GREEN COOPERATIVE ADAPTIVE CONTROL SYSTEMS IN THE VICINITY OF SIGNALIZED INTERSECTIONS

Final Report

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16. 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 report 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 control system is known as an Eco-Speed 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.

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EXECUTIVE SUMMARY

Recently, reducing energy and emissions of driving has become a global need more than ever before, and as a result, engineers and policy makers are striving towards getting the highest possible fuel efficiency out of vehicles. Along with this, communication between components of surface transportation is being developed to improve the safety [1]. This has resulted in development of wireless technologies and protocols that define Vehicle-to-Vehicle (V2V) and Vehicle-to-Infrastructure (V2I) communication. The research presented in this paper develops a fuel-optimization framework of such connected vehicles using advanced signal-change information, information about queued vehicles at signalized intersections and speed and headway of the lead-vehicles.

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-Speed Control.

Eco-Speed Control 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 five top-sold cars of 2011 within each the six Environmental Protection Agency (EPA) categories.

DESCRIPTION OF PROBLEM

Literature Review

The U.S. Department of Transportation (USDOT) Federal Highway Administration (FHWA) and other transportation agencies in developed nations have made significant advancements in various transportation technologies. In the mid-1990s, the FHWA's Intelligent Transportation System (ITS) Program emerged to increase the use of technology in the surface transportation sector [2]. 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. 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 [1].

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 [3]–[5]. A number of vehicle dynamics models have also been developed to accurately predict the physics of a vehicle [6], [7]. 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 [8]. 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).

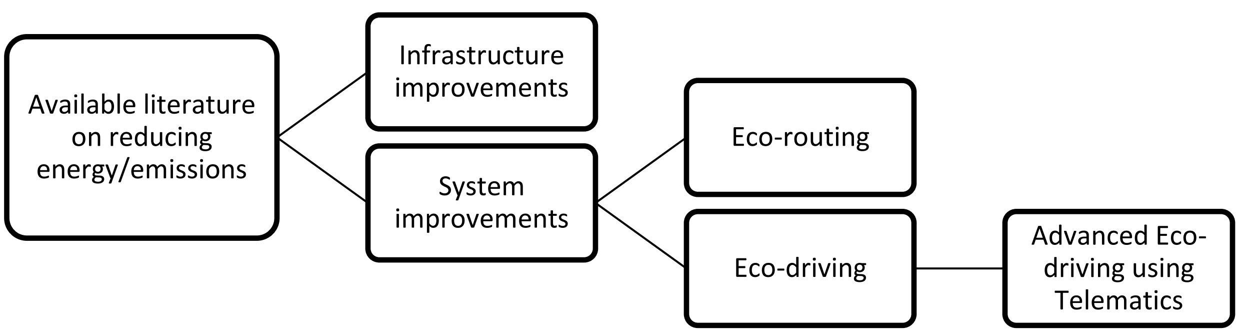


Figure 1: Classification of the literature review.

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 [9], [10]. Some traffic control improvements suggest the use of genetic algorithms to account for the dynamic routing of vehicles that have typically been neglected [11], while other field tests with genetic algorithms based on green-wave optimization revealed potential energy and emissions improvements [12].

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 [13]. 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.

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. 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 [17], [18]. 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. 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 the 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 the 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 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 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 [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 [42]. 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.

APPROACH AND METHODOLOGY

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.

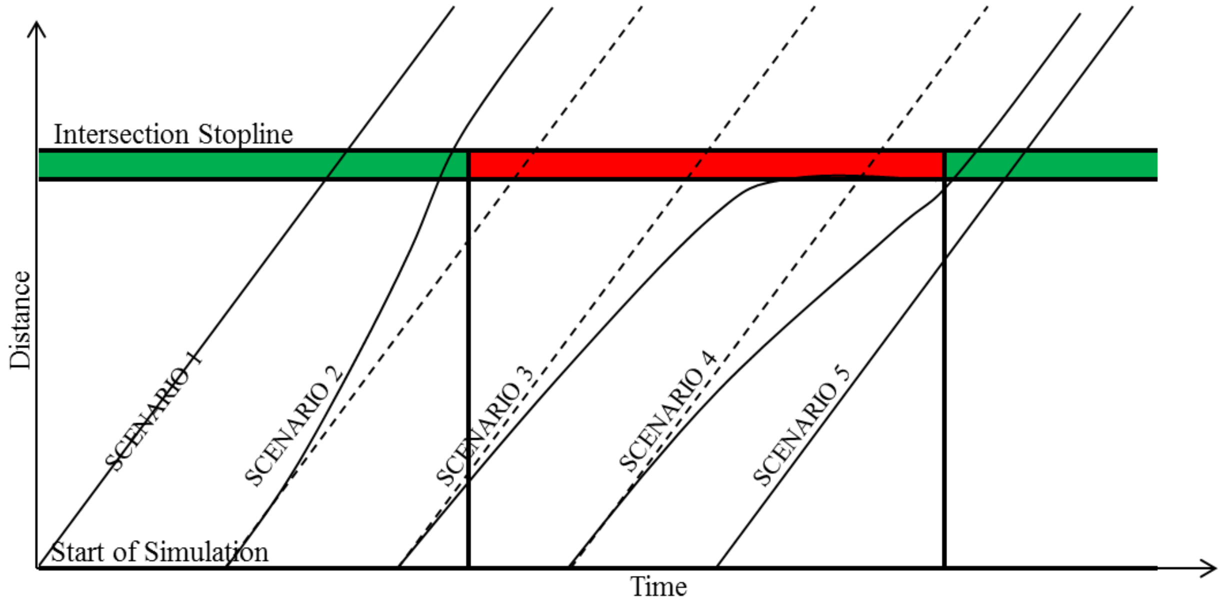


Figure 2: Speed profile of vehicles approaching a signalized intersection.

