
Eco-Driving in the Vicinity of Roadway Intersections – Algorithmic Development, Modeling, and Testing

by

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Abstract

Vehicle stops and speed variations account for a large percentage of vehicle fuel losses especially at signalized intersections. Recently, researchers have attempted to develop tools that reduce these losses by capitalizing on traffic signal information received via vehicle connectivity with traffic signal controllers. Existing state-of-the-art approaches, however, only consider surrogate measures (e.g. number of vehicle stops, time spent accelerating and decelerating, and/or acceleration or deceleration levels) in the objective function and fail to explicitly optimize vehicle fuel consumption levels. Furthermore, the majority of these models do not capture vehicle acceleration and deceleration limitations in addition to vehicle-to-vehicle interactions as constraints within the mathematical program.

The connectivity between vehicles and infrastructure, as achieved through Connected Vehicles technology, can provide a vehicle with information that was not possible before. For example, information on traffic signal changes, traffic slow-downs and even headway and speed of lead vehicles can be shared. The research proposed in this dissertation uses this information and advanced computational models to develop fuel-efficient vehicle trajectories, which can either be used as guidance for drivers or can be attached to an electronic throttle controlled cruise control system. This fuel-efficient cruise control system is known as an Eco-Cooperative Adaptive Cruise Control (ECACC) system. In addition to the ECACC presented here, the research also expands on some of the key eco-driving concepts such as fuel-optimizing acceleration models, which could be used in conjunction with conventional vehicles and even autonomous vehicles, or assistive systems that are being implemented in vehicles.

The dissertation first presents the results from an on-line survey soliciting driver input on public perceptions of in-vehicle assistive devices. The results of the survey indicate that user-acceptance to systems that enhance safety and efficiency is ranked high. Driver-willingness to use advanced in-vehicle technology and cellphone applications is also found to be subjective on what benefits it has to offer and safety and efficiency are found to be in the top list.

The dissertation then presents the algorithmic development of an Eco-Cooperative Adaptive Cruise Control system. The modeling of the system constitutes a modified state-of-the-art path-

finding algorithm within a dynamic programming framework to find near-optimal and near-real-time solutions to a complex non-linear programming problem that involves minimizing vehicle fuel consumption in the vicinity of signalized intersections. The results demonstrated savings of up to 30 percent in fuel consumption within the traffic signalized intersection vicinity.

The proposed system was tested in an agent-based environment developed in MATLAB using the RPA car-following model as well as the Society of Automobile Engineers (SAE) J2735 message set standards for vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) communication. The results showed how multi-vehicle interaction enhances usability of the system. Simulation of a calibrated real intersection showed average fuel savings of nearly 30 percent for peak volumes. The fuel reduction was high for low volumes and decreased as the traffic volumes increased. The final testing of the algorithm was done in an enhanced Traffic Experimental Simulation tool (eTEXAS) that incorporates the conventional TEXAS model with a new web-service interface as well as connected vehicle message set dictionary. This testing was able to demonstrate model corrections required to negate the effect of system latencies as well as a demonstration of using SAE message set parsing in a connected vehicle application.

Finally, the dissertation develops an integrated framework for the control of autonomous vehicle movements through intersections using a multi-objective optimization algorithm. The algorithm integrated within an existing framework that minimizes vehicle delay while ensuring vehicles do not collide. A lower-level of control is introduced that minimizes vehicle fuel consumption subject to the arrival times assigned by the upper-level controller. Results show that the eco-speed control algorithm was able to reduce the overall fuel-consumption of autonomous vehicles passing through an intersection by 15 percent while maintaining the 80 percent saving in delay when compared to a traditional signalized intersection control.

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1. Introduction

Introduction

The earth's fossil fuels are being continuously depleted and toxic gases are being emitted to the atmosphere at an alarming rate. The United States is one of the prime consumers of the petroleum in the world, burning more than 22 percent of the total petroleum refined on the planet. The transportation sector consumes nearly three-quarters of this and is the second largest carbon emitter in the country. The surface transportation sector is therefore challenged by three things – availability of the fuel to drive vehicles, emissions of greenhouse gases and vehicular crashes. Therefore, it is important to reduce petroleum consumption and make transportation more efficient and sustainable without degrading safety.

Progress has been made in reducing the energy consumption of vehicles and their associated carbon footprint for more than half a century bringing down the average passenger car fuel consumption from 18.4 liters per 100 km in 1975 to 10.1 liters in 2005. However the number of vehicles on the roadways and the total vehicle miles traveled is increasing since the last century. Researchers have been developing mathematical, statistical and even mechanical models to microscopically analyze the components of surface transportation. These include traffic flow models, microscopic emission and fuel-consumption models as well as crash worthiness models. Along with advancements in modeling and making efficient cars, efforts are being done to bring connectivity between components of a transportation system – infrastructure, vehicles and people to enhance safety.

The microscopic models not only form the basis for analysis of a transportation system, but also lay the foundation over which multiple cost-optimization models can be developed. Better connectivity between system components can add to the benefits of such optimization models by providing enhanced situational awareness and reducing the number and ambiguity of constraints. The research presented in this dissertation develops one such optimization algorithm that attempts to reduce vehicle fuel consumption levels and thereby reduce vehicle emissions using advanced information from multiple components of a transportation system.

Problem Statement

Vehicles have to stop at an intersection when receiving a red indication. Furthermore, vehicles also have to stop during a green indication if a queue of vehicles is still being served. These slow-downs or stops produce fuel consumption losses. The Texas Transportation Institute quantified the lost fuel due to idling at intersections alone to be 2.8 billion gallons each year. However, most intersections have a defined SPAT timing (Signal Phasing and Timing) on which it will switch phases. Technologies such as DSRC (Dedicated Short Range Communication) or other roadside transmitters can provide this information to vehicles. The research presented in this dissertation uses this SPAT information along with other available information to generate eco-driving vehicle trajectories on signalized intersection approaches.

This dissertation makes the following contributions:

1. Conduct an on-line survey to solicit driver input on advanced in-vehicle technologies in order to identify the prime benefits expected by users of these systems.
2. Develop a real-time optimization algorithm that explicitly considers the vehicle fuel consumption level while accounting for vehicle dynamics and inter-vehicle interaction constraints.
3. Test the algorithm in a state-of-the-art simulation tool using available SAE Connected Vehicle protocols.
4. Evaluate the proposed system performance in a simulation environment for the 30 top-sold light-duty vehicles in North America for different levels of system market penetration.

Research Methodology

Recently, researchers have attempted to develop tools that reduce these losses by capitalizing on traffic signal information received via vehicle connectivity with traffic signal controllers. As mentioned earlier, existing state-of-the-art approaches only consider surrogate measures (e.g. number of vehicle stops, time spent accelerating and decelerating, and/or acceleration or deceleration levels) in the objective function and fail to explicitly optimize vehicle fuel consumption levels. Furthermore, the majority of these models do not capture vehicle acceleration and deceleration limitations in addition to vehicle-to-vehicle interactions as constraints within the mathematical program. Consequently, this research effort develops an eco-drive system that focuses primarily on reducing fuel consumption without compromising safety by using the signalized intersection's SPAT information. This system is named Eco-Cooperative Adaptive Cruise Control (ECACC). In addition to developing the ECACC Algorithm, this research analyses a speed advisory system (Eco-Speed Control or ESC) that can give recommended instantaneous speeds to the driver based on inputs from him/her and the roadway using DSRC or radio communication.

The overall research approach is detailed in Figure 1.1 which is divided into three sections:

1. Introduction and Algorithm Development

This includes a discrete problem statement and past literature with respect to eco-driving and advanced eco-driving algorithms that defines speed optimization within the vicinity of intersections as given in Chapter 2. Analysis of the drawbacks of the past literature was used to develop a more robust algorithm, which is defined in Chapter 3. This algorithm assumes user-acceptance of advanced driver-assistance systems. Consequently, Chapter 4 was therefore solicits public perception towards advanced in-vehicle technology using a two-part stated-preference survey.

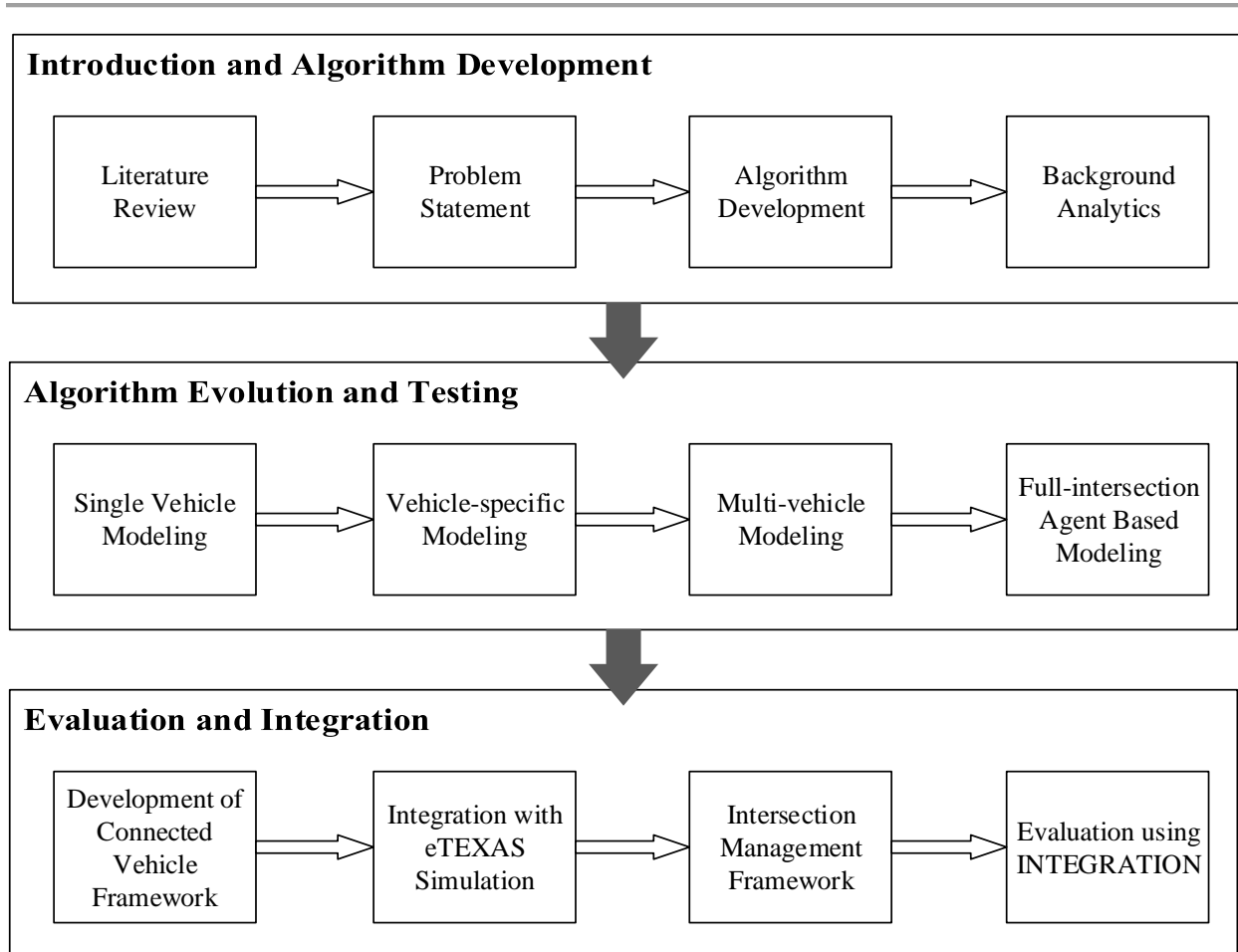


Figure 1.1- Overview of the research presented.

2. Algorithm Evolution and Testing

The algorithm was originally developed for a single-vehicle approaching a signalized intersection receiving SPAT information. In order to expand it to an actual agent-based modeling of a full intersection, the algorithm was modified to model vehicle-specific characteristics along with calibrating thirty top-sold vehicles in US to the model. Multi-vehicle modeling was then introduced using car-following and collision avoidance constraints along with sensitivity analyses for weather and grade impacts. These analyses are provided in Chapters 5 and 6.

3. Evaluation and Integration

In order to evaluate the proposed algorithm in an actual simulation environment, the algorithm was integrated with the state-of-the-art simulation tool - eTEXAS (enhanced Traffic Experimental Analytical Simulation). Since eTEXAS uses the standardized Connected Vehicle message set dictionary, SAE J2735, a connected vehicle framework was also developed in MATLAB to form an external communications protocol. The algorithm was additionally superimposed on an intersection management framework to provide a bi-level multi-objective optimization tool for automated vehicles. The system

was also integrated with the INTEGRATION tool to analyze the effect of varying penetration rates on the algorithm's efficiency. These are described in Chapters 7 and 8.

Research Contributions

While there has been past research addressing the issue of fuel optimization at signalized intersections using advanced signal information, they lacked comprehensiveness in research and use of explicit microscopic modeling in the optimization function. The research presented in this document contributes further by developing a robust algorithm, named Eco-Speed Control, which uses explicit fuel-based optimization functions as well as microscopic modeling in establishing constraints.

The specific contributions of the research include:

1. Developed a robust eco-drive system in the vicinity of intersections that explicitly models the vehicle fuel consumption and considers vehicle and surrounding vehicle constraints on the system performance.
2. Solicited user-acceptance in-vehicle driver assistance systems using stated-preference on-line public surveys.
3. Characterized the sensitivity of such a system to external variables, including weather and grade factors and internal variables such as vehicle type. Thirty top-sold vehicles that belong to different EPA classes were calibrated and tested using the proposed algorithm.
4. Developed a Connected Vehicles framework that uses SAE J2735 message sets developed by the Society of Automotive Engineers to evaluate the performance in a simulated connected vehicles environment. The multi-component system was developed using a cloud-based eTEXAS environment.
5. Enhanced the algorithm for use as a lower-level controller within the intersection Cooperative Adaptive Cruise Control (iCACC) system for management of autonomous vehicle intersections. This intersection management system looks at a broader, multi-objective, bi-level optimization of vehicle delay and fuel consumption levels.

Overall, the research presented in this dissertation develops a comprehensive tool for optimizing vehicle fuel consumption levels at signalized intersections and at intersections controlled using an autonomous vehicle control system.

Dissertation Layout

This dissertation document uses a manuscript format with multiple independent peer-reviewed papers that were published as part of this research and is divided in to nine sections. Please note that the papers follow a different format than the original publication to match the overall document format. Brief descriptions of each of these chapters along with their attributions are given below:

Chapter 1: This chapter gives an introduction to the proposed research effort along with the research objectives and an overall dissertation layout.

Chapter 2: A synthesis of previous published research on similar research. It also includes some of the previous research that laid the foundation to some of the models highlighted in this research.

Chapter 3: The basic algorithm development is explained in this chapter along with an extended write-up about the underlying microscopic models.

Chapter 4: This chapter, co-authored by Dr. Hesham Rakha and Dr. Ismail Zohdy is accepted for publication in the International Journal of ITS Research published by Springer. The chapter conducts an analytic review on the current state of implementation of in-vehicle technology and the public perception and acceptance towards it by a two-staged online survey series.

Chapter 5: Co-authored by Dr. Hesham Rakha, this chapter provides vehicle-specific modeling of the proposed ECACC system using sensitive variables such as speed-limits and vehicle types. Thirty different top-sold vehicles of the United States are calibrated and used in the analysis. This chapter is accepted for publication in the Journal of Intelligent Transportation Systems, Technology, Planning and Operations, published by Taylor and Francis.

Chapter 6: This chapter looks in to the specifics of Agent-Based Modeling of the proposed system using simulations of a real calibrated intersection in Blacksburg, Virginia. This chapter is accepted for publication in the Transportation Research Record: Journal of the Transportation Research Board and is co-authored by Dr. Hesham Rakha.

Chapter 7: Once the algorithm is tested in an agent-based modeling environment, the evaluation is done in a bi-level cloud-based simulation system that is based on the TEXAS simulation model in this chapter. This work, to date, was the only cloud-based traffic simulation with Connected Vehicle capability. The chapter that is co-authored with Dr. Hesham Rakha and Brian Badillo (Harmonia Holdings LLC.) was presented at the 93rd Annual Meeting of the Transportation Research Board, Washington DC, January 2014.

Chapter 8: A look at how eco-driving algorithms such as ECACC can be used in connection with intersection management algorithms is explained in this chapter. Co-authored by Dr. Hesham Rakha and Dr. Ismail Zohdy, this chapter is submitted for presentation at 94th Annual Meeting of the Transportation Research Board, Washington DC, January 2015.

Chapter 9: This chapter explains the conclusions and future research directions from this dissertation and explains some of the use-cases regarding potential experimental evaluation of the system.

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2. Literature Review

Literature Review

The U.S. Department of Transportation (USDOT) FHWA and other transportation agencies in developed nations have made significant advancements in various transportation technologies. In the mid-1990s, the FHWA's ITS Program emerged to increase the use of technology in the surface transportation sector [1]. Initial ITS applications were limited to Advanced Traffic Management Systems (ATMSs) and Advanced Traveler Information Systems (ATISs), but technology soon gained momentum in areas of communication and surveillance. In 2003, the VII Program was established by the FHWA to combine the benefits of technology to enhance roadway safety, reduce traffic congestion, and reduce vehicle emissions [2]. This was the first initiative to use information transfer and communication technologies on a large scale in the surface transportation sector. In 2009, VII was rebranded to IntelliDrive and in 2011 to Connected Vehicles [3][4].

Many research efforts have attempted to develop autonomous and self-driving vehicles. The major challenge, however, is handling the complexity of driving behavior. Researchers in this area have been modeling various driving maneuvers and decision making abilities so that an autonomous vehicle may drive in heavy traffic in the future. Car following, lane changing, and intelligent cruising have all played their roles in this domain. Products such as automated parallel parking, adaptive cruise control, and lane-change warning systems are some examples of such individual products. However, modeling a driver is computationally extensive and complex.

Modeling efforts have been able to predict fuel consumption and emissions of greenhouse gas emissions such as carbon dioxide, carbon monoxide, nitrogen oxides and hydrocarbons precisely for various driving scenarios. The Comprehensive Modal Emissions Model (CMEM), the VT-Micro model, the Virginia Tech Comprehensive Power-based Fuel Model (VT-CPFM), and the Vehicle Driveline model are some examples of state-of-the-art fuel consumption and emission models [5-7](Ahn, Rakha, Trani, & Van Aerde, 2002; H. A. Rakha, Ahn, Moran, Saerens, & Bulck, 2011a; H. Rakha, Ahn, & Trani, 2003). A number of vehicle dynamics models have also been developed to accurately predict the physics of a vehicle [8]. Since these models can collectively predict the vehicle motion and fuel consumption and emission levels, it should be possible to optimize the vehicle trajectory to minimize its fuel consumption. This is the basic principle used in most research efforts pertaining to reducing vehicle emission and fuel consumption levels.

Research efforts attempting to reduce the carbon footprint and fuel consumption associated with driving a vehicle have advanced significantly. On the vehicular side, non-propulsion system improvements such as improved vehicle aerodynamics, tire-rolling friction, vehicle weight reduction and propulsion system improvements such as transmission and drive train have enhanced the average fuel efficiency of passenger cars from 18.4 l/100 km in 1975 to 10.1 l/100

km in 2005 [9]. Innovations to improve the fuel efficiency and reduce the carbon footprint of gasoline-powered vehicles have and continue to be made. This section reviews the research work conducted on the non-vehicular side to improve energy and emissions of vehicles. The efforts are broadly categorized into two categories: improvements in infrastructure and improvements in the system (Figure 2.1).

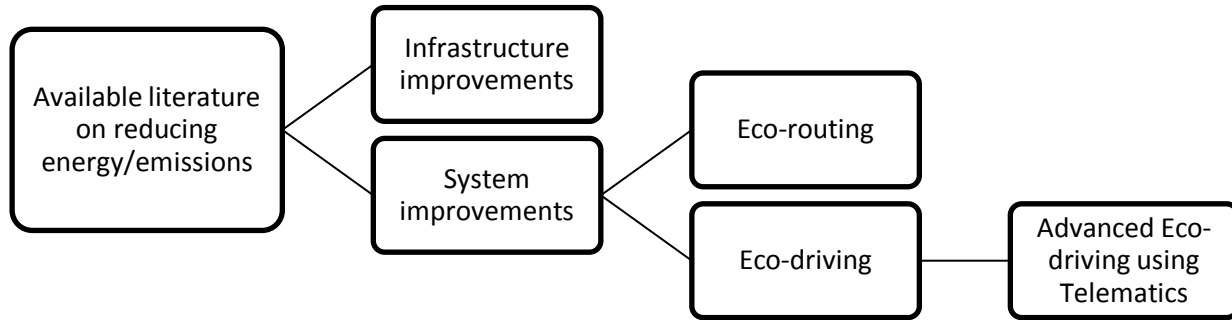


Figure 2.1 - Classification of the literature review

Infrastructure Improvements

Intelligent traffic signals have been utilized in an attempt to enhance arterial throughput, intersection safety, and energy/emission levels. Conventional systems of obtaining traffic signal timings used objective functions that minimized vehicle delays and stops. Some studies suggested using explicit fuel spent at intersections as objective functions in intersection timings. Use of such objective functions that incorporate fuel consumption is predicted to achieve reductions in fuel and carbon emissions in the range of 1.5 percent [10-11]. Some traffic control improvements suggest the use of genetic algorithms to account for the dynamic routing of vehicles that have typically been neglected [12], while other field tests with genetic algorithms based on green-wave optimization revealed potential energy and emissions improvements [13].

System Improvements

Researchers at the Laboratory of Energy and the Environment at the Massachusetts Institute of Technology (MIT) reported that approximately 7 percent energy of a vehicle is lost due to braking [9]. Hence, reducing braking was assumed a direct fuel savings strategy that gave result in driving practices (and driver assistive devices) known as eco-driving that assist drivers in achieving smoother speed variations. Intelligent Speed Adaptation (ISA) was an initiative in the UK aimed at developing driver assistive devices that advise drivers about desired speeds so as to avoid hard braking [14]. However, the initiative had its primary objective as traffic safety. As technology advanced, newer types of ISA devices were developed using Global Positioning System (GPS) technology to advise drivers about the speed limits set for the particular roadways [15-16]. The third generation of ISA devices included use of telematics to communicate real-time traffic information for speed advisories to drivers [17].

Even though the primary objective of ISA was reducing speed-limit violations from a traffic safety perspective, its inherent benefit was reducing fuel-consumption and emission levels due to smoother driver behavior [18]. The idea of having a smoother speed variation during driving is transformed into a variety of research topics pertaining to energy/emissions savings. Eco-driving and eco-routing were the sub-classification of driving system improvements found in a literature search. Eco-driving involves driving in an eco-friendly fashion, and eco-routing involves making a route choice that will consume minimum energy and produce minimum emissions. Advancements in eco-driving led to the use of telematics in making driving more intelligent and eco-friendly. This is termed advanced eco-driving and involves the use of some system to detect traffic, signals, or congestion and provide eco-advisory to drivers, including route advisory, speed advisory, etc.

Eco-driving

One of the most extensive research efforts conducted in the area of fuel consumption and emission reduction is eco-driving, which refers to driving in an eco-friendly and economical fashion. Preventing sudden speed changes in driving and maintaining a constant velocity around the fuel-optimal velocity of a vehicle have been associated with fuel consumption and emission reductions by various fuel consumption models [5-6]. However, a comparison of eco-driving and typical driver behavior showed no major differences in fuel consumption and emission levels when smaller vehicles were driven [19]. Studies conducted using vehicles equipped with resistive devices to prevent sudden velocity changes also showed no differences [20]. Some studies showed that eco-driving not only prevented sudden variations in speed but entailed predicting the optimum speed [21-22]. Studies about the freeway-based dynamic eco-driving systems showed fuel savings in the range of 10 to 20 percent and provided real-time traffic information to drivers [23]. Widodo et al. compared fuel consumed by vehicles during an Environment-Adaptive Driving (EAD) practice when inter-vehicle communication (IVC) was used and was not used. It was found that EAD had the potential to reduce the fuel consumed [24]. This study used the VT Micro-emissions model for comparison. However, EAD does not provide any speed advisories to drivers nor does it use communication of future signal changes to drivers.

Evaluation of Greek bus drivers trained to eco-drive showed nearly a 10.2 percent reduction in fuel consumption levels [25]. Smart driver advisory tools were used to aid non-trained drivers on eco-driving. These tools used a fuel-efficiency driver support tool that back calculated the instantaneous fuel consumed and compared it with optimal fuel consumption. The system was evaluated and found to enhance gas mileage by 7 to 14 percent [26]. However, improper design of advisory/support tools posed a challenge to its use. Participant surveys about the eco-driving system used in the Kia Soul showed that eco-driving increased the cognitive load on the driver

[27]. Other research involving the use of a device that calculated optimum vehicle trajectory showed the computational time of such complex models as great as half the total trip time [28].

Eco-routing

The advent of GPS-enabled navigation devices led to drivers adapting their driving route to goal-oriented route choice selection. Studies have shown that route choice does affect energy consumption and emissions and that a slower arterial route may produce better fuel efficiency and emission levels compared to a faster highway route [29]. Earlier navigation devices were programmable with shortest-path or shortest travel-time algorithms. As the buzzword “eco” flooded the research industry, eco-routing emerged. Earlier algorithms employed simple eco-routing techniques such as using weights for links based on fuel consumption/emission factors [30]. Link-weights also depended on grades of road segments [31]. As cloud computing and smart handheld devices became common terms, algorithms that modified on-the-fly with user-fed fuel consumption data for road segments were developed. The GreenGPS initiative is an example of this [32].

Advanced Eco-driving

The VII initiative proposed by the U.S. Department of Transportation has at its core wireless communications connecting vehicles with the infrastructure and with other vehicles [3]. This system allows vehicles to receive advanced notifications from intersection controllers that could potentially avoid idling. Idling has been identified to consume 2.8 billion gallons of fuel each year in the United States alone [33]. A few research efforts have been conducted to develop algorithms that would utilize traffic signal information to reduce vehicle energy consumption and emissions. These research efforts highlight the fact that if a road user is notified of the upcoming signal status, the vehicle speed can be adjusted accordingly to avoid hard-braking or hard-acceleration maneuvers, thereby improving energy consumption and emission levels. The project focus of this report uses advanced notification of signal status to adjust the speed of vehicle to produce fuel savings. Some similar studies are summarized below.

Wu et al. studied the energy/emission benefits of communicating Traffic Signal Status (TSS) to the road user via Changeable Message Signs (CMS) or an in-vehicle Advanced Driving Alert System (ADAS) and found benefits of up to 40 percent under hypothetical conditions [34]. This research, however, only aimed at alerting the driver of changing signal status from green to red. CMS or in-vehicle ADAS was used to alert the driver of Time to Red (TTR) so that the drivers could choose to decelerate slowly to a stop if they had little or no chance of passing the intersection prior to a red light. Authors identified potential benefits of preventing road users from maintaining a higher speed until the stop-bar if they knew they had to stop at the intersection and promoted decelerating gradually to a stop. However, they did not consider change of signal status to green using Time to Green (TTG) information to advice drivers to

reach an intersection when the signal turned green. This paper also did not consider potential benefits of utilizing a better acceleration maneuver after passing the intersection.

In 2010, Asadi and Vahidi developed a predictive cruise control system that used constrained optimum control to adjust cruising speeds to minimize the probability of stopping at intersections [35]. Optimum control was used to adjust the time of arrival of the vehicle to lie within green intervals at each intersection, and the adjusted speed was tracked to actual speed using a vehicle dynamics model. However, the system did not compare fuel consumed for alternate speed profiles, nor did the system provide a speed advisory to the drivers. Up to 47 percent savings in fuel and 5 percent savings in travel time were reported.

Tielert et al. endeavored to document the factors governing the impact of Traffic-Light-to-Vehicle-Communication (TLVC) on fuel consumption and emissions of individual vehicles [36]. This study used effective red-phase duration, which is the time difference between end of red-phase and time of arrival of vehicle if it did not reduce speed. The simulation used vehicles to follow various speeds within a certain interval to compare the effect of speed adaptation. The Passenger car and Heavy duty Emission Model (PHEM) was used to compare the effect on energy and emissions. Major factors identified to govern the impact of TLVC on energy and emissions were gear ratios and communication distance. Savings of up to 22 percent and 8 percent were identified in single-vehicle cases and multi-vehicle cases, respectively.

Sanchez et al. developed the logic to be used by a driver approaching a stoplight if he/she was notified of the upcoming change of signal status [37]. The authors assumed Intelligent-Driver Model Prediction (IDMP) for the simulation studies, which used the available information about the green interval to adjust the vehicle speed. The Akcelik and Biggs fuel consumption model [38] was used to compare results of various driver-modeling predictions but not when developing the logic. Results indicated a 30 percent reduction in fuel consumption and an increase in the average speed of the car platoon.

Malakorn and Park assessed the energy and emissions of an IntelliDrive-based Cooperative Adaptive Cruise Control (CACC), which used Vehicle-to-Vehicle (V2V) and V2I communications over Adaptive Cruise Control (ACC) to further reduce headway and improve safety [39]. This system used constrained optimum control with the objective of minimizing acceleration and deceleration distances and idling time using TSS information. The system communicated favored trajectory information to vehicles equipped with CACC. However, it used fixed deceleration distance during simulation studies and entirely neglected speed profiling past the intersection. The VT Micro-emissions model was used only in evaluating the strategy but not in the actual optimization algorithm.

Mandava et al. introduced a modified intelligent speed adaptation logic called arterial velocity planning during which the speed profile for a vehicle approaching a signalized intersection was calculated to reduce fuel consumption and provide dynamic advice to the driver [40]. The system used an optimization algorithm to minimize the acceleration/deceleration rates when the signal status information was available in advance to increase the probability of encountering a green light. The algorithm used a vehicle-dynamics model for acceleration computations; however, it did not use any fuel consumption models. The CMEM model was used for evaluation of benefits. Benefits of 12 to 13 percent in fuel consumption and 13 to 14 percent for CO₂ emissions were identified.

While these research efforts aimed at assisting drivers with how to approach an intersection so as to avoid idling, some work about artificial intelligence revealed the feasibility of using intelligent traffic signal agents that will self-evolve to changing traffic conditions in order to maximize intersection capacities [41]. During an effort named TRAVOLUTION, the German carmaker Audi and the GEVAS software firm tested the idea of green-wave optimization with genetic algorithms using car-to-infrastructure communication [13]. The test cars were equipped with car-to-infrastructure communication devices to receive signal information. The entire set of driver advisories and green-wave optimization could reduce fuel consumed by 21 percent on average. However, no information about the parameters/models used in computing speed advisories is publicly available.

In most of the aforementioned literature, drivers were provided optimized speed advisories about the ideal speed profile to be followed in order to minimize fuel consumption. However, no research used an explicit optimization objective of reducing fuel consumption. The goal of reducing fuel consumption in all these cases is transformed to simpler functions of acceleration/deceleration rates, or duration or even the time of arrival at the intersection. During this research, the objective function of reducing fuel consumption will be retained, which will potentially provide better intersection fuel efficiency for any given scenario by comparing alternate speed profiles.

Cruise Control Systems

Cruise control systems were introduced in the 1900s to reduce driving load on humans and the most traditional cruise control systems used centrifugal governors to adjust throttle based on engine load. They have developed into intelligent systems that focus on safety since then. The modern cruise control was introduced in the 1950s and had the capability of maintaining driver-set speed using a solenoid. In the 1970s, newer types of cruise controls penetrated the market that were electronic and had a digital memory, which lets drivers pause and resume the cruising operation.

Newer research on cruise control systems were enabled by the electronic engine management systems. It made controlling the mechanical units in vehicles easier and more accurate. Adaptive Cruise Control (ACC) systems were introduced in the 21st century and enabled intelligent cruising with collision avoidance with lead vehicles. Radar (or LIDAR) sensors in the front of the vehicle are used to measure time-headways to detect speed changes required to avoid forward collision. Since then modifications to ACC around using additional information to alter vehicle speeds started. Cooperative Adaptive Cruise Control (CACC) aimed closely-spaced heavy-vehicle platooning using inter-vehicle communication and adaptive cruise control systems. Some research on CACC focused incorporating signal information also to the cruise control system using vehicle-infrastructure communication.

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3. Algorithm Development

Algorithm Development

From the previous section, it is clear that the models developed in previous research efforts focusing on optimizing vehicle fuel consumption levels near signalized intersections using signal information lacks clarity. All of these models used a simplified objective function for optimization such as minimizing the deceleration level or minimizing the cruising distance. None of these models had an explicit fuel consumption model in its objective function and that is one of the advancements addressed here. The project highlighted during this report retains the original objective function of minimizing fuel consumed in the entire maneuver near a signalized intersection while optimizing speed profiles of vehicles approaching the intersection. The term “entire maneuver” in this context sums the vehicle fuel consumption from the point where it receives advanced signal information until a fixed distance downstream of the intersection to enable it to revert to its original state (speed).

The system leverages dedicated short-range communication (DSRC) capabilities between the roadway infrastructure and vehicles. The optimization is conducted in two steps: (1) Computation of a proposed time to intersection based on available intersection data (queued vehicle information), lead-vehicle information (if any) and signal change information (TTR or TTG); and (2) Computation of a fuel-optimal speed profile using the computed time to intersection, vehicle acceleration model, roadway characteristics and microscopic fuel consumption models.

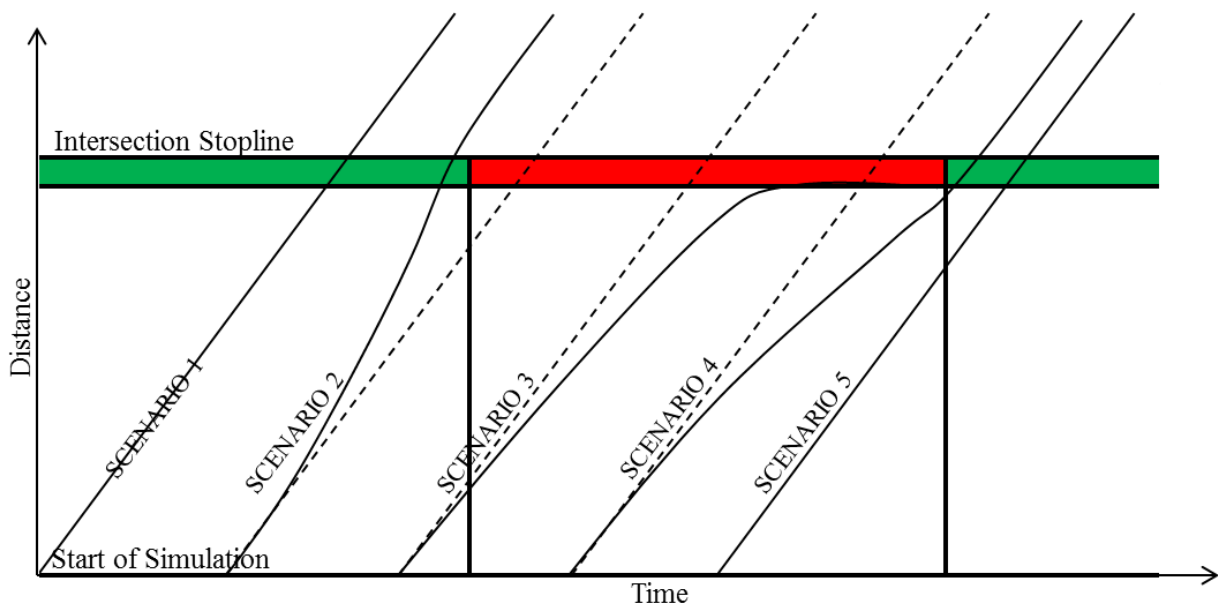


Figure 3.1: Speed profile of vehicles approaching a signalized intersection.

Depending on the upcoming signal change, namely Time to Red (TTR) or Time to Green (TTG) information, Distance to Intersection (DTI) and its current speed (v_a), there are different

scenarios, a vehicle can be in. They are shown in Figure 3.1. A vehicle with no advanced information cannot change its profile as shown in the Figure. The scenarios as shown are summarized below:

Scenario 1:

As the vehicle receives upcoming signal change information from the intersection using Infrastructure-to-Vehicle (I2V) communication, it computes whether the vehicle will receive a green light at the stop line if it proceeded at its current speed; if it does, the system provides an advisory to proceed cautiously at the current speed.

Scenario 2:

If the TTR is not sufficient for the vehicle to pass the intersection at green at its current speed but is sufficient if the vehicle accelerates to the maximum allowed speed on the roadway, then the vehicle is advised to accelerate and pass cautiously through the intersection.

Scenario 3:

If the TTR is not sufficient for the vehicle to pass the intersection, then the vehicle is advised to come to a slow stop and wait for the next green light.

Scenario 4:

This is when TTG is longer than the vehicle's TTI at the current speed. Hence, by reducing the average speed of the vehicle across the distance to the stop-line, a delay can be incurred in the vehicle trajectory so that the time to intersection is sufficient to receive a green light and to clear any available queues. This reduction in average speed can be achieved using an infinite number of vehicle trajectories; the focus of this research is to compute the most fuel-optimal way of accomplishing this.

Scenario 5:

When the current phase is red, but will turn green as the vehicle reaches the intersection, then no change in vehicle's velocity profile is suggested to keep the same.

Figure 3.2 shows a logical diagram of events that will lead to eco-vehicle speed control near an equipped signalized intersection [1]. As the vehicle enters the DSRC range of an intersection, it receives information about upcoming signal changes, lead-vehicle information and roadway information. It is at this point, when the eco-vehicle speed control system starts its optimization algorithm and provides an instantaneous speed advisory to the driver. At the point of this report, the authors have not considered human-vehicle interaction on how the speed advisory is handled by the driver and is assumed autonomous driving by the eco-vehicle. It should be noted, however, that the algorithm is re-calculated every time-step and thus would be able to respond to driver errors in responding to system recommendations.

