AERIS: Eco-Vehicle Speed Control at Signalized Intersections Using I2V Communication

FINAL REPORT

FHWA-JPO-12-063

June 2012

U.S. Department of Transportation

Research and Innovative Technology Administration

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TECHNICAL REPORT DOCUMENTATION PAGE

1. Report No. FHWA-JPO-12-063	2. Government Accession No.	3. Recipient's Catalog No.
4. Title and Subtitle AERIS: Eco-Vehicle Speed Control at Signalized Intersections Using I2v Communication		5. Report Date June 2012 6. Performing Organization Code:
7. Author(s) Hesham A. Rakha, Raj Kishore Kamalanathsharma and Kyoungho Ahn		8. Performing Organization Report No.
9. Performing Organization Name and Address Virginia Polytechnic Institute and State University 3500 Transportation Research Plaza Blacksburg, VA 24061 and Virginia Tech Transportation Institute Center for Sustainable Mobility 3500 Transportation Research Plaza Blacksburg, VA 24061		10. Work Unit No. 11. Contract or Grant No.
12. Sponsoring Agency Name and Address United States Department of Transportation, Research and Innovative Technology Administration 1200 New Jersey Ave, S.E. Washington, DC 20590		13. Type of Report and Period Covered Final 14. Sponsoring Agency Code
15. Supplementary Notes		

16. Abstract

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17. Key Words AERIS, vehicle emissions reduction strategies, eco-driving, vehicle fuel consumption modeling, speed profiling		18. Distribution Statement No restrictions. Document available from: National Technical Information Services, Springfield, Virginia 22161	
19. Security Class (of this report) Unclassified	20. Security Class (of this page) Unclassified	21. No. of Pages 36	22. Price

Form DOT F 1700.7 (8-72) Reproduction of completed page authorized

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Abstract

The earth's fossil fuels are being continuously depleted, and as surface transportation is one of the prime consumers of petroleum, it is important to reduce petroleum consumption and make transportation more efficient and sustainable. Researchers have endeavored to reduce energy consumption by vehicles and their associated carbon footprints for more than half a century. Innovations in engines, infrastructure, and roadway design and signal timing have played roles in enhancing fuel efficiency of vehicles by more than 83 percent over the past 30 years. Along with fuel efficiency, transportation researchers aimed at enhancing the safety of the public have discovered that connecting vehicles with infrastructure has a great potential in making roads safer for everyone. This began an era in advancements focusing on Vehicle Infrastructure Integration. The current Connected Vehicles Technology program by the Federal Highway Administration aims to establish connectivity between vehicles, infrastructure and mobile devices. Apart from traffic safety, connectivity between elements in transportation can yield fuel saving benefits, which is the focus of this report.

This report concentrates on a velocity advisory tool, or decision support system, for vehicles approaching an intersection using communication capabilities between the infrastructure and vehicles. The system uses available signal change information, vehicle characteristics, lead vehicle characteristics, and intersection features to compute the fuel-optimal vehicle trajectory. The proposed system involves a complex optimization logic incorporating roadway characteristics, lead vehicle(s) information, vehicle acceleration capabilities and microscopic fuel consumption models to generate a fuel-optimal speed profile. The research also develops a MATLAB application named eco-vehicle speed control in order to demonstrate the potential of an in-vehicle application of such a technology.

1 Introduction

The United States is one of the prime consumers of petroleum in the world, burning more than 22 percent of the total petroleum refined on the planet [1]. The transportation sector consumes nearly three-quarters of this and is the second largest carbon emitter in the country [1,2]. Idling vehicles waste more than 2.8 billion gallons of gasoline each year [3]. Efforts to reduce the environmental impacts of driving and improve fuel efficiency of vehicles started during the late 1960s. Mechanical improvements such as enhanced aerodynamics, engine design, and transmission enhancements have improved average passenger car fuel efficiency from 18.4 l/100 km in 1975 to 10.1 l/100 km in 2005 [4]. However, the number of vehicles on the nation's roadways continues to increase, as is the total vehicle miles traveled.

As fossil fuel estimates decreased and atmospheric pollution due to greenhouse gases increased, the environmental policy makers pushed for lower and lower fuel consumption and emissions in vehicles, and researchers looked towards sustainable transportation. Eco-driving, fuel-optimal routing, operational enhancements in vehicles and alternative fuel engines are some examples of innovations highlighting sustainable transportation. On the infrastructure side, improved pavement surfacing, introduction of advanced traffic signals that function in an adaptive way and improvements in roadway design are helping this cause.

In the United States and other developed countries worldwide, communication systems and information technology penetrated the surface transportation sector. As a part of the Federal Highway Administration (FHWA) Intelligent Transportation Systems (ITS) Program, the roadway infrastructure in the United States was retrofitted with sensors designed to collect traffic data and provide users an overview of congestion so that they can make informed route-choice decisions. In addition, the USDOT connected vehicle program, formerly called Vehicle Infrastructure Integration (VII) program, promises communication between vehicles, infrastructure and mobile devices [5].

The research reported here focuses on reducing fuel consumption by controlling speed trajectories of vehicles approaching an intersection using Signal Phasing and Timing (SPaT) data obtained via Vehicle-to-Infrastructure (V2I) communication. The system discussed here analyzes possible velocity trajectories for a vehicle approaching an intersection and draws conclusions regarding the most fuel-optimal strategy under the given conditions. It assumes that signal controllers at intersections could communicate to the approaching vehicles and provide them with vital intersection characteristics, queued vehicle information and upcoming signal change information.

2 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 [6]. 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 [7]. This was the first initiative to use information transfer and communication technologies on a large scale in the surface transportation sector. In 2011, VII was rebranded as the Connected Vehicle Research program [5,8].

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 [9–11]. A number of vehicle dynamics models have also been developed to accurately predict the physics of a vehicle [12]. 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 [4]. 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 1).

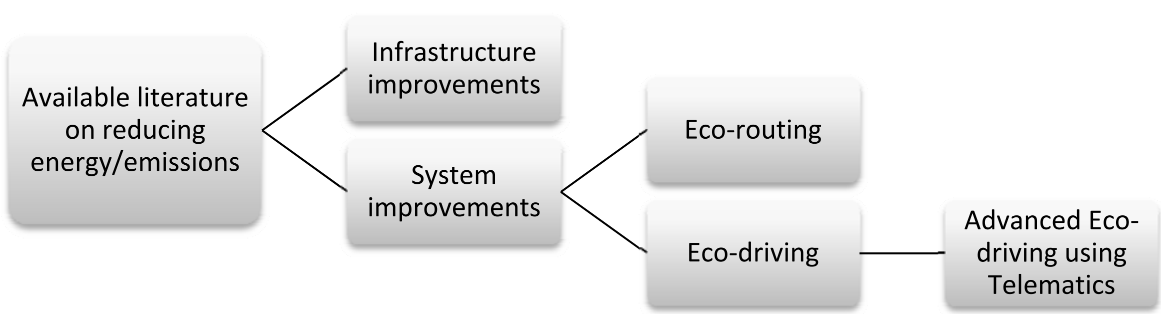

Figure 1. Classification of the literature review

2.1 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 [13], [14]. Some traffic control improvements suggest the use of genetic algorithms to account for the dynamic routing of vehicles that have typically been neglected [15], while other field tests with genetic algorithms based on green-wave optimization revealed potential energy and emissions improvements [16].