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 2. 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.

The overall ECACC system logic is illustrated in a flowchart in Figure 3. 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.

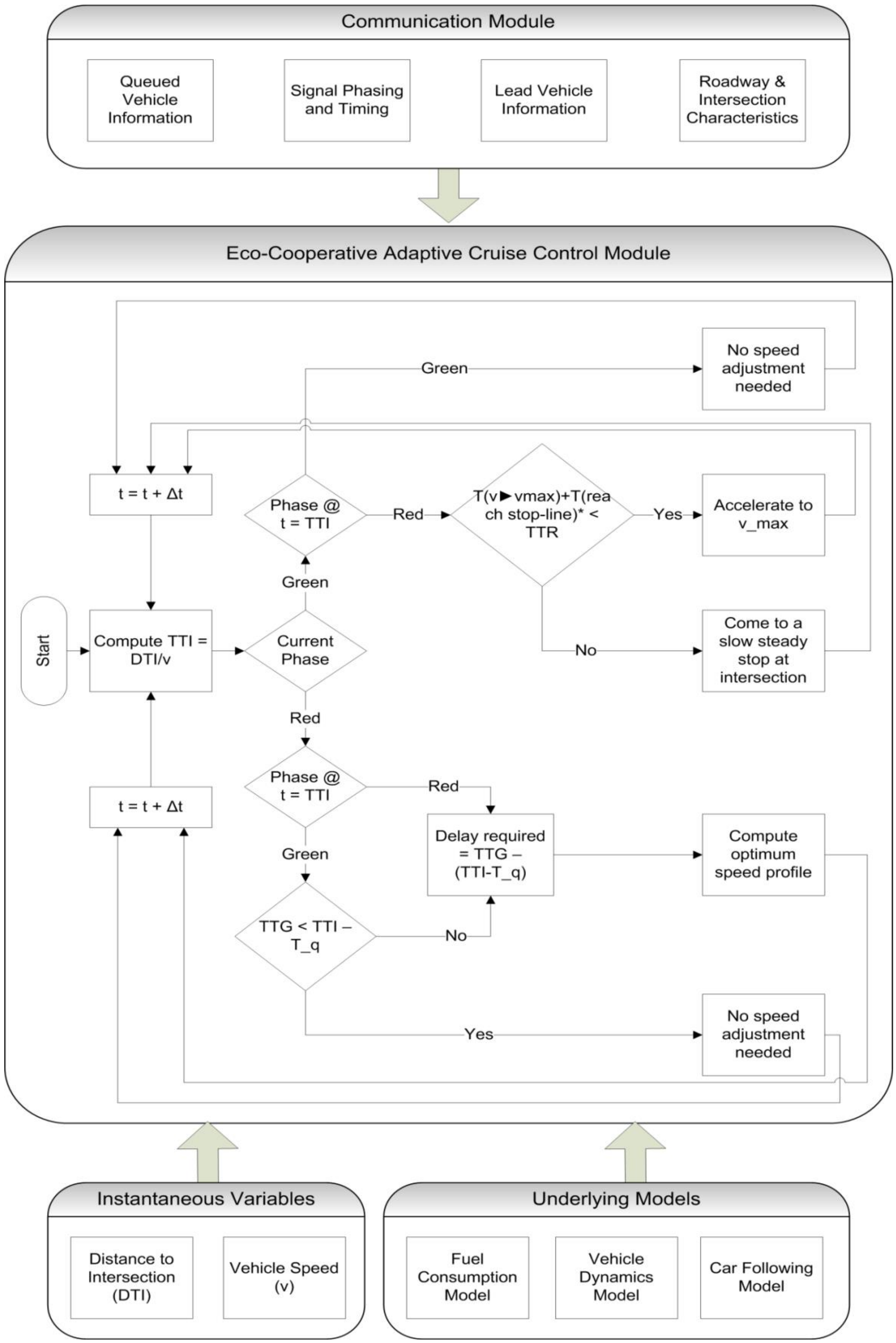


Figure 3: Logical model of ECACC system.