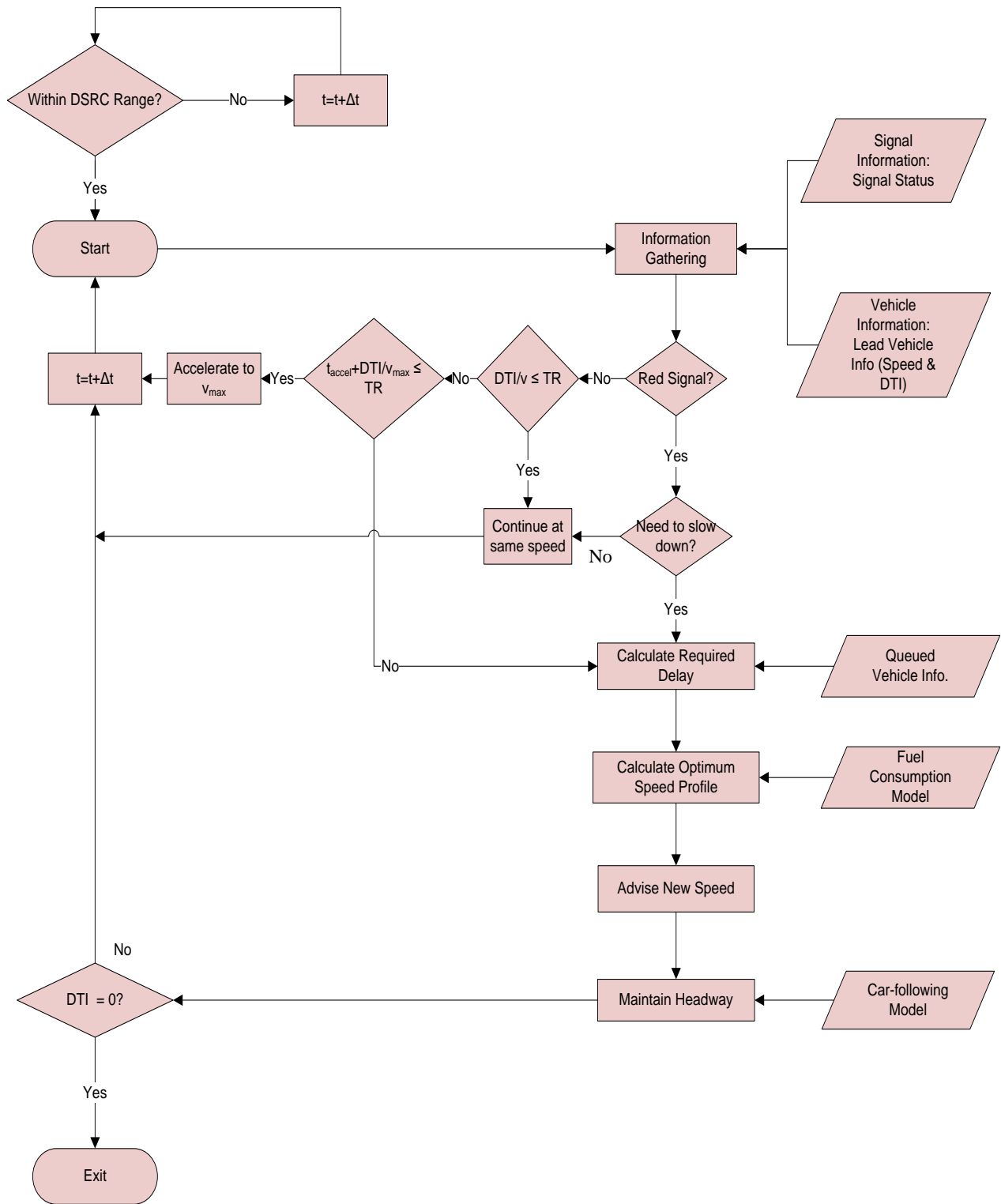


Figure 3.2 – Logic used for ECACC Algorithm

The fourth scenario discussed above is a complex optimization function with the objective of minimizing fuel consumed. In order to make the system more accurate, the acceleration of the vehicle to a target speed past the stop-line is also considered. This optimization function is solved under the constraints of a given travel distance upstream (which is DTI), fixed time to reach the intersection (which is the TTG plus any clearance time needed for queues), and fixed roadway and vehicle characteristics (such as grade, engine power, frictional coefficients, etc.). The eco-vehicle does check for these scenarios and runs the optimization algorithm every time-step.

This section deals with the speed-profile optimization and its components, deriving equations and constraints for the optimization and explanation of physical models and fuel consumption models used in the system.

Speed-profile prediction

The speed-profile optimization is conducted to find the fuel-optimum speed profile of a vehicle that is informed of TTG. This logic applies when the time to intersection needs to be increased to some extent to incorporate signal change from red to green and dissipation of any queued vehicles. The vehicle movement is physically divided into three parts: deceleration part, cruising part and acceleration part. The constant deceleration model and the Rakha and Lucic acceleration model are used here [2]. The cruising part is optional and is conducted upstream to maintain the constraints and downstream to fix the optimization across a constant distance. Figure 3.3 shows the trajectory optimization of an eco-vehicle near a signalized intersection.

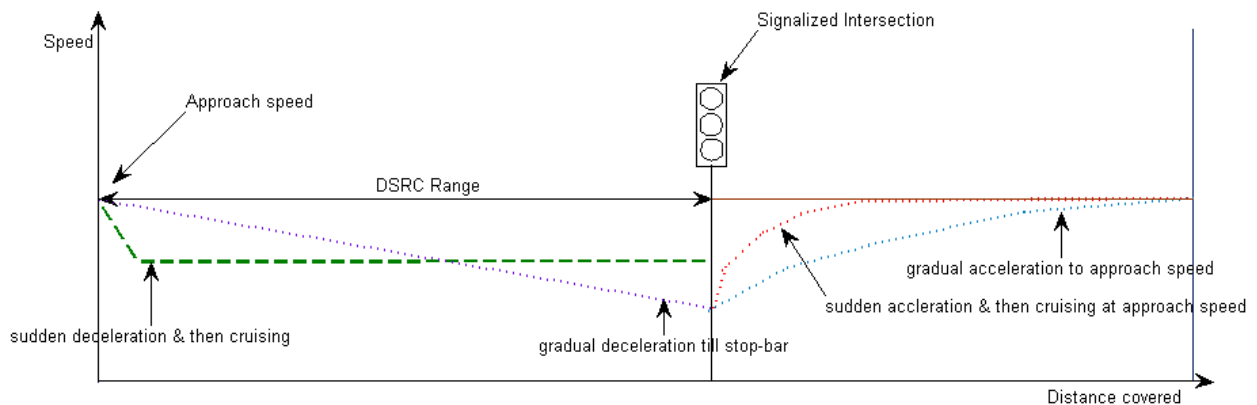


Figure 3.3 - Extent of trajectory optimization near a signalized intersection.

The speed profile of a vehicle approaching an intersection will have two components: (a) upstream of the traffic signal and (b) downstream of the traffic signal. The upstream portion introduces the desired delay to the vehicle in order to ensure that it arrives at the correct time. This is accomplished by advising the driver to decelerate to some cruising speed and cruise for the remainder of the distance. This cruising distance is zero when the initial deceleration is a

minimum value. The deceleration-cruising pair is determined by the effective Time to Intersection (TTI) needed and the DTI at the point the SPaT information is received. The downstream portion comprises accelerating back to the original speed. A lower speed at the intersection will cause the vehicle to have a larger acceleration maneuver, which adds to the total fuel consumed. This forms a trade-off between initial deceleration and speed at intersection. A higher initial deceleration level will result in a lower final speed at the intersection and hence higher fuel consumption associated with acceleration back to the original speed.

Upstream Trajectory of the Vehicle

As mentioned before, the eco-speed control model uses TTG information of an upcoming signal to alter an approaching vehicle's TTI to ensure that the vehicle traverses the intersection in a fuel-efficient manner. In this section, the equations governing motion of the vehicle upstream of the intersection are derived. Let v_a be the approach speed when the traffic signal information is received and x be the distance to the intersection. Also, denote the TTI be t and TTG be $t+\Delta t$. The eco-speed control model alters the average speed from $v_a = x/t$ to a new average speed $v = x/(t+\Delta t)$. The change in speed profile should maintain x and $t+\Delta t$. Infinite pairs of parameters of deceleration level, d and speed at the stop line, v_s can satisfy this condition. The minimum value of d , d_{min} allows the vehicle to decelerate until the stop-line when it can safely accelerate and pass through the intersection. Any value of deceleration greater than d_{min} has an associated cruising phase at speed v_s in order to maintain the x and $t+\Delta t$ parameters.

The speed profile shown by the solid line in Figure 3.4 represents the speed profile of the vehicle if it travels at a constant minimum deceleration level in order to ensure that the vehicle traverses the distance x in time $t+\Delta t$. Let this value of deceleration be d_{min} . The speed profile shown by the dash-dotted line in Figure 3.4 represents the vehicle speed profile if the objective is to minimize the time spent decelerating. The vehicle decelerates at a maximum feasible rate of d_{max} m/s² to a speed v_s m/s initially and then cruises at that this speed across a distance x_r . Within these two solutions is an infinite number of solutions for d ranging between d_{min} and d_{max} (i.e. $d = [d_{min}, d_{max}]$).

Using equations for conservation of x and $t+\Delta t$, the value of d_{min} can be derived as

$$d_{min} = \frac{v_a - v_s}{t + \Delta t} \quad (1)$$

$$\text{where } v_s = \frac{2x}{t + \Delta t} - v_a \quad (2)$$

For any greater value of d , the following equation provides the positive solution of v_s :

$$v_s = v_a - (d \pm Gg)(t + \Delta t) + \sqrt{(d \pm Gg)((d \pm Gg)(t + \Delta t)^2 - 2v_a(t + \Delta t) + 2x)} \quad (3)$$

Here G is the roadway grade and g is the gravitational acceleration (9.81 m/s^2). The following equation computes x_r (upstream cruising distance) corresponding to any given d as

$$x_r = x - \frac{v_a^2 - v_s^2}{2(d \pm Gg)} \quad (4)$$

It should be noted that when $d = d_{min}$, $x_r = 0$. These equations can derive various speed profiles between the two bounding deceleration levels. The instantaneous speed vector and a microscopic fuel consumption model are used to estimate fuel consumed for different vehicle trajectories.

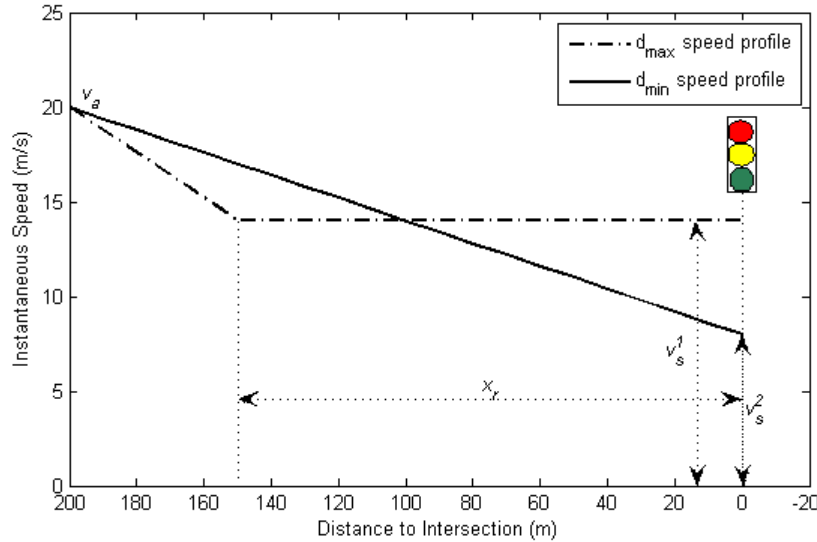


Figure 3.4 - Vehicle trajectory upstream.

Downstream Trajectory of the Vehicle

Once the vehicle clears the intersection, its task is to accelerate back to its original speed. Unlike deceleration, the acceleration speed profile is non-linear and vehicle dependent. This project used a vehicle dynamics model for light-duty acceleration to compute the downstream speed profiles of vehicles [2]. In order to optimize the fuel consumed for the downstream portion, it is necessary to consider alternate throttle levels when accelerating from v_s to v_a . Speed profiles corresponding to throttle levels of 20 to 100 percent are considered. A final comparison of the total fuel consumed is made for a constant distance that is computed as the distance required in accelerating at the minimum throttle level. In the case of greater throttle levels, this will entail accelerating and cruising at v_a for the remainder of the distance (Figure 3.5).

Hence, the equation for total fuel consumed downstream of the traffic signal is computed as

$$FC_i(ds) = FC_i(v_s \rightarrow v_a) + FC_{cruise}(v_a) \times (x_{max} - x_{i-acc}) \quad (5)$$

where $FC_i(ds)$ is the fuel consumed downstream of the traffic signal for case i , $FC_i(v_s \rightarrow v_a)$ is the fuel consumed while accelerating from v_s to v_a for case i , $FC_{cruise}(v_a)$ is the fuel consumed per

meter cruising at speed v_a , x_{max} is the maximum distance covered during acceleration from v_s to v_a in any case, and x_{i-acc} is the distance covered during acceleration in the case i .

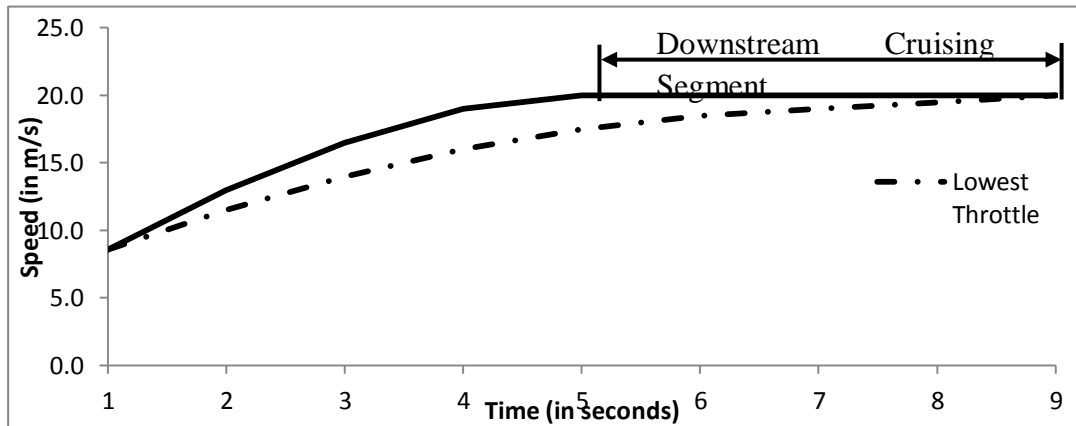


Figure 3.5 - Downstream trajectory of the vehicle.

Underlying Models

The speed control module defined in this report uses state-of-the-art microscopic traffic models to define instantaneous vehicle velocities and to predict future fuel consumed. The three primary models used here are:

- a) Constant deceleration model
- b) Vehicle dynamics acceleration model [2]
- c) VT-CPFM [3]

At this stage, the project mainly covers the speed control of the first vehicle arriving at an intersection and hence does not use any car-following logic. However, it should be noted that proper implementation of this system involves use of car-following models to analyze car-to-car interaction on the signalized arterial. This section expands on the microscopic models used during the project.

Vehicle Deceleration Model

The vehicle is assumed to undergo an initial deceleration upstream of the intersection to incorporate the required delay, and this deceleration is assumed constant and optionally followed by a cruising portion for the remainder of the DTI. The system does not consider a case involving acceleration upstream of the intersection. All acceleration occurs downstream of the traffic signal stop line.

Vehicle Acceleration Model

Once past the intersection, the vehicle accelerates to its original speed, and the time and distance at which it accelerates depends on the accelerator pedal level or simply the throttle level. In order to compare cases of any throttle level, a constant distance upstream is considered, which is defined by the distance covered during the application of minimum throttle. For any throttle level more than the minimum, some cruising is required at the final speed for the remainder of the

fixed distance. This deals with the acceleration model used during this project and is a non-linear model unlike the deceleration model. The modeling of vehicle accelerations involved the use of a vehicle dynamics model. Vehicle dynamics models compute the maximum vehicle acceleration levels from the resultant forces acting on a vehicle (mainly vehicle tractive force that is a function of the driver throttle input and the various resistance forces).

Equation 6 computes the vehicle tractive effort F . Rakha and Lucic introduced the β factor into Equation 6 in order to account for the gearshift impacts at low traveling speeds when trucks are accelerating [1]. This factor is set to 1.0 for light-duty vehicles. The f_p factor models the driver throttle input level and ranges from 0.0 to 1.0. The sum of the aerodynamic, rolling, and grade resistance forces acting on the vehicle, as demonstrated in Equation 7, forms the vehicle resistance force.

$$F = \min \left(3600 f_p \beta \eta_d \frac{P}{v}, m_{ta} g \mu \right) \quad (6)$$

$$R = \frac{\rho}{25.92} C_d C_h A_f v^2 + m g \frac{c_{r0}}{1000} c_{r1} v + c_{r2} + m g G \quad (7)$$

where f_p is the driver throttle input [0,1] (unitless; field studies have shown that it is typically 0.60); β is the gear reduction factor (unitless); η_d is the driveline efficiency (unitless); P is the vehicle power (kW); m_{ta} is the mass of the vehicle on the tractive axle (kg); g is the gravitational acceleration (9.8067 m/s²); μ is the coefficient of road adhesion or the coefficient of friction (unitless); ρ is the air density at sea level and a temperature of 15°C (1.2256 kg/m³); C_d is the vehicle drag coefficient (unitless), typically 0.30; C_h is the altitude correction factor (unitless); A_f is the vehicle frontal area (m²); c_{r0} is rolling resistance constant (unitless); c_{r1} is the rolling resistance constant (h/km); c_{r2} is the rolling resistance constant (unitless); m is the total vehicle mass (kg); and G is the roadway grade at instant t (unitless).

The vehicle acceleration is calculated as a ratio of the difference between the tractive forces and resistance forces and the vehicle mass (i.e., $a = (F - R)/m$). The vehicle speed at $t + \Delta t$ is then computed using Euler's first-order approximation as

$$v(t + \Delta t) = v(t) + 3.6 \frac{F(t) - R(t)}{m} \Delta t \quad (8)$$

Fuel Consumption Model

This section describes the fuel consumption model used in computing the fuel-optimal vehicle trajectory. Fuel consumption models generally fall into one of the following two categories: macro and micro models. Macro models estimate vehicle total fuel consumption based on aggregate characteristics such as average speed, total distance traveled, and average traffic volume. However, microscopic fuel consumption models calculate instantaneous fuel

consumption levels based on instantaneous operational characteristics. This study uses a microscopic model since optimizing speed trajectories requires estimating vehicle fuel consumption based on instantaneous vehicle operational data.

This study uses the VT-CPFM-1 due to its simplicity, accuracy, and ease of calibration [3]. The fuel consumption model utilizes instantaneous power as an input variable and can be calibrated using publicly available fuel economy data (e.g., Environmental Protection Agency [EPA]-published city and highway mileage). Thus, the calibration of model parameters does not require gathering any vehicle-specific data.

The fuel consumption model is formulated as Equation (9), where α_0 is the fuel consumption rate (g/s or l/s) for idling conditions and $P(t)$ is the instantaneous total power in kilowatts (kW). The idling fuel consumption rate is estimated using Equation (10), where P_{mfo} is idling fuel mean pressure (400,000 Pa), ω_{idle} is idling engine speed (rpm), d is engine displacement (liters), Q is fuel lower heating value (43,000,000 J/kg for gasoline fuel), and N is the number of engine cylinders. Estimation of the model coefficients (α_1, α_2) uses the fuel consumption rates of the standard fuel economy cycles (e.g., EPA-published city and highway mileage).

Here F_{city} and F_{hwy} are the total fuel consumed for the EPA city and highway driving cycles, respectively. The value of F_{city} is adjusted to represent the engine transient operation since the EPA city cycle includes the cold start operation in the Bag 1 of Federal Test Procedure (FTP). T_{city} and T_{hwy} are the durations of the city and highway cycles (1875s and 766s). In addition, P_{city} and P_{city}^2 represent the total power used and total sum of the squared power during the city driving cycle, expressed as $\sum_{t=0}^{T_{city}} P(t)$ and $\sum_{t=0}^{T_{city}} P(t)^2$ respectively. Similarly, P_{hwy} and P_{hwy}^2 are estimated for the highway cycle.

$$FC(t) = \begin{cases} \alpha_0 + \alpha_1 P(t) + \alpha_2 P(t)^2 & \forall P(t) \geq 0 \\ \alpha_0 & \forall P(t) < 0 \end{cases} \quad (9)$$

$$\alpha_0 = \max \left(\frac{P_{mfo} \omega_{idle} d}{22164 \times QN}, \frac{\left(F_{city} - F_{hwy} \frac{P_{city}}{P_{city}} \right) - \varepsilon \left(P_{city}^2 - P_{hwy}^2 \frac{P_{city}}{P_{hwy}} \right)}{T_{city} - T_{hwy} \frac{P_{city}}{P_{hwy}}} \right) \quad (10)$$

$$\alpha_1 = \frac{F_{hwy} - T_{hwy} \alpha_0 - P_{hwy}^2 \alpha_2}{P_{hwy}} \quad (11)$$

$$\alpha_2 = \frac{\left(F_{city} - F_{hwy} \frac{P_{city}}{P_{hwy}} \right) - \left(T_{city} - T_{hwy} \frac{P_{city}}{P_{hwy}} \right) \alpha_0}{P_{city}^2 - P_{hwy}^2 \frac{P_{city}}{P_{hwy}}} \geq \varepsilon = 1E-06 \quad (12)$$

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4. Survey on Increasing In-Vehicle Technology Use

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Survey on Increasing In-Vehicle Technology Use: Results and Findings

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The use of advanced technology in automobiles has increased dramatically in the past couple of years. Driver-assisting gadgets such as navigation systems, advanced cruise control, collision avoidance systems, and other safety systems have moved down the ladder from luxury cars to more basic vehicles. Concurrently, auto manufacturers are also designing and testing driving algorithms that can assist with basic driving tasks, many of which are being continuously scrutinized by traffic safety agencies to ensure that these systems do not pose a safety hazard. The research presented in this paper brings a third perspective to in-vehicle technology by conducting a two-stage survey to collect public opinion on advanced in-vehicle technology. Approximately 64 percent of the respondents used a smartphone application to assist with their travel. The top-used applications were navigation and real-time traffic information systems. Among those who used smartphones during their commutes, the top-used applications were navigation and entertainment.

Introduction

Use of technology in our daily life is increasing so rapidly that we see computers and computerized devices everywhere. As far as automobiles are concerned, where we once only had cruise control units, power windows, and remote lock/unlock devices in our vehicles, we now have navigation systems, voice-command operating systems, adaptive cruise control systems, and automated parking control systems. Researchers are also developing driverless vehicles, and transportation authorities in many countries are legislating inter-vehicular communications to enhance safety. For instance, the U.S. Department of Transportation started the Connected Vehicle research program, partnering with auto manufacturers and research universities to include more connectivity and technology in automobiles [1]. Auto manufacturers are equipping vehicle dashboards with more gadgets, while regulators such as the National Highway Traffic Safety Administration (NHTSA), citing safety reasons, are working towards new legislation that limits technology in vehicles [2].

For decades, researchers have been studying how to make driving more safe, fuel efficient, and comfortable. As a result, we now have vehicles that park themselves, cruise themselves, and even drive themselves. On the other hand, there are studies in which researchers analyze how effective or distracting these systems are. This has left a gap in research, namely, identifying what the end users want in their vehicles—more or less technology and the kind of assisting devices. An extensive background study suggested that most similar surveys reflect a non-scientific approach through publishing blog platforms or newspapers. All of these were

consumer surveys that can be used as a comparison tool for different user interfaces and ease of use. The 2012 J.D. Power U.S. Initial Quality Study revealed that most of the complaints that new-car owners have relate to high-tech gadgets in their cars and how these gadgets interact with drivers [3].

Consequently, this paper is intended to fill the gap between the perceptions of end users and vehicle manufacturer implementations using statistics from a scientifically designed online survey implemented in two stages. These stated preference surveys were intended to solicit a sample population's opinions on the use of advanced technology in automobiles. The first stage of the survey, conducted in 2012, highlights the generalized implications on how typical drivers react to equipping their vehicles with different levels of automation. In particular, two types of advanced cruise control systems were analyzed in this survey, namely Adaptive Cruise Control (ACC) and Cooperative Adaptive Cruise Control (CACC). The second stage of the survey, conducted in 2013, focused on identifying public opinion about the benefits sought from these advanced technologies. This survey highlights and ranks the aspects of driving or riding that the public would like to be automated.

A review of the literature reveals that most researchers have focused their efforts on testing the performance of new technology (e.g., advanced cruise control systems) and have assumed that drivers will accept such technologies. For example, some of the studies developed dynamic optimal speed advising algorithms on the vehicle side and compared system performance to actuated traffic signal control [4][5]. For connected vehicles, many researchers have studied the impact of advanced cruise control (ACC and/or CACC) systems using simulation/simulator experiments (e.g., [6] and [7]). In addition, a few attempts in the literature have been made to create simulators (or simulation software) for modeling fully automated/autonomous vehicles (e.g., Dresner and Stone [8-10]).

However, a very limited number of researchers have attempted to study the impact of new technologies on driver behavior and driver distraction. In a NHTSA study, test vehicles with multiple vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) safety applications were tested using a total of 688 drivers, ages 20 to 70. The study concluded that, following the driver clinic, over 90 percent of the participants expressed a desire to have V2V communication safety features in their personal vehicles [11]. In the same context, the AAA Foundation for Traffic Safety (AAAFTS) in cooperation with the Automobile Club of Southern California (ACSC) conducted a survey to assess drivers' experiences with ACC systems [12]. The overarching goal of that study was to learn more about the extent to which ACC systems enhance or detract from safety. The results of this study showed that most of the ACC owners indicated that the system helped them to drive more safely; however, the younger respondents (less than 65 years old) were more likely to report a need for safety improvements to the system.

In summary, most of the previous research addressed advanced technologies in vehicles from an operations perspective and neglected driver acceptance and/or the behavioral adaptation of drivers. This paper attempts to overcome some of the previous research shortcomings by collecting public opinion on new in-vehicle technologies through a user survey.

Study Objectives

The objective of this research was to collect public opinion on the recent increase of in-vehicle technology and gadgets that are enabled by telematics and connected vehicle technology using two online surveys. In this study, two survey questionnaires were specifically designed to solicit public opinion on the desired level of advanced technology in vehicles and highway systems as well as to quantify the public's perception of these issues. While the phrase "technology in cars" could mean anything from Bluetooth to voice-command operations, this study deals with technology enabling safety and efficiency of driving. This includes systems such as ACC or connected vehicle applications using CACC systems.

Major demographic characteristics such as age group, gender, education, and occupation were used to classify the responses and to draw statistically significant results. This survey is intended to address some questions regarding public acceptance of various driver-assistance systems and levels of vehicle automation. Some of these are:

1. Identifying possible demographic characteristic effects (age, gender, etc.) on driver acceptance of in-vehicle technologies;
2. Soliciting driver input on the intrusion of smart phone applications in transportation;
3. Ranking the various types of systems that drivers like or dislike in their vehicles;
4. Soliciting driver acceptance regarding various levels of vehicle and highway automation.

As far as the paper layout is concerned, the survey methodology is described along with sampling the population characteristics, design and implementation of the survey, and post-survey adjustments. An extensive section on the findings from this survey is provided along with charts of major public responses and a list of major conclusions.

Methodology

Advanced automobile technology is primarily controlled by two parties: the automobile manufacturers and governing authorities. The automobile manufacturers are equipping vehicles with driver-assistance devices (including forward collision warning [FCW] systems, drowsy driver sensors, etc.) and the governing authorities such as NHTSA are developing regulations to ensure that such systems do not produce a safety hazard. Between these two parties, there are 211,000,000 licensed drivers in the United States (as of 2009) who will be the actual end users of such systems [13]. The research presented in this paper solicited a sample of drivers in the United States for their perceptions of advanced in-vehicle technologies and what types of innovations in transportation they would like to see.

Scientifically designed online surveys are considered an effective and quick tool to collect responses from a variety of audiences. The surveys used in this study had the following stages of implementation:

1. Sample size computation: This was done primarily to define the statistical significance of the study. The sample size was derived from the population size as well as confidence intervals and levels.
2. Design of questionnaire: The questionnaire was designed to incorporate the questions that would yield necessary data for the research in a set of easy-to-read plain English questions. Any technical descriptions were simplified to ensure layman understanding.
3. Seeking necessary approvals: As per institutional requirements, some survey review and approval was necessary since this research involved human subjects.
4. Invitations and publicity: This step was of utmost importance in the overall success of the survey. It involved solicitations through known listservs, electronic mailing lists, and social networking groups. Survey respondents were volunteers who chose to respond to the posting.
5. Survey closure: Once the number of respondents reached the desired sample size plus some buffer considering the potential for incomplete responses, the survey was removed from the Web.
6. Data analysis: The responses collected during the open period were post-processed to remove any incomplete responses. The final processed data were then analyzed to derive conclusions.

Sampling

The sample size required for the survey to be statistically significant is calculated using the following equations.

$$x = [z(c/100)]^2 \times r \times (1-r) \quad (1)$$

$$n = \frac{Nx}{(N-1)E^2 + x} \quad (2)$$

where N is the population size, r is the fraction of response of interest, $Z(c/100)$ is the critical value for the confidence interval c , and E is the margin of error allowed. Assuming the population's response is not skewed and the sample is random, we consider an r -value of 0.5. A confidence interval of 5 percent and a confidence level of 95 percent will yield a minimum required sample size estimate of 385, where the population size is assumed to be all licensed drivers in the United States over the age of 18. Table 4.1a shows the number of licensed drivers in the United States based on the 2009 census (the latest available) [13]. Only drivers of age 18 and above were considered for the survey due to Institutional Review Board (IRB) requirements.

Survey design

Since the survey population consists of any licensed driver in the United States, the survey questions were designed to be simple and easy to understand. The first survey was conducted in

2012 and spanned nearly 4 weeks. The survey was designed to provide valuable statistics showing the relationship between demographics and drivers' perceptions of increased in-vehicle technology and their acceptance of future systems. The second survey in 2013 was specifically designed to expand on the benefits that end users are receiving from the current level of technology and the perceived benefits of future systems. The survey population was solicited using emails to known listservs as well as social networks and tweets. IRB approval was sought and received for the specifically designed questionnaires and the survey process. As per IRB requirements, respondents less than 18 years of age were not included in the study. The masking of any identifying information about respondents, including response location and IP address, was a requirement for IRB approval.

Post-survey adjustments

The surveys were online for over 4 weeks collecting survey responses from respondents who volunteered to fill out the questionnaire. There were some adjustments that were done after survey closure. They are listed here:

1. Responses with empty answers were removed. This included responses with any question left unanswered.
2. In some questions, the respondents could type out their own answers rather than selecting a given choice. Some of these answers were similar to the responses that could be selected. These options were merged.
3. Answers that were not part of and different from the choice set were individually categorized, putting similar views together.
4. Responses were linked based on certain demographics and respondent areas of expertise so that meaningful conclusions could be made.
5. Post-stratification weights were used to adjust the responses to match the actual population. The adjustment also helped to form matching demographics for both surveys. This will be explained in the following subsection.

Survey Results and Findings

Post-processing yielded a set of over 400 survey responses for each of the surveys, which was well over the minimum sample size required. However, the demographic distribution has to be matched between the surveys and with the population in consideration. Post-stratified weights were used to match the stratified sample proportions to the population distribution given in Table 4.1a. This method expanded the responses from the age groups that had lesser responses (over 65 years) and contracted the responses from the age groups that had the most responses (25 to 40 years). While post-stratification could be done based on several factors including socioeconomic ones, age is being considered here since the socioeconomic distribution of the licensed U.S. population consists of multiple variables that need factored weighing. Table 4.1b shows the calculation of post-stratification weights for making the respondent population comparable with the actual population of licensed drivers in the United States aged 18 and above.

Table 4.1 – Population distribution of licensed drivers in U.S. (2009 census data)

Age Group	Number of Licensed Drivers	% of Population
18 to 24	23,647,000	11.43
25 to 40	55,906,000	27.02
41 to 65	94,404,000	45.63
Over 65	32,899,000	15.92
Total (18 and up)	206,856,000	100.00

Post-stratification of survey respondents

Age Group	Pop. Ratio	Sample Proportion		Stratification Weight	
		Part 1	Part 2	Part 1	Part 2
		18-24	0.114	0.212	0.242
25-40	0.270	0.645	0.450	0.42	0.60
41-65	0.456	0.122	0.290	3.74	1.57
Over 65	0.159	0.021	0.018	7.57	8.83

These weights were then used to weigh the responses to the survey made by the respondents based on their age group. The weighted results are considered to replicate the actual population’s behavior (Table 4.1). Stratification also aligns the respondent demographics of the second part of the survey with the actual population, thereby making the results from both surveys comparable. In order to preserve the demographic representation of the population under consideration, no trimming was made on the weights and hence the number of weighted responses was equal to the number of actual responses. In the following sections, survey results based on different criteria are explained.

Demographics

Figure 4.1 shows the demographic distribution of survey respondents with respect to age, gender, education level, and car usage. The dissimilarity in age distribution was negotiated by the post-stratification process. The prominent respondent education level was a four-year college degree and had a 35:65 gender split as shown. Over 87 percent of the respondents drove more than twice a week. Other demographic features are also shown in Figure 4.1. It was also seen that there is a bias between the education demographic and gender. For example, only 6 percent of the respondents listed their highest education as being less than a four-year degree. Therefore, a chi-squared test was performed to see if the responses were independent of the respondents’ education or gender.

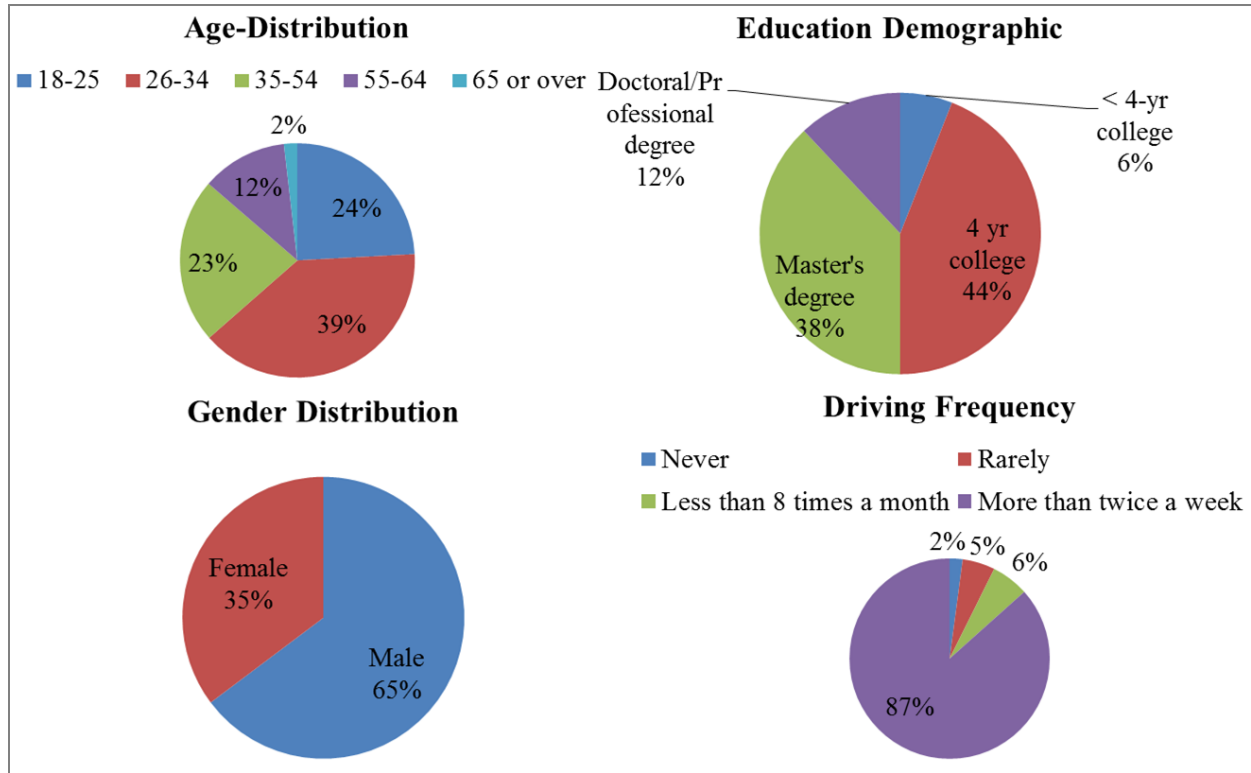


Figure 4.1 – Distribution of respondent population based on demographics.

Independence tests using Pearson’s chi-squared test were done with the test variables being whether the respondents support advanced technology in automobiles and what level of highway automation is desired. The test factors were age group, gender, education, and the respondent’s area of expertise. Table 4.2 shows the chi-squared values for a significance level of 0.05. Tests indicate that the responses were independent of respondent demographics. In other words, the demographic characteristics of the participants (respondents) did not affect their responses concerning the support of technology or the desired level of highway automation. It could be stated that many of these results are consistent with a previous study [12].

Table 4.2 – Chi-squared test of sample results.