2.2 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 [4]. 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 [17]. 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 [18], [19]. The third generation of ISA devices included use of telematics to communicate real-time traffic information for speed advisories to drivers [20].

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 [21]. 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.

2.2.1 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 [9], [10]. 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 [22]. Studies conducted using vehicles equipped with resistive devices to prevent sudden velocity changes also showed no differences [23]. Some studies showed that eco-driving not only prevented sudden variations in speed but entailed predicting the optimum speed

[24], [25]. 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 [26]. 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 [27]. 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 [28]. 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 [29]. 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 [30]. 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 [31].

2.2.2 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 [32]. 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 [33]. Link-weights also depended on grades of road segments [34]. 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 [35].

2.2.3 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 [5]. 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 [3]. 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 [36]. 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 advise 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 [37]. 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 [38]. 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 [39]. 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 [40] 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 a connected vehicle-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 [41]. 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 [42]. 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 CO_2 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 [43]. 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 [16]. 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.

3 Model Description

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 2 shows a logical diagram of events that will lead to eco-vehicle speed control near an equipped signalized intersection [44]. 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.

3.1 Scenarios

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 (va), there are different scenarios, the eco-vehicle can be in. These are summarized as follows:

3.1.1 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.

3.1.2 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.

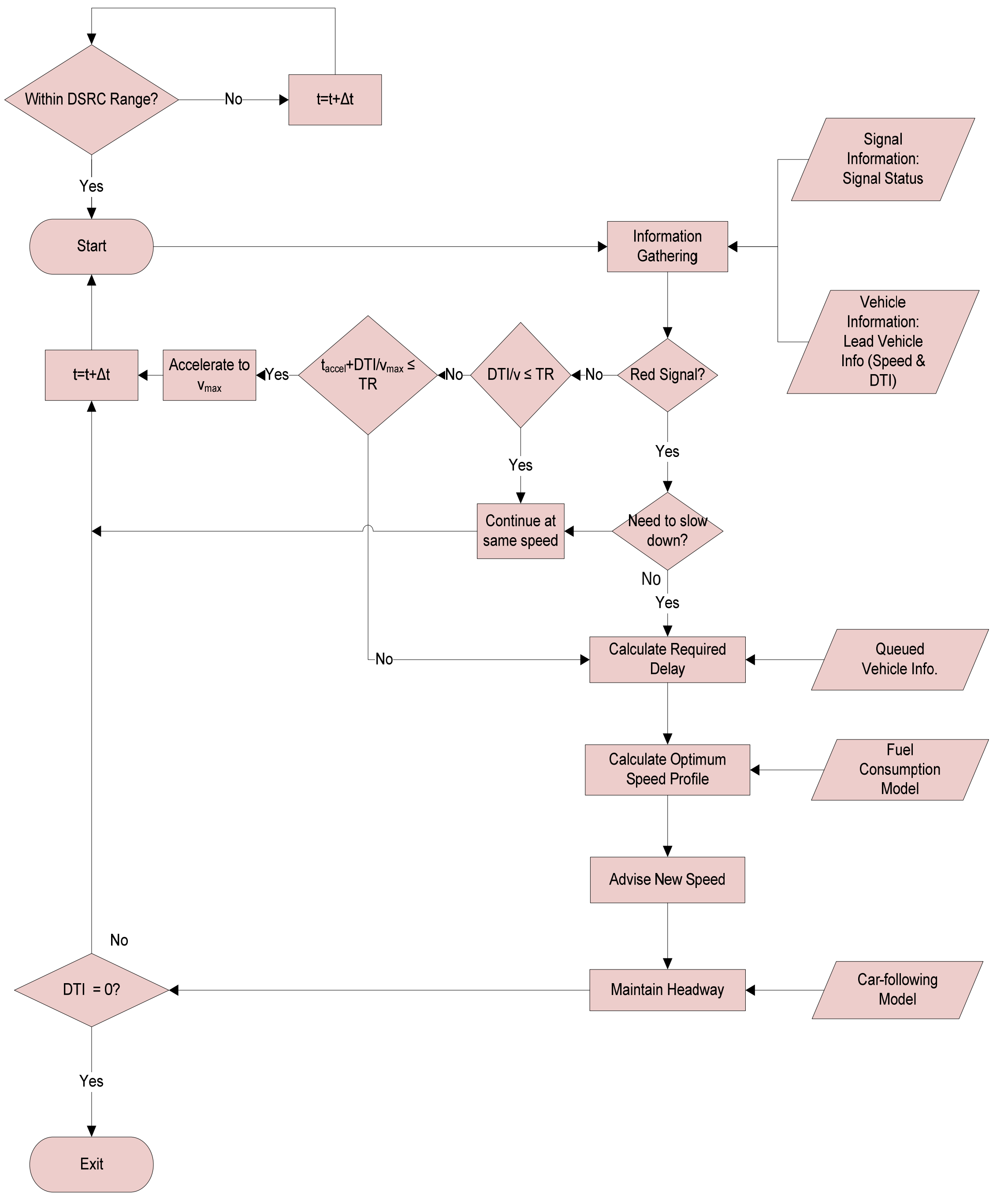

Figure 2. Eco-Vehicle Speed Control Logic

3.1.3 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.

3.1.4 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.

The last 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 stopline 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.

3.2 Speed-profile Optimization Logic

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 [12]. 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 shows the trajectory optimization of an eco-vehicle 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 a higher fuel consumption associated with acceleration back to the original speed.

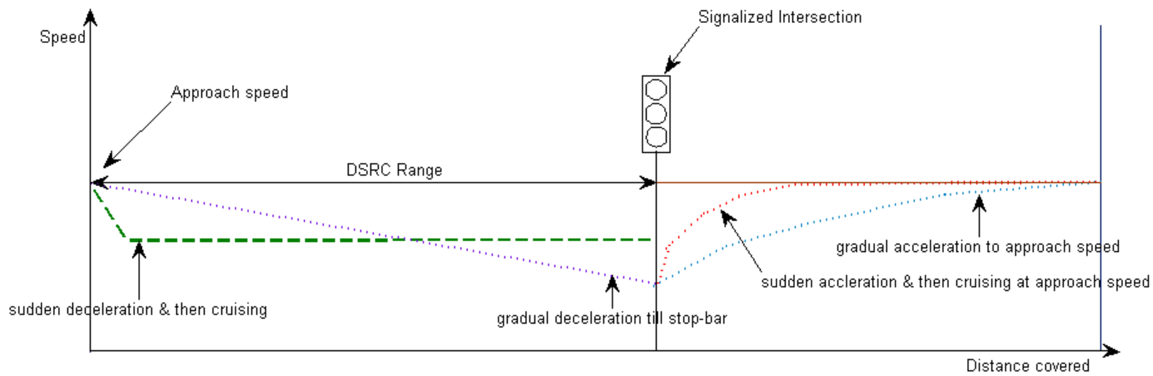

Figure 3. Extent of trajectory optimization near a signalized intersection

3.2.1 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 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 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/s^2 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. $d = [d_{min}, d_{max}]$).