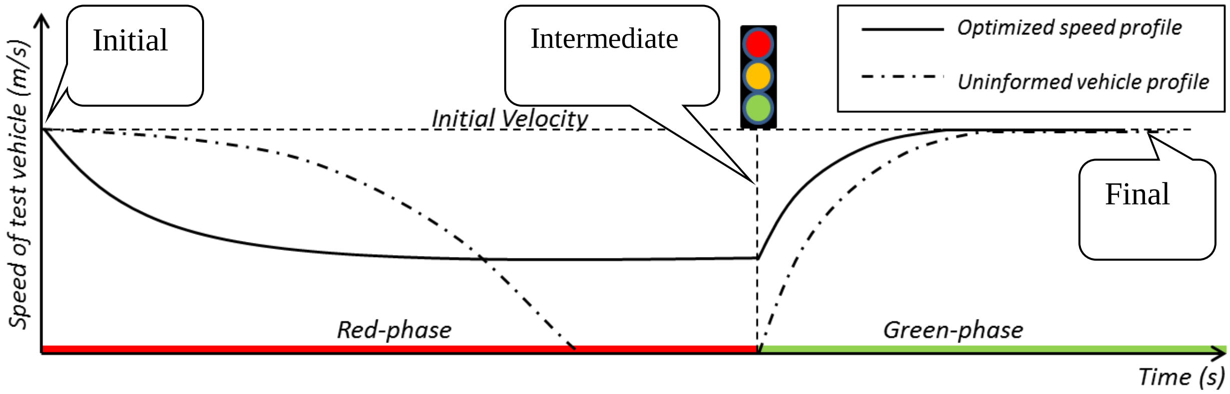


Figure 4: Comparison of optimized versus uninformed speed profile in the vicinity of intersection.

In Figure 4, 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 4 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:

Minimize: $J_u + J_d$ (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:

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

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).
2. $t_s = t_g + t_q$ (Time t_s = time to green (t_g) plus time to clear any queues (t_q)).
3. $v(t+\Delta t) = v(t) + \dfrac{F(t) - R(t)}{m}\Delta t$ (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 4):

- *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 [43]. Alternatively, use of an A-star path-finding algorithm [44] 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 Dijsktra'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.

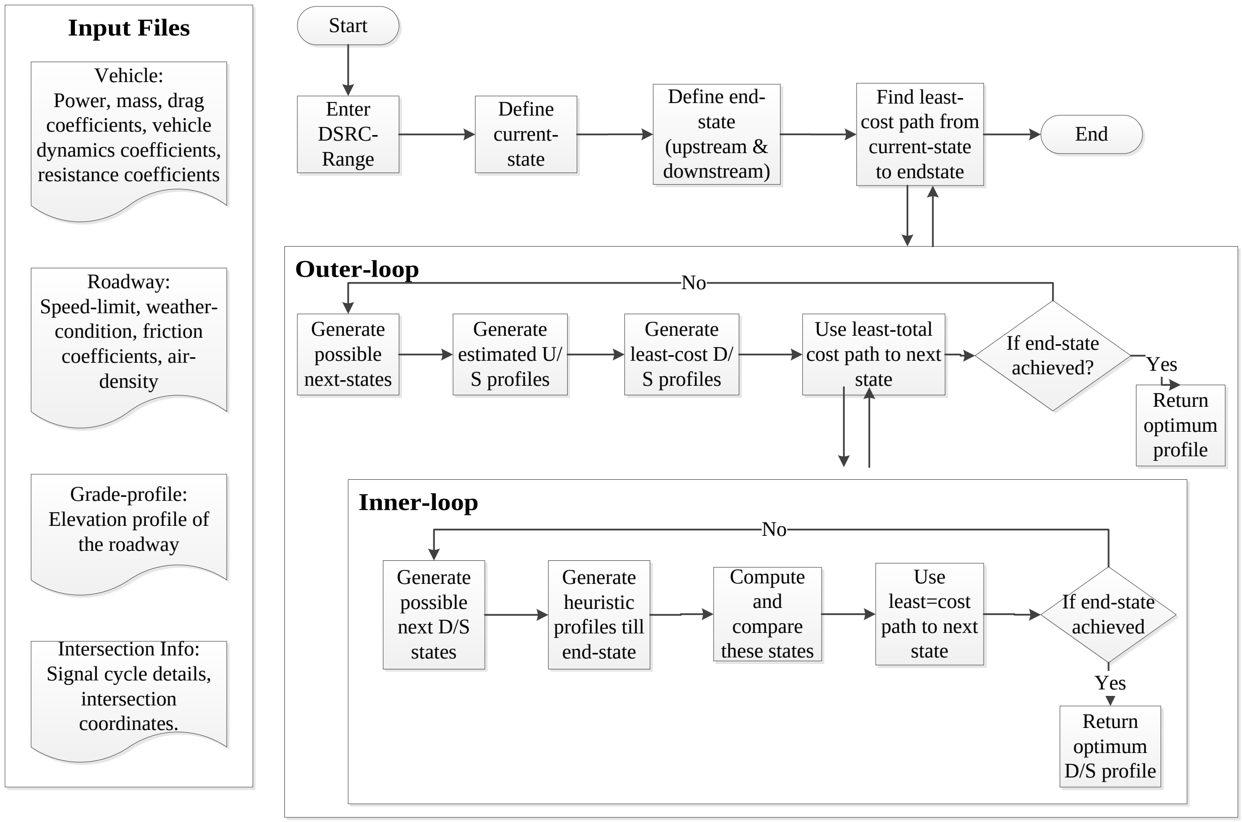


Figure 5: Modified A-star optimization logic used in ECACC.