	Support technology in vehicles	Prob > Chi Sq.	Desired level of highway automation	Prob > Chi Sq.
Age	3.279	0.9932	18.064	0.1138
Gender	5.504	0.2394	9.228	0.0556
Education Level	11.402	0.7840	21.465	0.1613
Area of Expertise	6.049	0.1955	4.473	0.3457

The survey also identified the most common commute mode among the respondents to which the results can be associated. The responses to the frequency of use of each transport mode were recorded for this purpose and were then weighted to rank them according to how often they were used. This ranked list is given below:

1. Car/Truck/Motorcycle
2. Walk
3. Transit Bus
4. Bike
5. Metro/Light Rail
6. Heavy Rail

Smartphone Applications

There has been an increasing trend of smartphone applications that help with multiple aspects of transportation. Smart-navigation, real-time traffic information, weather information, etc., are just a start of the growing influence information technology has on the way people commute. Though using cellphones while driving is discouraged and even legally banned in many states, smartphones contribute to bringing real-time information to drivers so that they can make informed choices on routes and modes. Around 64 percent of the survey respondents have used smartphones to help with their commutes in some way.

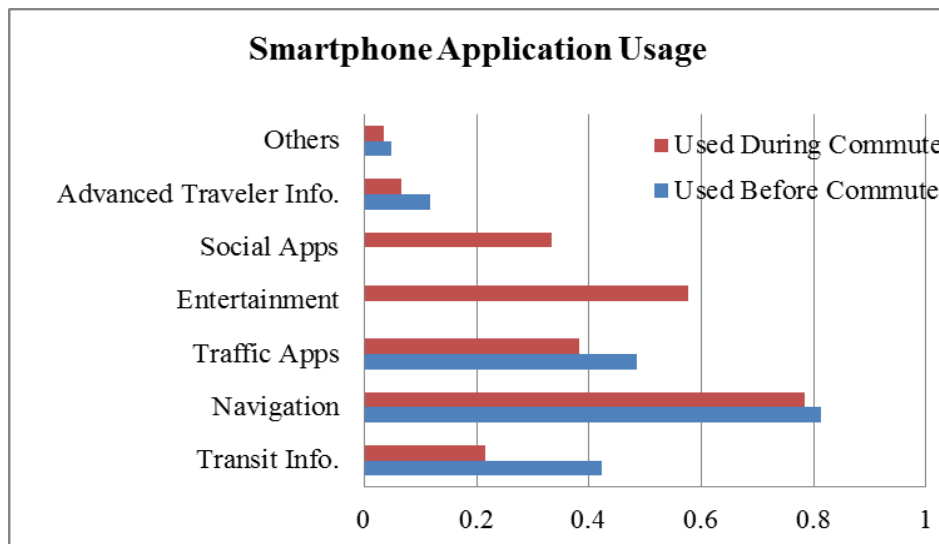


Figure 4.2 – Smartphone applications that are used in connection with commute/travel.

Figure 4.2 shows the top smartphone applications that are used in connection with commuting and travel. Smartphone applications are ranked based on the percentage of respondents who have used them. Navigation applications held the top position, with nearly 80 percent of people using them both prior to and during the trip. Traffic and transit applications held the next positions for the top apps that were used by the respondents to help with their trips. As far as the applications that are used by respondents during trips are concerned, entertainment and traffic applications

followed navigation apps in ranking. It should be noted that social apps and entertainment apps that were used prior to commuting were dropped since they rarely help with trip decisions.

Advanced Control Systems

A variety of vehicle control systems have been recently introduced in the market under different trade names as we move closer to self-driving vehicles. For example, ACC can detect slowing lead vehicles and adjust the speed accordingly to maintain a safe headway. CACC communicates with neighboring vehicles for more responsive safety applications, including red-light running and intersection collision avoidance. In contrast to these advances, the results from the survey reveal that adoption of traditional cruise control has been mixed with nearly 20 percent of the respondents never using it. However, 34 percent of respondents use cruise control whenever possible. Figure 4.3 shows the statistics on whether the respondents use traditional cruise control while driving and whether they are aware of the new advancements in cruise control technology. In order to test public awareness of the new types of assistive cruise control systems, respondents were asked if they were aware of ACC systems. An approximately 50:50 split was shown in the responses. This indicates the respondents' average knowledge about the new technologies coming up in the transportation industry.

Cruise Control System Usage

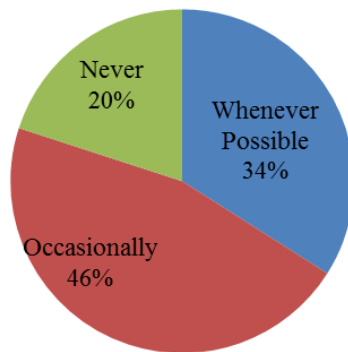


Figure 4.3 – Percentage distribution of how often respondents use cruise control while driving.

The penetration level of any new technology that affects how people drive depends on its trustworthiness. Most survey respondents highlighted the importance of “learning” in their perceived trustworthiness of advanced technology in driving-assistance systems. Around 15 percent of the survey respondents did not trust the two advanced cruise control systems, namely ACC and CACC. The survey questionnaire provided brief descriptions of these systems so that respondents could make judgments. ACC maintains a constant headway by detecting the speed of the lead vehicle and CACC adjusts cruise speeds using advanced information from surrounding cars and infrastructure equipment. These results are shown in Figure 4.4.

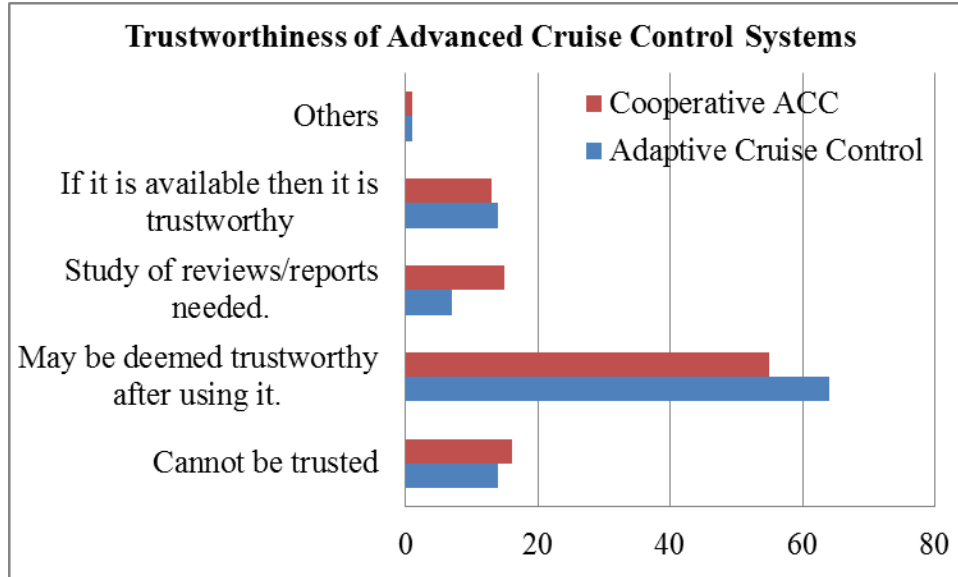


Figure 4.4 – Percentage distribution of trustworthiness of advanced cruise control systems.

As far as the statistics are concerned, 49 percent of the respondents had heard about ACC systems. Figure 4.5 shows the perceived trustworthiness of these two types of cruise control systems to the public. A total of 64 percent of the respondents would trust ACC systems after using them. This learned trustworthiness is approximately 55 percent for CACC systems. A total of 14 and 13 percent of the respondents indicated that they would trust these respective systems if they were available for use by the public. Around 7 and 14 percent, respectively, thought they might trust these systems after studying safety reports and consumer reviews, and less than 1 percent had views that were not listed in the questionnaire, most of which reflected the opinion that it was not an issue of trustworthiness but an issue of need.

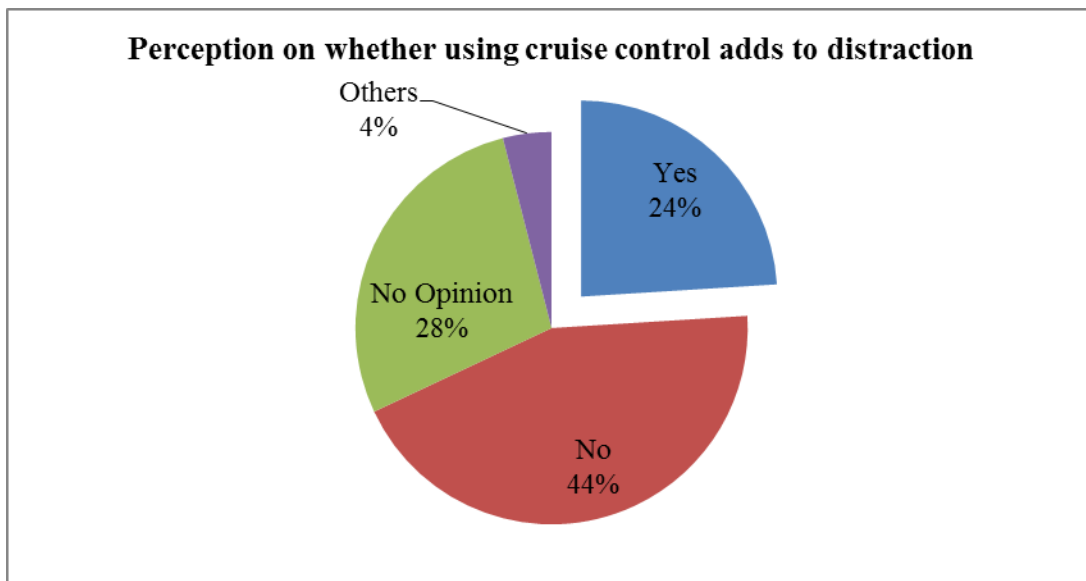


Figure 4.5 – Effect of using cruise control on distraction while driving.

Anti-distracted driving has been the primary safety campaign by NHTSA and other traffic safety organizations. Recent studies have indicated that high-tech gadgets add to driver distraction [14]. This survey also analyzed public perception on driver distraction as a result of technology. In one question, respondents were asked if they thought they were distracted while using cruise control. A summary of the results is shown in Figure 4.5. Only 24 percent of the respondents agreed that they were more likely to be distracted while using cruise control. Around 44 percent of the respondents thought cruise control and driver distraction were unrelated, and 28 percent of the respondents had a neutral opinion.

Driver-assistance Systems

Vehicle control systems are just a part of some of the automation we see in today's cars. Automobile companies are equipping vehicles with multiple systems to make driving and riding more comfortable, entertaining, and economical. The survey respondents were asked to rank the types of systems they would want in their vehicles, and the results are given in Figure 4.6a. Systems that enhance the safety of passengers were ranked at the top by over 60 percent of respondents. The second highest-ranked systems were those that make vehicles more fuel efficient. The entertainment and social systems that are being added by some of the manufacturers came the lowest on the ranking, with over 75 percent respondents marking them as least important.

In order to perceive what benefits end users expect from advanced driver-assistance applications, the respondents were asked to rank benefits (shown in Figure 4.6b). Rank-weighted responses were used to give overall rank to all of the systems and were computed as the sum of the products of the number of responses with their corresponding ranks. These benefits were consequently ranked in the following order:

1. Enhanced safety
2. Reduced travel time and delays
3. Fuel economy
4. Driver and passenger comfort
5. Reduced workload while driving

Additionally, the respondents were asked if they were in favor of adding more technology to automobiles. Over 89 percent of the respondents supported more technology in automobiles, with around 45 percent strongly supporting this idea. Only 3 percent of all respondents opposed increased use of technology in automobiles. These results provide valuable input for researchers working on developing driver-assistance systems as to what areas to focus development on. Consequently, these results indirectly show the hierarchy of the price that users would pay for these systems.

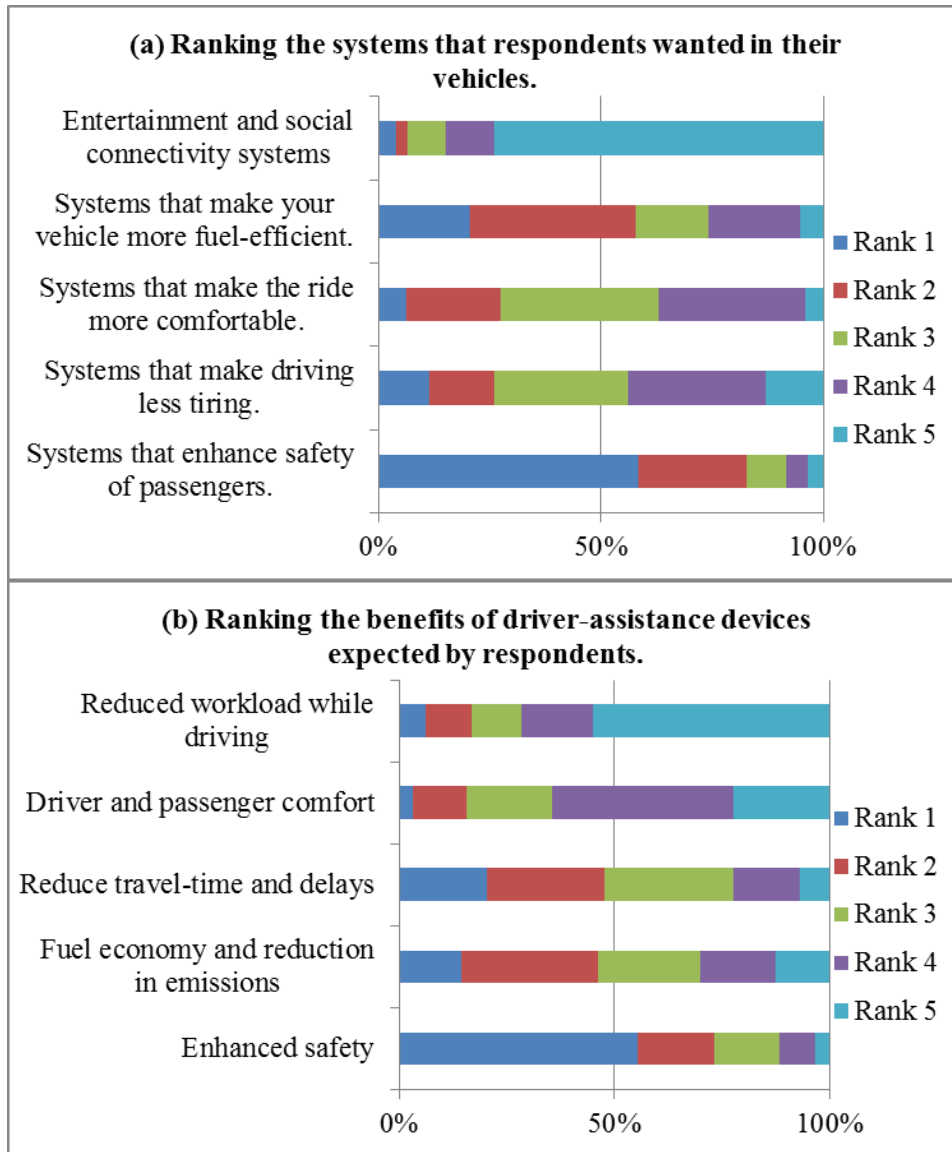


Figure 4.6 – Respondent ranking of various driver assistance systems and the benefits sought from them.

Vehicle Automation

Numerous labs and research groups are in the process of developing autonomous driving systems. As guidance, NHTSA has identified major milestones on the way to fully automated vehicles. Five levels of automation have been identified currently, as given in Table 4.3. Specific definitions of these terms are available in [15]. The survey presented in this paper attempted to address the public perception of an automated driving environment. While the definitions of these levels are too complex to be explained in layman’s terms, the survey used well-defined systems that can cover these five milestones. Respondents rated how much they would want these systems.

Table 4.3 – Various levels of automation as identified by NHTSA

Level	Description
0	No Automation
1	Function-specific Automation
2	Combined Function Automation
3	Limited Self-Driving Automation
4	Full Self-Driving Automation

The following system definitions were used in the research:

1. System 1: Systems that provide information about the trip, such as routes, congestion, incidents, etc.
2. System 2: Systems that assist with driving, such as signal timing information, blind-spot occupancy, etc.
3. System 3: Systems that enhance safety, such as automated braking systems, collision avoidance, etc.
4. System 4: Systems that enable automated highway driving using lane centering and safe headways.
5. System 5: Self-driving systems which need no human input other than destination.

Figure 4.7 shows the public perception of the aforementioned systems. As shown, as the system becomes more and more complex and intrusive, the drivers are less receptive to the system. For example, nearly 90 percent of the respondents are receptive to System 1, which does not intrude on the driver’s role whereas only 33 percent of the respondents are receptive to a self-driving system (System 5).

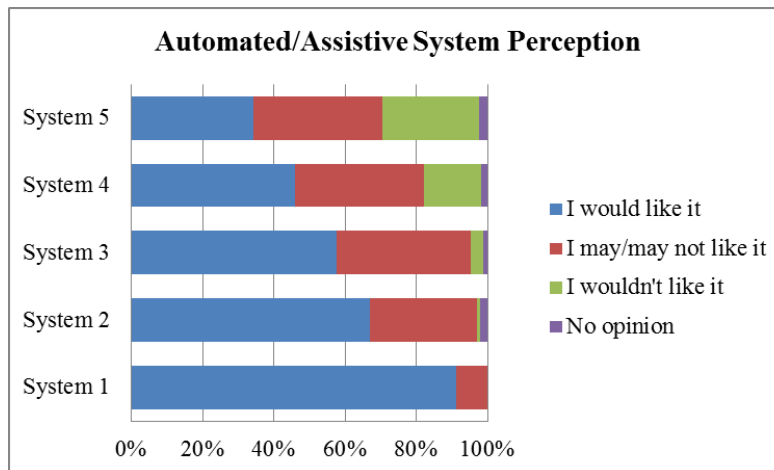


Figure 4.7 – Respondent opinions on various levels of automation systems.

Conclusions

The survey conducted and analyzed in this paper evaluates the public perception of increased technology in vehicles and highway systems. The two-part survey covered multiple facets of advanced technology in driver-assistance devices. Results from this study are expected to help researchers focus their research into the latest innovations in connected vehicle research and advanced vehicle systems. The results could also be used by auto manufacturers in critical decisions regarding equipping vehicles with in-vehicle gadgets. The stated preference survey responses were able to yield a confidence interval of 5 percent and a confidence level of 95 percent. Post-stratification was done to match the respondent population's age groups with the actual population's age groups.

Findings from the survey highlight the following conclusions:

1. Demographic factors such as age, gender, and education had no impact on the respondents' answers to questions regarding in-vehicle technology.
2. Approximately 64 percent of the respondents have used a smartphone application to assist with their travel. The top-used applications were navigation and real-time traffic information systems.
3. Among those who used smartphones during their commute, the top-used applications were navigation and entertainment.
4. More than 24 percent of respondents thought that they are more distracted while using cruise control. As far as the trustworthiness of advanced cruise control systems such as ACC and CACC systems is concerned, up to 60 percent of the respondents felt that they would need to get acquainted with these systems before making a judgment. This conclusion may be true with any new innovation.
5. The top driver-assistance systems that respondents voted for are systems that enhance the safety of passengers and systems that make vehicles more fuel efficient. Among the benefits that the respondents sought from advanced driver assistance systems, the top ones were enhanced safety and reduced travel time and delays.
6. Advancements in social and entertainment systems in the vehicles were ranked lowest by the respondents.
7. More respondents voted for systems that are non-intrusive (over 90 percent) than fully autonomous (35 percent).

These conclusions are expected to help bridge the gap between the advancing research and development of in-vehicle technology, including vehicle automation, and public expectations of those technologies that will influence their acceptance by end users.

Acknowledgements

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5. Leveraging Connected Vehicle Technology to Enhance Vehicle Fuel Efficiency in the Vicinity of Signalized Intersections

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Leveraging Connected Vehicle Technology and Telematics to Enhance Vehicle Fuel Efficiency in the Vicinity of Signalized Intersections

Raj Kishore Kamalanathsharma and Hesham Rakha

Driving on highways and arterial roadways involves vehicle acceleration, braking, cruising, coasting, and idling episodes. As the vehicle speed deviates from its “fuel optimum speed,” additional fuel is consumed and thus reducing the vehicle fuel efficiency. The research presented in this paper develops a connected vehicle application entitled Eco-Cooperative Adaptive Cruise Control (ECACC) that uses Infrastructure-to-Vehicle (I2V) communication to receive Signal Phasing and Timing (SPaT) data, predict future constraints on a vehicle’s trajectory, and optimize its trajectory to minimize the fuel vehicle’s consumption level. The trajectory optimization is made using a moving horizon dynamic programming (DP) approach. A modified A-star algorithm is developed to enhance the computational efficiency of the DP for use in real-time implementations. The model is calibrated and tested on 30 top-sold vehicles in the United States and is demonstrated to provide fuel savings within the vicinity of signalized intersections in the range of 5 to 30 percent.

Introduction

Vehicle trajectories on arterials and freeways can be considered as a combination of five driving episodes – acceleration, deceleration, cruising, coasting and idling. Speed variations occur due to numerous factors, including: vehicle-vehicle interaction, traffic control device constraints, infrastructure limitations and even driver distraction. This speed variations result in additional fuel consumption because of travel at non-optimum speeds and the extra power exerted while accelerating. Avoiding these speed variations is not always possible without compromising safety and/or respecting traffic control devices.

Consequently, optimizing the vehicle trajectory to minimize its fuel consumption can significantly enhance the vehicle fuel efficiency. Such an optimization tool predicts the future constraints that the vehicle will be subject to and generates a speed profile that is fuel-optimal. This prediction of future constraints was impossible until vehicle connectivity was introduced. In addition to the safety benefits, this technology promises valuable information to the vehicles and traffic controllers such as speed-acceleration-brake status and signal phasing and timing (SPaT) information. This information can be leveraged to develop spatial and temporal constraints to optimize the vehicle trajectory to achieve maximum fuel efficiency. The research presented in this paper develops a vehicle trajectory optimization tool entitled Eco-Cooperative Adaptive Cruise Control (ECACC).

ECACC is a type of Cooperative Adaptive Cruise Control (CACC) that works in conjunction with signalized intersections to optimize vehicle trajectories to minimize fuel consumption levels. The method used in this paper focuses on optimizing the trajectory of a vehicle approaching an intersection capable of communicating signal change information to the on-coming vehicles. Since the mathematical program is non-linear and complex, a dynamic programming (DP) framework is developed that uses a modification of the A-star path-finding algorithm to enhance the computational efficiency. Microscopic simulations of vehicles approaching a traffic signal revealed fuel-savings in the range of 5 to 30 percent in the vicinity of intersections for the 5 top-sold cars of 2011 within each the 6 Environmental Protection Agency (EPA) categories.

As far as the paper layout is concerned, it starts with a discussion of the literature currently available on the use of V2I/I2V communication to optimize vehicle fuel consumption. This is followed by a description of the problem statement and methodology used in developing the ECACC algorithm along with alternate optimization techniques tested. This section also describes the microscopic models used in this study followed by how the simulation analysis was conducted. Finally, the results and findings of the simulation study as well as a discussion on the conclusions of the research are presented.

Background

Around the world, transportation and environmental agencies have been concerned with depleting petroleum resources with a continuing reliance on these sources. In addition, stopping for red lights and other idling events consume 2.8 billion gallons of gasoline in the United States alone each year (Schrank et al., 2010). Concurrently, new technology is booming in the transportation industry with smarter vehicles and smarter intersections. Initiatives to use vehicle-to-vehicle and vehicle-to-infrastructure communication to make transportation systems more efficient and safer have been well studied for decades (ITS JPO, 2012). The connected vehicle technology and similar research world-wide has drawn attention of researchers and public because of the scope it opens in the field of future transportation systems. Only a handful of researchers have used the availability of such information to enhance fuel efficiency of vehicles. These research efforts highlight the fact that if a road user is notified of the upcoming signal status, the vehicle speed can be adjusted accordingly to avoid hard-braking or hard-acceleration maneuvers, thereby improving energy consumption and emission levels (Rakha & Kamalanathsharma, 2011).

Wu et al. studied the energy/emission benefits of communicating Traffic Signal Status (TSS) to the road user via Changeable Message Signs (CMSs) or an in-vehicle Advanced Driver Alert System (ADAS) (Wu et al., 2010). The proposed system allows drivers to develop the optimal course of action without any form of optimization. Asadi and Vahidi developed a predictive cruise control system that uses constrained optimal control to adjust cruising speeds to minimize the probability of stopping at intersections (Asadi & Vahidi, 2010). Tielert et al. used the

effective red-phase duration, which is the time difference between the end of red-phase and time of arrival of the vehicle if it did not reduce its speed to establish the factors governing the impact of Traffic-Light-to-Vehicle-Communication (TLVC) on vehicle fuel consumption and emission levels of individual vehicles (Tielert et al., 2010).

Sanchez et al. developed the logic to be used by a driver approaching a traffic signal if he/she was notified of the upcoming change of signal status (Sanchez et al., 2007). This logic, however, did not formulate the problem as an explicit optimization problem with microscopic fuel consumption model estimates as the objective function, but instead adjusted vehicle speeds to reach the stop-line during the green indication, which may or may not be possible in real-life. Malakorn and Park used constrained optimal control with the objective of minimizing acceleration and deceleration distances and idling time using Traffic Signal Status (TSS) information (Malakorn & Park, 2010). Mandava et al. introduced an arterial velocity-planning tool that calculates the speed profile for a vehicle approaching a signalized intersection to reduce fuel consumption and provide dynamic advice to the driver (Mandava et al., 2009). The system minimizes acceleration and deceleration levels to achieve its objective.

In recent studies, researchers were able to look closely at the same logic, i.e, optimizing the speed profile of vehicles to achieve fuel efficiency using SPaT data. Mahler and Vahidi studied reducing idling at red-lights using a probabilistic prediction of signal timings (Mahler & Vahidi, 2012). In this study, the authors used a predictive algorithm to predict the signal phases for upcoming signals and adjusted vehicle speeds in a way to minimize the probability of arriving during a red interval. Kamal et al. developed a predictive control model that predicts the road traffic conditions ahead and generates an optimal control input for vehicles (Kamal et al., 2012).

While the aforementioned literature used advanced signal information to optimize vehicle trajectories, only a few attempted to optimize the vehicle fuel consumption level. Furthermore, these efforts attempted to minimize vehicle deceleration/acceleration levels, as opposed to explicitly minimizing the fuel consumption level (Xia et al., 2013). In addition, all studies used a linear fuel consumption model to evaluate the alternative control strategies. It should be noted that the use of a linear power model would recommend full throttle accelerations and full braking decelerations to achieve fuel efficiency (also known as bang-bang control). These findings contradict empirical observations. Consequently, the proposed research effort extends the state-of-the-art literature in the following ways: (1) we develop an explicit fuel consumption optimization algorithm; (2) we use a polynomial fuel consumption model to ensure that a non-bang-bang control system is developed; (3) we use a moving horizon DP approach to continuously optimize the vehicle trajectory; and (4) we explicitly consider the vehicle dynamics constraints in the optimization algorithm. Specifically, the proposed DP algorithm uses a path-finding algorithm to select the “least-cost” path by discretizing the solution-space and solving for

the optimum vehicle trajectory. A modified version of the A-star algorithm is developed and used to enhance the computational efficiency of the algorithm.

Methodology

An ECACC system is a driver-assistance tool that provides advisories regarding the most fuel efficient trajectory to navigate an intersection using SPAT information from I2V communication. A vehicle equipped with the ECACC (test-vehicle) is assumed to have the following capabilities:

- a. Dedicated Short-Range Communication (DSRC) or cellular communication to receive packets of SPAT and auxiliary messages broadcasted using I2V communication. This enables the test vehicle to precisely know the upcoming signal change as well as any information regarding queued vehicles at the intersection stop-line.
- b. Adaptive Cruise Control (ACC) system, which implements the speed recommendations provided by the ECACC controller. Alternatively, we can assume that the driver follows the speed recommendations made by the system using some in-vehicle display system.
- c. Global Positioning System (GPS) to compute its distance from the signalized intersection.
- d. The test vehicle is manually steered by the driver since this paper does not address lateral vehicle movement. Only longitudinal movement is considered and optimized.

The overall ECACC system logic is illustrated in a flowchart in Figure 5.1Figure 5.. The flowchart demonstrates that the ECACC optimization is repeated every Δt to adjust for changes in conditions such as changes in SPaT data (which occurs when pre-emptive and vehicle actuation calls are placed to the controller). The inputs to the system are received through a communication module which can be adapted to the technology being used (such as cellular or DSRC) as well as from the vehicle's on-board units that track the vehicle's velocity and acceleration and a GPS unit that tracks the location of the vehicle. Using these data as well as the basic microscopic models, the ECACC module optimizes the vehicle trajectory in order to minimize the total fuel consumption over a fixed distance of travel. The optimum speed advisory can then be displayed to the driver or to a speed-governance unit.

Figure 5.2 shows that according to a vehicle's time to intersection (TTI) computed from its speed and distance to intersection (DTI), a test-vehicle can be in one of the four scenarios. These are shown in Figure and are explained below:

Scenario 1: As the vehicle receives upcoming signal-change information from the intersection via I2V communication, it determines whether the vehicle will receive a green indication at the stop line if it proceeded at its current speed; if it does, then the optimal course of action is to proceed without any reductions in speed.

Scenario 2: If the Time to Red (TTR) is not sufficient for the vehicle to pass through the intersection during a green signal indication if the vehicle continues at its current speed but is

sufficient if the vehicle accelerates to the maximum allowed speed on the roadway, then the optimal course of action is to accelerate and proceed through the intersection in the current phase. This saves fuel from lost inertia, idling and accelerating back to its desired speed.

Scenario 3: If the TTR is not sufficient for the vehicle to proceed through the intersection and the time-to-green (TTG) to the next phase is large enough that the vehicle has to alter its trajectory, then the optimal course of action is nothing but coming to a complete stop and waiting for the next green indication.

Scenario 4: This is when the TTG is longer than the vehicle's Time to Intersection (TTI) at the current speed. Hence, by reducing the average speed while traveling to the intersection, a delay can be incurred in the vehicle trajectory so that the TTI is sufficient to receive a green indication after clearing any available queues.

Scenario 4 provides most flexibility as far as fuel savings are concerned. While scenarios 1 through 3 are generally easy to optimize, the last scenario requires a simulation/optimization algorithm. This simulation/optimization algorithm must consider constraints imposed by the traffic signal and vehicle dynamics, as follows: (a) temporal constraints based on the signal timings, (b) temporal and spatial constraints based on the queue dissipation times and the travel time to the intersection, (c) speed constraints enforced by speed-limits, and (d) vehicle deceleration/acceleration constraints enforced by the vehicle dynamics. Since these scenarios are defined based on TTI, it is possible to construct similar constraints when phase lengths are short resulting in multiple phases while the vehicle approaches the intersection stop-line. The above problem is a complex optimal control problem with the control variables being the brake pedal input and gas pedal input (throttle) that the driver applies. Deceleration and acceleration can be easily computed using these control variables (or vice-versa) using the vehicle dynamic equations.

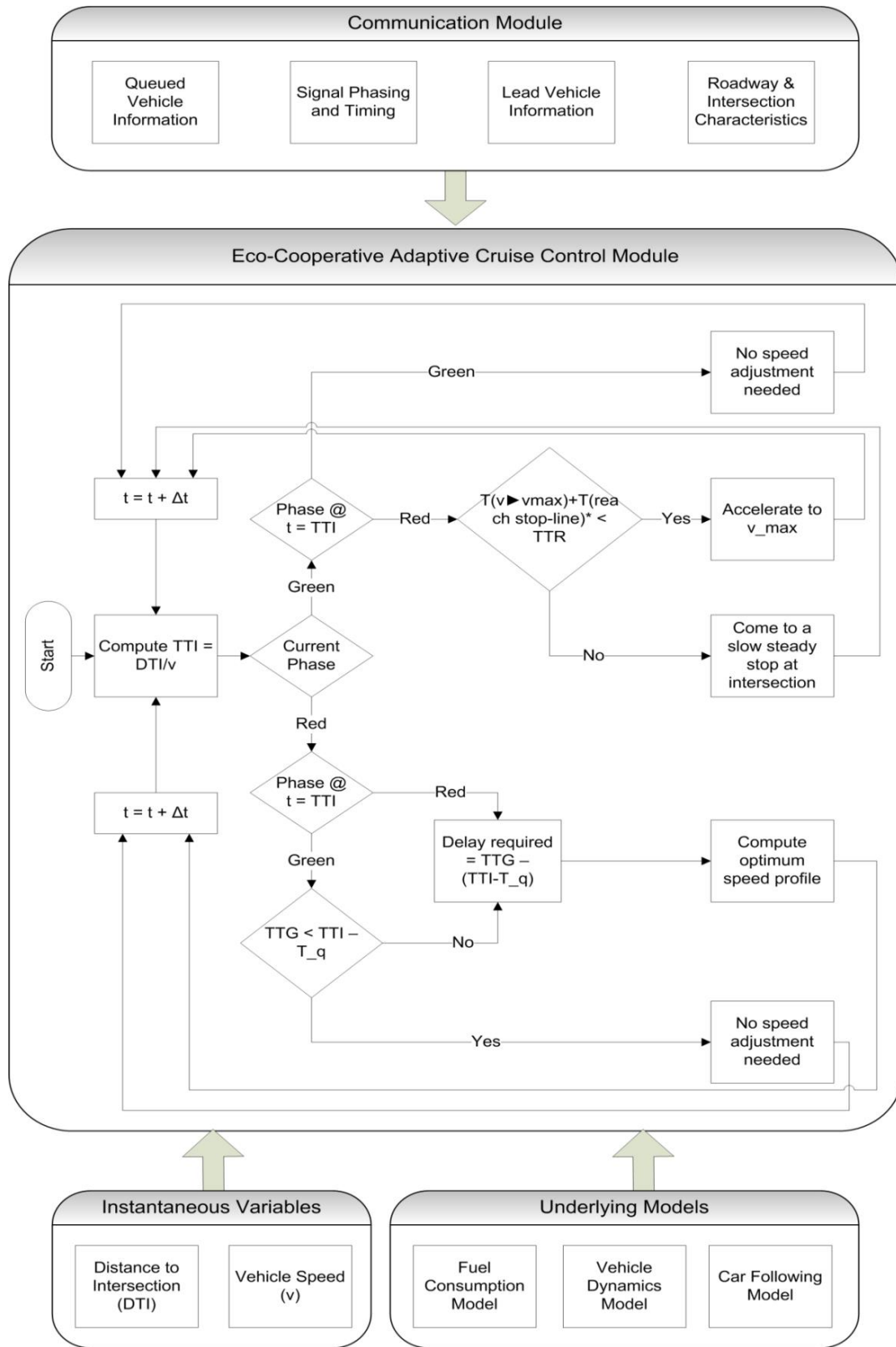


Figure 5.1: Logical Model of ECACC System

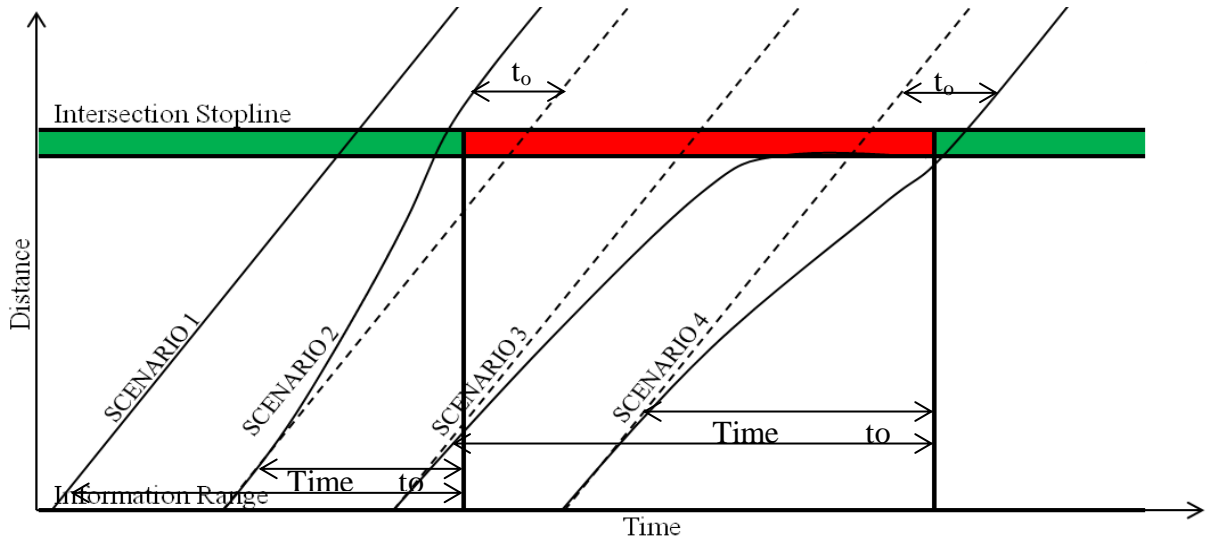


Figure 5.2: Speed profile of vehicles approaching a signalized intersection.

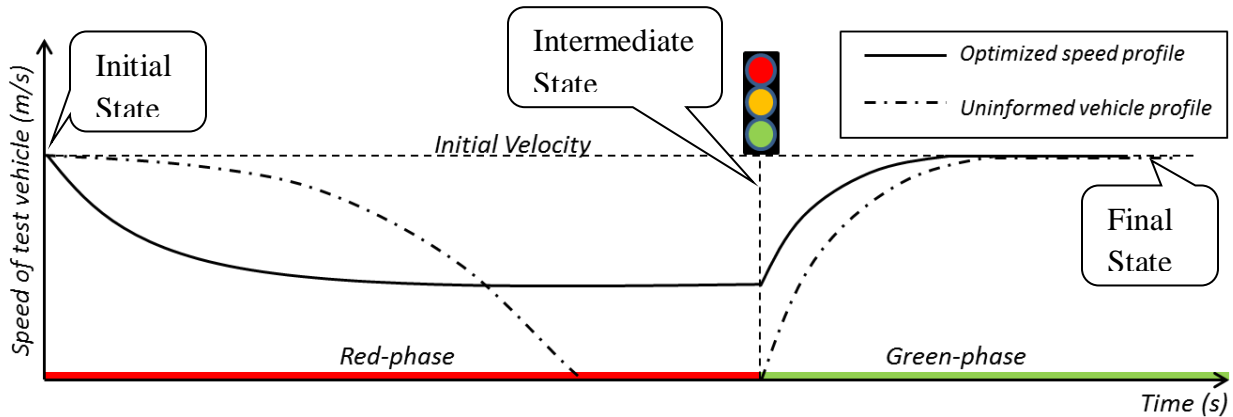


Figure 5.3: Comparison of optimized versus uninformed speed profile in the vicinity of intersection.