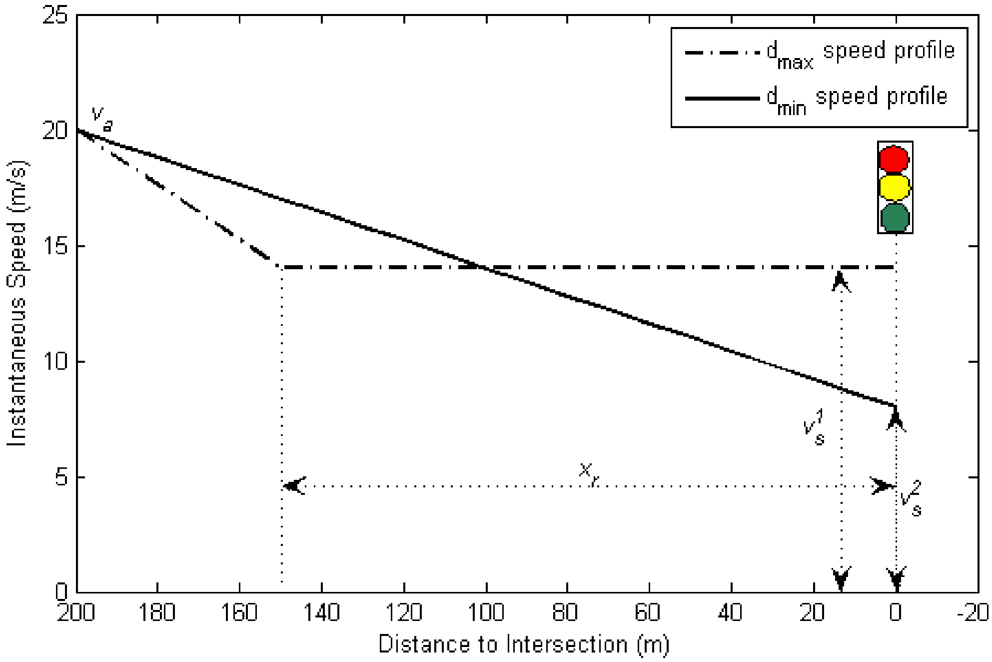

Figure 4. Vehicle trajectory upstream

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

$$d_{\min} = \frac{v_a - v_s}{t + \Delta t} \tag{1}$$

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

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

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

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

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

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.

3.2.2 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 [12]. 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 5).

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

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

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 $x_{i\text{-}acc}$ is the distance covered during acceleration in the case i.

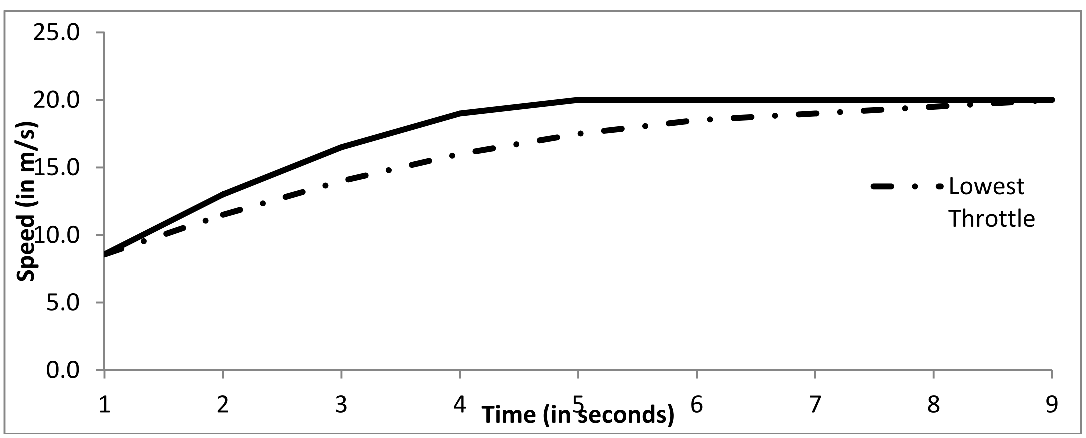

Figure 5. Downstream trajectory of the vehicle

3.3 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 [12]
c) VT-CPFM [9]

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.

3.3.1 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.

3.3.2 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.

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

$$R = \frac{\rho}{25.92} C_d C_h A_f v^2 + mg \frac{c_{r0}}{1000}\left(c_{r1} v + c_{r2}\right) + mgG \quad (7)$$

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/s^2); 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/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 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

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

3.3.3 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 [9]. 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.

$$FC(t) = \begin{cases} a_0 + a_1 P(t) + a_2 P(t)^2 & \forall\, P(t) \geq 0 \\ a_0 & \forall\, P(t) < 0 \end{cases} \tag{9}$$

$$a_0 = \max\left(\frac{P_{mfo} w_{idle} d}{22164 \times QN}, \frac{\left(F_{city} - F_{hwy} \frac{P_{city}}{P_{city}}\right) - e\left(P_{city}^2 - P_{hwy}^2 \frac{P_{city}}{P_{hwy}}\right)}{T_{city} - T_{hwy} \frac{P_{city}}{P_{city}}} \right) \tag{10}$$

$$a_1 = \frac{F_{hwy} - T_{hwy} a_0 - P_{hwy}^2 a_2}{P_{hwy}} \tag{11}$$

$$a_2 = \frac{\left(F_{city} - F_{hwy} \frac{P_{city}}{P_{hwy}}\right) - \left(T_{city} - T_{hwy} \frac{P_{city}}{P_{hwy}}\right) a_0}{P_{city}^2 - P_{hwy}^2 \frac{P_{city}}{P_{hwy}}} \geq e = 1\text{E-}06 \tag{12}$$

4 Example Illustration

To demonstrate the eco-vehicle speed control algorithm, an example is provided in this section. Consider a single vehicle approaching a signalized intersection with DSRC capability and assume that the current phase is red. The vehicle approach speed is 20 m/s on a roadway with a zero percent grade (level road) at standard air temperature and pressure. At a distance of 200 m from the intersection stop-line, it receives information regarding the next green indication, which will start in 14 seconds and has no queued vehicles. If the vehicle continues at its current speed it will reach the stop-line in 10 seconds suggesting that a delay of 4 seconds is needed in order to travel through the green indication.

This delay can be introduced in different ways as explained in the previous chapter. Various speed profiles can be generated that satisfy the following input: v_a = 20 m/s, x = 200 m, t = 14 s, and Δt = 4 s. The minimum deceleration level d_{min} is computed to be 0.82m/s^2. The corresponding speed at the stop-line v_s is computed to be 8.57 m/s. Table 1 shows possible scenarios where $d > d_{min}$ up to a deceleration level of 0.6 g, along with associated fuel consumed. Note that for any value of d greater than d_{min} there is an associated cruising phase. Vehicle characteristics of a Chevrolet Malibu were used for the example demonstration.

Table 1. Fuel consumed by Chevy Malibu during deceleration

d (m/s^2)	v_s (m/s)	t_{decel}(s)	t_{cruise}(s)	F_{decel}(l)
0.82	8.57	14.00	0.00	7.119
0.83	9.87	12.20	1.80	7.27
0.89	11.12	9.97	4.03	7.861
1.00	12.00	8.00	6.00	8.394
1.21	12.72	6.01	7.99	8.987
2.13	13.60	3.01	10.99	10.062
5.90	14.07	1.00	13.00	10.817

Table 1 shows seven of the infinite possible scenarios with columns denoting deceleration in m/s^2, speed at the intersection in m/s, time spent decelerating upstream of the traffic signal in seconds, time spent cruising prior to the stop-line in seconds, and fuel consumed during the deceleration phase. Table 1 shows that gradual deceleration to the stop-line as denoted by Case 1 is the most fuel-efficient deceleration maneuver. However, it results in a lower speed at the stop-line (v_s) compared to the other cases and would require greater fuel, F_2, to accelerate back to v_a.