The pseudo-code for this problem, depicted in Figure 5, 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 6. Table 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 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

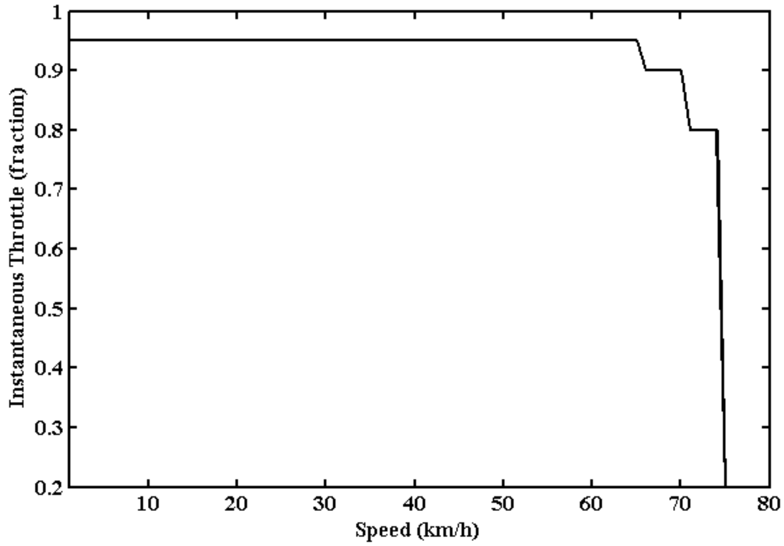


Figure 6: Optimized throttle profile for accelerating from 0 to 75 km/h.

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 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 briefly described in this section. The queue-dissipation time can be computed as in [45] using state-of-the-art queuing models such as [46].

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 [7]. 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:

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

$$R(t) = \frac{\rho}{25.91} C_d C_h A_f v^2(t) + mg \frac{c_{r0}}{1000}\left(c_{r1} v(t) + c_{r2}\right) + mgG(t) \tag{3}$$

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 + Δt is then computed using Euler's first order approximation as:

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

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 [4]. 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 [4].

The fuel consumption model is formulated as follows:

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

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:

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

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:

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

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

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

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. The suitability of this model in real-time ITS applications is also studied.

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 [47]. A total of 30 different calibrated vehicles that correspond to the five top-sold vehicles of six different EPA categories (compact cars, mid-size cars, full-size cars, sport utility vehicles, mini passenger vans and light-duty trucks) were used [48]. The DSRC communication range was assumed to be 200 m as recommended by the SAE. The 2100 simulation runs included a total of five vehicle offset times (2, 4, 6, 8 and 10 s) and seven 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 Appendix A. 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 [49], [50]. 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.

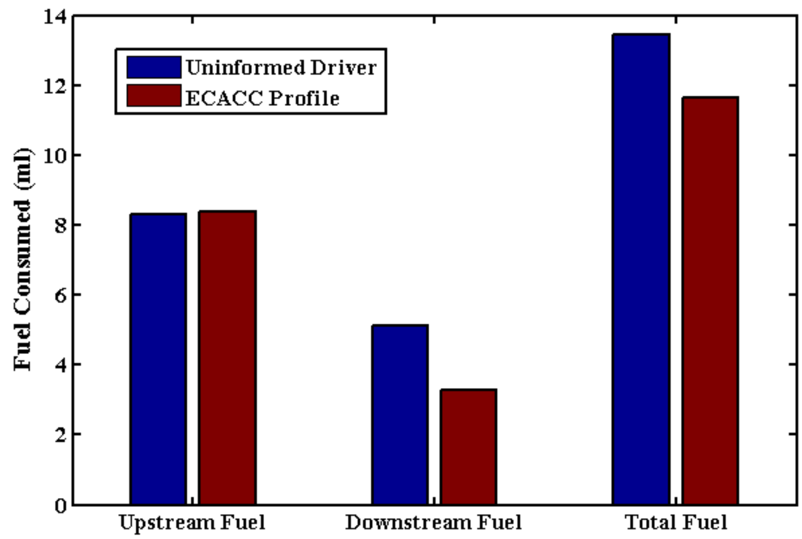


Figure 7: Comparison of fuel consumed by an uninformed vehicle and a test vehicle for a particular case.

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 1, 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 7 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 7 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 8 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 8 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 8(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 achieve 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 8b). 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 8 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 9). 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.