In Figure 5.3, two profiles are shown for the same case of a test vehicle approaching a red-signal that will turn green in the near future. A vehicle that is blind to information will come to a stop and idle until the traffic signal changes to green (dash-dotted line). The test-vehicle, however, is informed of an imminent change to green in the near future and thus can modify its speed profile to maintain the same average speed, but travel through the intersection at a higher speed (solid line). In doing so, it will encounter minimal loss of inertia and also reduce the level of acceleration needed to return to its desired speed. Figure also defines the three states of transition for the vehicle – (i) Initial State, (ii) Intermediate State and (iii) Final State.

Problem Formulation

The ECACC system uses optimization to generate a velocity profile for vehicles that correspond to least fuel in navigating through the intersection. The mathematical formulation for the optimal

control problem is stated below and consists of an upstream component and a downstream component:

$$\text{Minimize: } J_u + J_d \quad (1)$$

where $J_u = \int_{t_0}^{t_s} FC(t)dt$ defined as the upstream fuel consumed,

and $J_d = \int_{t_s}^{t_f} FC(t)dt$ defined as the downstream fuel consumed.

where the limits of integration are: t_0 , which is the start time of the optimization (usually, the time the vehicle receives the SPaT information); t_s , which is the predicted time that the vehicle should reach the intersection stop-line to proceed safely during a green indication; and t_f , which is the time that the vehicle accelerates back to its original speed. In order to fix an optimization horizon downstream, we define a downstream distance (x_d) and the vehicle is assumed to cruise to that distance after accelerating back. It should be noted that t_s is computed from the time at which the signal changes to green plus any additional time required to clear queues formed at the intersection during the red indication. This translates the objective function to:

$$\text{Minimize } \int_{t_0}^{t_s} FC_u(t).dt + \int_{t_s}^{t_f} FC_d(t).dt$$

$$\text{where } FC(t) = \begin{cases} \alpha_0 + \alpha_1 P(t) + \alpha_2 P^2(t) & \forall P(t) \geq 0 \\ \alpha_0 & \forall P(t) < 0 \end{cases}$$

where $P(t) = f(v(t))$ (Instantaneous power is a function of instantaneous velocity.)

Subject to:

1. $\int_{t_0}^{t_s} v(t).dt = x_s$ (Distance covered between t_0 and t_s is x_s - distance to intersection).
2. $t_s = t_g + t_q$ (Time t_s = time to green (t_g) plus time to clear any queues (t_q)).
3. $v(t + \Delta t) = v(t) + \frac{F(t) - R(t)}{m} \Delta t$ (Maximum acceleration at any instant is constrained by tractive and resistive forces).
4. $\int_{t_s}^{t_f} v(t).dt = x_d$ (Distance covered downstream is a constant x_d).
5. $v(t) \leq v_{lim} \forall t$ (Speed is within the limit at all times).

The computation equations for the fuel consumption model (Virginia Tech Comprehensive Power-based Fuel Model) including $P(t)$ and the vehicle dynamics model that constrain the maximum acceleration are given in the forthcoming sub-section on underlying models.

Solution Approach

The ECACC system defined in this research uses a recursive path-finding logic in order to optimize the vehicle velocity profile. The overall upstream and downstream fuel consumption is optimized by considering dynamic programming logic to find the least-cost path of transition between three states (shown in Figure):

- *Initial State:* This is when the vehicle receives the SPaT information and the ECACC system elects to incur a delay. The time, speed and location of the vehicle are known for this state.
- *Intermediate State:* This is when the vehicle reaches the stop-line when the traffic signal turns green or the queue is cleared. The time and location of the vehicle at this state are known.
- *Final State:* This is when the vehicle accelerates back to its original speed downstream. The position and speed of the vehicle are known at this state.

Constraints from the optimization problem is used to construct these states defined by their respective times and locations. The optimization using DP principles, considers both upstream and downstream conditions to generate the optimal control strategy. Since dynamic programming is used the solution space is discretized and compared to achieve the most optimal one. The discretization upstream is done by various levels of brake-pedal inputs and downstream is done by various levels of throttle (gas-pedal inputs). Distance conservation constraints (1 and 4) are used to create downstream and upstream profiles corresponding to each discretization. For example, the downstream profile is generated to maintain a fixed average speed defined by the distance-to-intersection (x_s) and time it should reach the stop-line (t_s).

In order to account for errors in driver input, changes in traffic signal timings, and/or latency in communications the ECACC logic is repeated every Δt time-step so that the system adjusts to deviations from the optimum strategy. The DP approach is ideal when a closed-form analytical formulation is not available and when conditions change dynamically. The problem is solved as a least-cost path-finding problem where a vehicle at a specific approach velocity attempts to reach the stop-line considering a fixed average speed and then accelerates back to the same approach speed while consuming minimum fuel. A high level of discretization refines the solution but significantly increases the computational load. Preliminary experimentation with the Dijkstra's path-finding algorithm revealed long computation times (Dijkstra, 1959). Alternatively, use of an A-star path-finding algorithm (Hart et al., 1968) not only resulted in minimum deviation from the Dijkstra formulation, but was significantly computationally faster.

Both Dijkstra's and the A-star path finding algorithms find the least cost path in a step-by-step incremental process. At each time-step, Dijkstra's algorithm computes the most efficient path by searching the entire solution space. The algorithm is computationally slow since it has to evaluate all possible paths. On the other hand, the A-star algorithm uses a "heuristic" or an estimate of the remaining cost at each time step in order to reduce the search space. A unique version of the A-star algorithm was developed in this research effort to solve the optimization problem as will be described in the next subsection. A comparison of the A-star and Dijkstra algorithms revealed multi-fold benefits in computational speed, which is of utmost importance in

this context given that the system is envisioned to run in real-time in a moving horizon framework.

Modified A-star Algorithm

The A-star algorithm is a path-finding algorithm that is similar to Dijkstra’s algorithm except that it uses a heuristic estimate of the cost after each time-step to reduce the solution space. In simple terms, it uses recursive path-finding logic in which the optimum state advances each time-step by selecting the least-cost path for the previous movement plus a heuristic estimate of the future movements. This estimated cost is based on a heuristic that assumes that the driver input remains constant over the entire horizon. In this research effort, a modified version of the A-star algorithm was developed since a temporal/spatial constraint is required at the stop-line. Two simultaneous loops of the A-star algorithm are required to model the upstream and downstream components as shown in Figure 5.4.

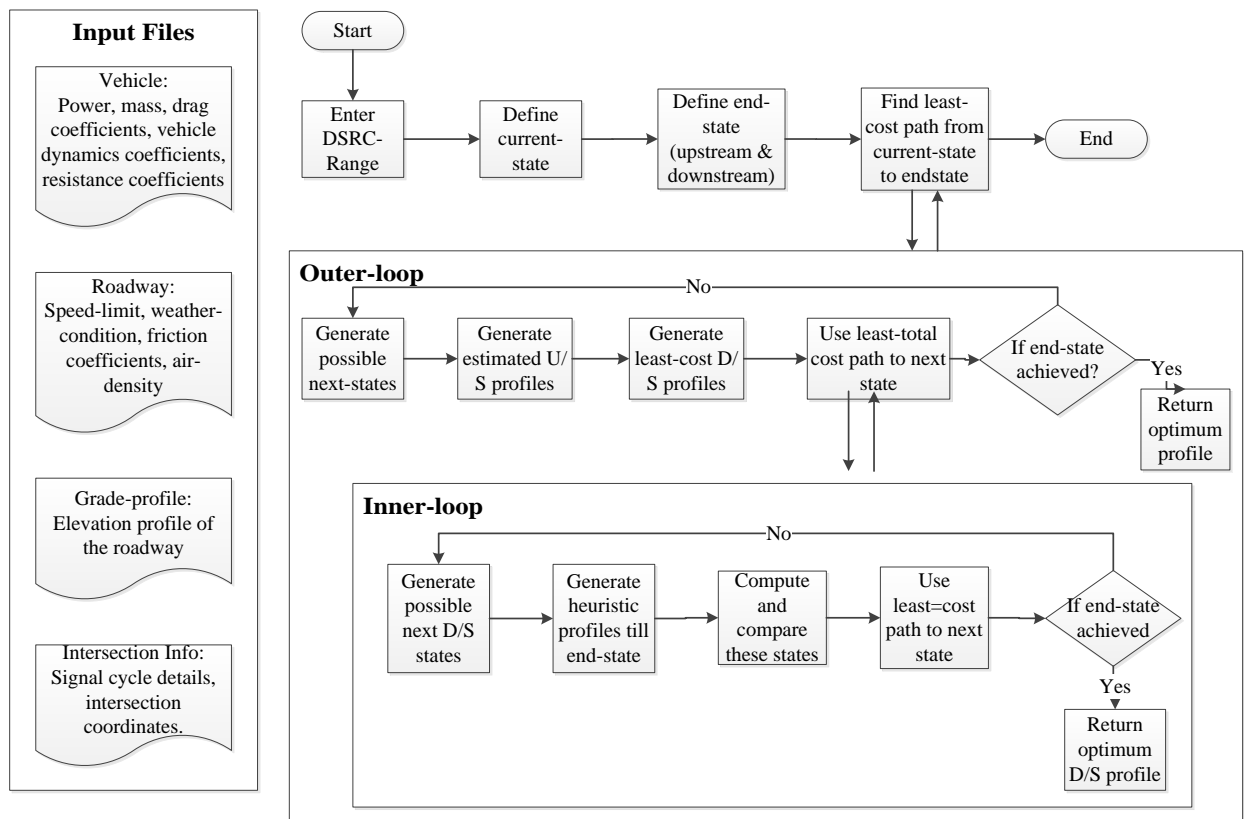


Figure 5.4: Modified A-star Optimization Logic used in ECACC

The pseudo-code for this problem, depicted in Figure, can be cast as follows:

1. Receive SPaT information, DTI, approach speed (v_a), position, and queued vehicle information.
2. Identify the cases where a delay is required in its trajectory.
3. Compute the average speed required to achieve the desired offset $t_d = t_s - \frac{DTI}{v_a}$.

4. Assume $S(0)$ to represent the current state and $S(M)$ and $S(N)$ the intermediate and final states, respectively.
5. Construct a vector of possible next states up to $S(M)$, $S(i)$ and the corresponding fuel consumed to move from $S(0)$ to $S(i)$ is given by $(G(i))$.
6. For each of these $S(i)$'s, compute the estimated fuel $(H(i))$ for transition from $S(i)$ to $S(M)$ assuming the vehicle deceleration level remains constant.
7. Compute the fuel consumed to move from $S(M)$ to $S(N)$
 - 7.1. For each $S(M)$, compute the fuel consumed $(X(j))$ to move from $S(M)$ to $S(M+1)$ for all throttle levels j .
 - 7.2. For each $S(M+1)$, estimate the fuel consumed $(Y(j))$ required to continue from $S(M+1)$ to $S(N)$ at the same throttle level j .
 - 7.3. Select the throttle level corresponding to the least fuel consumption downstream (min $Z(j) = X(j)+Y(j)$).
8. Select the next state based on the minimum total fuel consumed $F(i) = G(i)+H(i)+Z(j)$.
9. Repeat 5 through 8 each time step until state $S(M)$ is reached.
10. Run 7 each time step until state $S(N)$ is reached.

The use of the A-star algorithm results in fast and efficient computations. Specifically, the solution can be derived in less than a second depending on the discretization level and approach speed. All complex microscopic models can be easily integrated in the logic without compromising the computational time, while achieving a good solution. For illustration purposes, the algorithm is tested on a 2011 Honda Accord accelerating from a stop to a speed of 75 km/h. We have considered only the acceleration portion of the maneuver so as to demonstrate the logic on a simple scenario. The optimized throttle is shown in Figure 5.5. Table 5.1 provides the fuel consumed by the vehicle while accelerating and cruising at the final speed in order to cover the same distance at various throttle levels. As shown, the largest or least throttle input does not provide the optimum solution to the problem as previous literature suggests; instead the optimum solution is somewhere in between both levels. While this example demonstrates how the A-star algorithm can compute the optimum vehicle trajectory, the modified A-star algorithm defined previously, extends the logic by considering the various constraints imposed on the vehicle trajectory.

Table 5.1: Fuel Consumed for Acceleration Using Optimum Throttle Versus Low or High Throttles.

Throttle	Acceleration Fuel (l)	Acceleration Distance (m)	Cruising Distance (m)	Cruising Fuel (l)	Total Fuel (ml)
0.25	0.0101	161.15	0.00	0.0000	10.0915
0.50	0.0066	82.56	78.59	0.0033	9.9372
0.75	0.0057	60.61	100.54	0.0043	9.9693
1.00	0.0055	55.03	106.12	0.0045	10.0062
Optimized	0.0061	71.08	90.07	0.0038	9.9247

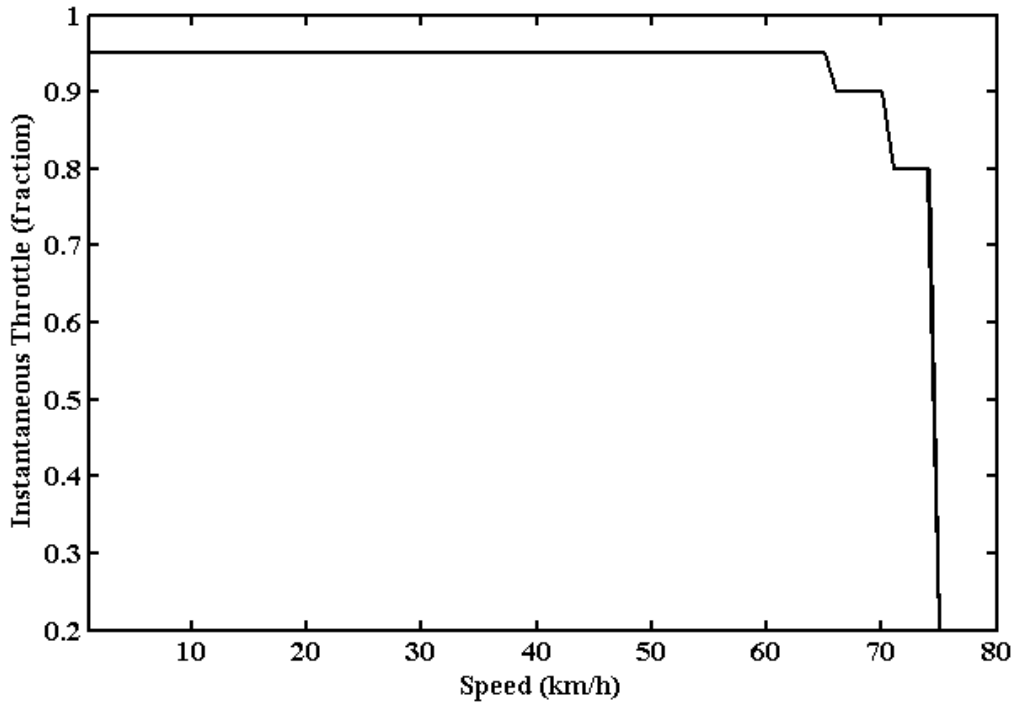


Figure 5.5: Optimized throttle profile for accelerating from 0 to 75 km/h

Underlying Models

The equations provided in the previous sections may appear simple; however, the problem is complex because of the various temporal, spatial, and vehicle dynamics constraints imposed on the solution. Specifically, the model must explicitly capture of the various forces acting on the vehicle to capture its longitudinal motion in addition it must apply a nonlinear fuel consumption model to estimate the fuel consumption. In addition the vehicle trajectory is subject to a number of temporal and spatial constraints. The simulation component of the proposed algorithm is composed of two building blocks, namely: a vehicle dynamics model and a vehicle fuel consumption model. These two models are described are briefly described in this section. The queue-dissipation time can be computed as in (Kamalanathsharma & Hancock, 2012) using state-of-the-art queuing models such as (Marshall & Berg, 1997).

Vehicle Dynamics Model

The estimation of mode-specific fuel consumption and emission levels entails modeling the vehicle deceleration, cruising, idling, and acceleration modes of operation. In modeling vehicle decelerations, we assume a constant deceleration level for the entire maneuver which could be easily replicated by any braking system or even by a human driver. However, modeling vehicle accelerations involves use of a vehicle dynamics model (Rakha et al., 2004). Vehicle dynamics models compute the maximum vehicle acceleration levels from the resultant forces acting on a vehicle (mainly vehicle tractive force that is a function of the engine throttle input and the

various resistance forces). The equations for the tractive and resistive forces acting on a vehicle are given below:

$$F(t) = \min \left(3600 f_p \beta \eta_d \frac{P(t)}{v(t)}, m_{ta} g \mu \right) \quad (2)$$

$$R(t) = \frac{\rho}{25.91} C_d C_h A_f v^2(t) + m g \frac{C_{r0}}{1000} (C_{r1} v(t) + C_{r2}) + m g G(t) \quad (3)$$

Equation 2 computes the vehicle tractive effort F at a given velocity v (in m/s). Rakha and Lucic introduced the β factor in order to account for the gearshift impacts at low traveling speeds when trucks are accelerating. This factor is set to 1.0 for light duty vehicles. The f_p factor models the driver throttle input level and ranges from 0.0 to 1.0. Other parameter definitions are: η_d is the driveline efficiency (unitless); $P(t)$ is the vehicle power (kW) at instant t ; m_{ta} is the mass of the vehicle on the tractive axle (kg); g is the gravitational acceleration (9.8067 m/s^2) and μ is the coefficient of road adhesion or the coefficient of friction (unitless).

The sum of the aerodynamic, rolling, and grade resistance forces acting on the vehicle, as demonstrated in Equation 3, forms the vehicle resistive forces. The parameter definitions for this equation are: ρ is the air density at sea level and a temperature of 15°C (1.2256 kg/m^3); C_d is the vehicle drag coefficient (unitless), typically 0.30; C_h is the altitude correction factor (unitless); A_f is the vehicle frontal area (m^2); C_{r0} is rolling resistance constant (unitless); C_{r1} is the rolling resistance constant (h/km); C_{r2} is the rolling resistance constant (unitless); m is the total vehicle mass (kg); and $G(t)$ is the roadway grade at instant t (unitless). The vehicle acceleration is calculated as the ratio of the difference between tractive and resistance forces and the vehicle mass (i.e., $a = (F - R)/m$). The vehicle speed at $t + \Delta t$ is then computed using Euler's first order approximation as:

$$v(t + \Delta t) = v(t) + 3.6 \frac{F(t) - R(t)}{m} \Delta t \quad (4)$$

Fuel Consumption Model

The proposed simulation/optimization algorithm uses a microscopic fuel consumption model to compute the instantaneous fuel consumption level. The total fuel consumed is then computed as the summation of the fuel consumed each time step. The Virginia Tech Comprehensive Power-based Fuel Model, Type 1 (VT-CPFM-1) is used in this particular research because of its simplicity, accuracy, and ease of calibration (Rakha et al., 2011). This fuel consumption model utilizes instantaneous power as an input variable and can be calibrated using publicly available fuel economy data (i.e., EPA published city and highway fuel ratings). Thus, the calibration of model parameters does not require gathering any vehicle-specific data. A detailed description of the model and the calibration process is beyond the scope of this paper but can be found in the literature (Rakha et al., 2011).

The fuel consumption model is formulated as follows:

$$FC(t) = \begin{cases} \alpha_0 + \alpha_1 P(t) + \alpha_2 P(t) & \forall P(t) \geq 0 \\ \alpha_0 & \forall P(t) < 0 \end{cases} \quad (5)$$

where α_0 , α_1 and α_2 are the model parameters that can be calibrated for a particular vehicle and $P(t)$ is the instantaneous total power in kilowatts (kW). The power exerted at any instant t is computed as:

$$P(t) = \left(\frac{R(t) + 1.04ma(t)}{3600\eta_d} \right) v(t) \quad (6)$$

where m is the vehicle mass, $a(t)$ is the acceleration at instant t , η_d is the driveline efficiency, $v(t)$ is the velocity at instant t and $R(t)$ is the resistance force on the vehicle given by Equation 3.

The parameters α_0 , α_1 and α_2 in equation (5) can be calibrated using the following equations:

$$\alpha_0 = \max \left(\frac{P_{mfo} \omega_{idle} d}{22164 \times QN}, \frac{\left(F_{city} - F_{hwy} \frac{P_{city}}{P_{hwy}} \right) - \varepsilon \left(P_{city}^2 - P_{hwy}^2 \frac{P_{city}}{P_{hwy}} \right)}{\left(T_{city} - T_{hwy} \frac{P_{city}}{P_{hwy}} \right)} \right) \quad (7)$$

$$\alpha_1 = \frac{F_{hwy} - T_{hwy} \alpha_0 - P_{hwy}^2 \alpha_2}{P_{hwy}} \quad (8)$$

$$\alpha_2 = \frac{\left(F_{city} - F_{hwy} \frac{P_{city}}{P_{hwy}} \right) - \left(T_{city} - T_{hwy} \frac{P_{city}}{P_{hwy}} \right) \alpha_0}{\left(P_{city}^2 - P_{hwy}^2 \frac{P_{city}}{P_{hwy}} \right)} \geq \varepsilon = 1E - 06 \quad (9)$$

where P_{mfo} is idling fuel mean pressure (400,000 Pa), ω_{idle} is idling engine speed (rpm), d is engine displacement (liters), Q is fuel lower heating value (43,000,000 J/kg for gasoline fuel), and N is the number of engine cylinders. Estimation of the model coefficients (α_1 , α_2) uses the fuel consumption rates of the standard fuel economy cycles (i.e., EPA published city and highway mileage). Here F_{city} and F_{hwy} are the total fuel consumed for the U.S. Environmental Protection Agency (EPA) city and highway driving cycles, respectively. The value of F_{city} is adjusted to represent the engine transient operation, since the EPA city cycle includes the cold start operation in the Bag 1 of Federal Test Procedure (FTP). T_{city} and T_{hwy} are the durations of the city and highway cycles (1875s and 766s). In addition, P_{city} and P_{city}^2 represent the total power used and total sum of the squared power during the city driving cycle, expressed as $\sum_{t=0}^{T_{city}} P(t)$ and $\sum_{t=0}^{T_{city}} P(t)^2$ respectively. Similarly, P_{hwy} and P_{hwy}^2 are estimated for the highway cycle. It should be noted that the researchers have developed a MATLAB tool, which is freely available, that calibrates the model parameters using this procedure.

The model uses a second-order power term in order to ensure that the control problem does not result in a bang-bang control system where the optimal control strategy is to decelerate at maximum braking, idle, and accelerate at full throttle. Further details on this model as well as computation equations is available in the literature (Rakha et al., 2011). The suitability of this model in real-time ITS applications is also studied by (Saerens et al., 2013).

Analysis

The effectiveness of the proposed system was tested by running 2100 agent-based simulations in a MATLAB environment. The combination of controller-agents, ECACC-agents and driver-agents were used specifically so that they act independently, while also interact with each other. Use of microscopic models to define vehicle movement and interactions ensures the simulation generates comparable results to commercial simulation tools. The communication between the agents was forced to follow the Connected Vehicles (CV) standards being set by the Society of Automotive Engineers (SAE) J2735 messages, which is currently not defined in any of the state-of-the-art simulation tools (SAE, 2010). A total of 30 different calibrated vehicles that correspond to the 5 top-sold vehicles of 6 different EPA categories (compact cars, mid-size cars, full-size cars, sport utility vehicles, mini passenger vans and light-duty trucks) were used (NADA, 2011). The DSRC communication range was assumed to be 200 m as recommended by the SAE (SAE, 2010). The 2100 simulation runs included a total of 5 vehicle offset times (2, 4, 6, 8 and 10 s) and 7 different approach speeds (30, 40, 50... 90 km/h). The time to green values were computed prior to simulations based on approach speeds and distances to the intersection.

The various vehicle parameters that are required to calibrate the vehicle dynamics and fuel-consumption models were found through an extensive search of manufacturer websites and catalogs of the identified vehicles. These parameters (both generic and calibrated) are summarized in an appendix to the paper. It should be noted that since the sales data for 2011 were considered, the vehicle parameters pertain to 2011 base models of all vehicles. The VT-CPFM MATLAB calibration tool was used to generate the model coefficients. EPA uses combined passenger and cargo volumes for passenger car categorization and the Gross Vehicle Weight Rating (GVWR) for other vehicle types. These values were used to create vehicle models that replicate the acceleration/deceleration characteristics of typical vehicles for simulation purposes. Calibrated fuel-consumption models were used, both in generating the optimized speed profile and also in comparing the measures of effectiveness between the base case and the test case.

The base case simulation involved simulating a vehicle that is uninformed of the traffic signal change (i.e. has no communication with the controller and thus does not receive SPaT information). The microscopic behavior of this vehicle was programmed using ITE's Traffic Engineering Handbook and AASHTO's recommended deceleration and acceleration values at intersections (AASHTO, 2011; ITE, 2009). Specifically, an average deceleration value of 3 m/s^2 and an average acceleration of 1.1 m/s^2 were used to reflect these guidelines. The test case used the proposed ECACC logic. For these two cases, the fuel-consumption was estimated using the VT-CPFM fuel model and comparisons were made.

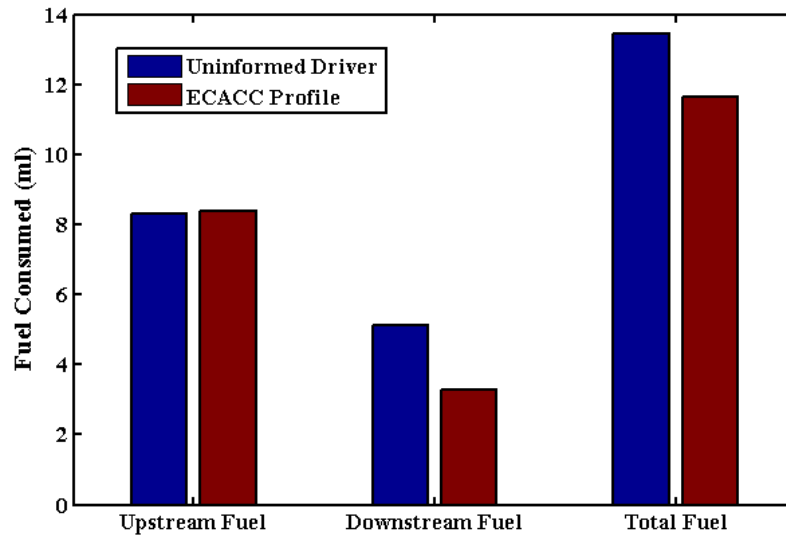


Figure 5.6: Comparison of Fuel Consumed by an uninformed vehicle and a test vehicle for a particular case.

Results and Findings

While previous studies either minimized or maximized acceleration/deceleration levels without explicitly minimizing the fuel consumption level, this study explicitly minimizes the vehicle fuel consumption level. As shown in Table, the optimum profile is not achieved when the throttle input is maximum or minimum, but instead decreases as the vehicle approaches its desired speed. Contrary to what has been reported in the literature, we have to consider both the upstream and downstream profiles in order to optimize the vehicle motion. This is shown in Figure 5.6 which compares the optimum profile generated by the ECACC system versus an uninformed driver who coasts to the stop-line while the signal is red and then accelerates to their original speed.

Figure 5.6 shows the fuel consumed for a 2011 Honda Accord approaching an intersection at 72 km/h (20 m/s). The vehicle receives SPaT information at a distance of 200 meters from the intersection that the signal will turn from red to green in 14 seconds which implies a 4-second delay in its trajectory. Using this data, the vehicle incurs a 4-second delay so as to reach the stop line after 14 seconds and then accelerates back to its original speed downstream of the traffic signal. The blue-bars show the fuel consumed by a vehicle that does not receive SPaT information and the red-bar shows the ECACC vehicles that do receive SPaT information. While the upstream fuel consumption is lower for the uninformed driver (since it involves only coasting), the downstream fuel consumption is significantly higher.

Since the vehicle fuel efficiency varies for different vehicle classes, the major measure of effectiveness used is the relative difference in fuel between the base case and the ECACC test case. Figure 5.7 shows the average fuel savings as a function of different variables, namely: (a) approach speed and (b) the required delay to be incurred to proceed through the intersection. The

dashed line in Figure 5.7 shows the absolute difference in fuel between the test case and base case (labeled on the left y-axis) and the solid line shows the percentage difference in fuel between the test case and the base case (labeled on the right y-axis). Figure 5.7(a) shows that the fuel savings are proportional to the vehicle's approach speed. For example, fuel savings of 5 percent were achieved for approach speeds of 30 km/h whereas fuel savings of 23 percent were achieved when the vehicle approach speed was 90 km/h. A major reason for these fuel savings is associated with the potential to make larger adjustments to the vehicle trajectory at higher speeds. The simulation results also show that the possible fuel savings reduce with increasing vehicle delay times (Figure 5.7b). In other words, if more delay is required in the vehicle's nominal speed profile, the lesser the fuel savings are. This is because a longer delay results in a lower average speed upstream of the intersection and a lower speed from which the vehicle should accelerate back to its original speed. This results in a higher loss of inertia. While a 2-second vehicle delay yielded an average benefit of 17.5% fuel savings, a 10-second delay only yielded 13.3% fuel savings within the vicinity of intersections.

Figure 5.7 also shows the absolute values of fuel saved in the vicinity of an intersection. Even though these values look small when a single intersection is considered, the average miles-per-gallon increase for a corridor with closely spaced intersections is found to be over 12.75 percent. Contrary to previous research (Johansson et al., 2003) that indicated that vehicles with larger engines benefit most when such eco-driving principles are used, the simulations show that compact cars benefitted equally to Light-Duty Trucks (LDTs) when they used the ECACC system (Figure 5.8). However, it should be noted that the absolute savings are higher for LDTs. Even though the results characterize the benefits that can be achieved by implementing the ECACC system, these results are only representative of the fuel that can be saved in the vicinity of intersections. This approach could be extended to enhance driving episodes in cities by considering the entire corridor rather than an isolated intersection. Other than at signalized intersections, the results from these simulation studies provide valuable information on the most-fuel efficient acceleration maneuver which could be used in any driving condition.

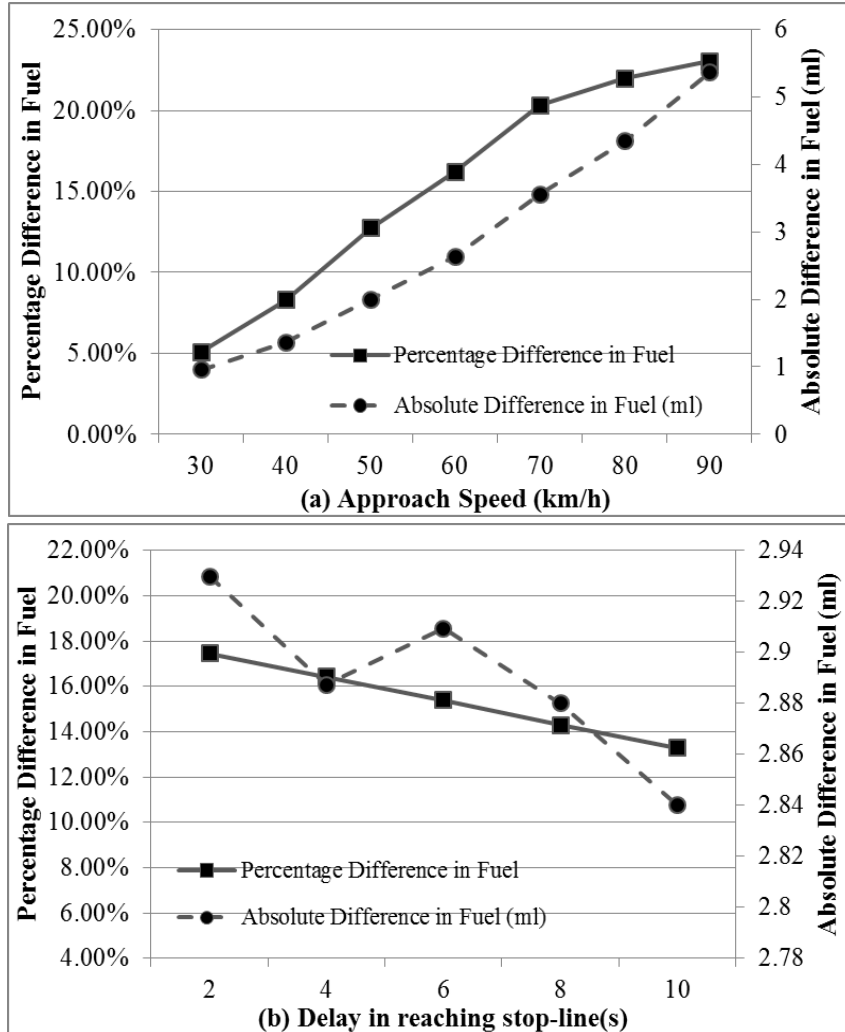


Figure 5.7: Categorized average fuel savings between the test-cases and base-cases.

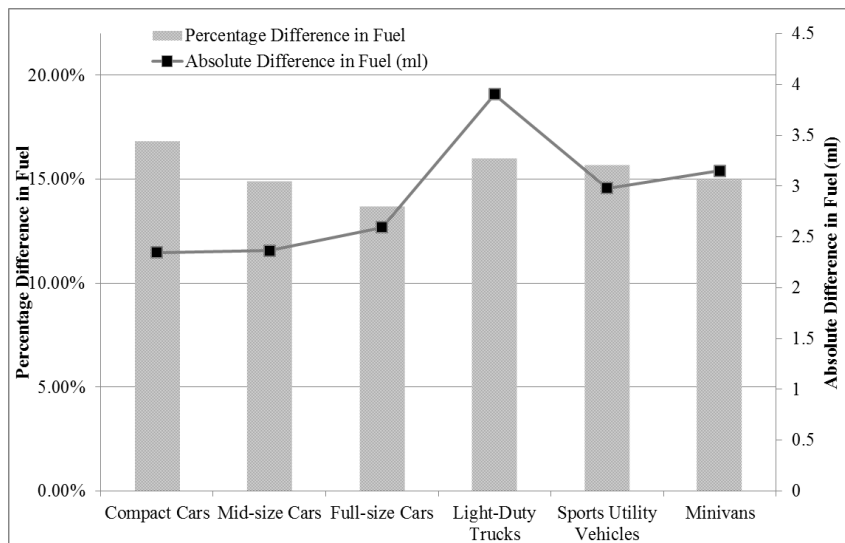


Figure 5.8: Percentage Savings in Fuel Averaged Across EPA Categories

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6. Agent-based Modeling of Eco-Speed Control at Signalized Intersections

(R.K. Kamalanathsharma, H.A. Rakha, "*Agent-based Simulation of Eco-Speed Controlled Vehicles at Signalized Intersections*," (in-press) Transportation Research Record: Journal of the Transportation Research Board)

Agent-based Simulation of Eco-Speed Controlled Vehicles at Signalized Intersections

Raj Kishore Kamalanathsharma and Hesham Rakha

Eco-Speed Control systems attempt to reduce vehicle fuel consumption levels by optimizing vehicle trajectories in the vicinity of signalized intersections while accounting for traffic signal timing constraints. The proposed algorithm uses dynamic programming to compute the minimum-fuel vehicle trajectory required to navigate through the intersection subject to several constraints, including: vehicular interactions, traffic signal timing changes and vehicle/roadway constraints. The proposed application uses infrastructure-to-vehicle and vehicle-to-vehicle communication to receive traffic signal and vehicle data. The research presented in the paper develops an agent-based modeling tool to simulate and test the system under varying traffic volume and market penetration levels. The simulation model uses a variety of microscopic inputs such as the roadway vertical profile, roadway surface condition, traffic volumes, and traffic signal timing information. The system was tested on a sample signalized intersection producing fuel consumption reductions of 30 percent and travel speed increases of 200 percent on average within the vicinity of the intersection. Actual savings in total trip time, average speed and fuel consumed will depend on the trip profile including the number of intersections, and total trip length.

Introduction

With the introduction of Connected Vehicles (CVs) and Vehicle Infrastructure Integration (VII) initiatives worldwide, vehicles and infrastructure will be able to communicate and share important data. Vehicles can broadcast their speed, heading, acceleration and other information using Basic Safety Messages (BSMs) and signalized intersections can broadcast information about upcoming traffic signal timing changes and intersection geometry information using SPaT (Signal Phasing and Timing) and MapDATA messages [1]. While the primary focus of vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication is traffic safety as is the case with red-light running prevention and intersection collision warning systems, they can also be leveraged to make advanced eco-driving possible. The messages broadcast by the infrastructure and vehicles provide valuable eco-driving information as to when vehicles will have to stop and when they may proceed, thereby allowing for the construction of vehicle trajectories that minimize their fuel consumption level using advanced computation.

The eco-speed control logic being tested in this paper optimizes vehicle trajectories using information broadcast through V2V and I2V communication to predict what the upcoming signal status will be and what other constraints affect the vehicle trajectory and then optimize the vehicle movement to minimize its fuel consumption level. Unlike earlier eco-driving models that

used SPaT information, the algorithm tested in this paper uses an explicit fuel-consumption based objective function to generate the most fuel-efficient vehicle trajectory. The eco-speed control logic optimizes a vehicle's trajectory using a dynamic programming approach subject to a set of constraints such as upcoming traffic signal timing constraints, vehicle acceleration and deceleration limitations and the location and speed of lead vehicles. Preliminary analysis of this approach stated benefits averaging 15 percent in terms of fuel savings, however, these tests were done using a single vehicle (or a platoon of vehicles) approaching an intersection with assumed characteristics [2].