The fuel consumption for the entire maneuver, including decelerating, cruising, and accelerating, is then computed, as shown in Table 2. The acceleration fuel includes a small cruising section at the speed of v_a to make the total downstream distance covered the same during all the throttle cases. The vehicle dynamics model is used to compute the instantaneous speeds when accelerating to the original speed for different throttles, and the throttle level corresponding to minimum fuel was used to build cases.

Table 1 shows that the case with a gradual deceleration of 0.82 m/s^2 over the entire travel to the stopline was the most fuel optimal when we consider upstream movement only. However, Table 2 shows that the case involving an initial deceleration of 2.13 m/s^2 for 3 seconds, cruising at 13.60 m/s for 11 seconds to reach the stopline, and then accelerating at 30% throttle to 20 m/s is the most fuel optimal when we consider the entire maneuver. Figure 6 shows a 3-dimensional plot comparing the fuel consumed for each of the cases in a matrix of deceleration and acceleration cases.

Table 2. Fuel consumed in downstream movement of a Chevy Malibu

d (m/s^2)	v_s (m/s)	30 %	40 %	50 %	60 %	70 %	80 %	90 %	100 %
0.82	8.57	42.16	45.82	49.12	52.02	53.53	56.08	57.75	59.72
0.83	9.87	40.74	44.37	46.38	49.66	51.20	53.55	55.50	57.52
0.89	11.13	40.13	42.28	44.81	47.49	49.90	51.17	53.13	53.30
1.00	12.00	38.40	40.69	43.61	45.30	48.19	49.45	51.45	52.75
1.21	12.72	38.57	40.77	42.78	45.17	46.53	47.53	50.56	52.57
2.13	13.60	37.00	39.20	41.04	43.54	44.25	46.99	48.94	49.12
5.9	14.07	37.72	39.99	40.39	42.50	43.87	46.38	48.25	48.48

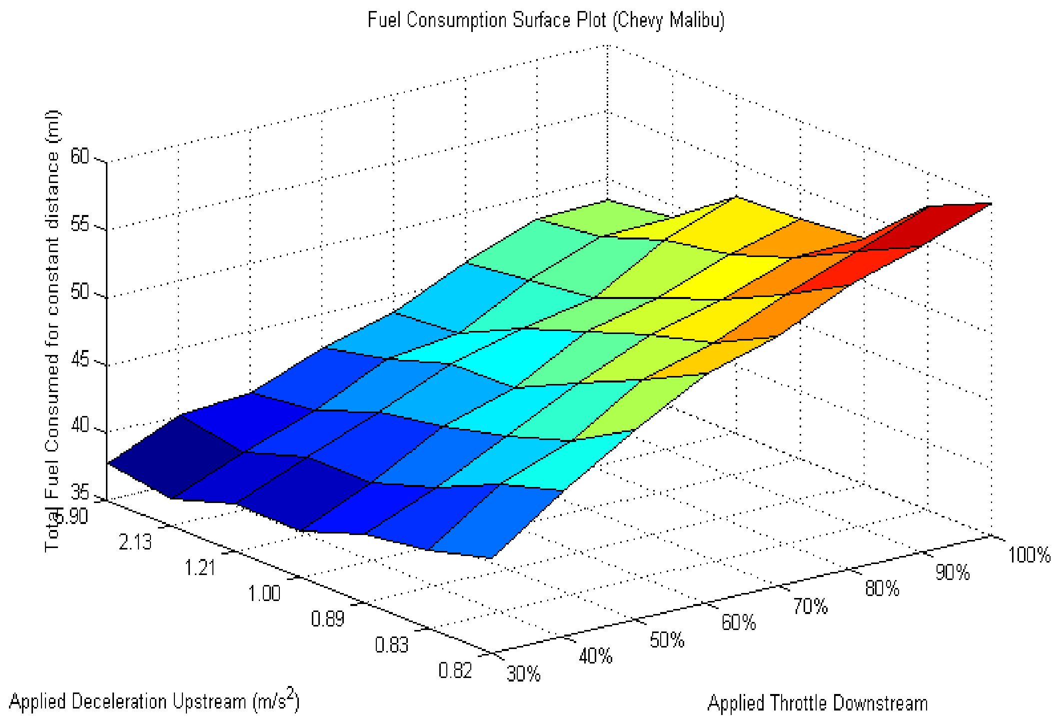

Figure 6. Fuel consumption plot for Chevy Malibu in three dimensions

5 Case Studies

In the example illustrated in the previous section, it was shown that the most fuel-optimal path is a complex function and is not necessarily the vehicle trajectory that involves minimum deceleration, maximum deceleration or some constant function of TTI or DTI. The example simulated one simple case of a vehicle approaching a red light and was optimized for minimum fuel consumption assuming the characteristics of a Chevrolet Malibu. However, more simulations were needed to prove the importance of a well-defined optimization function using vehicle dynamics and fuel consumption models. Additional simulations were also aimed at evaluating the proposed system.

Hence, simulations in MATLAB were conducted for the proposed eco-vehicle speed control application considering different vehicle models, different approach speeds, and different desired delay estimates. The following assumptions are made: (a) only the lead vehicle approaching the signalized intersection is considered (and no inter-vehicle interaction) and (b) SPaT information is available from the intersection controller via I2V communication. The analysis includes 80 cases (Figure 7) comprising four different vehicle types, four different approach speeds and five different TTGs. Table 3 provides the characteristics of the four vehicles used during the simulation analysis. The DTI in all cases was fixed on 200 m (which was assumed to be the range of DSRC dedicated to Connected Vehicles Technology), and the TTG was such that the vehicles should incur a delay of 2, 4, 6, 8 and 10 seconds from their normal trajectories in order to receive a clear intersection. For each case, a matrix of speed profiles was built according to the procedures described earlier.

Table 3. Details of the vehicles simulated in case study

Characteristics	Vehicle 1	Vehicle 2	Vehicle 3	Vehicle 4
Make	SAAB	Mercedes	Chevrolet	Chevrolet
Model	95	R350	Tahoe	Malibu
Year	2001	2006	2008	2007
Engine Size (L)	2.3	3.5	5.3	2.2
EPA Mileage (City/Highway)	21/30	16/21	14/20	24/34

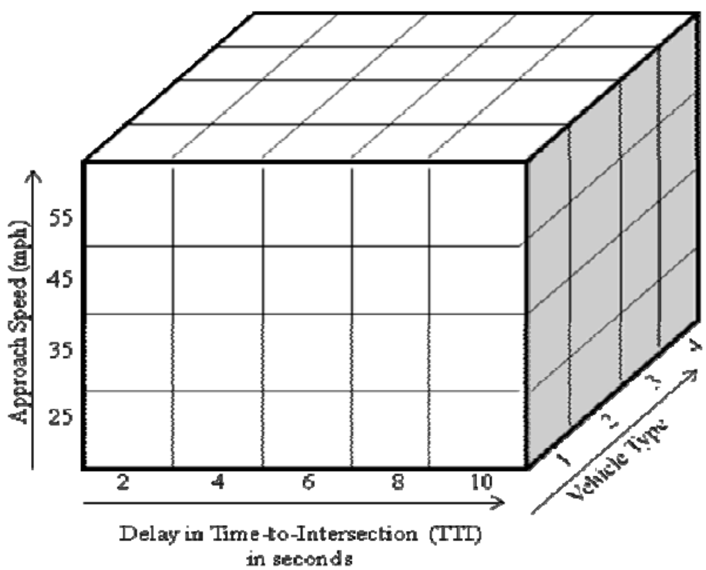

Figure 7. Variables analyzed for case-study simulations of speed control algorithm