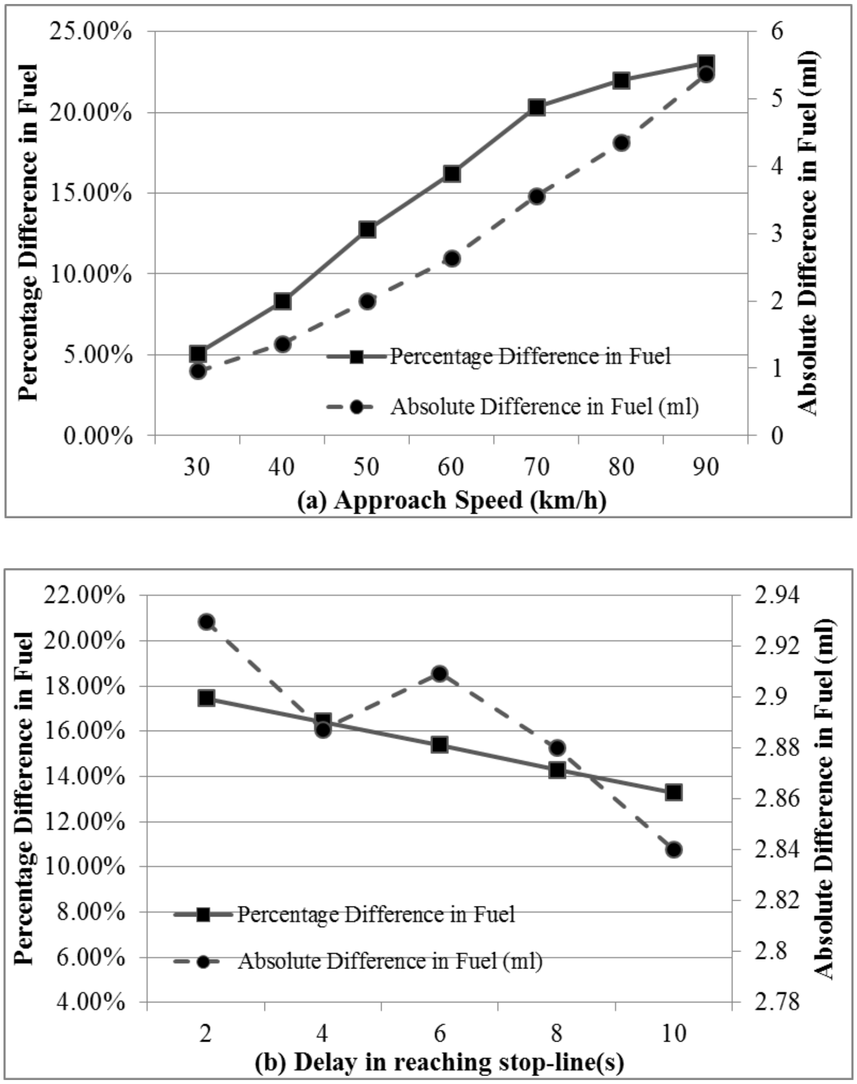


Figure 8: Categorized average fuel savings between the test-cases and base-cases.

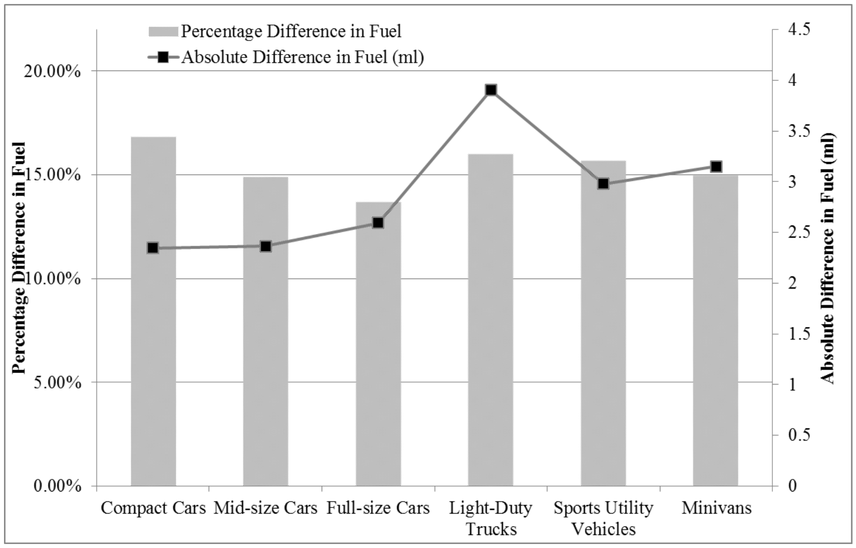


Figure 9: Percentage savings in fuel averaged across EPA categories.

Agent-Based Simulation Analysis

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 (ESC) 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 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 [51], [52].

Figure 10 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.

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 Basic Safety Messages (BSM) and SPaT messages between the signal controller and vehicle agents [47]. Other traffic flow models used in this simulation tool are identical to those used in the INTEGRATION software [52]. 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 in single lane approaches.
4. The dynamic programming framework uses the empirical Marshall and Berg [46] 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.