The simulation tool developed in this paper uses agent-based modeling to model vehicles as reactive agents that compute and implement their own desired trajectory by receiving inputs from other agents including surrounding vehicles and the intersection controller. The ability to model actual roadway volumes, intersection geometry and grade makes it possible to use the tool to analyze a real intersection using real intersection timings and geometry. The simulation tool also uses calibrated microscopic parameters of real-world vehicles as well as microscopic longitudinal motion models to capture vehicle interactions. Two measures of effectiveness are studied in this paper, including point-to-point fuel consumption savings and the changes in the vehicle's average speed. This study in particular deals with the simulation of an intersection in Blacksburg and considers intersection-specific geometric details including the grade-profile as well as signal timings and approach volumes.

As far as the layout of the paper is concerned, the following section provides an overview of the eco-speed control algorithm and compares it with other models in the literature. This section also describes the microscopic models used in the agent-based simulator. This is followed by a description of how the agent-based simulator is established using models that define important traffic flow parameters along with setting inputs and obtaining outputs from the simulation tool. Lastly, the paper presents a discussion of the results and findings from a real-intersection simulation from Blacksburg, VA for varying volumes followed by a summary of the conclusions of the study.

Background

Many intersections in the United States are being retrofitted with radio devices that can establish communication between the vehicles and the traffic signal controller as part of the Connected Vehicles initiative. These devices use Dedicated Short Range Communication (DSRC) to broadcast important messages wirelessly [3]. Among these messages is the SPaT message broadcasted by the intersection controller. This message provides information on when the current signal phase will end [3]. This information was designed to prevent road-users from red-light running and other collision course scenarios. Alternatively, the MapDATA message set communicates the intersection geometry to equipped vehicles [3]. The Basic Safety Message (BSM) is another message broadcasted by equipped vehicles. This message includes the speed,

acceleration, heading, length, width, and location of the vehicle [3]. This message, also known as the heartbeat message is designed to enhance roadway safety by improving situational awareness of vehicles.

Recently, researchers started investigating the benefits of using these message sets, particularly the SPaT messages, to predict signal changes and devise a system that computes the vehicle's fuel-optimum trajectory. For example, Asadi and Vahidi developed a cruise control system that used constrained optimization to minimize the probability of reaching the stop-line during a red indication by varying the vehicle speed within a user-specified interval [4]. Malakorn and Park developed an IntelliDrive-based Cooperative Adaptive Cruise Control system with the objective function to minimize the distance traveled while decelerating, accelerating as well as idling time when Traffic Signal Status (TSS) information is available [5]. Mandava et al. developed an arterial velocity planning algorithm which used minimized deceleration and acceleration levels to compute an "optimized" vehicle trajectory at an intersection [6]. In a recent study by Xia et al, the proposed dynamic eco-driving system for signalized arterial corridors used a binary decision based advisory system that minimizes the acceleration and deceleration at an intersection and assumes this strategy saves fuel [7].

In summary, all studies reported in the literature used simplified objective functions rather than optimizing the actual fuel usage at an intersection because instantaneous fuel consumption models are non-linear making the problem computationally complex and hard to solve. The eco-speed control algorithm presented in this paper, however, uses optimization techniques that are based on dynamic programming to explicitly minimize the vehicle's fuel consumption level while accounting for car-following, vehicle dynamics, and signal timing constraints. The algorithm specifically discretizes the solution space both in time and space and then uses a moving horizon minimum path-finding algorithm to generate the 'least-fuel-cost' trajectory required to navigate through the intersection for a given set of constraints. This paper specifically builds an agent-based simulation tool to test this proposed eco-speed control logic. This tool uses state-of-the-art longitudinal vehicle motion models including car-following, collision avoidance and vehicle dynamics models to model vehicles navigating through an intersection.

Eco-Speed Control Logic

The eco-speed control algorithm attempts to minimize the vehicle fuel consumption level of vehicles traveling through a signalized intersection by optimizing their trajectories using information communicated via a Connected Vehicles environment, particularly, using V2I/I2V communication to receive upcoming traffic signal changes and V2V communication to receive surrounding vehicle speed and location information. As stated above, the objective of the optimization problem is to minimize the fuel consumed by a vehicle while navigating an intersection. This includes motion of the vehicle both upstream and downstream of the intersection while considering the following constraints:

1. Temporal and Spatial constraints by the signal timings and intersection geometry,
2. Temporal and Spatial constraints based on the queue-dissipation at the intersection stop-line, if any.
3. Speed constraints enforced by speed-limits,
4. Vehicle acceleration and deceleration constraints based on vehicle dynamics equations of motion (such as roadway coefficient of friction, drag coefficient etc.),
5. Collision avoidance constraints to prevent collisions with surrounding vehicles,
6. Steady-state car-following constraints to maintain a safe headway with its lead vehicle.

The optimization logic uses several microscopic models in its constraints as listed above and also uses a power-based fuel consumption model in its objective function. The optimization of the vehicle trajectory occurs between two horizons – upstream and downstream. The upstream horizon starts when a vehicle approaching an intersection receives its first SPaT message about the upcoming signal change and accordingly chooses to accelerate, decelerate or continue at its current speed. This horizon ends when the vehicle passes the stop-line. Alternatively, the downstream horizon starts at the stop-line and extends to a fixed distance downstream of the intersection. The vehicle is assumed to accelerate back to its desired speed over this distance. The proposed mathematical program is presented in Table 6.1. Since the microscopic models used in the constraints as well as the objective function are non-linear, we discretize the solution space and use recursive path-finding principles to find the optimal vehicle trajectory. An A-star path finding algorithm is used to find the optimal solution considering a discretized upstream and downstream solution space using two control variables: deceleration (as a function of the brake-pedal input) and acceleration (as a function of gas-pedal input). The full logic of this mathematical program and the proposed solution algorithm is provided in the literature [8].

The A-star algorithm used in this paper recursively finds the least-cost path until the next time-step by comparing the net fuel consumed for each discretization possible, which is computed as the sum of the estimated fuel consumed over the next time horizon plus a heuristic estimate of the consequential fuel consumed till the end of optimization horizon. Analysis has shown that this approach to path-finding is significantly computationally faster than the Dijkstra's path-finding algorithm [9].

Table 6.1: Proposed Eco-Speed Control Mathematical Program

$$\text{Minimize } \int_{t_0}^{t_s} FC_u(t).dt + \int_{t_s}^{t_f} FC_d(t).dt$$

$$\text{where } FC(t) = \begin{matrix} \alpha_0 + \alpha_1 P(t) + \alpha_2 P^2(t) & \forall P(t) \geq 0 \\ \alpha_0 & \forall P(t) < 0 \end{matrix}$$

where $P(t) = f(v(t))$ (Instantaneous power is a function of instantaneous velocity.)

Subject to:

1. $\int_{t_0}^{t_s} v(t).dt = x_s$ (Distance covered between t_0 and t_s is x_s - distance to intersection).

-
- $\int_{t_s}^{t_f} v(t).dt = x_d$ (Distance covered downstream is a constant x_d).

-
-
2. $t_s = t_g + t_q$ (Time t_s = time to green (t_g) plus time to clear any queues (t_q)).

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-
-
3. $v(t) \leq v_{lim} \forall t$ (Speed is within the limit at all times).

-
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-
4. $v(t + \Delta t) = v(t) + \frac{F(t) - R(t)}{m} \Delta t$ (Maximum acceleration at any instant is constrained by tractive and resistive forces).

-
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-
-
5. $v(t + \Delta t) = \sqrt{v_{lead}(t + \Delta t)^2 + 25920d_{max} \left(\tilde{s}_n(t + \Delta t) - \frac{1}{k_j} \right)}$ (Collision avoidance with maximum permissible deceleration).

-
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-
-
-
-
6. $v(t + \Delta t) = \frac{(-c_1 + c_3 u_f + \tilde{s}_n(t + \Delta t) - \sqrt{A})}{2c_3}$ (Van Aerde's car-following model equation for steady state). where, $A = (c_1 - c_3 u_f - \tilde{s}_n(t + \Delta t))^2 - 4c_3 (\tilde{s}_n(t + \Delta t) u_f - c_1 u_f - c_2)$

where:

- a. t_0 is the start time of the optimization (usually, the time the vehicle receives the SPaT information),
- b. t_s is the predicted time that the vehicle should reach the intersection stop-line to proceed safely,
- c. t_f is the time at the end of optimization horizon and represents the time to navigate a fixed downstream distance x_d .
- d. $FC(t)$ is the instantaneous fuel consumption estimated using instantaneous power $P(t)$ using the Virginia Tech Comprehensive Power-based Fuel Model coefficients α_0, α_1 and α_2 . $P(t)$ is calculated as a function of instantaneous velocity and acceleration.
- e. x_s is the distance to the stop-line at start of optimization (t_0) and x_d is the fixed distance considered downstream (at time t_f).
- f. t_q is the estimated time to clear any queue at the stop-line.
- g. $F(t)$ and $R(t)$ are the instantaneous tractive and resistive forces acting on the test vehicle with mass m .
- h. v_{lead} is the speed of lead vehicle, d_{max} is the maximum acceptable deceleration, $s_n(t + \Delta t)$ is the predicted vehicle spacing at time $(t + \Delta t)$ and k_j is the jam density (veh/km).

- i. c_1 , c_2 and c_3 are calibration constants for the Van Aerde Model, u_f is the free-flow speed (km/h) and u_c is the speed at capacity (km/h).

Underlying Microscopic Models

The proposed simulation/optimization algorithm uses a microscopic fuel consumption model to compute the instantaneous fuel consumption level. The total fuel consumed is then computed as the summation of the fuel consumed over all the time steps. The Virginia Tech Comprehensive Power-based Fuel Model, Type 1 (VT-CPFM-1) is used in this particular research because of its simplicity, accuracy, and ease of calibration [10]. This fuel consumption model utilizes instantaneous power as an input variable and can be calibrated using publicly available fuel economy data (i.e., EPA published city and highway fuel ratings). Thus, the calibration of model parameters does not require gathering in-field or laboratory vehicle-specific data. A detailed description of the model and the calibration process is beyond the scope of this paper but can be found in the literature [10].

The fuel consumption model is formulated as follows:

$$FC(t) = \begin{cases} \alpha_0 + \alpha_1 P(t) + \alpha_2 P(t) & \forall P(t) \geq 0 \\ \alpha_0 & \forall P(t) < 0 \end{cases} \quad (1)$$

where α_0 , α_1 and α_2 are the model parameters that can be calibrated for a particular vehicle and $P(t)$ is the instantaneous total power in kilowatts (kW). The model parameters are calibrated using model-specific EPA estimates for city and highway cycles. The power exerted at any instant t is computed as:

$$P(t) = \left(\frac{R(t) + 1.04ma(t)}{3600\eta_d} \right) v(t) \quad (2)$$

where m is the vehicle mass, $a(t)$ is the acceleration at instant t , η_d is the driveline efficiency, $v(t)$ is the velocity at instant t and $R(t)$ is the resistance force on the vehicle given by:

$$R(t) = \frac{\rho}{25.92} C_D C_h A_f v(t)^2 + 9.8066m \frac{C_r}{1000} (c_1 v(t) + c_2) + 9.8066mG(t) \quad (3)$$

where ρ is the density of air at sea level at a temperature of 15°C, C_D is the vehicle drag coefficient, C_h is a correction factor for altitude and computed as $1 - 0.085H$ (altitude in km), A_f is the vehicle frontal area in m^2 , and C_r , c_1 and c_2 are rolling resistance parameters.

The estimation of mode-specific fuel consumption and emission levels entails modeling the vehicle deceleration, cruising, idling, and acceleration modes of operation. In modeling vehicle decelerations, we assume a constant deceleration level for the entire maneuver which could be easily replicated by any braking system or even by a human driver. However, modeling vehicle accelerations involves use of a vehicle dynamics model [11]. Vehicle dynamics model computes the maximum vehicle acceleration level from the resultant forces acting on a vehicle (mainly

vehicle tractive force that is a function of the engine throttle input and the various resistance forces). The equations for the tractive and resistive forces acting on a vehicle are given below:

$$F(t) = \min \left(3600 f_p \beta \eta_d \frac{P}{v(t)}, m_{ta} g \mu \right) \quad (4)$$

$$R(t) = \frac{\rho}{25.91} C_d C_h A_f v(t)^2 + m g \frac{c_{r0}}{1000} (c_{r1} v(t) + c_{r2}) + m g G(t) \quad (5)$$

Equation 4 computes the vehicle tractive effort F at a given velocity v (in km/h). Rakha and Lucic introduced the β factor in order to account for the gearshift impacts on heavy vehicle behavior while accelerating at low speeds. This factor is set to 1.0 for light duty vehicles. The f_p factor models the driver throttle input level and ranges from 0.0 to 1.0. Other parameter definitions are: η_d which is the driveline efficiency (unitless); P is the maximum vehicle power (kW); m_{ta} is the mass of the vehicle on the tractive axle (kg); g is the gravitational acceleration (9.8067 m/s²) and μ is the coefficient of road adhesion or the coefficient of friction (unitless).

The sum of the aerodynamic, rolling, and grade resistance forces acting on the vehicle, as demonstrated in Equation 5, forms the vehicle resistive forces. The parameter definitions for this equation are: ρ is the air density at sea level and a temperature of 15°C (1.2256 kg/m³); C_d is the vehicle drag coefficient (unitless), typically 0.30; C_h is the altitude correction factor (unitless); A_f is the vehicle frontal area (m²); c_{r0} is rolling resistance constant (unitless); c_{r1} is the rolling resistance constant (h/km); c_{r2} is the rolling resistance constant (unitless); m is the total vehicle mass (kg); and G is the roadway grade at instant t (unitless). The vehicle acceleration is calculated as the ratio of the difference between tractive and resistance forces and the vehicle mass (i.e., $a = (F - R)/m$).

The vehicle speed at $t + \Delta t$ is then computed using Euler's first order approximation as:

$$v(t + \Delta t) = v(t) + 3.6 \frac{F(t) - R(t)}{m} \Delta t \quad (6)$$

Agent-Based Simulation Tool

The simulation tool developed in this paper is based on agent-based modeling principles. The model was built to test the proposed eco-speed control algorithm using two major measures of effectiveness. Agent-based modeling was used since the vehicles were simulated to run independently in response to external stimulants using underlying algorithms. Particularly, the vehicles followed fuel-optimum trajectory generated using information received from the traffic signal controller and other vehicles. This vehicle trajectory generation used two separate principles for the two simulation cases. The base case used an algorithm which performs a non-eco-speed control longitudinal motion modeling and is based on an underlying longitudinal model that includes a steady-state car-following model, a collision avoidance model and a vehicle dynamics model. The test case used the proposed eco-speed control logic which generates a fuel-efficient vehicle trajectory for the given sets of constraints.

The simulation components include both active and reactive agents – active agents act independently on a preset mode and the reactive agents react to external stimulants. The following components make up the simulation tool in this research:

1. **Vehicle Generation:** This module generates vehicle arrivals to the intersection by reading approach volumes defined in a volume file. The arrivals are generated following a uniform distribution for the arrival times for the given approach volumes. Vehicles are assigned a random speed that is uniformly distributed between 0.7 to 1.0 times the roadway speed-limit which is the commonly observed spot-speed on similar roadways [12]. Each vehicle is randomly picked from a pool of calibrated vehicles and then post processed to ensure that vehicles follow a safe headway at the time of their generation. Vehicles are generated at a distance of 200 meters from the intersection. This is selected because this is the typical range of DSRC devices.
2. **Pool of calibrated vehicles:** Thirty top-sold vehicles in the United States for the 2011 base model are calibrated for the microscopic traffic models used in this research including their mass, drag coefficient, frontal area, fuel-consumption coefficients etc. These vehicles form six EPA categories including compact, mid-size, full-size, sports utility, mini-passenger vans and light-duty trucks.
3. **Simulation Engine:** This is the main simulator module that performs the agent-based simulations using two agents – the traffic signal controller and the vehicle agents. This module uses either of ECS module or the NECS module (defined separately) to generate the vehicle trajectories based on traffic control models.
 - a. **Signal Controller Agent:** This active agent reads information from a signal file and generates signal phases according to a preset cycle. The signal controller also generates SPaT information to be received by oncoming vehicle agents.
 - b. **Vehicle Agents:** These reactive agents use external stimulants and microscopic traffic models to model their longitudinal motion. Since these external factors change, the trajectory is updated every time-step. As mentioned before, the vehicles use SPaT information and works on eco-speed control logic for the test case. Each vehicle agent is associated with its calibrated parameters including vehicle dynamics and fuel consumption coefficients.
4. **NESC Module:** This module is used during the base-case simulation run in which vehicles do not use advanced signal information as a constraint in generating their trajectories. It generates the vehicle trajectory in response to the lead-vehicle's speed and headway and the current signal status. The NESC (Non Eco-Speed Control) trajectory uses Traffic Engineering Handbook's average deceleration and acceleration values at an intersection stop-light of 3 m/s^2 and 1.1 m/s^2 , respectively for instances where traffic signals change.
5. **ESC Module:** This module generates the vehicle trajectories for the test-case using the aforementioned Eco-Speed Control logic. The system uses SPaT information from the traffic signal controller in conjunction with other traffic flow models such as car-

following and collision avoidance to generate a fuel-efficient velocity profile for the vehicles.

6. **Underlying Models:** This includes a microscopic fuel consumption model entitled VT-CPFM, the Rakha-Pasumarthy-Adjerid (RPA) vehicle longitudinal model [13] that includes a vehicle dynamics model for constraining vehicle accelerations, the Van Aerde steady-state car-following model and a collision avoidance model as described previously. It should be noted that the RPA model is currently implemented in the INTEGRATION software [14, 15].

Figure 6.1 shows a logical diagram that defines the agent-based simulation tool used in this research using the above components. The tool aggregates simulation results that are processed to compare the two measures of effectiveness segregated, based on their approach direction. The roadway grade and other frictional characteristics are defined in the Roadway Characteristic File and are used in the traffic flow models.

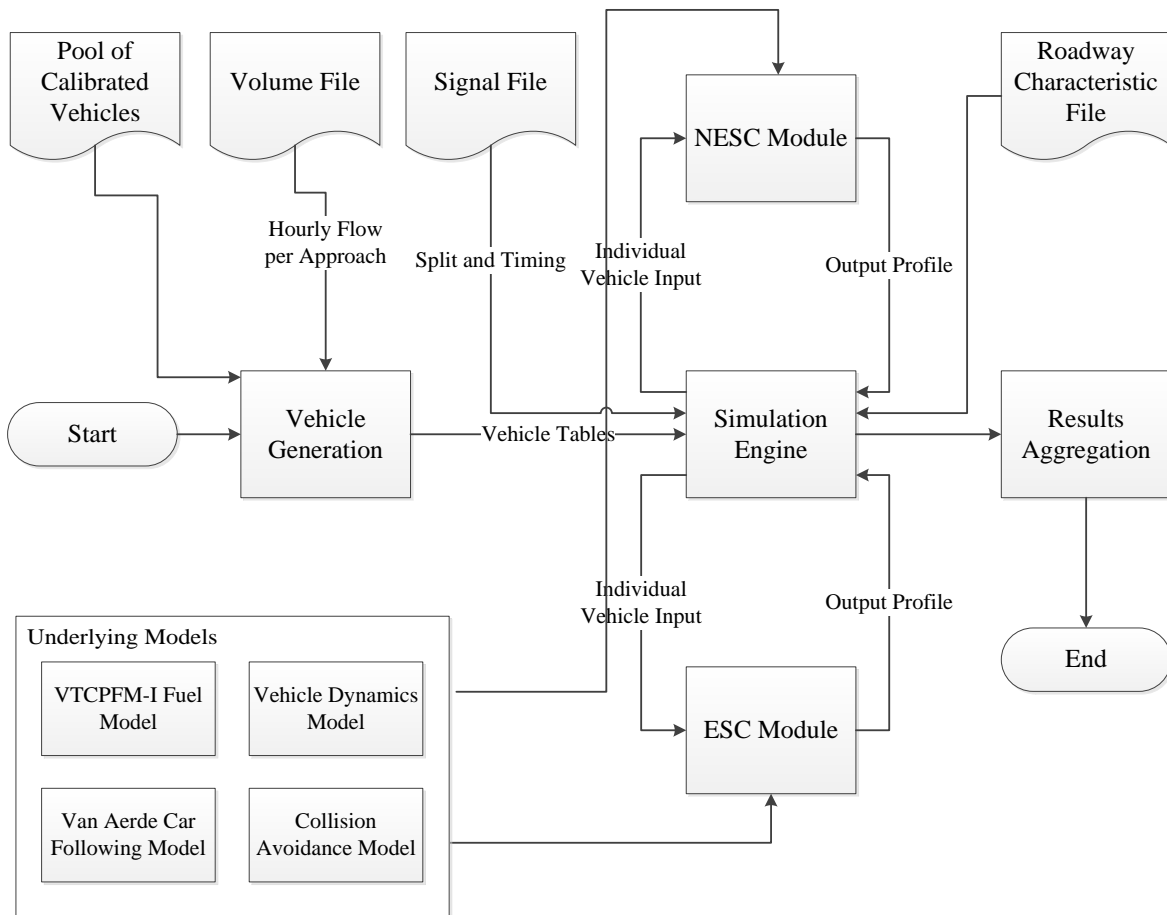


Figure 6.1: Agent-based Simulation Logic

The agent-based simulation tool presented here was used to measure the effectiveness of the proposed eco-speed control strategy since state-of-the-art simulation software cannot directly model the Connected Vehicle standards set forth by the Society of Automotive Engineers. This

particular simulation tool uses the SAE J2735 framework for communicating BSM and SPaT messages between the signal controller and vehicle agents [16]. Other traffic flow models used in this simulation tool are identical to those used in the INTEGRATION software [17]. This makes the tool reliable when used in conjunction with calibrated vehicle and roadway models. The tool, however, has the following shortcomings:

1. The vehicles follow the generated trajectory perfectly by assuming use of electronic throttle controls or driving agents with zero perception and reaction times.
2. Lateral displacement is not considered in this tool and assumes perfect steering by the driving agent.
3. Currently the model does not simulate lane-changing behavior and hence can only be used single lane approaches.
4. The dynamic programming framework uses the empirical Marshall and Berg [18] equations to compute the queue dissipation times.
5. Roadway weather conditions are captured by altering the roadway friction and rolling resistance coefficients. The model does not consider visual and other human-related factors in modeling weather impacts on driver behavior.

Simulation Case Study

In order to analyze the effectiveness of the eco-speed control strategy on the two measures of effectiveness, a real intersection was simulated using the proposed tool. The intersection of South Main Street and Washington Street in downtown Blacksburg (Virginia) was simulated. This intersection is shown in Figure 6.2 and some of the features are highlighted below:

1. South Main Street is US 460 Business and carries the major traffic direction.
2. Washington Street connects Virginia Tech campus on the west side to residential areas on the east side.
3. All approaches are single lane and hence lane-change behavior need not be considered.
4. Left turns have dedicated lanes on all the approaches.
5. All approaches are on a grade and the proposed simulation tool uses the actual grade function of the roadway.
6. Speed limit on all approaches is 25 miles per hour.
7. Traffic signal timing data and approach volumes are made available by the Town of Blacksburg.

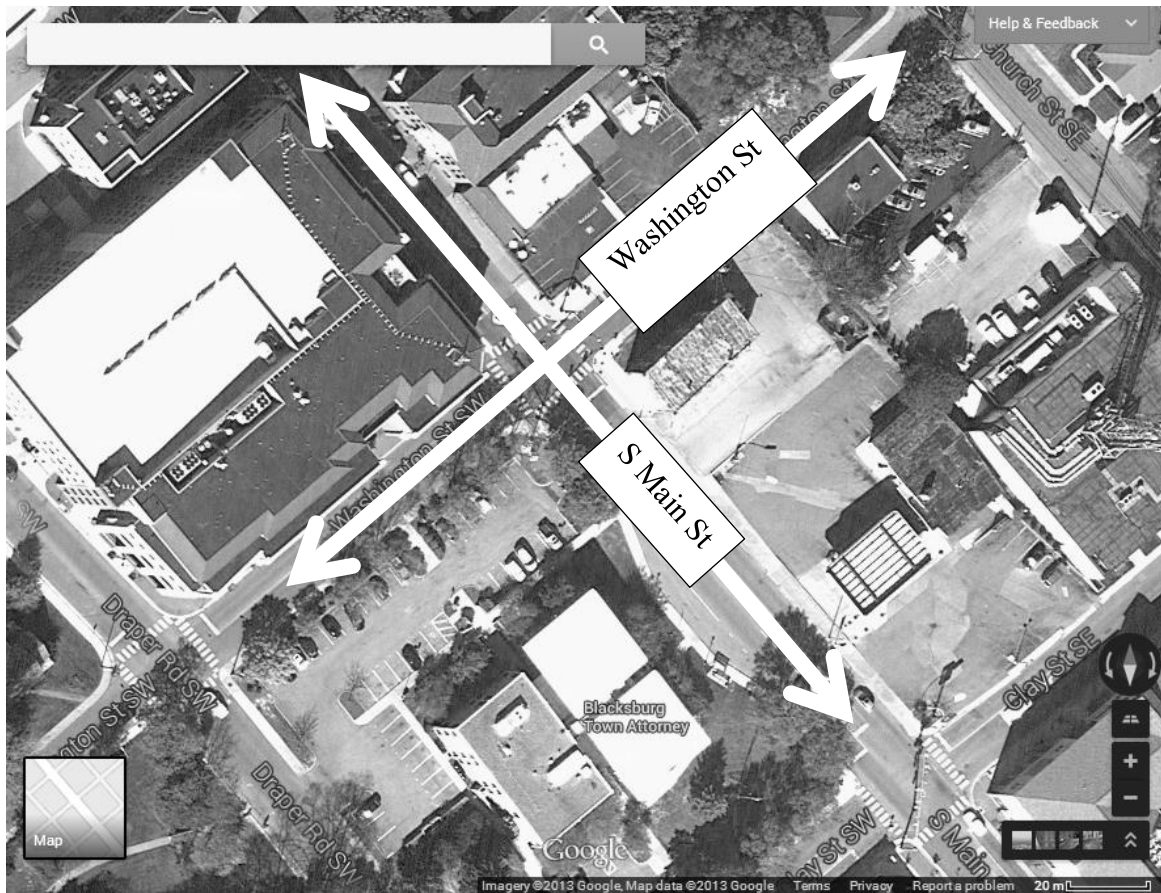


Figure 6.2 - Google Maps image showing the test-intersection in Blacksburg, VA

Model Calibration

The agent-based model described in this paper uses several vehicle-specific traffic-flow models that define the microscopic behavior of vehicles. The calibration of these models entailed three calibration efforts, as follows:

1. The calibration of the Van-Aerde's steady-state car-following model entailed calibrating four parameters, namely: the free-flow speed, the speed-at-capacity, the saturation flow rate, and the jam density.
2. Calibration of the vehicle dynamics model was done using the vehicle-specific parameters such as mass, drag coefficient, frontal area, engine power etc. These data were obtained for the 30 vehicles in the vehicle pool from the auto manufacturer websites. Parameters used were pertaining to 2011 model year vehicles sold in the United States.
3. Calibration of the VT-CPFM model parameters – α_0 , α_1 and α_2 also used the vehicle specific EPA mileage estimates for city and highway cycle in addition to other physical characteristics. These parameters were calibrated using a calibration tool developed earlier [19, 20].

Estimation of Measures of Effectiveness

The two measures of effectiveness studied were (i) the average travel speed to proceed through the intersection and (ii) the total fuel consumed. This test intersection was simulated using the proposed tool for various percentages of peak approach volumes to analyze the impact of the eco-speed control strategy. Evening peak volumes were used in this study and indicated that the peak travel directions are between North and South (Table 6.2). East to West traffic was only marginal (44 veh/h). The cycle-length for the particular intersection was 120 seconds with 10 seconds lost-time and a 80:30 phase split. Assuming a lane capacity of 1600 passenger cars per hour, the factored capacities for the different approaches for the actual green-times are given in Table 2. The analyses of the results obtained from the intersection simulation are presented in the following section.

Table 6.2 - Obtained Peak Volumes for the Test Intersection

Direction	Turn Movement	Hourly Volume	Total Approach Volume	Green:Cycle length	Factored Capacity
Washington St. (Eastbound)	Left	95	253	30s:120s	400
	Through	59			
	Right	99			
Main St. (Southbound)	Left	14	659	80s:120s	1067
	Through	589			
	Right	57			
Washington St. (Westbound)	Left	10	44	30s:120s	400
	Through	30			
	Right	5			
Main St. (Northbound)	Left	47	611	80s:120s	1067
	Through	552			
	Right	13			

Model Validation

In order to validate the agent-based simulation tool developed in MATLAB, it was tested against the state-of-the-art simulation tool INTEGRATION using the base case intersection. The tool developed in this paper and INTEGRATION uses the same underlying traffic flow models for steady state car-following behavior, vehicle acceleration and deceleration etc. The test intersection was simulated for 4 different volume factors in both simulation tools. The link-lengths are assumed 200 meters and the values in Table 6.2 are used for the simulation. The following measures of effectiveness are compared:

1. Average trip time per vehicle to travel from its origin to destination.
2. Average travel speed of vehicles in the simulation in meters per second.
3. Average fuel consumed per vehicle (or per trip).

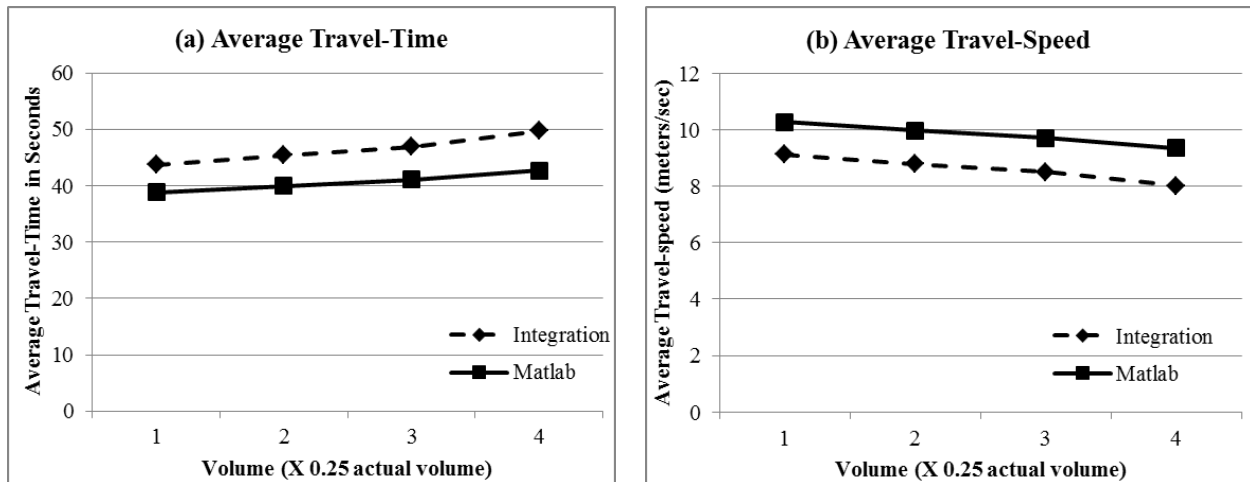


Figure 6.3 - Validation Results of Travel-time and Speed Estimates with INTEGRATION

Figures 6.3 and 6.44 shows the three different measures of effectiveness estimated for the four different volume combinations. As shown in Figure 6.3, the average values of travel-time and speed are similar for both the tools. The values are within 10 percent of each other which validates the agent-based simulation tool models against INTEGRATION. The small change in the values is because of the difference in the way both tools model vehicle turn-penalties. Figure 4 shows the average fuel consumption per vehicle in both the tools. It has to be noted that INTEGRATION uses VT-Micro fuel consumption model whereas the proposed tool uses VT-CPFM fuel model. VT-micro model uses empirical parametric based calculations whereas VT-CPFM model uses instantaneous power for the calculations. This difference in modeling is evident in Figure 6.4.

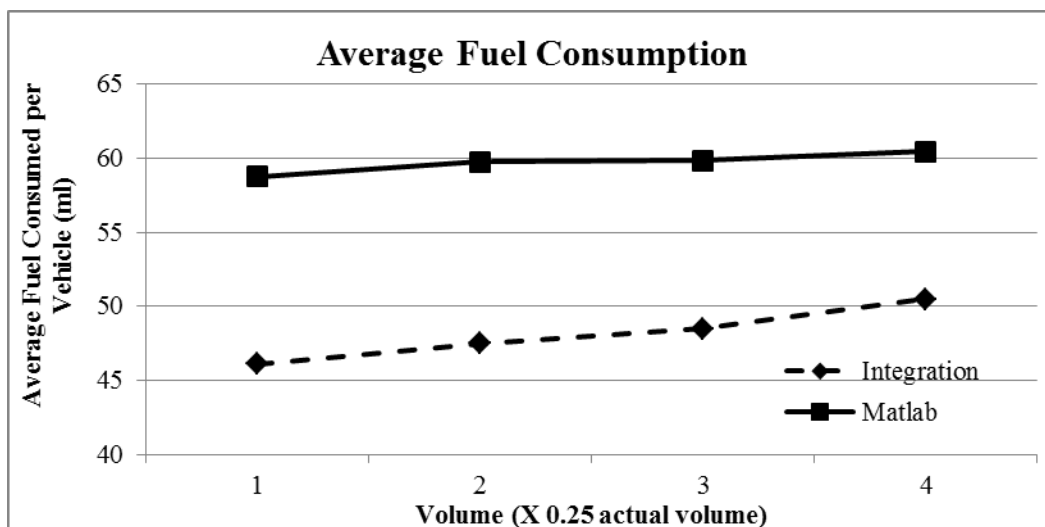


Figure 6.4 - Fuel consumption comparison between INTEGRATION and MATLAB tool

Results and Findings

Agent-based simulations were conducted on the Blacksburg intersection using two control strategies considering four traffic demand scenarios. The base case entailed no exchange of SPaT information with oncoming vehicles. Alternatively, in the test case vehicles received SPaT messages communicated via I2V communication. These vehicles then used the aforementioned eco-speed control strategy to optimize their trajectories. The two measures of effectiveness studied were:

- i. Average percentage reduction in fuel consumed (upstream and downstream) for vehicles on each approach when the eco-speed control strategy was used:

$$MOE_{fuel,i} = \frac{\sum_1^{n_i} (FCN_u + FCN_d) - \sum_1^{n_i} (FCE_u + FCE_d)}{\sum_1^{n_i} (FCN_u + FCN_d)} \times 100 \quad (7)$$

where FCN_u and FCN_d are the fuel consumed for conventional driving upstream and downstream, FCE_u and FCE_d are the fuel consumed when the eco-speed control strategy upstream and downstream is applied, n_i is the number of vehicles approaching from approach i .

- ii. Percentage change in the average speed of vehicles over the 400m section of roadway (from 200m upstream to 200m downstream of the intersection) as:

$$MOE_{speed,i} = \sum_i^{n_i} \frac{\frac{(x_u + x_d)}{t_{ne,j}} - \frac{(x_u + x_d)}{t_{e,j}}}{\frac{(x_u + x_d)}{t_{e,j}}} \times \frac{n_i}{100} \quad (8)$$

where x_u and x_d are the distances upstream and downstream, $t_{ne,j}$ is the time taken by j th vehicle to cover this distance during conventional driving, $t_{e,j}$ is the time taken by j th vehicle while using eco-speed control strategy, n_i is the number of vehicles approaching the intersection from approach i .

Table 6.3 - Cases simulated for the test intersection.

Case	Fraction of Peak Volume	Actual tested volume				Corresponding v/c			
		EB	WB	SB	NB	EB	WB	SB	NB
1	0.25	11	63	165	153	0.03	0.16	0.15	0.14
2	0.50	22	127	330	306	0.06	0.32	0.31	0.29
3	0.75	33	190	494	458	0.08	0.47	0.46	0.43
4	1.00	44	253	659	611	0.11	0.63	0.62	0.57
5	1.25	55	316	824	764	0.14	0.79	0.77	0.72
6	1.50	66	380	989	917	0.17	0.95	0.93	0.86
7	1.75	77	443	1153	1069	0.19	1.11	1.08	1.00

Each of the seven different traffic demand cases is presented in Table 6.3. Each case was simulated 20 times yielding a total of 140 1-hour simulations of the evening peak traffic demand. The measures of effectiveness compared were an average of these 20 simulations. It has to be noted that simulations were done up to 175% of the peak volume to generate cases in which the volume-capacity ratio was over 1.0 (representing over-saturated conditions). For the actual peak volume (case 4), the volume-to-capacity ratio is a maximum of 0.63. The actual test volume is given in vehicles per hour. The volume-to-capacity ratio is too small for East-bound traffic in this particular intersection with a maximum value of 0.19 corresponding to 175 percent peak volume.

Figure 6.5 and Figure 6.6 show the MOEs categorized according to the approach and also the overall intersection MOE. Washington Street is the minor approach and Main Street is the major approach. The values for the MOEs corresponding to different directions of the same street are shown in the same graph. It has been shown that the proposed eco-speed control strategy reduces the fuel consumption level for the given intersections by 27 to 32 percent. An enhancement of average speed (denoted by reduction in delay) is anywhere between 1.6 to 2.4 times. Further analysis of the system indicates that as far as the delay and fuel consumption is concerned, major street traffic receives more benefits over minor street traffic since the cycle time split of minor and major street volumes is biased (25:75). This causes the minor street traffic to wait longer at red-light and thereby negating the benefits from the eco-speed control strategy. At the current peak traffic volume (case 4), the increase in average fuel consumption of vehicles was found to be 29.5 percent and the average increase in point to point travel time was found to be 2.3 times. Cases 5 through 7 show the values of the two measures of effectiveness for traffic demands greater than the current peak demands.