The amount of fuel consumed for 140 vehicle trajectories was compared to determine the fuel-optimal trajectory for each of the 80 cases. A combination of 20 upstream cases and 7 downstream cases, totaling 140 cases were compared for the most fuel-efficient speed profile in each of these cases. The fuel consumption was computed as the summation of the fuel consumed by the vehicle to decelerate from v_a to v_s, cruise at v_s, accelerate back from v_s to v_a, and cruise at v_a across a distance that makes total distance constant for all the cases. Figure 8 provides a sample application to one of the test vehicles. Each value in the matrix displays the fuel consumed for that specific vehicle trajectory, which is defined by the deceleration level (y-axis) and acceleration level (x-axis). Using the deceleration level, one can estimate the corresponding v_s and x_r. Figure 8 indicates that for a vehicle approaching an intersection at 72 km/h (45 mph) that must incur a delay of 4 seconds, the optimal vehicle trajectory entails decelerating at the maximum deceleration level d_{max} and accelerating at the minimum throttle level. This conclusion was consistent for all four vehicles tested.

The same analysis was conducted for the various approach speeds of 25, 35, 45 and 55 mph and required delays (2, 4, 6, 8 and 10 seconds) in order to establish whether the fuel-optimal action is vehicle, speed or delay dependent. It was seen that the optimal action downstream always included minimal throttle (0.3 in this case). However, the optimal course of action upstream differed. Table 4 shows the optimum deceleration values for all the cases. Clearly, the optimum course of action is not only vehicle dependent but depends on the approach speed and the delay required in the vehicle trajectory. In order to measure the effectiveness of the proposed system, fuel savings were measured against the optimized scenario and the average of all scenarios. This measure provides an estimate of the potential fuel savings near the intersection when the proposed eco-speed control algorithm is used. The values on Table 5 are derived using the following relation:

$$S_{i,j} = \frac{\text{avg}\,(F_{d,t}) - \min\,(F_{d,t})}{\text{avg}\,(F_{d,t})} \times 100\ \% \qquad (13)$$

where

$S_{i,j}$ = % Savings for induced delay i and approach speed j

$F_{d,t}$ = Fuel consumed (for the case i,j) when deceleration upstream is d and throttle downstream is t.

$$\text{Avg}\,(F_{dt}) = \frac{\sum_{d=d_{min}}^{d_{max}} \sum_{t=0.3}^{1} F_{d,t}}{n_{i,j}} \qquad (14)$$

Savings up to 30% over the average fuel consumption were identified. Even though these values hold true only near intersections, they project to a significant value for signalized arterials where closely spaced intersections are present. Table 5 presents the percentage deviation in fuel consumption between the selected fuel-optimum trajectory and the average of all possible scenarios tested. These values indicate the maximum potential fuel savings that can be achieved by such a system.

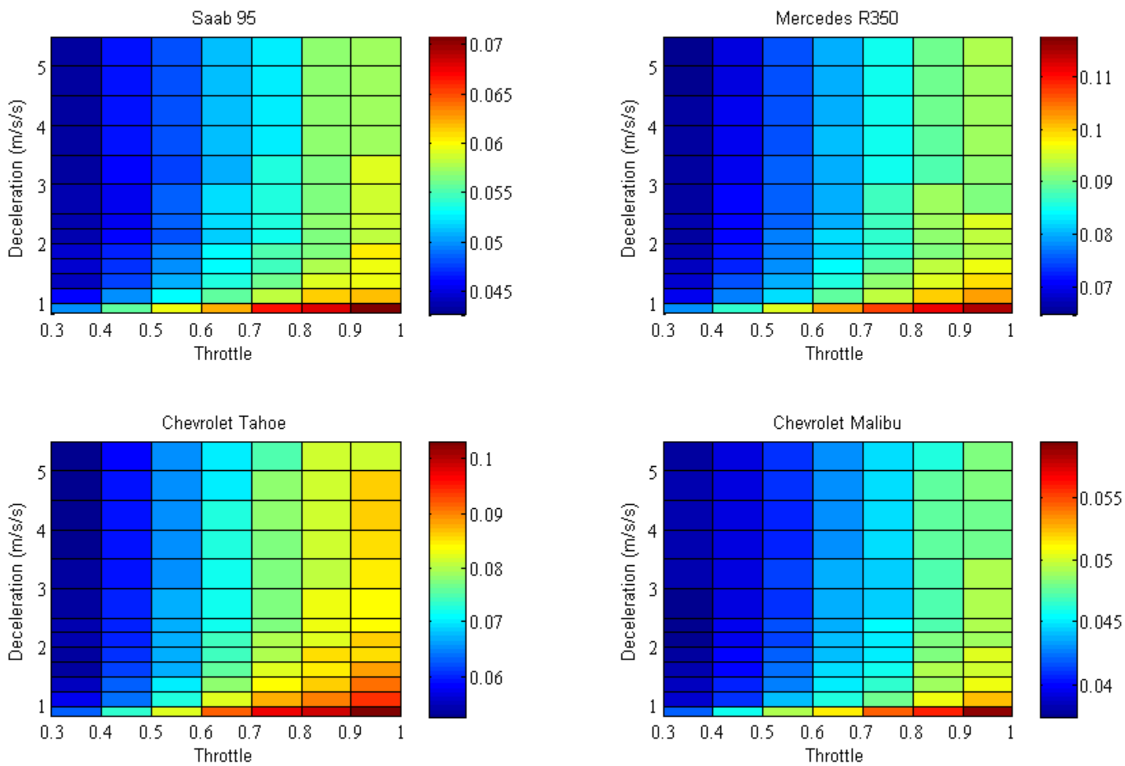

Figure 8. Sample fuel consumption matrix (in litres) used to find optimum speed profile (when v_a = 45mph and delay = 10s)

Table 4. Fuel optimum deceleration for 80 cases (in m/s/s)

(a) SAAB 95

Delay (s)	Approach Speed (mph) 25	35	45	55
2	0.25	0.75	3.25	4.75
4	0.25	3.50	5.75	5.75
6	0.50	5.00	5.75	5.50
8	0.75	5.75	5.75	5.75
10	2.00	5.75	5.25	5.75

(b) Mercedes R350

Delay (s)	Approach Speed (mph) 25	35	45	55
2	0.25	0.75	3.25	2.25
4	0.25	3.50	2.00	3.00
6	0.50	1.75	2.50	5.50
8	0.75	5.75	5.75	5.75
10	2.00	5.75	5.00	4.50

(c) Chevrolet Tahoe

Delay (s)	Approach Speed (mph) 25	35	45	55
2	1.00	2.00	1.00	4.75
4	5.75	3.50	5.75	5.00
6	2.75	5.00	5.75	5.50
8	3.25	5.75	4.50	5.75
10	3.75	5.75	5.25	5.75

(d) Chevrolet Malibu

Delay (s)	Approach Speed (mph) 25	35	45	55
2	0.25	0.50	1.75	2.50
4	5.75	1.25	5.75	3.00
6	0.25	1.00	5.75	5.50
8	0.75	5.75	5.75	5.50
10	1.00	5.75	4.75	4.25