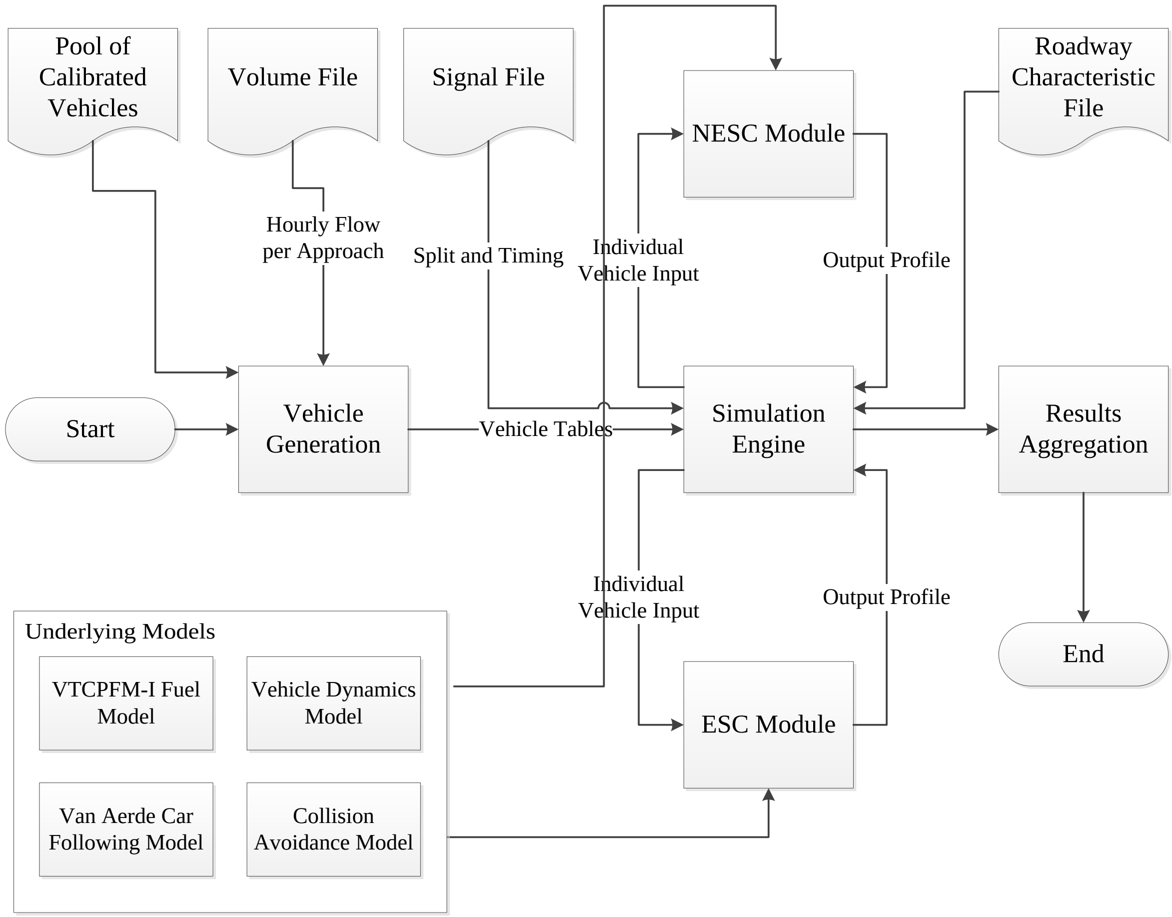


Figure 10: Agent-based simulation logic.

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 11 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.

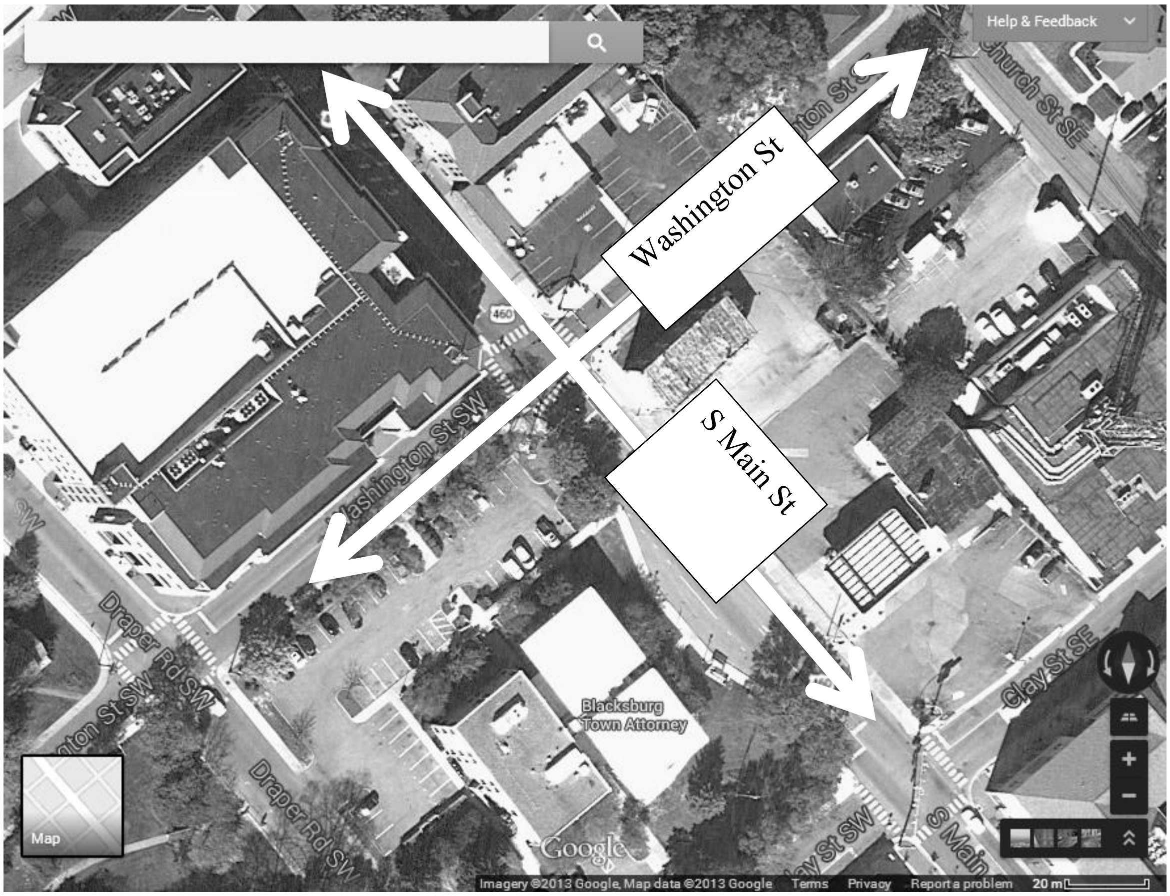


Figure 11: Google Maps image showing the test-intersection in Blacksburg, VA.