Figure 6.5(a) shows that the westbound traffic (dashed line) incurs more fuel savings relative to the eastbound traffic (dotted line) on the minor street. This is because the greater volume of eastbound traffic requires queue dissipation at the onset of green leaving little or no room for eco-speed control optimization to produce fuel savings. The savings in fuel with respect to various approach volumes show that lower traffic volumes provide opportunities for higher fuel savings. Figure 6.5(b) shows the percentage reduction in fuel for the two directions of the major street. Vehicles on this street saved an average of 31 to 37 percent fuel during its course. Owing to the comparable volumes on both directions, the fuel savings have comparably closer values as shown. Figure 5(a) and (b) shows that the major street traffic saves around 10 times more fuel than the minor street traffic because of a shorter red-phase. Figure 6.5(c) shows the percentage reduction in fuel for the overall simulation at different approach volumes. The average reduction was between 27 and 32 percent with the highest being for the lowest volume and lowest for the highest volume.

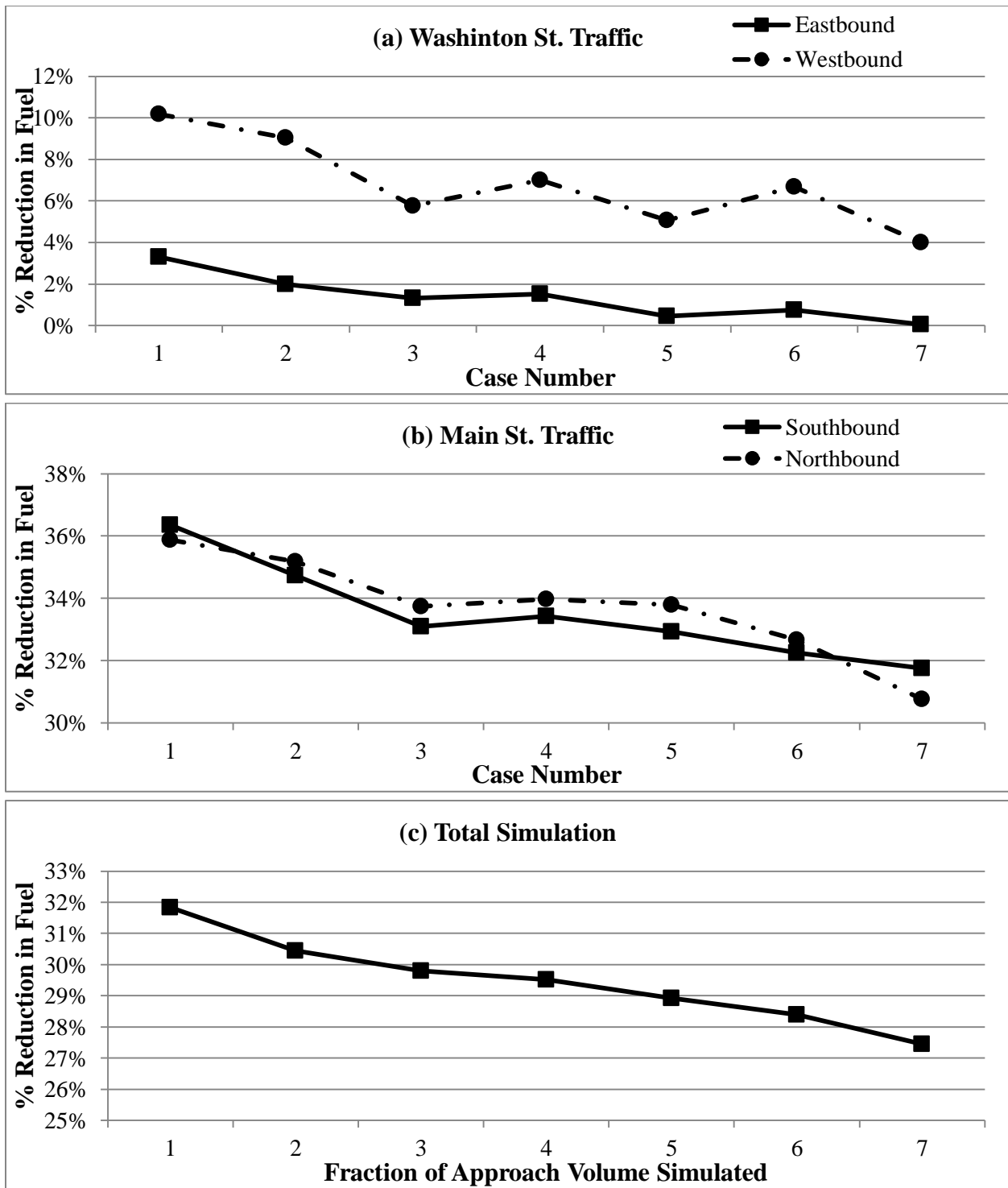


Figure 6.5 - Percentage Reduction in Fuel Consumption for Different Approaches

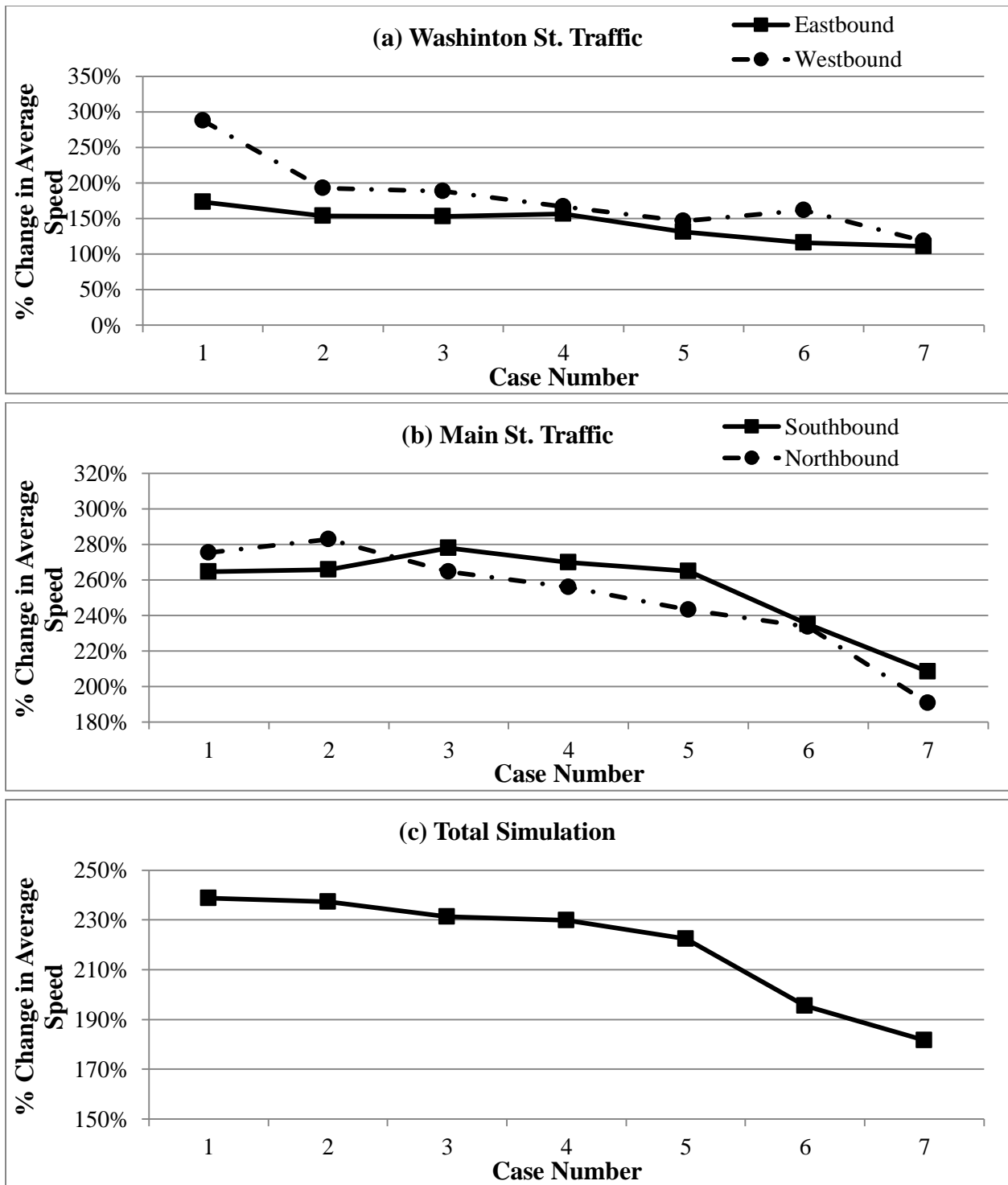


Figure 6.6 - Percentage Change in Average Travel Speed (point-point) for Different Approaches

Figure 6.6 shows the percentage deviation in average travel speed (point-to-point) for the four approaches as well as the overall values. The average travel speed was computed from the point to point travel time and denotes the reduction in delay as well. Figure 6.6(a) and (b) shows the deviation in average speed for the traffic on the minor street and the major street respectively.

The values for the eastbound minor street were relatively constant for all the volumes tested while it changed dramatically for westbound traffic from 287 percent to 118 percent. The percentage deviations in average speed as shown in Figure 6.6(b) for the major street were comparable in both directions. Figure 6.6(c) shows the overall change in average speed of vehicles when eco-speed control strategy was used. The values ranged from 239 to 182 percent and showed a declining trend for increasing volumes. It should be noted that this change in travel speed in the vicinity of the intersection does not conclude equivalent reduction in actual trip travel-time. The actual difference in average travel speed and travel time depends on the total trip profile such as trip length, number of intersections etc.

In order to test the statistical significance of these observed changes in fuel consumption levels and point-to-point travel times, a t-test was conducted for the 20 simulation runs for each of the seven cases. All differences were found to be statistically significant at a 0.05 significance level.

Conclusions

The research given in this paper expands on an agent-based modeling tool to simulate eco-speed controlled vehicles at an intersection. Eco-speed control is a Connected Vehicle application that uses signal phasing and timing information from the signal controller to generate and implement a fuel-optimum vehicle trajectory by discretizing the solution space and finding the minimum path in the solution space. The agent-based simulation tool proposed uses Connected Vehicle standards given in the SAE framework to communicate between vehicles (V2V) and the vehicles and infrastructure (V2I/I2V). The tool uses the INTEGRATION longitudinal vehicle motion model to simulate the vehicles that are calibrated to real vehicle characteristics. The proposed tool was used to test the eco-speed control strategy at a single lane, four legged intersection in Blacksburg, Virginia using real estimates of approach volumes and signal timings. Approach volumes considered correspond to various fractions of the current evening peak demand up to 175 percent, so as to have a scenario for over-saturated conditions ($v/c > 1.0$). The following conclusions can be made from the simulation results:

1. Eco-speed control is able to reduce the overall fuel consumption of vehicles by around 30 percent in the vicinity of intersections.
2. The increase in average travel-speed for all the cases was 210 percent.
3. Fuel savings were greater for the major street than the minor street for the test intersection because of the short red-time for the major approach.
4. Lower volumes yielded more fuel savings and higher percentage increase in average travel-speed.
5. The biased minor-street volumes caused the fuel savings for the higher-volume leg to be lower. This is because of the extended time to intersection caused by queuing.
6. Fuel savings and percentage increase in average travel speed were comparable for the major approaches since they had comparable demands.

While these conclusions present interesting inferences regarding the agent-based simulation tool, further enhancements are warranted from this study. This includes simulating multiple intersections and signalized corridors which run on coordinated and uncoordinated signals. The simulation tool presented in this paper presents a comprehensive and novel approach to test eco-driving strategies such as the one used in this paper in a simulation environment owing to its agent-based logic and ability of vehicle agents to react to external stimulants. A model validation is also warranted as a future work when actual field experiments can be done using the proposed eco-speed control approach.

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7. Cloud-based Simulation of Eco-Speed Control

(R.K. Kamalanathsharma, H.A. Rakha and B. Badillo, "*Simulation of Connected Vehicle Applications in a Cloud-based Environment*" 93rd Annual Meeting of the Transportation Research Board, Washington DC, January 2014.)

Simulation Testing of Connected Vehicle Applications in a Cloud-based Environment

Raj Kishore Kamalanathsharma, Hesham Rakha and Brian Badillo

Connected Vehicle Program applications are being developed by researchers in the United States and worldwide in an attempt to leverage data-packets transmitted and received through vehicle-to-vehicle and vehicle-to-infrastructure communication. The majority of these application evaluations do not conform to J2735 messaging standards set forth by the Society of Automotive Engineers. Consequently, this paper develops an enhanced version of the enhanced Traffic Experimental Analytical Simulation (eTEXAS) tool that runs on a server and provides XML-based message sets that conform to current Connected Vehicle standards. An eco-speed control algorithm that was developed earlier is integrated with the eTEXAS platform to receive signal timing and phasing data through infrastructure-to-vehicle and vehicle-to-vehicle communication. The application uses this information to optimize vehicle trajectories so as to reduce their fuel consumption levels while proceeding through the intersection. The platform was tested in a cloud environment and produced a 5.5 percent reduction in the total intersection fuel consumption level and a 9 percent increase in the average vehicle speed on a sample intersection. The results also showed that latency correction is critical in designing and implementing connected vehicle applications.

Introduction

The Vehicle Infrastructure Integration envisioned more than a decade ago has caught the attention of researchers and transportation professionals only recently due to the advancements in technology that enables its implementation [1]. The potential safety benefits that can be leveraged out of it in addition to the supplementary applications such as congestion mitigation and environmental applications has encouraged researchers world-wide to pursue this area. The Connected Vehicles initiative in the United States has caused rapid growth in the research on multiple aspects of this system along with standards development and a large-scale pilot implementation in Ann Arbor, MI [2]. Simultaneously, the Society of Automotive Engineers (SAE) is developing and revising a communication standard (SAE J2735), to standardize the data that will be broadcasted as a result of vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication using Dedicated Short Range Communication (DSRC) and Wireless Access in Vehicular Environment (WAVE) communications standard [3, 4]. However, except for eTEXAS, no other available traffic simulation software can explicitly model V2I and V2V communication as per J2735 standards.

Most Connected Vehicle applications that are simulated use the software's application programming interface to devise a custom communication channel which may not replicate the

real-life DSRC protocols [5, 6]. This presents a gap between development of Connected Vehicle applications and their simulation testing without the use of a proper communication framework. The research presented in this paper expects to close this gap by presenting a cloud-based eTEXAS simulation model which uses SAE J2735 communication standards to test an eco-speed control application. The enhanced Traffic Experimental Analytical Simulation (eTEXAS) model works on a server and can interact with remote applications using XML-based web-services. This enables testing of Connected Vehicle applications without needing to install any simulation software. Such a simulation set up also helps in testing the communication framework of the test application because the eTEXAS uses SAE J2735 message sets to communicate with external modules. The integration of Vehicle Messaging System (VMS) enables remote application to modify vehicle trajectories during the simulation runs. This feature is used to apply the Eco-Cooperative Adaptive Cruise Control (ECACC) trajectory instructions on the vehicles within the simulation environment. Please note that the abbreviation VMS used in this paper is different from Variable Message Signs used by traffic engineers.

As far as the paper layout is concerned, the next section provides a background on the TEXAS model and the connected vehicle application being tested. This is followed by a description of the cloud-based simulation tool along with the simulation set-up that was used in this particular research. The final sections include major findings and conclusions of this study along with future research directions.

Background

SAE J2735 standards consist of a DSRC Message Set Dictionary that describes the different message data frames and data elements that are broadcast in a Connected Vehicles environment [3]. All Connected Vehicle applications are expected to follow these communication standards to receive information and broadcast them. Only a few Connected Vehicle applications have explicitly used a DSRC communication framework for simulation tests [7]. Therefore, the testing of these applications should use a program that can replicate the actual standards while communicating with the simulated traffic agents (vehicles and controllers). The research discussed in this paper presents such a cloud-based simulation tool which simulates traffic at an intersection and generates the corresponding Signal Phasing and Timing (SPAT), MapDATA message sets along with the Basic Safety Messages (BSM) to be received by a remote application and uses a simulation-specific Vehicle Messaging System (VMS) and Signal Controller Messaging System (SCMS) to communicate back. This tool is available through a web-based interface with the TEXAS simulation model running in its core. The test Connected Vehicle application is the eco-speed control application which generates fuel-optimized velocity profiles for vehicles in an intersection using constraints of signal change information, queued vehicle information as well as information about other vehicles on the same lane.

The TEXAS model is a high-quality, single intersection, microscopic traffic simulation model developed at The University of Texas at Austin. The model acronym stands for Traffic

Experimental Analytical Simulation [8]. In order to enhance the applicability of the TEXAS model, the enhanced TEXAS model was developed with a web-interfaced Java program to achieve platform independence and was integrated with SAE J2735 compatibility by Harmonia Holdings Group, LLC [9]. The eTEXAS model features a cloud-in-the-loop simulation where the simulation takes place on a server environment while the remote computers will have the ability to run it using web-services. Representational State Transfer (REST) services are used to communicate with the server-based simulation which makes it possible for the remote computers to use any compatible program. In this particular research MATLAB program is used to remotely communicate and control the simulation. The enhanced TEXAS program also features other Connected Vehicle features such as varying penetration rates for On-Board Units (OBU), grouping the On-Board Units based on their feature availability, ability to define the frequency of broadcast of different message sets and configuring Road-Side Equipment (RSE) and OBUs.

The ECACC application tested in this research is a speed-advisory tool that uses a vehicles location, speed and information about the upcoming signal change to generate a fuel-efficient vehicle trajectory to be followed by the vehicles [7]. The application uses dynamic programming based on least-cost path-finding methods to optimize the vehicle trajectory to minimize the fuel consumed upstream and downstream of the intersection. A detailed description of the ECACC logic is provided in the literature [7]. Agent-based modeling using MATLAB has shown fuel savings of around 15 percent. In the proposed set-up, the remote application that resides in MATLAB uses DSRC-based SPAT and BSM messages from the eTEXAS simulator to generate the fuel-optimal vehicle trajectory and then uses VMS to inject the proposed path to the vehicles in the simulation environment.

Methodology

The cloud-based eTEXAS simulation model uses a REST web-service to communicate back and forth between remote computers. Users can upload TEXAS project intersection and simulation files to the server and then run it on the server on a time-step based mode. The complete simulation logic of the server set up is given in Figure 7.1. Users use two different services to read outputs and execute simulation. They are: (a) WaveService, which is used to fetch the XML J2735 messages generated at each time-step based on the DSRC/WAVE technologies and (b) ExecService, which is used to execute commands such as advancing a simulation and injecting a VMS command. In order to generate message-sets, certain apps have to be defined in the simulation which corresponds to different messaging functionalities. The apps used in this particular research are given in Table 7.1. It has to be noted that these scenarios are applied along with appropriate underlying microscopic models such as acceleration/deceleration models and car-following models. The fuel-optimized trajectories are generated using A-star path-finding algorithms. The full algorithm is previously published and is beyond the scope of this paper. Interested readers can refer to [7] for information.

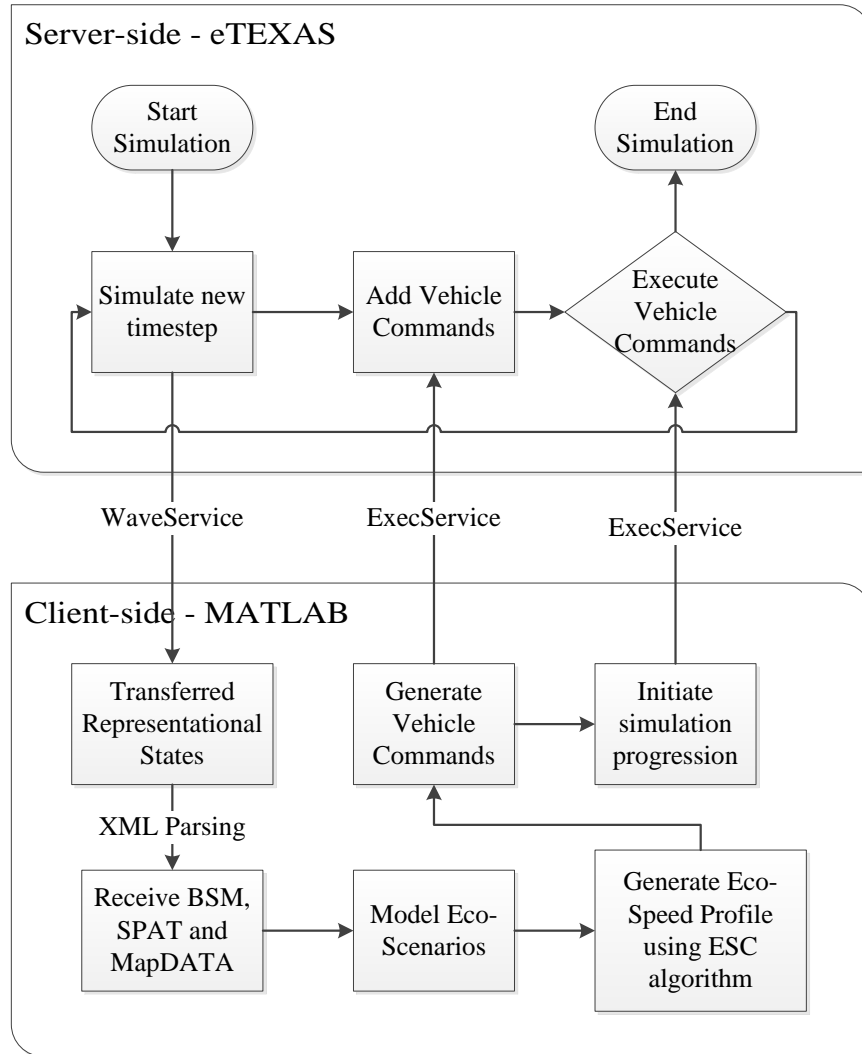


Figure 7.1 - Cloud-based Simulation Logic in the case of ETEXAS

Java Archive (JAR) files have inside access to simulation parameters such as vehicle status, signal states, and lane geometry and can produce messages such as BSM, SPAT and MapDATA. ‘Remote’ apps are user-defined Connected Vehicle applications that utilize the J2735 messages being broadcasted during the simulation to perform some useful algorithm, In this research, the eco-speed control application is the ‘Remote’ app and is responsible to use J2735 message sets to develop eco-driving speed profiles for vehicles.

As shown in Figure 7.1, the entire simulation logic is divided physically as server-side and client-side. MATLAB is the client-side application used in this research and it uses XML-parsing to read the XML content generated by the server at each simulation step. This XML file consists of three different message sets based on a defined frequency: BSM messages of all the vehicles, SPAT message for all the lane sets and MapDATA messages that describes intersection geometry. A 32-character unique alphanumeric application ID is used to fetch these message sets from the server. The BSM and other messages received from the server follow the SAE J2735

message set standards. Figure 7.2 shows a reverse parsing tool developed by SAE to generate these message sets. The MATLAB client program uses the same logic as the SAE tool to parse the XML information for use in the algorithm. Once the MATLAB parses this XML file, it generates a table of vehicle data along with its speed, distance to intersection, position on the network and details about current phase for its lane-set. The eco-speed control algorithm then uses these details to predict the future constraints of each vehicle and to generate a fuel-optimal velocity profile which are then changed to VMS commands.

Table 7.1 - J2735 Messaging Apps Installed in ETEXAS

App	App-ID	Type	Description
BSM	'BSM-producer'	JAR	Generates 'BSM blob' messages which is a hexadecimal long string with the basic data elements from the Basic Safety Message set. A <i>frequency</i> parameter is added to this app to define broadcast frequency. This app is installed on on-board units in vehicles.
BSMV	'BSMVerbose-producer'	JAR	Generates the Basic Safety Message set in verbose format consisting of 14 different data elements. This app is installed on on-board units in vehicles and also consists of <i>frequency</i> parameter.
MAP	'MapData-producer'	JAR	Generates the MapData that specifies the intersection geometry and is installed in the Road-Side Equipment (RSE). This app also consist of a <i>frequency</i> parameter
SPAT	'SPAT-producer'	JAR	Generates the Signal Phasing and Timing message set from the signal controller and broadcasts it via the RSE at a set <i>frequency</i> .
Remote	'Eco-Speed Control'	Remote	This app is used to communicate with the simulation using Wave Service and get the DSRC message sets to the client computer. There are no parameters associated with this app and it is installed on the RSE.

The vehicle control (VMS) commands generated during the eco-speed control are sent to the server using the ExecService for implementation in the next time-step. The commands can either be to accelerate or decelerate to a certain speed. A typical VMS command injected to the simulation uses four variables: a 32-character alphanumeric execution ID, a numeric vehicle ID, accelerate or decelerate command and final speed in meters per second. The eTEXAS Webapp also uses XML based keys to advance the simulation. These steps are repeated every time-step

and forms the logic of a cloud-based simulation program where the actual simulation takes place in a server using the inputs and algorithms coded in a remote computer. The use of the actual communication standards helps Connected Vehicle application developers to implement and test the algorithm in a standard framework with all the latency and wireless communication realism that would result from an actual system.

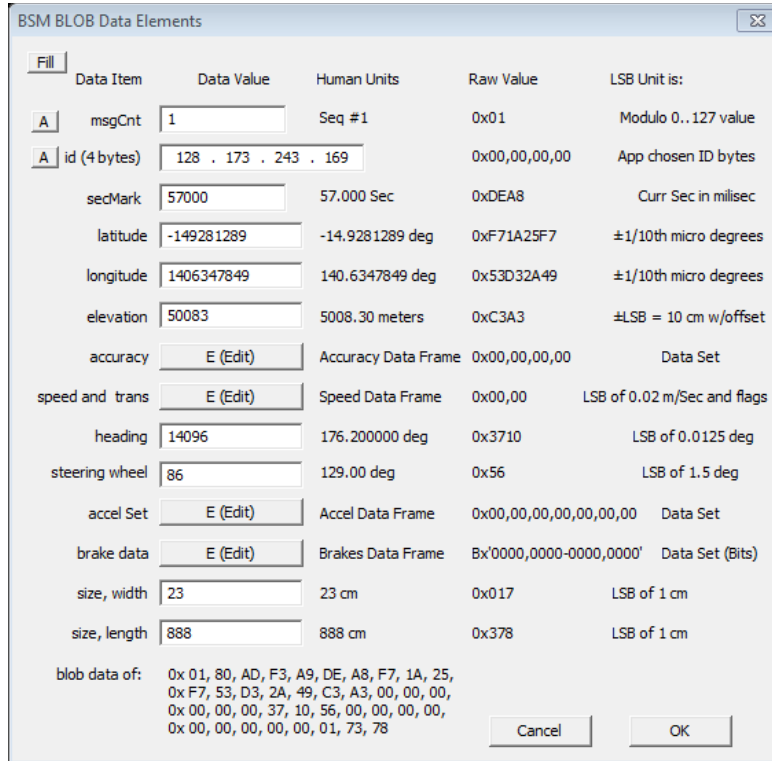


Figure 7.2 - BSM Message Editor from SAE Website

Case-Study: Eco-Speed Control Algorithm

An eco-speed control module further uses the information about each vehicle including its speed, location, signal phasing information for that approach etc. to model eco-scenarios by generating a least-cost velocity path from that position to reaching a position downstream constrained by the changing traffic light, position and speed of other vehicles on the same lane and the vehicle's acceleration and deceleration characteristics. The eco-speed control models five different scenarios based on the speed, current phase on the lane, time remaining on the current phase and other constraints on a vehicle that is approaching the signalized intersection. They are shown in Figure 7.3 as a time-space diagram.

These scenarios are explained below. The full logic of this algorithm is given in Reference [7].

1. Scenario 1: Here, the vehicle is in a lane which is currently being served green and will last until the vehicle passes the intersection safely. The vehicle is given no commands and proceeds at the same speed.

2. Scenarios 2 and 3: Here, the vehicle is in a lane which is currently being served green, but will turn to red before it reaches the stop-line. In this case, the vehicle is either commanded to accelerate to the speed-limit and pass through the intersection before green phase ends (Scenario 2), or to slow-down and stop and wait for the next green (if the former is not possible) which forms Scenario 3.
3. Scenario 4: Here, the vehicle is in a lane which is currently being served red and will last until the vehicle reaches stop-line. In this case, an alternate profile is generated to allow for some delay in its trajectory so that the vehicle reaches the intersection at a lower-speed and when the signal is green. This profile is then given as a command to the vehicle to decelerate to a certain speed until it clears the intersection and then accelerate back to the original speed.
4. Scenario 5: Here, the vehicle is in a lane which is currently being served red, but will turn to green and clear the queued traffic by the time it reaches the stop-line at the current speed. The vehicle is commanded to proceed safely at the current speed.

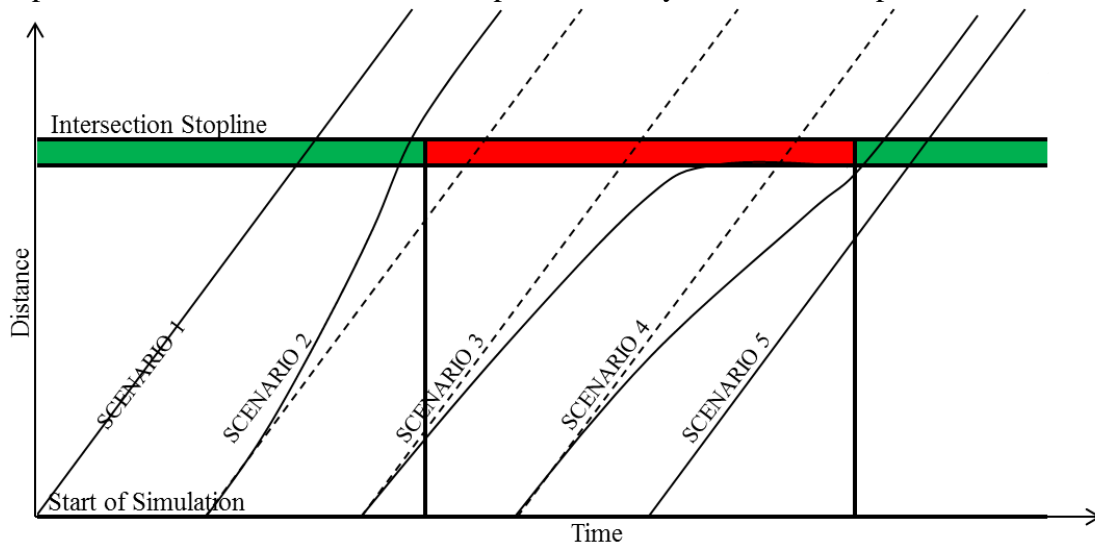


Figure 7.3: Speed profile of vehicles approaching a signalized intersection.

It has to be noted that these scenarios are applied along with appropriate underlying microscopic models such as acceleration/deceleration models and car-following models. The fuel-optimized trajectories are generated using A-star path-finding algorithms. The full algorithm is previously published and is beyond the scope of this paper. Interested readers can refer to [7] for information.

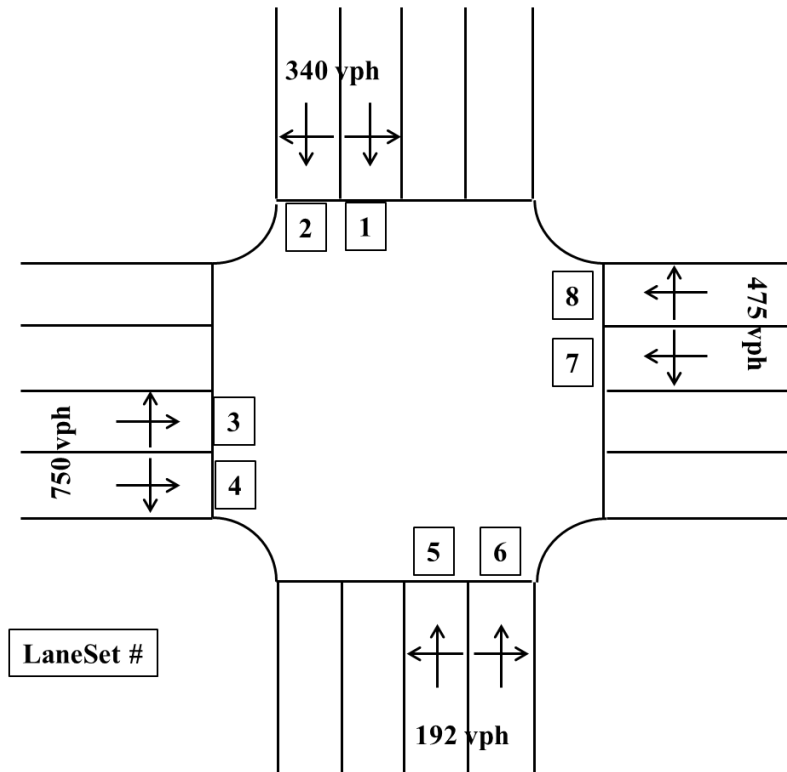


Figure 7.4 - Intersection Layout

Simulation Set-up

The proposed cloud-based simulation set up was used to simulate a typical four-legged signalized intersection running on a pre-timed signal cycle. The details of the simulation set up including the approach volumes and phasing data is given in Table 7.2. Each inbound and outbound approaches consist of two lanes (lane-set number shown) with the lane permissions as shown in Figure 7.4. An assumed speed-limit of 30 miles per hour is considered for the two intersecting roadways. The approaches and the roadway are considered to be on a zero-grade surface so that effect of grade can be neglected from the underlying models. Simulation time was 1200 seconds (20 minutes) with zero warm-up time. The frequencies set for BSM message broadcast was 0.1 second, SPAT message broadcast was 1 second and MapDATA broadcast was 10 seconds. Since only one intersection is considered, the MapDATA remains the same over all time-steps. The eco-speed control was done every second (since the original eTEXAS model's simulation fidelity was 1 second) and the XML parsing used spherical transformation to convert latitudes and longitudes in the BSM to specific distances to the intersection. SPAT messages used current phasing numbers as 1 (green), 3 (yellow) and 4 (red) as defined in the J2735 dictionaries. All message sets that were produced followed SAE standards and required conversions to human-readable values.

Table 7.2 – Approach Volumes and Signal Controller Details for the Simulation Setup

Parameter	Values
Length of Inbound Lanes	1100 ft
Length of Outbound Lanes	250 ft
Speed-limit	30 mph
Leg 1 Details:	Volume: 340 vph
	LTR Split: 18:68:14
Leg 2 Details:	Volume: 750 vph
	LTR Split: 10:77:13
Leg 3 Details:	Volume: 192 vph
	LTR Split: 15:63:22
Leg 4 Details:	Volume: 475
	LTR Split: 6:84:10
Intersection Details:	Type: Pretimed (68s cycle)
	Green Split: 20s: 40s (2 phases)

Since the TEXAS model lacks fuel consumption models, the remote MATLAB module saves instantaneous vehicle profiles at each time-step. This trajectory is then used to compute the fuel consumed by vehicles. Virginia Tech Comprehensive Power-based Fuel Model (VT-CPFM) is used as the microscopic fuel consumption model for this computation. Two cases of simulations are performed. The base case is without any eco-speed control commands and therefore corresponds to the conventional simulation. Web-service is still used to manage the simulation and to collect the vehicle trajectories. In the test-case, the remote MATLAB program generates VMS commands that correspond to optimized velocity profile. In this case also, the vehicle trajectories are saved in the remote computer. Post-simulation analysis includes use of the trajectory files to compare and evaluate the test Connected Vehicle application based on two different measures of effectiveness: average travel time vehicles in the simulation and average fuel consumption of vehicles in the simulation.

Adjustment for Latency

The simulation set-up that is based on eTEXAS includes certain latencies in the system that need to be accounted for while running the ECACC application. Primarily there are two types of latencies that the simulation needs to adjust its settings so as to prevent errors:

1. Latency in the received SPAT and BSM messages: The SPAT and BSM message that is received by the system through WaveService is 1-timestep old. Hence, before calculating the optimum speed profile to the intersection, the change in SPAT and position of the vehicle has to be deduced using its current speed and position.
2. Latency in implementing a VMS command: Any VMS commands generated and given to the simulation through ExecService will be implemented only in the next time-step. This latency requires the eco-speed control algorithm to forecast the position and traffic signal status for

when a command will be implemented in order to make an accurate fuel-optimized speed profile.

These latencies are adjusted for in the remote Connected Vehicle application and most of these latencies are reflected in a real-world application because there will be a delay in vehicles to create and broadcast the BSM messages and for the controller to broadcast the SPAT messages. This is in addition to the computation time required by the connected vehicle application.

Results and Findings

The proposed cloud-in-the-loop simulation framework was used to simulate vehicles approaching an intersection given in the previous section for two different cases. The base case represents the conventional intersection case where the V2I and V2V communication is not used for any application and in the test case, V2I and V2V communication is used by vehicles to predict the future speed constraints and to generate a fuel-optimum velocity profile using the algorithm in [7]. Five random-seed simulations were done for the given intersection to yield meaningful results. MATLAB-based webservices was used to capture each vehicle's position and instantaneous speed. For all the microscopic modeling purposes, these vehicles were assumed to hold the characteristics of a 2011 Honda Civic (which falls under the EPA compact car category). The Virginia Tech Comprehensive Power-based Fuel Model (VT-CPFM) was used to derive the instantaneous fuel consumed by vehicles using vehicle-specific parameters given in Table 7.3.