Table 5. Percentage deviation of the fuel consumed during optimized trajectory over average of all tested trajectories

(a) SAAB 95

Delay (s)	Approach Speed (mph) 25	35	45	55
2	13.12%	14.86%	17.84%	20.63%
4	10.54%	15.99%	20.24%	22.48%
6	9.31%	15.67%	19.89%	22.81%
8	9.33%	15.15%	19.97%	21.17%
10	7.84%	15.12%	7.85%	8.57%

(b) Mercedes R350

Delay (s)	Approach Speed (mph) 25	35	45	55
2	12.58%	17.66%	21.10%	24.24%
4	11.64%	18.39%	23.41%	25.90%
6	12.22%	18.53%	23.36%	25.57%
8	11.68%	17.77%	22.90%	24.30%
10	9.63%	17.52%	10.24%	10.58%

(c) Chevrolet Tahoe

Delay (s)	Approach Speed (mph) 25	35	45	55
2	7.70%	19.28%	27.90%	32.16%
4	11.22%	21.98%	29.54%	33.36%
6	10.08%	20.60%	29.42%	33.54%
8	10.57%	20.79%	28.02%	31.77%
10	9.62%	20.19%	15.44%	16.41%

(d) Chevrolet Malibu

Delay (s)	Approach Speed (mph) 25	35	45	55
2	11.42%	11.61%	15.39%	16.87%
4	10.99%	14.95%	16.97%	19.73%
6	9.48%	14.76%	18.14%	20.53%
8	8.22%	14.90%	18.49%	19.69%
10	7.85%	15.11%	7.88%	8.64%

Given that the optimization only entails computing the optimal deceleration level, the mathematical program can be cast as

$$\min F = a_0 \frac{2(x - x_r)}{(v_a + v_s)} + \left(a_0 + a_1 P\Big|_{v=v_s} + a_2 P^2\Big|_{v=v_s}\right)\frac{x_r}{v_s} + FC_{f_p=0.3}(v_s \rightarrow v_a)\ . \qquad (15)$$

Here the first term in the equation is the fuel consumed while decelerating, the second term is the fuel consumed while cruising, and the third term is the fuel consumption while accelerating at the minimum throttle level (f_p=0.3). This equation is a function of a single control variable (d) given that v_s and x_r can be computed once d is known using Equations 3 and 4, respectively, and v_a, x, t, and Δt are known. The constraints of this mathematical problem are $d = [d_{min}, d_{max}]$ and $v_s \geq 0$.

6 Application Development

In the previous sections, it was shown that by using a well-defined optimization function a fuel-optimal speed profile could be generated for a given scenario. The speed profile is case-dependent, and cannot be computed by minimizing the acceleration and deceleration levels or by minimizing the time the vehicle spends accelerating. Instead, the speed profile and possible fuel savings depend on the approach speed, TTI, and DSRC range (Tables 4 and 5). The simulations were programmed in MATLAB environment and evaluated. The measure of effectiveness used was fuel savings. However, the possibility of implementation in an in-vehicle environment needed to be studied, so a MATLAB application was developed to operate as an optimization tool for fuel consumption modeling using speed adjustments. The MATLAB application uses a Graphical User Interface (GUI) to interact with users and receive "scenario information" and computes the fuel-optimum vehicle trajectory.

The MATLAB application is programmed as a GUI with multiple pages using the algorithm illustrated in Figure 2. The sections of the GUI are described below:

Page 1:
Figure 9 shows the first page of the MATLAB application and comprises a general introduction to the application and the credits to the developing laboratory.

Page 2:
As shown in Figure 10, a physical modeling of the vehicle under consideration is detailed. Four vehicles are standardized in the application, or the users can define a vehicle using its physical and mechanical characteristics. The application also requires users to input calibrated model variables for VT-CPFM-1 in this page if they are defining an unsaved vehicle.

Page 3:
Figure 11 illustrates an input page where users set the intersection and arterial characteristics. Intersection characteristics include DTI, approach speed, TTG and

minimum permitted speed. Arterial characteristics such as jam density, queue length, etc. aid in the computation of the time required for queue discharge.

Page 4:
Shown in Figure 12 is an output page where users can run optimization of the scenario and receive verbal advisory about the fuel-optimum action. It also generates a table of fuel consumed in milliliters corresponding to a set of deceleration rates and acceleration throttles.

Page 5:
Figure 13 illustrates a summarization of the optimal action with the optimum vehicle speed profile plotted against time.