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 – $\alpha 0$, $\alpha 1$ and $\alpha 2$ 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 [53].

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 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 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 four different volume factors in both simulation tools. The link-lengths are assumed 200 meters and the values in Table 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).

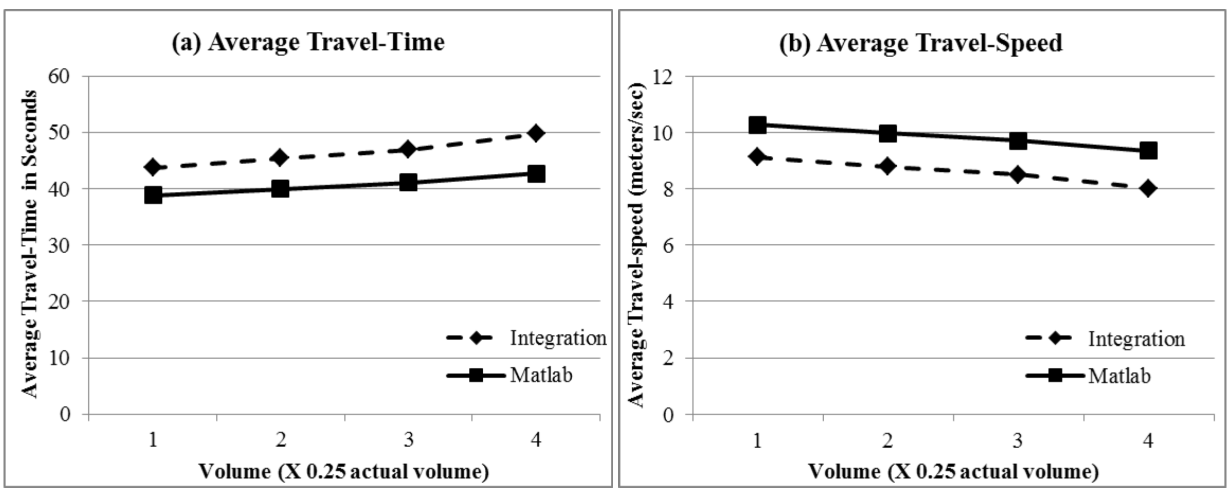


Figure 12: Validation results of travel-time and speed estimates with INTEGRATION.

Figures 12 and 13 shows the three different measures of effectiveness estimated for the four different volume combinations. As shown in Figure 12, 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 13 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 13.

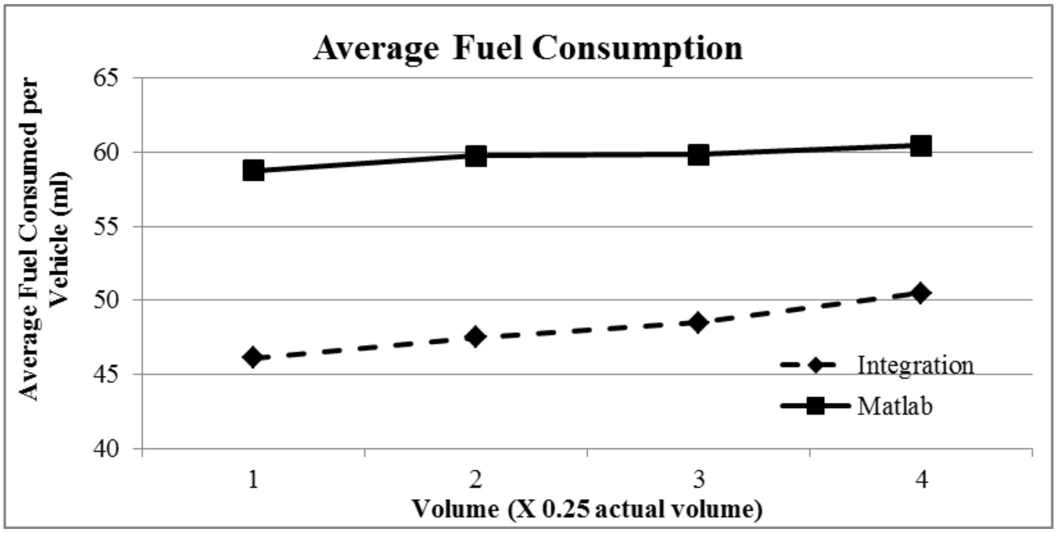


Figure 13: Fuel consumption comparison between INTEGRATION and MATLAB tool.