Table 7.3 - Vehicle-specific parameters for Honda Civic

Parameter	Value
Drag Coefficient (Cd)	0.30
Frontal Area (m ²)	2.32
Engine Efficiency	0.92
Percentage Mass on Tractive Axle	0.60
Mass (kg)	1453
Power (kW)	132
VT-CPFM Alpha 0	0.00047738
VT-CPFM Alpha 1	0.00005363
VT-CPFM Alpha 2	0.000001

The connected vehicle application for eco-speed control uses instantaneous information from vehicles and the intersection controller to generate optimized velocity profiles for vehicles. These optimum profiles are then converted to VMS (Vehicle Messaging Service) commands given to the simulation server to slow-down or speed-up vehicles to a particular speed. Therefore the base case represented by conventional vehicles approaching a conventional intersection is said to be before implementation of VMS commands and the test-case where vehicles follow a fuel-optimized eco-profile is after the implementation of VMS commands. Two different measures of effectiveness were used in the simulations to see if the connected vehicle application

was performing well. They were average speed of travel by the vehicles and total fuel consumed by the vehicles. These parameters were for the total distance of travel from 1100 feet upstream when the vehicles enter the simulation to 250 feet downstream when it exits. Since the DSRC range is around 1100 feet, the vehicles receive their first data-packet as it enters the simulation and begins to generate a fuel optimum speed profile.

Figure 7.5 shows the average speed of each vehicle along with their vehicle IDs. For easier representation, only 300 vehicles are shown in the figure, but the trend remains the same. The red '+' mark represents the average speed of each vehicle in meters per second before the implementation of VMS commands and therefore represents non-optimized profiles. The blue 'x' mark represents the average speed of each vehicle after the implementation of VMS commands. They represent fuel-optimized velocity profiles. It can be seen that the average speed of fuel-optimized profiles are higher than those of non-eco profiles. An average gain in speed of 9.23 percent was found across all simulated vehicles when VMS was implemented with a highest value of over 180 percent. Figure 7.6 shows the total fuel consumed by each vehicle and non-optimized vehicles consume more fuel over optimized vehicles (eco-profiles). The reduction in fuel was an average 5.54 percent when VMS commands were implemented with highest reduction marked at over 62 percent.

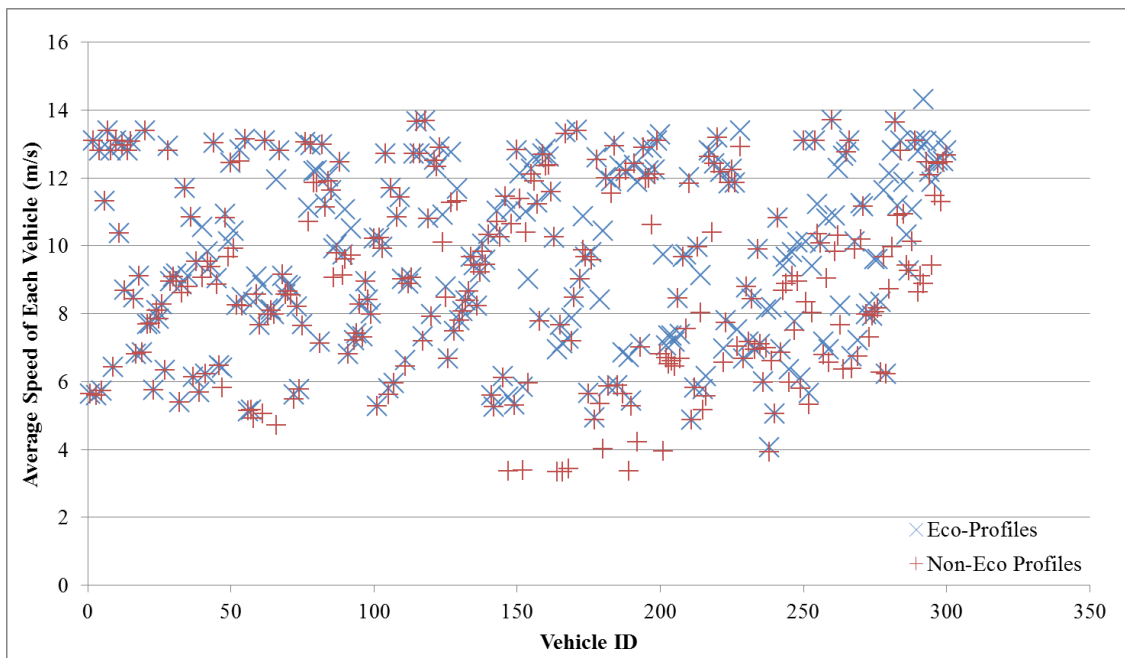


Figure 7.5 - Average speeds of vehicles before and after VMS implementation

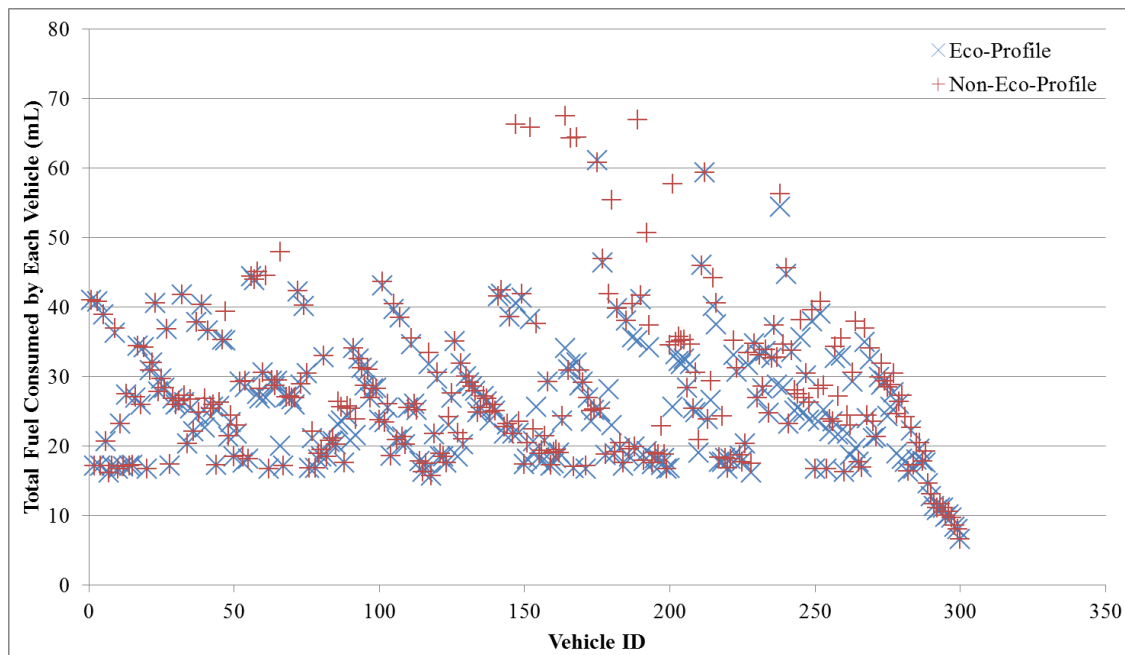


Figure 7.6 - Fuel consumed by vehicles before and after implementation of VMS commands

It was noted that latency played a major role in implementing the connected vehicle application. When latencies were not considered, the applications used ‘outdated’ SPAT and BSM data to generate VMS commands which negatively impacted the results. An increase in average fuel consumption of 13 percent was found when latency was not corrected for. This was because the algorithm used outdated SPAT information and thus the vehicles had to abruptly alter their speed-profile near the intersection since the forecasted change did not materialize. Proper latency corrections in forecasting SPAT information as well as implementing VMS commands were vital to the connected vehicle application.

Conclusions

The research presented in this paper introduces a cloud-in-the-loop simulation tool that is based on TEXAS micro-simulation tool that allows traffic simulations on remote servers that can be managed using any software using web-services. The tool also uses actual SAE J2735 standards as the back-bone for implementation of connected vehicle applications in the simulation environment. The system was integrated with eco-cooperative adaptive cruise control system and tested on a sample signalized intersection. Since the test framework used real SAE standards for V2V and V2I communication, it replicated a real connected vehicle environment along with their associated system latencies. Cloud-based simulations of ECACC system were conducted using a sample intersection, and following conclusions were made:

1. Proper latency corrections are critical in developing connected vehicle applications. These latencies account for delays in receiving the DSRC messages as well as latencies in running the application in real-time.

2. The simulation testing of the ECACC system on a sample intersection showed an increase in vehicle average speed by approximately 9.2 percent and a reduction in average fuel consumption in the order of 5.5 percent considering a compact car.
3. The total fuel consumed by vehicles showed that there is a significant reduction in fuel consumed by some vehicles while other vehicles remain unchanged. A similar trend was observed for the average speed.

As is the case with any research effort further research is required to test the system considering different vehicle types, different traffic demand levels, different intersection configurations, and different signal timings.

Acknowledgements

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8. Multi-Objective Optimization and Management of Autonomous Vehicles at Intersections

(R.K. Kamalanathsharma, I.H. Zohdy, H.A. Rakha, "*Multi-Objective Optimization and Management of Automated Vehicles at Intersections*," (under-review) 94th Annual Meeting of the Transportation Research Board, Washington, DC, January 2015.)

Multi-Objective Optimization and Management of Automated Vehicles at Intersections

Raj Kishore Kamalanathsharma, Ismail Zohdy and Hesham Rakha

The research presented in this paper develops a multi-objective optimization algorithm for the control of autonomous and semi-autonomous vehicles at intersections. Specifically, three objectives are considered, namely: safety (i.e. ensuring vehicles do not collide), minimizing vehicle delay, and minimizing vehicle fuel consumption levels. The solution to this mathematical program is achieved through a bi-level optimization. At the upper level the system minimizes the intersection delay subject to collision avoidance constraints. At the lower level vehicle fuel consumption levels are minimized using a dynamic programming optimization framework. Preliminary analysis using agent-based simulations revealed delay reductions of approximately 82 percent and fuel savings of approximately 79 percent compared to conventional signalized intersection control. The addition of the lower-level fuel optimization controller reduces the intersection fuel consumption level 10 percent relative to the use of single-level controller.

Introduction

Surface transportation sector is faced with three major problems, namely, congestion, environmental degradation as well as human fatalities. Congestion on American roadways accounted for almost 4.8 billion hours and an extra 3.9 billion gallons of fuel [1-2]. Driving is also one of the top contributors of human fatalities world-wide with over 90 percent of them attributed to human error [3]. Automated vehicles are considered an answer to these problems and most auto-manufacturers are working on commercializing them in the near future. Advanced ITS research has enabled connectivity between vehicles and infrastructure components for addressing some of the problems and to smoothen the transition to an automated driving environment. In the United States, these deployments and developments form the basis of Connected Vehicles Program which is currently piloted at multiple cities [4].

Once we have connectivity between vehicles and the infrastructure components and there are automated longitudinal controls for the vehicles, researchers foresee implementation of advanced intersection control algorithms [5-6]. Past efforts have addressed algorithms that optimize intersections for delay minimization, economy and above all crash avoidance [6-8]. However, the research in this paper presents a multi-objective intersection algorithm that works on two levels to generate crash-free, delay- and fuel-optimized vehicle trajectories. First, the algorithm generates a vehicle arrival time and intersection-entry speed for all vehicles to ensure no vehicles collide while minimizing the total vehicle delay. Second, the algorithm generates the most fuel-efficient vehicle trajectories that satisfy the arrival times using dynamic programming.

The next sections describe some of the past research done in this area followed by a description of the bi-level optimization process. Subsequently, agent-based simulation analysis is described to demonstrate the effectiveness of the proposed algorithm with regards to intersection delay and fuel usage. The final section highlights the findings, results and conclusions of the research analysis.

Background

Several researchers have proposed optimizing vehicle movements, both autonomous and non-autonomous, through an intersection [6, 9]. However, the optimization objective was either to minimize vehicle delay or to minimize vehicle fuel consumption levels [6-8]. Some research efforts used inputs from a fixed traffic signal as a constraint to alter the vehicle's trajectory while other efforts assumed fully autonomous control without any traffic signals by reserving conflict points to ensure no vehicle conflicts occur while at the same time minimizing the total intersection delay. As far as the research efforts on intersection management of vehicles using V2I cooperation is concerned, Lee and Park proposed a Cooperative Vehicle Intersection Control (CVIC) system that enables cooperation between vehicles and infrastructure for effective intersection operations and management [9].

Researchers have also used V2I communication to construct fuel-efficient vehicle trajectories [10]. For example, Asadi and Vahidi developed a predictive cruise control system that uses constrained optimal control to adjust cruising speeds to intersections by minimizing the probability of stopping [11]. Malakorn and Park used constrained optimal control that minimizes acceleration and deceleration distances using advanced signal information [12]. In recent studies, several algorithms were developed to use Signal Phasing and Timing (SPaT) Information that is available as a part of the Connected Vehicle deployment to compute fuel-optimum vehicle trajectories [8, 10]. Most of these research efforts assumed some form of communication between the vehicles and the infrastructure. Only few of them have used explicit optimization objectives such as minimizing delay and minimizing fuel consumption. No research to date has looked into a multi-objective optimization of vehicle movements through an intersection to minimize both vehicle delay and the fuel consumption levels while ensuring no crashes occur.

The research proposed in this paper uses a bi-level optimization structure to enable this. At the first level, the intersection management tool described earlier uses a moving horizon optimization approach to generate vehicle arrival times and speeds at the stop-line in order to avoid collisions while minimizing the intersection delay. At the second level, a dynamic programming approach is used to compute the fuel-optimum vehicle trajectory that satisfies the vehicle speed and arrival time at the stop-line given at the first level. This research use Rakha and Lucic vehicle dynamics model [13] to predict the maximum vehicle acceleration based on the instantaneous tractive and resistive forces, the Virginia Tech Comprehensive Power-based Fuel Model [14] to compute the microscopic fuel consumption levels and Van Aerde steady-state

car-following model to model vehicle longitudinal motion [15]. These can model microscopic vehicular behavior using physical characteristics of vehicles as well as the roadway and intersection characteristics including weather.

Methodology

The algorithm described in this paper aims at optimizing vehicle trajectories through an intersection while achieving three objectives – crash avoidance, minimizing overall delay and minimizing the fuel-consumed by individual vehicles. In order to satisfy these objectives, the optimization task is divided into two levels which are described in the following sub-sections. Vehicles are assumed to have automated longitudinal control and the intersection is assumed to be managed by an optimization controller. This assumption is made to avoid the modeling of human perception-reaction times (PRTs), but can be adjusted to model these delays if they are empirically established. The optimization controller, unlike conventional controllers, generates optimized vehicle trajectories which are forced on the vehicles using V2I communication.

Upper Level Optimization

At this level, the vehicle arrivals at the stop-line are optimized for minimizing the total intersection delay while ensuring that no vehicles collide. This is done by fixing the speed of vehicles at two anchor points on each approach. Vehicle speeds at these anchor points are fixed to a safe value and speed-profiles of vehicles are adjusted during the travel between them so that they will arrive at the stop-line at a time that will prevent simultaneous occupancy of conflict points. This arrival time at the intersection stop-line is assumed as the control variable while optimizing overall intersection delay.

Figure 8.1 shows a typical 4-legged intersection along with a representation of what anchor points are and the speed-profiles anchored to these points. Each approach is divided into two zones. In Zone 1, all vehicles attain the maximum speed so as to provide room for optimization during the Zone 2. In the absence of conflicting vehicles, a vehicle could cross Zone 2 and the intersection at maximum speed. This case is called the zero-delay case and is represented by a non-variable speed profile in Zone 2. It has to be noted that for turning vehicles, this maximum speed is less than the speed-limit. In order to facilitate the optimization process to minimize delay and to prevent simultaneous conflict point occupancy, all vehicles are assumed to incur speed variation while in Zone 2.

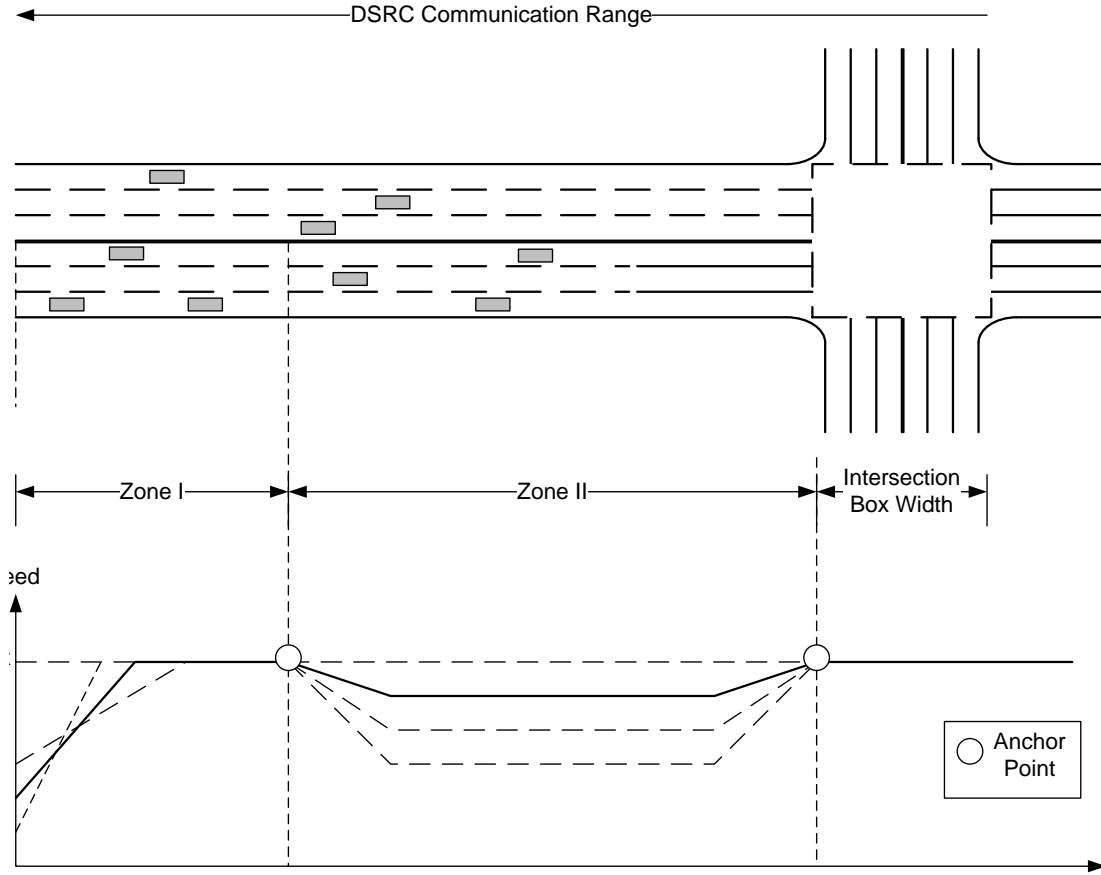


Figure 8.1 Optimization zones in a typical 4-legged intersection.

The upper level optimization incorporates generating vehicle arrival times at the stop-line so as to satisfy the condition of minimum overall delay:

$$\text{Min: } \sum_{i=1}^n D_i$$

Subject to:

$$(OT_i + D_i) - (OT_j + D_j) \geq H_{\min}(l_{im} l_{jm});$$

$$i \neq j, \forall i, j \in \Omega, \forall m \in \Psi$$

$$|(OT_i + D_i + \tau_{mn}) - (OT_k + D_k + \tau_{nm})| \geq \Delta\tau(l_{im} l_{kn} c_{mn});$$

$$i \neq k, \forall i, k \in \Omega^1, \forall m, n \in \Psi$$

$$(OT_i + D_i + \tau_{mn}) \geq \max[(OT_f + D_f + \tau_{mn}), (OT_p + D_p + \tau_{mn})];$$

$$\forall i \in \Omega^1, \forall f, p \in \Omega^0, \forall m, n \in \Psi$$

$$D_i \geq 0; \quad \forall i \in \Omega$$

where:

i, j, f, p : vehicle identification number;

D_i : Time delay incurred by vehicle i ; for the ideal case it will be zero (no deceleration occurred in Zone II);

OT_i : The optimum arrival time of vehicle i at the PIB (Entrance Point to the IB). OT_i is estimated assuming that each vehicle accelerates to maximum speed in Zone I and continues to travel at the maximum speed until PIB. The arrival time is calculated based on the mathematical equations presented in the following sub-section);

Ω^0 : The set of vehicles that entered the IZ the last time step and are still in the IZ in the current time step;

Ω^1 : The set of vehicles that enter into IZ at current time step;

Ω : The set of vehicles in IZ at current time step ($\Omega = \Omega^0 + \Omega^1$);

m, n : Lane identification number;

Ψ : The set of lanes at the intersection;

$l_{im} := 1$ if vehicle i enters into IB from lane m ; and 0 otherwise, with $\sum_{m \in \Psi} l_{im} = 1$.

$c_{mn} := 1$ if vehicle i from lane m has a conflict point with vehicles traveling on lane n ; and 0 otherwise, with $\sum_{m, n \in \Psi} c_{mn} = 1$.

τ_{mn} : Travel time from the point PIB of lane m entering into IB to the conflict point of lane n ; Distances to each conflict points are based on the intersection geometry. It is assumed that all vehicles will be running at maximum speed in the IB, thus, τ_{mn} is fixed for all vehicles from the same lane m to same conflict point mn (to facilitate the optimization process). It should be noted that the maximum speed may be different for different movements.

$\Delta\tau$: The duration of time that a vehicle occupies the conflict point, in other words, the safety interval between two consecutive vehicles occupying the same conflict point. To simplify the model formulation and calculation, we assumed $\Delta\tau$ to be identical for all vehicles. This assumption can be relaxed for future testing.

H_{min} : The minimum headway between vehicles in the same lane.

The entire algorithm is available in Reference [6].

Lower Level Optimization

At this level, vehicle speed profiles are optimized for minimum fuel consumption using a dynamic programming approach. In this case, the trajectory of each vehicle for upstream and downstream of the intersection is considered during optimization and uses the spatio-temporal constraints dictated by the upper-level optimization such as anchor-point locations and speeds and times of arrival at these points. An additional constraint of downstream speed and location is added to account for vehicle acceleration downstream to get back to the initial speed. The optimization problem uses Virginia Tech Comprehensive Power-based Fuel Model [14] in its objective function as follows:

$$\text{Min: } \int_{t_0}^{t_s} FC_u(t).dt + \int_{t_s}^{t_f} FC_d(t).dt$$

$$\text{where } FC(t) = \begin{cases} \alpha_0 + \alpha_1 P(t) + \alpha_2 P^2(t) & \forall P(t) \geq 0 \\ \alpha_0 & \forall P(t) < 0 \end{cases}$$

$P(t)$ is the instantaneous power which is a function of instantaneous velocity and acceleration. The limits of the integration are t_0 , which is the start time of the optimization (usually, the time the vehicle receives the SPaT information); t_s , which is the predicted time that the vehicle should reach the intersection stop-line to proceed safely during a green indication; and t_f , which is the time that the vehicle accelerates back to its original speed.

In order to solve this non-linear optimization problem, a dynamic programming approach is used where we discretize the solution space and then use recursive path-finding principles to generate optimal control variables. Acceleration and deceleration are the control variables used in this optimization. As shown in Figure 8.2, we have three defined spatio-temporal points for each vehicle. These points are:

- i. First anchor point where the location, time and speed of the vehicle is fixed.
- ii. Second anchor point where the location and time are fixed. The speed of the vehicle depends on the turn movement.
- iii. Downstream of the intersection where the location and speed of the vehicle are fixed.

Path-finding logic is used to find the least cost path that passes through these points while conserving microscopically defined speed and acceleration models and car-following models. The solution space is discretized and a recursive A-star algorithm is used to find the optimum solution. The optimum state advances each time-step by selecting the state that corresponds to the least cost to reach that state plus a heuristic estimate of the future cost to move to the final state. The dynamic programming algorithm works every time-step to incrementally find the “least fuel-consumed” path between these three points with n discretization using the following cost function:

$$\text{Min} \{ C_{0 \rightarrow i} + C_{i \rightarrow i+1} + H_{i+1 \rightarrow n} \}$$

where

0 to n are the discretized states,

$C_{0 \rightarrow i}$ is the cost till i^{th} state,

$C_{i \rightarrow i+1}$ is the cost from i^{th} state to $(i+1)^{\text{th}}$ state and

$H_{i+1 \rightarrow n}$ is the heuristic estimate cost from $(i+1)^{\text{th}}$ to n^{th} state.

A full description of the algorithm is given in Reference [10].

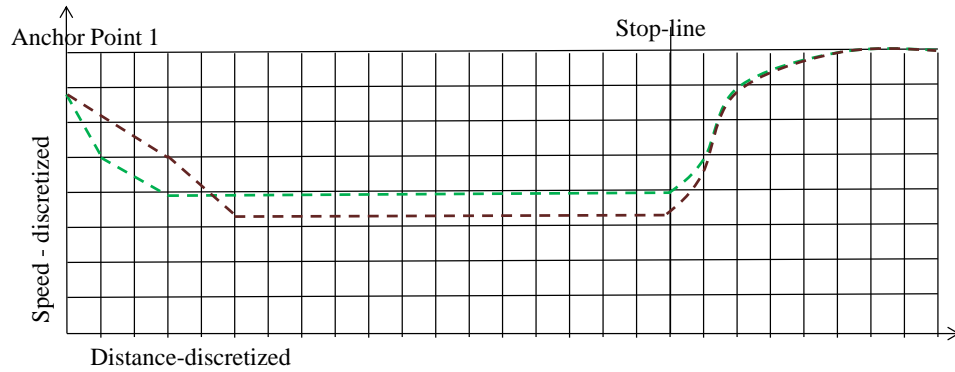


Figure 8.2 Discretizing solution space to find optimum path to traverse through defined states.

It should be noted that since the vehicle arrival times at the stop-line are conserved after the upper-level optimization, the overall delay does not change after lower-level optimization. The outputs of the lower level of optimization are the actual vehicle profiles that correspond to least fuel consumption, least overall delay and crash avoidance.

Optimization Controller

The bi-level optimization controller proposed in this paper aims at optimizing the trajectories of the vehicles that pass through an intersection and is shown in Figure 8.3. The intersection controller is assumed to have V2I communication to force these speed profiles into incoming vehicles rather than a conventional approach with red, yellow and green. The controller receives inputs from vehicles using Basic Safety Messages as they enter the Zone 1 which includes vehicle-specific parameters as well as their locations and speeds. The upper-level optimization is then done to generate vehicle arrivals at the intersection stop-line that corresponds to minimizing overall intersection delay. Speed-rules for each vehicle according to their turn movement are also generated. This serves as the input to the lower-level optimization where the vehicle table is classified based on whether they need to incur a negative delay, zero delay or positive delay in Zone 2. Optimization is then done to generate speed profiles that correspond to least-fuel consumption for each vehicle while conserving the delay. In order to test the proposed strategy, a simulation case-study is done and described in the next section.

The pseudo-code for the entire algorithm is given below:

1. Initialization – The controller acquires information about all vehicles in the Zone 1 and recommends them to attain maximum speed.
2. First Anchor Point – This defines the initial state of optimization which include initial speed v_a , distance to stop-line x_s and time-stamp t_a .
3. Second Anchor Point – This is defined at the stop-line by the upper-level controller. This includes vehicle speed v_s and time-stamp t_s .
4. Case-based categorization – categorize vehicles into sets based on the delay it has to incorporate between t_a and t_s .

5. Lower-level Optimization – As defined in previous sub-section, the a-star algorithm is used to find out discretized states of the vehicles that gives least fuel consumption.

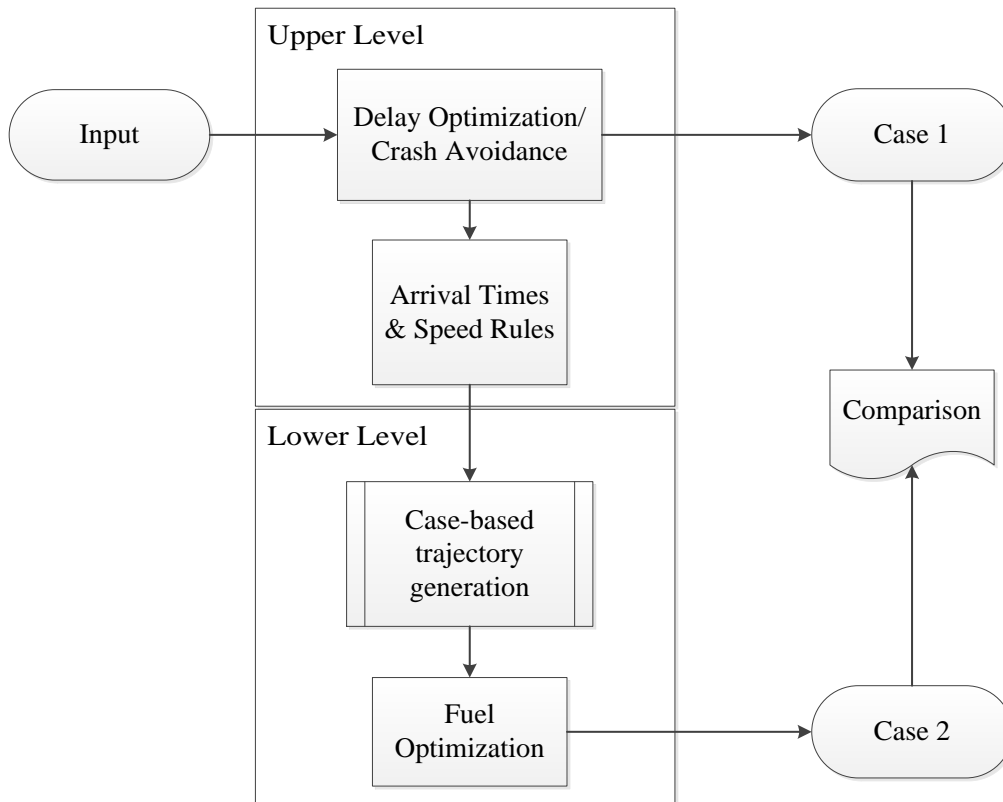


Figure 8.3 Multi-Objective Optimization Framework

Simulation Analysis

In order to test the effectiveness of the proposed multi-objective optimization algorithm, a generic four-legged intersection was simulated in an agent-based test bed that was programmed in MATLAB. The testing tool used the microscopic longitudinal models that are used by INTEGRATION software. Figure 8.4 shows a schematic of the simulated intersection with three lanes for each approach dedicated to left, through and right movement to avoid complexity due to lane-changes. The roadway speed limit was assumed to be 35 miles per hour and 16 different volume combinations are simulated as shown in Table 8.2 to get a volume-capacity ratio of 0.2 to 0.9. The measures of effectiveness tested were overall intersection delay and fuel-consumption per vehicle to overcome the intersection. These calculations used vehicle-specific parameters. In this paper, all vehicles are assumed to replicate the parameters of a 2010 Honda Civic as shown in Table 8.1. This assumption helps in gauging the results against a calibrated conventional simulation done in INTEGRATION. The origin-destination demand consisted of 20 percent of the traffic turning left and right and the remainder proceeding through the intersection. The maximum speed in the intersection was constrained by the turn movement for each vehicle with

the through vehicles traveling at the speed-limit and left and right turning vehicles traveling at 80 and 60 percent of the speed-limit.

The simulation analysis used three cases to simulate the sixteen volume scenarios. These are:

1. Conventional Case – This case assumed conventional signalized intersection that ran an optimized signal cycle computed by Synchro 6 software. This simulation was done in INTEGRATION.
2. Base Case – In this case, a single layer of optimization where vehicles approaching the intersection had minimum overall delay and avoided crashes was simulated to compare with past literature that aims at a single objective function.
3. Test Case – This case simulated the actual multi-objective optimization proposed in this paper.

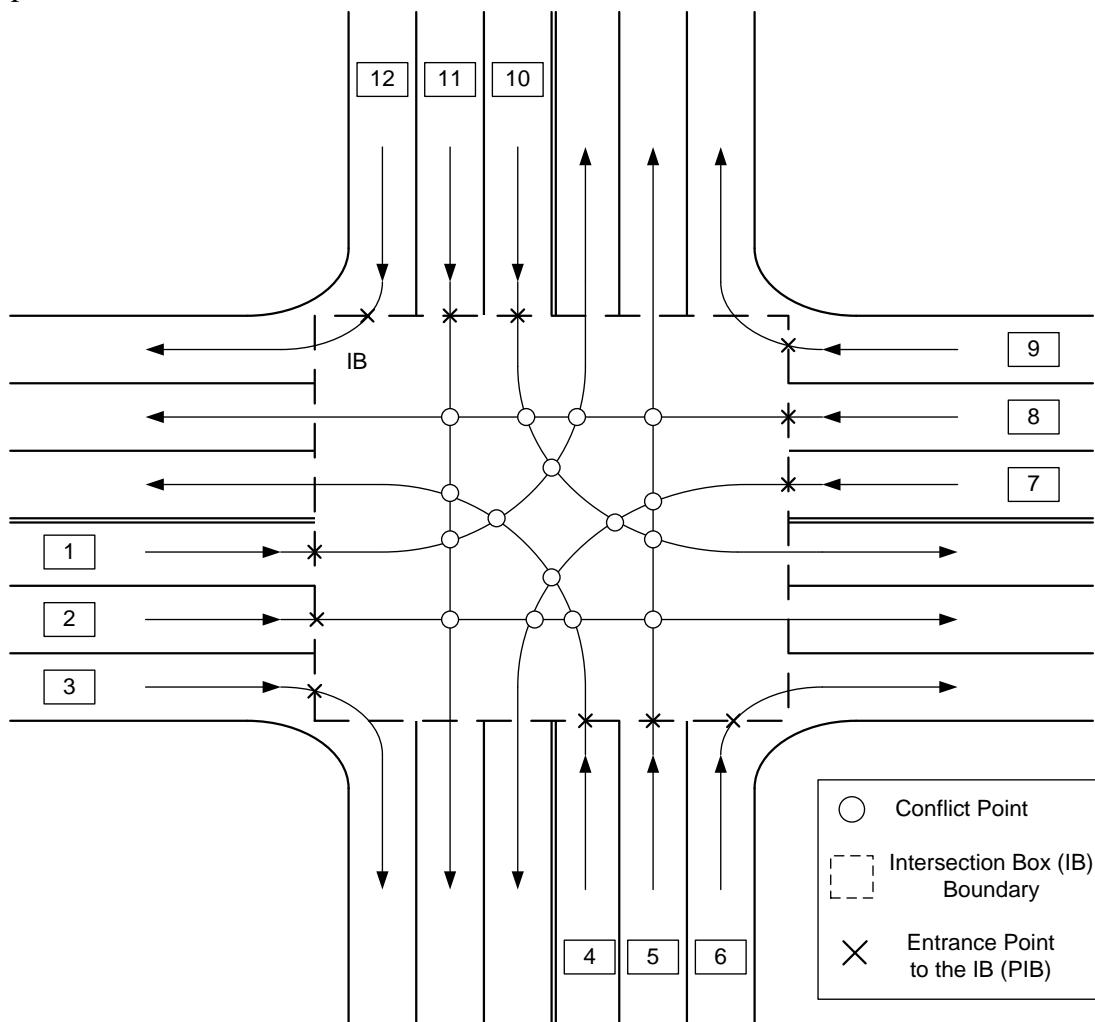


Figure 8.4 Sample intersection showing conflict points

A comparison of results is shown in Table 8.2 where the MoEs such as Average Fuel/Vehicle is compared for the three cases and the Average Delay/Vehicle is compared between the base case and the conventional case. It has to be noted that this value is same for both base case and test

case and hence not compared. Table shows that the proposed multi-objective optimization cause an average fuel savings of around 79 percent and average delay reduction of around 82 percent with respect to conventional signal control. Average fuel savings of around 11 percent was found with respect to just optimizing the delay (base case). Figure 8.5 shows the comparison of average fuel usage by vehicles between the Test Case and the Base Case. As shown, the fuel consumed for both the cases increase as v/c ratio increase. However, the average fuel consumption for the test case is always 10 to 15 percent lower than the average fuel consumption in the base case.

Table 8.1 Microscopic parameters used to generate MoEs.

Parameter	Value
Drag Coefficient (Cd)	0.30
Frontal Area (m ²)	2.32
Engine Efficiency	0.92
Percentage Mass on Tractive Axle	0.60
Mass (kg)	1453
Power (kW)	132
VT-CPFM Alpha 0	0.00047738
VT-CPFM Alpha 1	0.00005363
VT-CPFM Alpha 2	0.00000100

Table 8.2 Simulation results for the 16 scenarios.

Scena rio	Major Vol (vph)	Mino r Vol (vph)	Test Case	Base Case		Conventional Case	
			Avg Fuel/ Veh (l)	Avg Delay/V h (s)	Avg Fuel/ Veh (l)	Avg Delay/Ve h (s)	Average Fuel/ Veh (l)
1	500	250	0.0197	1.1	0.0215	11.5	0.105
2	600	300	0.0193	1.2	0.0216	11.8	0.085
3	700	350	0.0194	1.6	0.0218	13.3	0.092
4	800	400	0.0197	2.1	0.0220	13.4	0.094
5	900	450	0.0197	2.2	0.0221	13.3	0.093
6	1000	500	0.0199	2.7	0.0222	14.1	0.090
7	1100	550	0.0200	3.0	0.0225	15.0	0.092
8	1200	600	0.0201	3.3	0.0225	16.1	0.097
9	1300	650	0.0202	3.4	0.0225	16.8	0.094
10	1400	700	0.0204	3.7	0.0227	15.7	0.094
11	1500	750	0.0205	3.9	0.0228	19.0	0.094
12	1600	800	0.0205	4.2	0.0229	19.5	0.095
13	1700	850	0.0206	4.3	0.0229	18.8	0.096
14	1800	900	0.0206	5.2	0.0233	21.0	0.097
15	1900	950	0.0208	5.2	0.0234	25.1	0.098
16	2000	1000	0.0204	4.0	0.0229	26.4	0.098

The proposed bi-level controller is case-based and involves different constraints based on the vehicle trajectory whether there was a positive speed change prior to the intersection or a negative speed change. Negative speed changes are applicable to cases in which the vehicles have to decelerate before they accelerate to the maximum possible speed in order to honor the crash-avoidance constraint in the upper level optimization. Figures 8.6 and 8.7 shows the comparison of average fuel usage by vehicles in the cases where they have a positive speed change versus negative speed change. The average reduction in the fuel usage for cases with positive speed changes was 9 percent, as shown in Figure 8.6. For the cases with negative speed change, the average reduction in fuel consumption was 12 percent, as shown in Figure 8.7. The higher fuel reduction for the negative speed changes is because the fuel optimization algorithm has greater opportunity to optimize the vehicle trajectory.