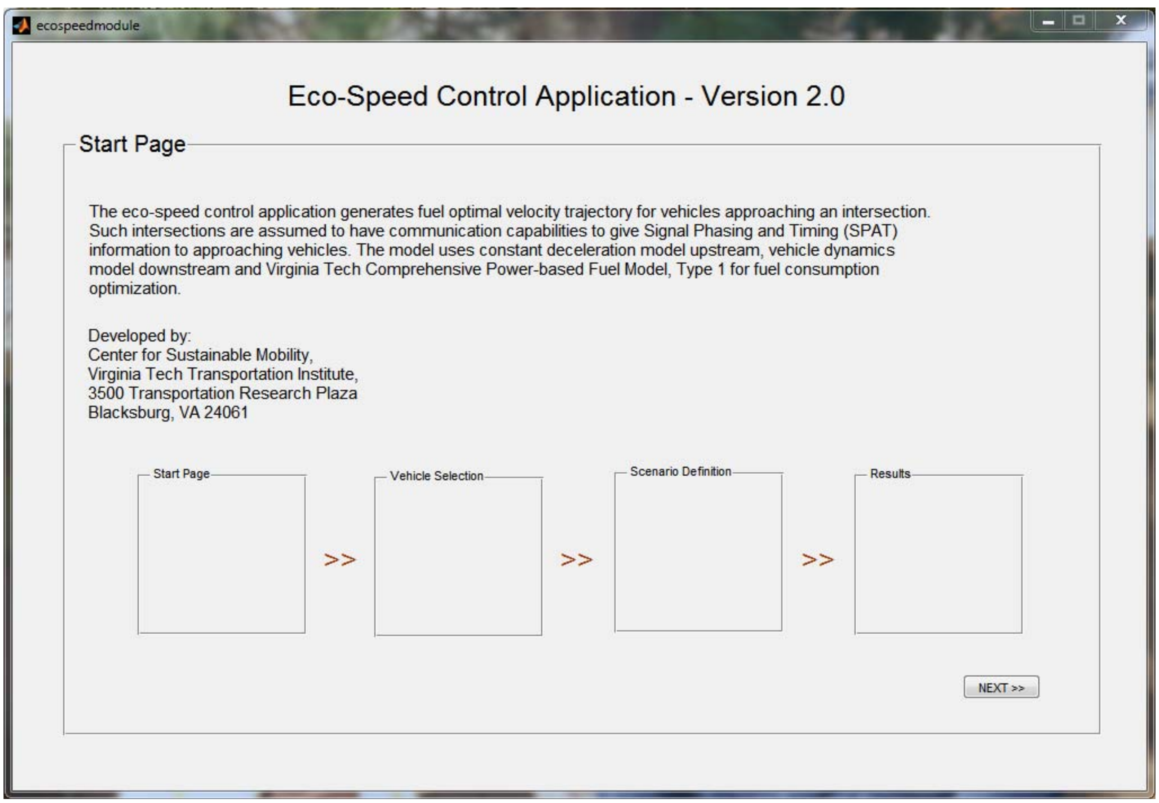

Figure 9. MATLAB Application, Page 1

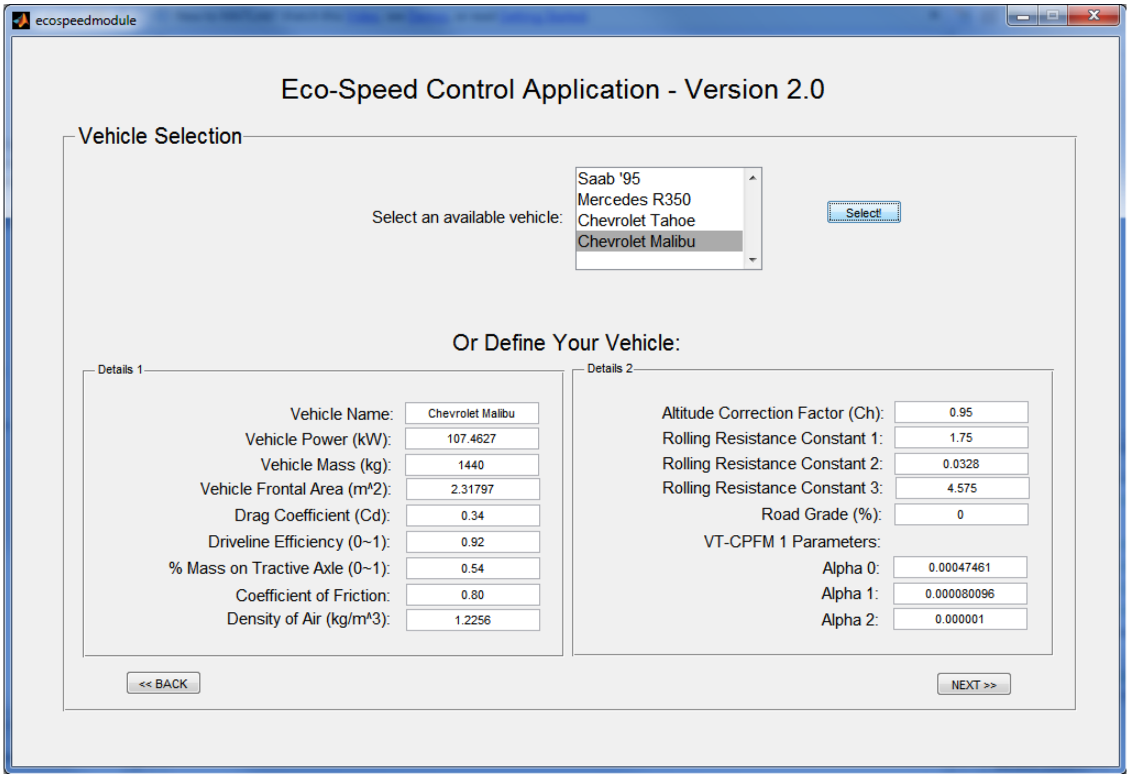

Figure 10. MATLAB Application, Page 2

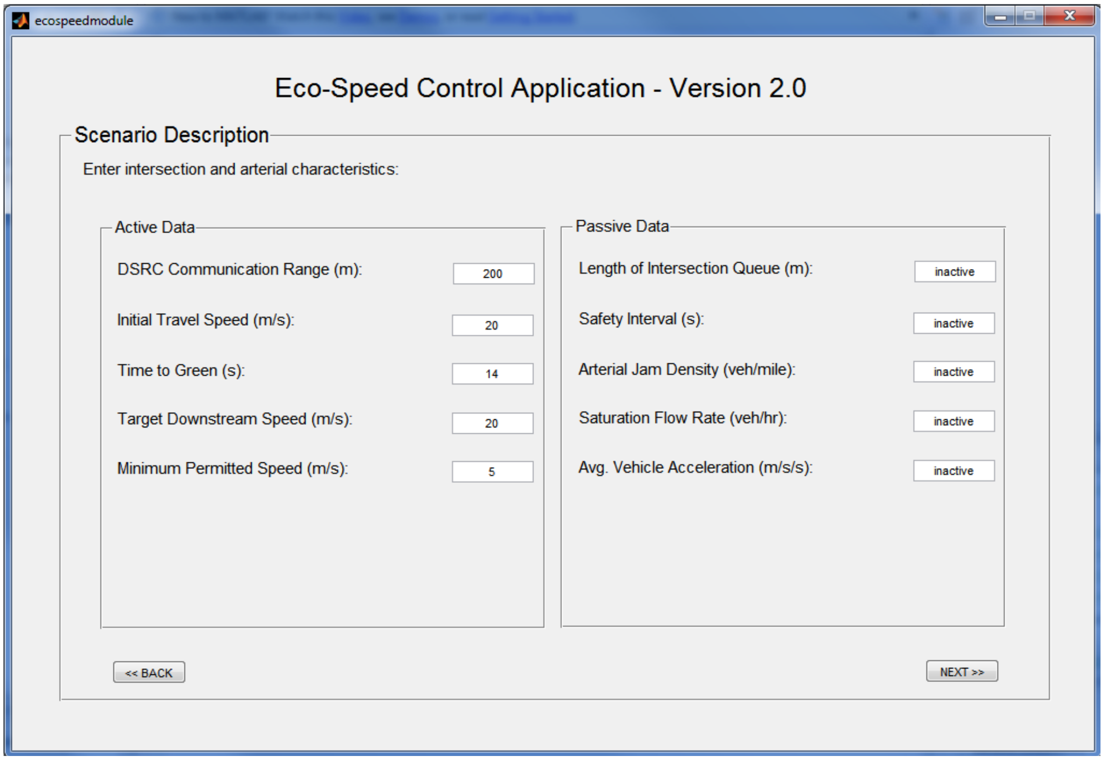

Figure 5. MATLAB Application, Page 3

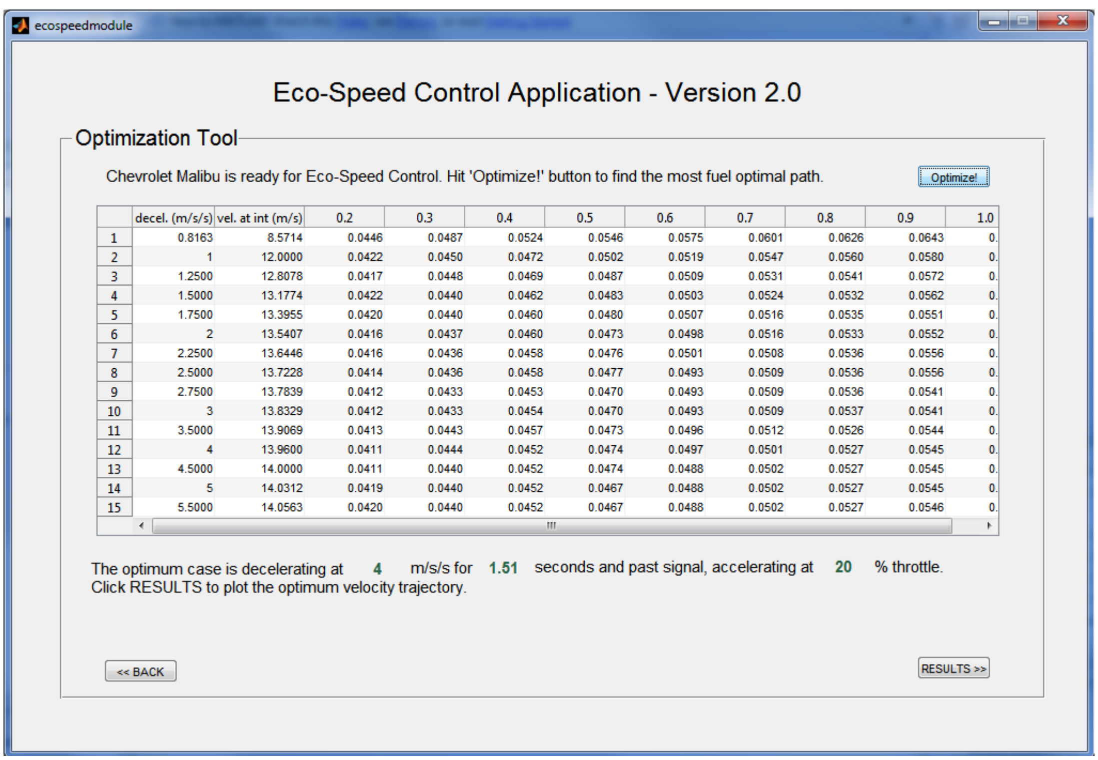

Figure 6. MATLAB Application, Page 4

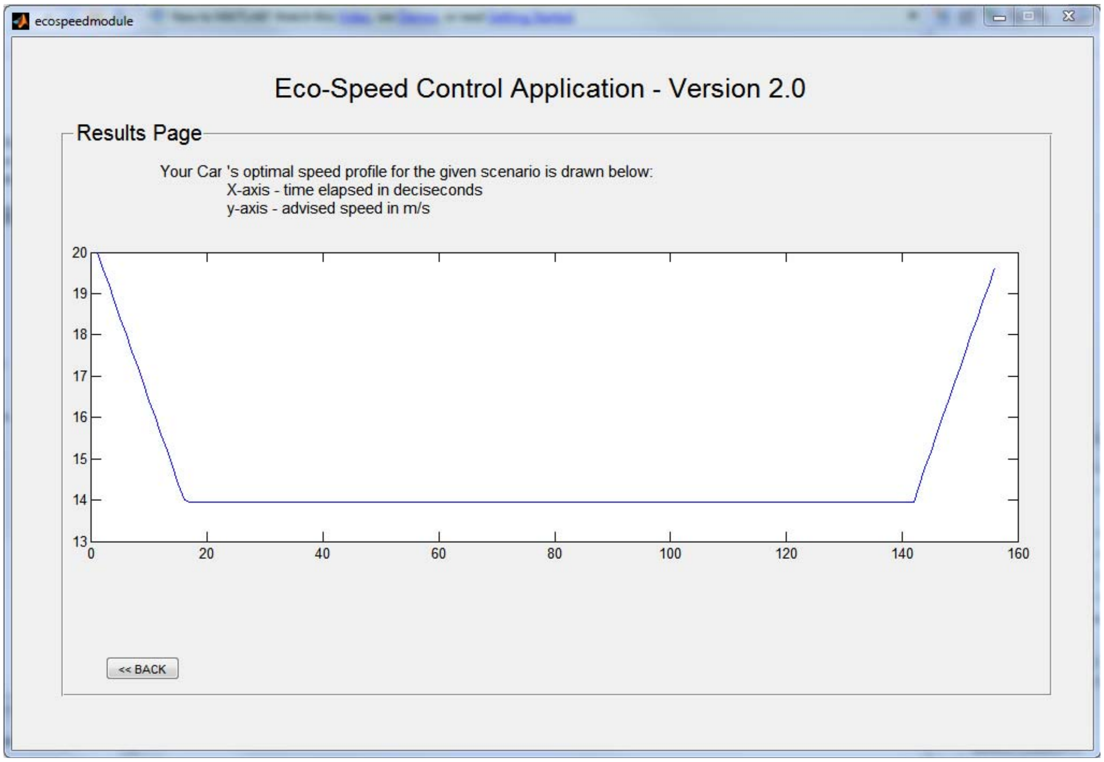

Figure 7. MATLAB Application, Page 5

7 Conclusions and Recommendations

This report focused on developing an eco-vehicle speed control system, which uses upcoming signal change information to alter a vehicle's velocity profile to minimize its fuel consumption. The report also evaluated the system using case-study simulations. While similar studies have been conducted as was demonstrated in the literature review, the robust objective function used in optimization and the accounting of the vehicle acceleration downstream of the traffic signal makes this application unique. The objective function used here employs an explicit fuel consumption model without making the system computationally complex. Previous work has used some simplified version of the objective function that did not have a fuel consumption variable in it. This section lists notable findings made during this research.

7.1 General Findings

1. The objective function should be robust and needs to include a fuel consumption model.
2. The objective function should incorporate both upstream and downstream maneuvers as fuel consumed downstream depends on the upstream maneuver and speed at intersection.
3. Use of advanced signal information has the potential to save fuel on signalized corridors by preventing sudden stopping and acceleration.

4. Fuel-optimal trajectory depends on approach speeds, delays required before reaching stop-lines, vehicle characteristics, etc. and cannot be generalized.
5. The possibility of an in-vehicle module/system/device for eco-vehicle speed control is shown by the developed MATLAB application.

While these are the general findings from this project, some case-specific findings were also drawn from the multitude of simulation runs using different scenarios and different vehicle types.

7.2 Findings from Case Studies

1. Acceleration upstream depends on speed at intersection, which relies on the chosen deceleration level. Therefore, for each deceleration level, the acceleration scenario has to be considered before making a conclusion about the fuel-optimal trajectory.
