economy (instantaneous fuel economy in miles per gallon)
   □ 7 Historical fuel economy (average fuel economy for the last 5 or 15 minutes)
   □ 8 Real-time fuel consumption cost (cumulative fuel consumption cost for the current trip)
   □ 9 Driving score (score indicating fuel-efficient driving performance)
   □ 10 Trip summary statistics (distance, travel time, average speed, average fuel economy, fuel consumed, fuel cost, and average driving score provided at the end of each trip)
   □ 11 Other, please specify: __________________________________________________________
   □ 12 Other, please specify: __________________________________________________________
   □ 13 Other, please specify: __________________________________________________________
   □ 14 Other, please specify: __________________________________________________________

12. Do you have any other comments about the driving feedback provided in this study?
    ________________________________________________________________________________
    ________________________________________________________________________________
    ________________________________________________________________________________

13. Do you have any other comments about this study?
    ________________________________________________________________________________
    ________________________________________________________________________________
    ________________________________________________________________________________