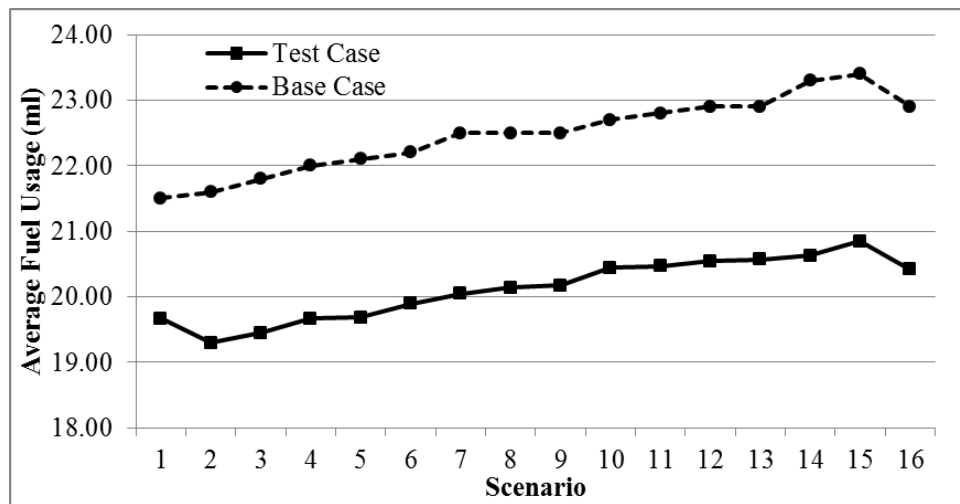


Figure 8.5 Fuel consumed per vehicle for test and base case.

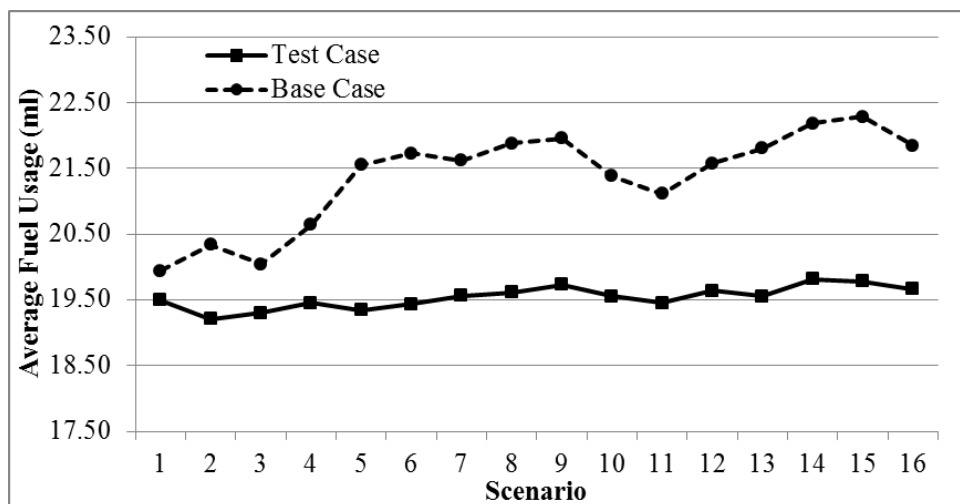


Figure 8.6 Vehicles with positive speed change

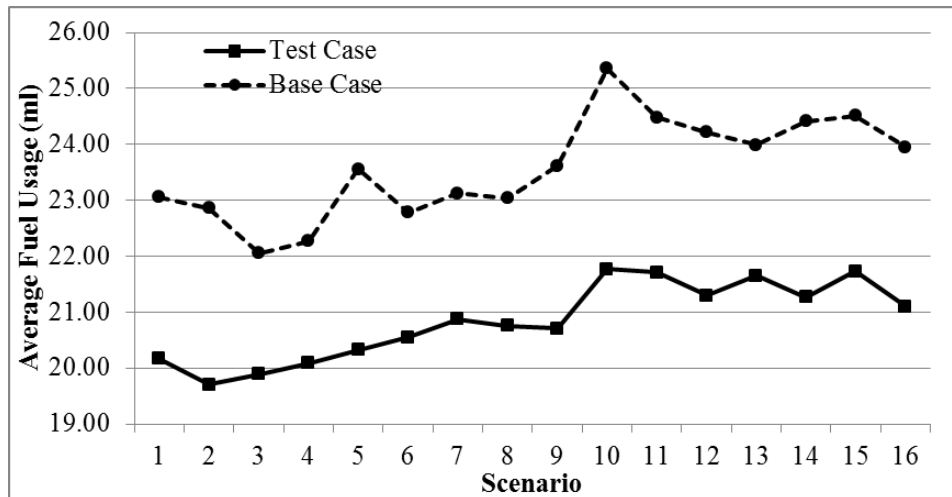


Figure 8.7 Vehicles with negative speed change

Conclusions

The research presented in this paper provides a novel approach to managing automated vehicles at intersections. The proposed multi-objective optimization algorithm minimizes vehicle delay subject to collision avoidance constraints at the upper level and then minimizes the vehicle fuel consumption levels at the lower level. Specifically, at the upper level, the algorithm generates vehicle arrival times at the stop-line along with an associated speed that is generated by the upper-level controller. At the lower level, the algorithm generates a fuel-optimized vehicle trajectory subject to the constraints set by the upper level controller. The proposed controller performance was compared to a single level controller using an agent-based simulation as well as with an optimally timed conventional signalized intersection. The approach volumes were ranged from 500 to 2000 vehicles per hour per approach so that the volume-capacity ratio will range between 0.2 and 0.9. Measures of effectiveness compared were fuel consumption and delay incurred per vehicle. A case-based classification was also made so as to compare the individual vehicles that had a positive speed change with the ones that had a negative speed change upstream of the intersection. The following conclusions were made from this simulation analysis:

1. It was found that the lower-level optimization produces fuel savings in the range of 10 to 11 percent on top of the upper-level optimization.
2. The upper-level optimization produces 76 percent fuel savings over conventional traffic signal control running on Synchro-optimized cycle.
3. The overall fuel-savings provided by the multi-objective optimization controller is of the order of 79 percent compared to conventional signal controllers.
4. When multiple volume combinations were simulated, the fuel savings yielded by the proposed algorithm was found to be independent of the approach volumes, whereas the actual fuel usage increased with increasing traffic volumes.
5. The proposed approach reduces the average delay by 82 percent when compared to conventional traffic signal control.

Case-based classification shows that vehicles that require a negative speed change spend more fuel since they have a positive delay than the vehicles with negative delay. However, the vehicles with positive delay have more fuel savings in percentage when the optimization is done for their trajectory generation than the ones with negative delay. This is intuitive because vehicles with positive delay have more room for optimizing their speed profiles than the ones with negative delay.

The multi-objective optimization algorithm presented and simulated in this paper warrants further analysis to modify and test this approach. More vehicle types could be analyzed versus a single vehicle type as used in this study. Also, the study presented here uses a MATLAB-based simulation approach. Even though it replicates the microscopic traffic models used in the INTEGRATION software, it would be worthwhile to test the system in a state-of-the-art simulation software. Lastly, the proposed approach assumes all vehicles have autonomous longitudinal control. Modifications to the algorithm are needed to use this system in a semi-automated world where the penetration rates of both longitudinal control systems as well as V2I communication are not 100 percent.

Acknowledgements

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9. Conclusions and Future Research

Conclusions

The research presented in this dissertation provides a comprehensive analysis of using advanced signal timing information as well as information about speed and spacing of surrounding vehicles to optimize the fuel consumption. This system, named, Eco-Cooperative Adaptive Cruise Control, was modeled, tested and evaluated in multiple simulation environments. As described in the introduction, chapters 4 through 8 are peer-reviewed manuscripts which autonomously describe various aspects of this research with its own conclusive remarks. In this chapter, the overall conclusions are made with respect to this dissertation.

Chapter 2 analyzed the previous and concurrent research efforts in the field of advanced eco-driving, using signal timing information. Multiple literatures were reviewed on optimizing fuel consumption at signalized intersections but most of them lacked a comprehensive analysis or even an explicit optimization function that incorporates microscopic fuel consumption models. Most researchers assumed fuel consumption to be tied directly with vehicle acceleration levels and used that as a control to optimize fuel consumption. This claim is not necessarily true and depends on a variety of other parameters. Chapter 3 described in brief how the algorithm is modeled to include multiple constraints that are prescribed by advanced signal information, vehicular and roadway parameters.

Current State of Use of In-Vehicle Technology

Chapter 4 makes some interesting conclusions regarding the current state-of-use of advanced in-vehicle technology using a two-part public opinion survey. The stratified results to match the licensed population of United States suggested that demographic factors had insignificant impact on respondent's opinion on advanced in-vehicle technology. This research piece analyzed respondent attitude towards multiple facets of in-vehicle technology such as advanced control systems including Cooperative Adaptive Cruise Control and Adaptive Cruise Control systems, smartphone applications, driver-assistance systems and potentially self-driving systems.

Around 64 percent of respondents use smartphone applications to assist with their travel with the top applications being navigation and traffic information. Only 24 percent of respondents agree that cruise control adds to their distraction while over 60 percent of respondents felt that system acquaintance is an important factor in judging new technology. Top driver assistance systems that are voted for includes safety enhancing systems and eco-driving systems. Over 90 percent respondents voted for non-intrusive systems while only 35 percent respondents voted for fully autonomous systems.

Modeling Results of ECACC

Chapter 5 analyzes vehicle-specific modeling of ECACC where the system was calibrated to 30 top-sold automobiles in the US which are attributed to six different EPA classes tabulated in Appendix A. MATLAB-based simulation analysis was done to test the sensitivity of the model

with respect to vehicle class, bounding speed-limits and green-time delay for optimization of speed profiles. The ECACC system was found to be sensitive to these three criteria and fuel savings were measured as absolute and relative values. Class-based analysis suggested that absolute fuel savings is highest in light-duty trucks and lowest in compact cars, whereas the relative fuel savings is vice-versa. However, the absolute and relative trends matched for other variables such as approach speed and green-time delay. A higher speed-limit caused greater fuel savings and a higher green-time delay caused lesser fuel savings. The green-time delay is defined as the time differential between the actual green time and the time to intersection of the vehicle prior to optimization.

Agent-based modeling of ECACC, as explained in Chapter 6, was performed to test the endurance of the system on a fully functional signalized intersection from Downtown Blacksburg. The intersection was simulated at a microscopic level including specific features such as grade and lane geometry. Reactive agents were used to simulate vehicles that run on ECACC logic with respect to changing signal conditions. Two measures of effectiveness were considered – the average fuel consumption and the average travel-time for the 400 meter vicinity of the intersection. It was found that over 30 percent fuel savings can be achieved within the vicinity of intersections when the algorithm is used. The proposed algorithm also caused an increase in the average travel-speed of vehicles by more than 210 percent. It was also found that the fuel savings were greater for the major street than the minor street owing to their uneven green split. Lower volumes yielded more fuel savings and higher percentage increase in the average travel speed.

Expanding ECACC Research

In order to test the endurance of the proposed system, it was integrated in to a modified version of TEXAS model which could replicate connected vehicles scenario and dual-component system. The eTEXAS uses cloud-based simulation models which could remotely be controlled using web-service modules. Chapter 7 provided a comprehensive description of this system which was consequently used to simulate the proposed eco-speed control algorithm with a standard four-legged intersection. Average increase in speed of 9.2 percent and average decrease in fuel consumption of 5.5 percent were found. The measures of effectiveness are different from the agent-based modeling results because of the difference in underlying models used by eTEXAS and the ones in the ECACC optimization. This research also presented the impact of considering and correcting for communication latencies in the connected vehicle environment.

Many researchers in the transportation industry have predicted fully autonomous vehicles in the near future. This dissertation tried to incorporate eco-driving concept in automated vehicle management at intersections. Chapter 8 demonstrates a bi-level multi-objective optimization tool that optimizes vehicles at intersections to avoid crashes, minimize delay and minimize fuel consumption. Multiple volume cases of a sample intersection were simulated in this chapter

proving 82 percent reduction in average vehicle delays and 79 percent reduction in vehicle fuel consumption compared to conventional signalized intersection control.

Overall Contributions

While there has been past research addressing the issue of fuel optimization at signalized intersections using advanced signal information, they lacked comprehensiveness in research and use of explicit microscopic modeling in the optimization function. The research presented in this document contributes further by developing a robust algorithm, named Eco-Speed Control, which uses explicit fuel-based optimization functions as well as microscopic modeling in establishing constraints.

The specific contributions of the research include:

1. Developed a robust eco-drive system in the vicinity of intersections that explicitly models the vehicle fuel consumption and considers vehicle and surrounding vehicle constraints on the system performance.
2. Solicited user-acceptance in-vehicle driver assistance systems using stated-preference on-line public surveys.
3. Characterized the sensitivity of such a system to external variables, including weather and grade factors and internal variables such as vehicle type. Thirty top-sold vehicles that belong to different EPA classes were calibrated and tested using the proposed algorithm.
4. Developed a Connected Vehicles framework that uses SAE J2735 message sets developed by the Society of Automotive Engineers to evaluate the performance in a simulated connected vehicles environment. The multi-component system was developed using a cloud-based eTEXAS environment.
5. Enhanced the algorithm for use as a lower-level controller within the intersection Cooperative Adaptive Cruise Control (iCACC) system for management of autonomous vehicle intersections. This intersection management system looks at a broader, multi-objective, bi-level optimization of vehicle delay and fuel consumption levels.

List of Publications

Following is a list of publications that were made as a part of this research to the date.

Journal Publications and Reports:

- R.K. Kamalanathsharma, I.H. Zohdy and H.A. Rakha, "*Survey on Increasing In-vehicle Technology Use: Results and Findings*," (in-press) International Journal of ITS Research, May 2014.

- R.K. Kamalanathsharma and H.A. Rakha, "*Agent-based Simulation of Eco-Speed Controlled Vehicles at Signalized Intersections*," (in-press) Transportation Research Record - Journal of Transportation Research Board, May 2014.
- R.K. Kamalanathsharma, H.A. Rakha, "*Leveraging Connected Vehicle Technology and Telematics to Enhance Vehicle Fuel Efficiency in the Vicinity of Signalized Intersections*," (in-press) Journal of Intelligent Transportation Systems, June 2013.
- H.A. Rakha, I.H. Zohdy and R.K. Kamalanathsharma, "*Agent-Based Game Theory Modeling for Driverless Vehicles at Intersections*," U.S. Department of Transportation Report, MAUTC-VT-2010-02, February 2013.
- H.A. Rakha, R.K. Kamalanathsharma, K. Ahn, "*AERIS: Eco-Vehicle Speed Control at Signalized Intersections using I2V Communication*", Final Report for Applications for Environment: Real-time Information Synthesis, Research and Innovative Technology Administration, June 2012.

Refereed Conference:

- R.K. Kamalanathsharma, I. Zohdy and H.A. Rakha, "*Multi-Objective Optimization of Automated Vehicles at Intersections*," (under review) 2014 IEEE Intelligent Vehicles Symposium, Dearborn MI, June 2014.
- R.K. Kamalanathsharma and H.A. Rakha, "*Simulation Testing of Connected Vehicle Applications in a Cloud-Based Environment*," 93rd Annual Meeting of the Transportation Research Board, Washington D.C., January 2014.
- R.K. Kamalanathsharma and H.A. Rakha, "*Agent-based Simulation of Eco-Speed Controlled Vehicles at Signalized Intersections*," 93rd Annual Meeting of the Transportation Research Board, Washington D.C., January 2014.
- R.K. Kamalanathsharma and H.A. Rakha, "*Fuel-Optimal Vehicle Throttle Control: Model Logic and Preliminary Testing*," 20th ITS World Congress Tokyo 2013, Japan, October 2013.
- R.K. Kamalanathsharma and H.A. Rakha, "*Eco-Cooperative Adaptive Cruise Control - A Cooperative Energy Efficient Application*," 20th ITS World Congress Tokyo 2013, Japan, October 2013.
- R.K. Kamalanathsharma and H.A. Rakha, "*Eco-Speed Control at Intersections Using Model-Specific Reactive Agents*," Conference on Agent-Based Modeling in Transportation Planning and Operations, Blacksburg, October 2013.
- R.K. Kamalanathsharma, I.H. Zohdy, H.A. Rakha, "*Public Perception on Increasing Use for Technology in Automobiles - Survey Findings*," 16th International IEEE Conference on Intelligent Transportation Systems, Netherlands, October 2013.
- R.K. Kamalanathsharma and H.A. Rakha, "*Multi-stage Dynamic Programming Algorithm for Eco-Speed Control at Traffic Signalized Intersections*," 16th International IEEE Conference on Intelligent Transportation Systems, Netherlands, October 2013.

- I.H. Zohdy, R.K. Kamalanathsharma, H.A. Rakha, "*Intersection Management for Autonomous Vehicles using Cooperative Adaptive Cruise Control Systems*," 92nd Annual Meeting of the Transportation Research Board, Washington-DC, January 2013.
- R.K. Kamalanathsharma, H.A. Rakha, "*Agent-based Modeling of Eco-Cooperative Adaptive Cruise Control Systems in the Vicinity of Intersections*," 15th International IEEE Annual Conference on Intelligent Transportation Systems, Anchorage-AK, September 2012.
- R.K. Kamalanathsharma, K.L. Hancock, "*Intelligent Preemption Control for Emergency Vehicles in Urban Corridors*", 91st Annual Meeting of the Transportation Research Board, Washington-DC, January 2012.
- H.A. Rakha, R. K. Kamalanathsharma, "*Eco-driving at Signalized Intersections using V2I Communication*," in 14th International IEEE Annual Conference on Intelligent Transportation Systems, Washington-DC, October 2011.

Future Research

As is the case with any research effort, there is always scope for further research. These additional research directions are described in this subsection. The ECACC system has been modeled, tested and evaluated with the objective to field implement the system. However, the state-of-instrumentation did not allow for a real-world implementation study. Therefore, the first warranted research direction will be an actual experiment on a connected vehicle test-bed. Further to this, the system can also be modified to consider additional constraints and therefore look at optimizing speed-profiles over an arterial with multiple intersections rather than just one intersection in this case.

Experimental Analysis

The Connected Vehicles/Infrastructure University Transportation Center is currently retrofitting the Smart Road intersection in Blacksburg, VA to incorporate connected vehicles capability which can be utilized for actual implementation analysis of the ECACC system. The Smart-Road intersection's custom controller can be used to create repeatable scenarios to change signal phases based to the vehicle's distance to the intersection (DTI). The Road-Side Equipment (RSE) with wireless capability can be used to communicate this information to the vehicles which will have portable devices generating and updating "fuel-optimum" vehicle trajectories. Figure 9.1 shows the typical concept of operations diagram for the proposed experiment. Driving experiments will involve drivers from different demographics to replicate an actual test population and will be done for the four cases described in this section. The vehicle will log the test vehicles' instantaneous speed, throttle levels, brake levels, fuel consumption and the road-grade so that comparison can be made between the cases.

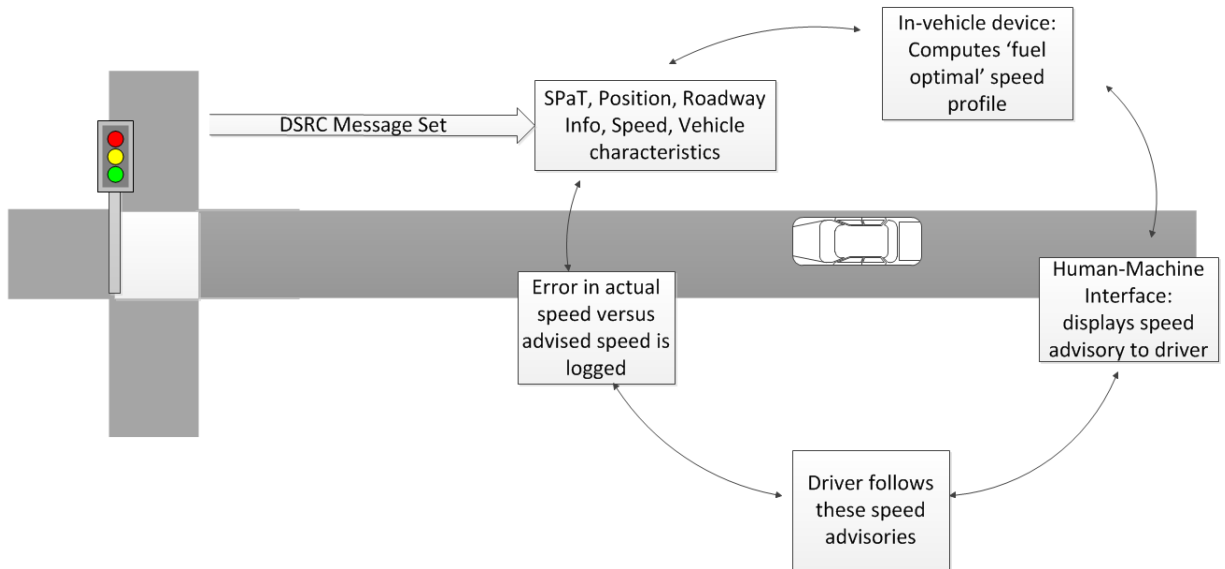


Figure 9.1 - Experimental Set-up

Case 1: Uninformed Driver

This will form the base case of experimentation and will involve drivers approaching the intersection in an uninformed manner. There will be no communication of SPaT information or driver advisory in this case. This is expected to replicate the pre-system scenario. This case will also be compared to the behavior extracted from the instrumented signals in the Blacksburg test-bed.

Case 2: Informed Driver

This will involve communication of SPaT information to drivers. The Driver-Vehicle Interface (DVI) will show “seconds to next signal change” to the driver. The driver uses this information and his/her perception about the situation to make speed changes and safely maneuver the intersection.

Case 3: Informed Driver with Speed Advisory

In this case, the SPaT information will be used by the in-vehicle devices to generate the fuel-optimum vehicle trajectory and then communicate the instantaneous speed recommendation to the driver using the DVI. The suggested speed and actual speed will be logged and could be used to generate an error function. The speed advisory will be updated every time-step to incorporate driver’s error in following the previous advisory.

Case 4: ECACC System

ECACC system test could be done if a specified speed profile could be implemented in a test-vehicle’s cruise control system by enhancing the Adaptive Cruise Control system. This case is similar to the previous one except that the driver perception on speed-following will not come in

to play. The cruise control's latency to follow speed will be studied in this case and will give a more accurate replica of the proposed algorithm.

Once the four cases are experimented, the logged data will be used to generate meaningful inferences on many research questions including the following:

- a. What are the implementation issues with respect to eco-speed control systems?
- b. What percentage fuel-savings can be expected from providing speed-advisories to drivers?
- c. What percentage of fuel-savings can be expected just by giving "seconds-to-next-signal-change" information to the drivers? Such systems already exist in many European and Asian countries on an infrastructure-based display system.
- d. What is the error-function with which a typical driver can follow instantaneous speed-advisories?

The proposed study will be the first of its kind field-testing of the proposed Eco-Speed Control Algorithm and will enable comparing simulation results with field study results. The study will also serve as the first step to identify implementation issues associated with Eco-Cooperative Adaptive Cruise Control and Eco-Speed Control strategies. This research will also address the issues of driver-acceptance of intelligent advisories such as how humans respond to alerts from an in-vehicle device or with what error humans or automated cruising devices can follow a particular advised speed profile. The error function generated for speed-following can be of high research value for studies involving speed-following.

Multi-Intersection Control

In the research established in this dissertation including development of the algorithm and its testing in an agent-based environment, the optimization of speed-profile was done on a per-intersection basis. A vehicle with ECACC capability is assumed to receive SPAT information from one intersection at a time and subsequently optimizes its speed-profile to overcome that particular intersection. However, when there are closely spaced intersections, the optimum speed-profile as a result of the first intersections' information would depreciate the possibility of fuel-savings in the next one. Therefore, when there is information from multiple intersections, a multi-window optimization approach can be used to form a speed-profile for the vehicles where it is constrained by green-windows from all the intersections at once. This enhancement to the algorithm would be an efficient way to negotiate signalized arterials where there are multiple close-spaced intersections. The algorithm can also help generate a speed-profile to avoid stoppage when vehicles are going against the coordinated green-signal intersections.

Appendices

Appendix A

Model parameters for top-sold cars in the US (2011 Base Models)

Make	Model	W (Kg)	C _d	Engine size (L)	EPA Estimate (mpg)		Max. Power (kW)	VT-CPFM 1 Parameters		
					C	H		α_0	α_1	α_2
Compact Cars (Passenger + Cargo Volume between 100 and 109 Cu. Ft.)										
Honda	Civic	1212	0.27	1.8	28	39	104.4	3.41E-04	5.83E-05	1.00E-06
Ford	Focus	1341	0.29	2.0	28	38	119.3	3.03E-04	5.41E-05	1.00E-06
Toyota	Corolla	1270	0.29	1.8	27	34	98.4	2.71E-04	7.69E-05	1.00E-06
Volkswagen	Jetta	1272	0.31	2.0	24	32	85.7	3.93E-04	1.81E-18	6.62E-06
Mazda	3	1329	0.26	2.0	24	33	110.3	3.79E-04	7.04E-05	1.00E-06
Mid-size Cars (Passenger + Cargo Volume between 110 and 119 Cu. Ft.)										
Toyota	Camry	1447	0.28	2.5	25	35	132.7	3.84E-04	5.44E-05	1.00E-06
Nissan	Altima	1442	0.31	2.5	23	32	130.5	4.32E-04	5.69E-05	1.00E-06
Ford	Fusion	1490	0.33	2.5	23	33	130.5	4.68E-04	4.61E-05	1.00E-06
Chevrolet	Cruze	1435	0.30	1.8	26	38	102.9	4.16E-04	4.08E-05	1.00E-06
Chevrolet	Malibu	1557	0.30	2.4	22	33	126.0	5.17E-04	4.31E-05	1.00E-06
Full-size Cars (Passenger + Cargo Volume between 120 or more Cu. Ft.)										
Honda	Accord	1487	0.30	2.4	23	34	132.0	4.89E-04	4.29E-05	1.00E-06
Hyundai	Sonata	1451	0.28	2.4	24	35	147.6	4.45E-04	4.76E-05	1.00E-06
Chevrolet	Impala	1613	0.33	3.6	18	30	223.7	7.93E-04	2.24E-05	1.00E-06
Chrysler	300	1814	0.32	3.6	18	27	217.7	6.47E-04	4.33E-05	1.00E-06
Dodge	Charger	1929	0.33	3.6	18	27	217.7	6.42E-04	4.01E-05	1.00E-06
Light-duty Trucks (Gross vehicle Weight Rating less than 8,500 lbs.)										
Ford	F150	2125	0.42	3.7	17	23	225.2	6.73E-04	-1.73E-20	2.51E-06
Chevy	Silverado	2024	0.43	4.3	15	20	145.4	7.79E-04	7.01E-20	2.99E-06
Dodge	Ram	2050	0.38	3.7	14	20	160.3	8.76E-04	-2.34E-19	3.04E-06
GMC	Sierra	2015	0.41	4.3	15	20	145.4	7.63E-04	5.40E-20	3.20E-06
Toyota	Tundra	2077	0.37	4.0	16	20	201.3	5.79E-04	5.34E-19	3.89E-06
Sports Utility Vehicles (Gross vehicle Weight Rating less than 10,000 lbs.)										
Ford	Escape	1466	0.38	2.5	23	28	127.5	4.08E-04	-3.50E-19	4.79E-06
Honda	CR-V	1536	0.41	2.4	21	28	134.2	5.40E-04	-2.52E-19	3.68E-06
Chevy	Equinox	1717	0.36	2.4	22	32	135.7	5.32E-04	2.89E-20	2.86E-06
Jeep	Cherokee	2028	0.37	3.6	16	23	216.2	7.26E-04	-8.39E-19	3.08E-06
Ford	Explorer	2210	0.35	3.5	17	25	216.2	6.86E-04	3.05E-05	1.00E-06
Mini-Vans (Gross vehicle Weight Rating less than 8,500 lbs.)										
Toyota	Sienna	1939	0.31	2.7	19	24	139.4	4.04E-04	6.66E-05	1.00E-06
Chrysler	Town Cntry	2110	0.33	3.6	17	25	211.0	6.76E-04	3.61E-05	1.00E-06
Dodge	Caravan	2046	0.33	3.6	17	25	211.0	6.82E-04	3.70E-05	1.00E-06
Honda	Odyssey	1967	0.35	3.5	18	27	184.9	6.88E-04	8.66E-19	2.50E-06
Nissan	Quest	1981	0.32	3.5	19	24	193.9	4.13E-04	6.24E-05	1.00E-06

Appendix B

Summary of Basic DSRC Message Sets

This white paper entails the message set description pertaining to the DSRC format as set by the standards given in SAE J2735. There are three levels of information carried by the Dedicated Short-Range Communication. They are, Message Sets, Data Frames and Data Elements. As the name suggests, message sets form the top of the hierarchy. Each message set consists of many data frames and each data frame consists of data elements. Data elements can also consist of multiple parts. Particularly three messages are described in this document as seemed appropriate. They are: Basic Safety Message (BSM), Signal Phasing and Timing Message (SPAT) and MapDATA Message (MAP). All definitions and terms are taken from the SAE International Surface Vehicle Standard, Dedicated Short Range Communications (DSRC) Message Set Dictionary (11/2009).

Basic Safety Messages

BSM consists of two parts. Part 1 messages are broadcasted 10 times per second and Part 2 messages are optional information which can be tailor-made for each scenario. Therefore only Part 1 message set is included in this document. As far as the Basic Safety Message is concerned, the hierarchy of data elements is given in the Figure 1.

The definitions of the data frames and data elements are given in the following indented list:

1. *msgCnt* stands for MsgCount (1 byte)
2. *id* is a TemporaryID (4 bytes)
3. *secMark* is the DSecond (2 bytes) – represented as milliseconds within a minute.
4. *pos* consists of PositionLocal3D data:
 - a. *lat* stands for Latitude (4 bytes) – expressed in $1/10^{\text{th}}$ of a micro-degree
 - b. *long* stands for Longitude (4 bytes) - expressed in $1/10^{\text{th}}$ of a micro-degree
 - c. *elev* stands for Elevation (2 bytes) – expressed in decimeters above or below the reference ellipsoid
 - d. *accuracy* stands for Positional Accuracy (4 bytes)
 - i. Semi-major accuracy – represented as 0.05m
 - ii. Semi-minor accuracy – represented as 0.05m
 - iii. Orientation of semi-major axis relative to true north
5. *motion* consists of the following:
 - a. *speed* denotes TransmissionAndSpeed (2 bytes)
 - i. Bits 1 to 13 is Speed represented as 0.02 m/s
 - ii. Bits 14 to 16 is TransmissionState
 - b. *heading* denotes Heading (2 bytes) expressed as 0.0125 degrees from North
 - c. *angle* denotes SteeringWheelAngle (1 byte) expressed at 1.5 degrees with right being positive
 - d. *accelSet* denotes AccelerationSet4Way (7 bytes)
 - i. long Acceleration – represented as 0.01 m/s²

- ii. lat Acceleration - represented as 0.01 m/s²
 - iii. vert Acceleraion - represented as 0.01 m/s²
 - iv. yaw YawRate – expressed as 0.01 degrees per second with right being positive
6. *control* consists of any motion control terms:
- a. *brakes* which shows the BrakeSystemStatus (2 bytes)
 - i. wheelBrakes as BrakeAppliedStatus (4 bits)
 - ii. wheelBrakesUnavailable (1 bit)
 - iii. spareBit (1 bit)
 - iv. traction as TractionControlState (2 bits)
 - v. abs as AntiLockBrakeStatus (2 bits)
 - vi. scs as StabilityControlStatus (2 bits)
 - vii. brakeBoost as BrakeBoostApplied (2 bits)
 - viii. auxBrakes as AuxiliaryBrakeStatus (2bits)
7. *size* includes the VehicleSize (3 bytes)
- a. *VehicleWidth* – in centimeters (10 bits)
 - b. *VehicleLength* – in centimeters (14 bits)

SPAT Message Definitions

SPAT messages can include information regarding one or multiple intersections. Information regarding each intersection comes under the dataframe *intersectionState*. The hierarchy of data frames and data elements is given in Figure 1.

The definitions of the data frames and data elements are given in the following indented list:

1. *name* stands for a string which is an optional human readable name.
2. *id* is a 32 bit field to identify the intersection and unique to a region.
3. *status* is optional and contains Advanced Traffic Controller status information (1 byte).
 - a. Manual control enabled/disabled.
 - b. Stop-time is activated/deactivated
 - c. Conflict Flash active/inactive.
 - d. Preempt active/inactive.
 - e. Priority active/inactive.
 - f. 3 bits reserved.
4. *lanesCnt* - number of lanes representing the same sign state.
5. *States* represent a single intersection controller state. It consists of the following:
 - a. *movementName* – optional definition of movement
 - b. *laneCnt* – number of lanes to follow
 - c. *laneSet* – contains the LaneNumber
 - d. Choice of current movement state:
 - i. *currState* – SignalLightState defines the current signal state being served (or the next). Please refer to table 1 for signal phase indication encoding.

- ii. *pedState* – represents the current or next known pedestrian signal state. (0 = unavailable, 1 = do not walk, 2 = flashing don't walk, 3 = walk)
 - iii. *specialState* – signal for a special lane-type (trains etc.)
 - e. *timeToChange* – moment in local UTC time when signal state will change (represented in 1/10th of a second).
 - f. *stateConfidence* – confidence of current phase data, where 0 = unknown estimate, 1 = minTime, 2 = maxTime and 3 = timeLikelyToChange.
 - g. Choice of current yellow state:
 - i. *yellState* – similar to currState
 - ii. *yellPedState* – similar to pedState
 - h. *yellTimeToChange* – similar to TimeToChange
 - i. *yellStateConfidence* – similar to stateConfidence
 - j. Optional Items:
 - i. *vehicleCount* – integer representing count of vehicles.
 - ii. *pedDetect* – represents pedestrian detection (0 = none, 1 = may be, 2 = one and 3 = some).
 - iii. *pedCount* – integer representing count of pedestrians
- 6. *priority* – uses SignalState Data Element consisting of 1 byte:
 - a. Bit 7 – if this state is currently active.
 - b. Bit 6~4 – preemption or priority value
 - c. Bit 3~0 – PreemptState or PriorityState definitions.
- 7. *Preempt* – similar to priority.

MapDATA Message Definitions

MapDATA in general is used with SPAT data and is broadcasted at intersections to describe complex intersection geometry and even high-speed curve outlines. It primarily consists of 6 elements:

1. *msgID* of type DSRCmsgID.
2. *msgCnt* of type MsgCount
3. *name* that represents a human readable name (optional)
4. *layerType* (optional)
5. *layerID* (optional), and
6. *intersections* of the type Intersection which is data frame by itself.

The hierarchical information about different elements that constitute this message set is given in the Figure on Page 2. The definitions of the data frames and data elements in the *intersection* data frame are given in the following list:

1. DescriptiveName – A string that can be read by humans (optional)
2. IntersectionID – id and refInterNum – A 32bit unique ID given to each intersection.
3. Position3D – uses WGS-84 coordinate system to locate the intersection center.
 - a. Latitude - in 1/10th of a micro degree.

- b. Longitude – in $1/10^{\text{th}}$ of a micro degree
 - c. Elevation – optional (in decimeters)
4. Heading – expressed in 0.0125 degrees from North.
5. LaneWidth – width for a lane in centimeters
6. IntersectionStatusObject – contains ATC status information
 - a. Manual control enabled/disabled.
 - b. Stop-time is activated/deactivated
 - c. Conflict Flash active/inactive.
 - d. Preempt active/inactive.
 - e. Priority active/inactive.
 - f. 3 bits reserved.
7. ApproachObject – details about the approaches and egresses of the intersection.
 - a. Position3D
 - b. LaneWidth
 - c. Approach (approach and egress)
 - i. DescriptiveName
 - ii. ApproachNumber – unique index value for each approach or egress.
 - iii. VehicleReferenceLane & SpecialLane – defines the characteristics of a driving lane or a special lane. VRL has to be at least one for each approach.
 1. LaneNumber – unique number for the lane
 2. LaneWidth
 3. VehicleLaneAttributes – explains possible movements from a vehicle lane.
 4. NodeList – nodeList and keepOutList – offset values that define, X, Y and Z to construct lanes.
 5. ConnectsTo – lanes to which a particular lane connects to.
 - iv. VehicleComputedLane
 1. LaneNumber
 2. LaneWidth
 3. VehicleLaneAttributes
 4. DrivenLineOffset – perpendicular offset of a computed lane from a reference lane in centimeters.
 5. NodeList
 6. ConnectsTo
 - v. BarrierLane – defines the lanes that represents barriers, medians etc.
 1. LaneNumber
 2. LaneWidth
 3. BarrierAttributes – describes the type of barrier (such as no curb, low curb etc.)

4. NodeList
- vi. CrosswalkLane
 1. LaneNumber
 2. LaneWidth
 3. CrosswalkLaneAttributes
 4. NodeList (nodeList and keepOutList)
 5. ConnectsTo
8. SignalControlZone (preemptZones and priorityZones) – describe the zones that are used by vehicles to preempt or prioritize the signal control.
 - a. DescriptiveName
 - b. SignalReqScheme – describes the type of preemption or priority associated using 1 byte.
 - c. LaneNumber
 - d. LaneWidth
 - e. NodeList