2. The lowest throttle level was found to be fuel efficient when the VT-CPFM model was used. However, it should be noted that lower acceleration at an intersection would affect the discharge rate and thus could reduce the approach capacity.
3. Initial deceleration depends on vehicle type, approach speed and delay to be induced in the trajectory due to late green and/or queue clearance.
4. Greater initial deceleration, cruising and slow acceleration is the fuel-optimal case when an approach speed is higher.
5. Lower initial deceleration, optional cruising and slow acceleration is the fuel-optimal case when an approach speed is lower.
6. In most cases where the delay to be induced was lower, the optimum case was that with lower initial deceleration upstream.
7. In cases where the delay to be induced was greater, the optimum case comprised sudden initial deceleration followed by cruising for the remainder of the upstream distance.
8. Even though the four vehicles simulated showed similar results, possible savings in fuel was greater for the ones with larger engines and lower for the ones with smaller engines.

These findings and conclusions warrant future research in this area. The eco-vehicle speed control is a very complex system if the assumptions that were made in the study were relieved. Considering the human-vehicle interaction to follow speed advisories, V2V interaction using car-following models, adaptive traffic systems, etc., can make the system closer to implementation as well as complex. The findings also reinforce the fact that the complexity of the objective function should be maintained to receive meaningful results rather than simplifying the approach. However, with today's computational advancements there exists the potential to implement even the most complex system in new vehicles and infrastructure.

Among the environmental effects of driving, Green House Gas (GHG) emissions play an important part and accumulated research attention around the world. GHG such as hydrocarbons, carbon dioxide, carbon monoxide, and nitrogen oxides are produced by internal combustion engines that run on gasoline. The research highlighted in this report could be extended to address these emissions. For example, carbon dioxide emissions are linearly correlated with fuel consumption levels [9].

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FHWA-JPO-12-063