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 (MOE) studied were:

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

$$MOE_{fuel,i} = \frac{\sum_{1}^{n_i}\left(FCN_u + FCN_d\right) - \sum_{1}^{n_i}\left(FCE_u + FCE_d\right)}{\sum_{1}^{n_i}\left(FCN_u + FCN_d\right)} \times 100 \quad (10)$$

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*.

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

$$MOE_{speed,i} = \sum_{i}^{n_i} \frac{\left(x_u + x_d\right)/t_{ne,j} - \left(x_u + x_d\right)/t_{e,j}}{\left(x_u + x_d\right)/t_{ne,j}} \times \frac{n_i}{100} \qquad (11)$$

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*.

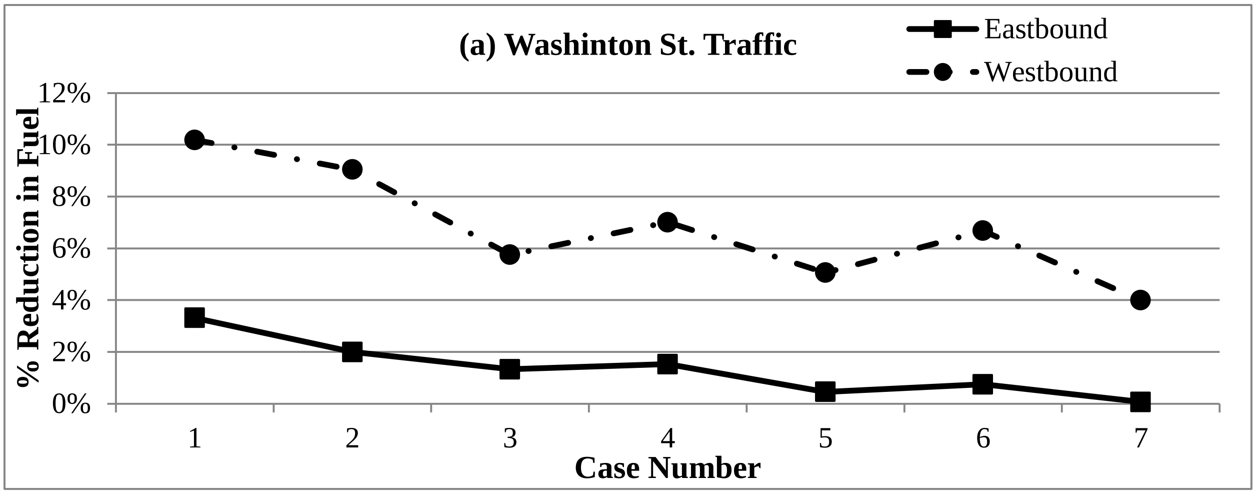
Table 3: Cases Simulated for the Test Intersection

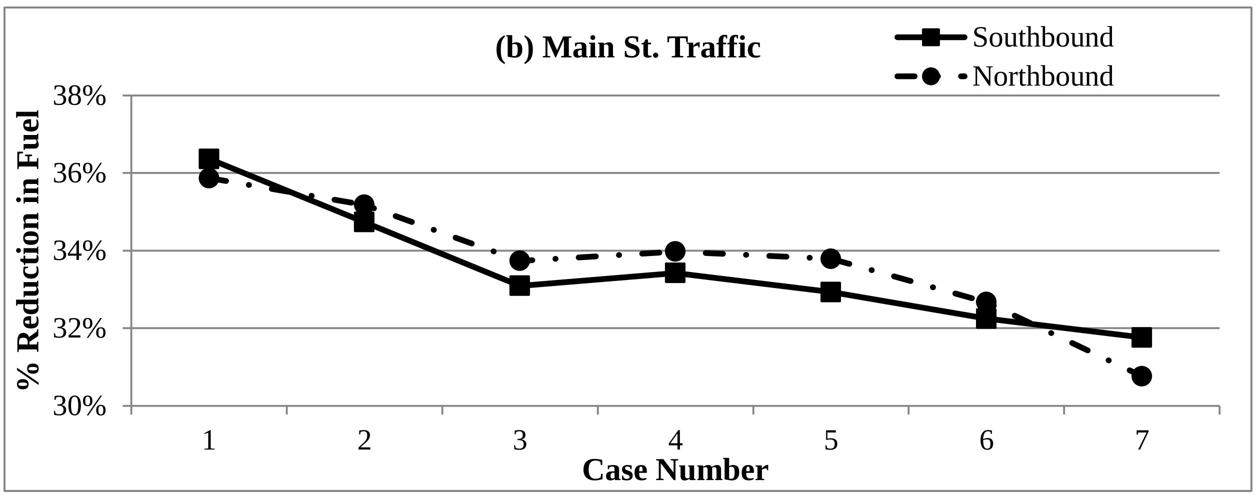
Case	Fraction of Peak Volume	Actual tested volume				Corresponding v/c			
		EB	WB	SB	NB	EB	WB	SB	NB
1	0.25	11	63	165	153	0.03	0.16	0.15	0.14
2	0.50	22	127	330	306	0.06	0.32	0.31	0.29
3	0.75	33	190	494	458	0.08	0.47	0.46	0.43
4	1.00	44	253	659	611	0.11	0.63	0.62	0.57
5	1.25	55	316	824	764	0.14	0.79	0.77	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 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.

Figures 14 and 15 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 14(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 14(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 14(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 14(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.





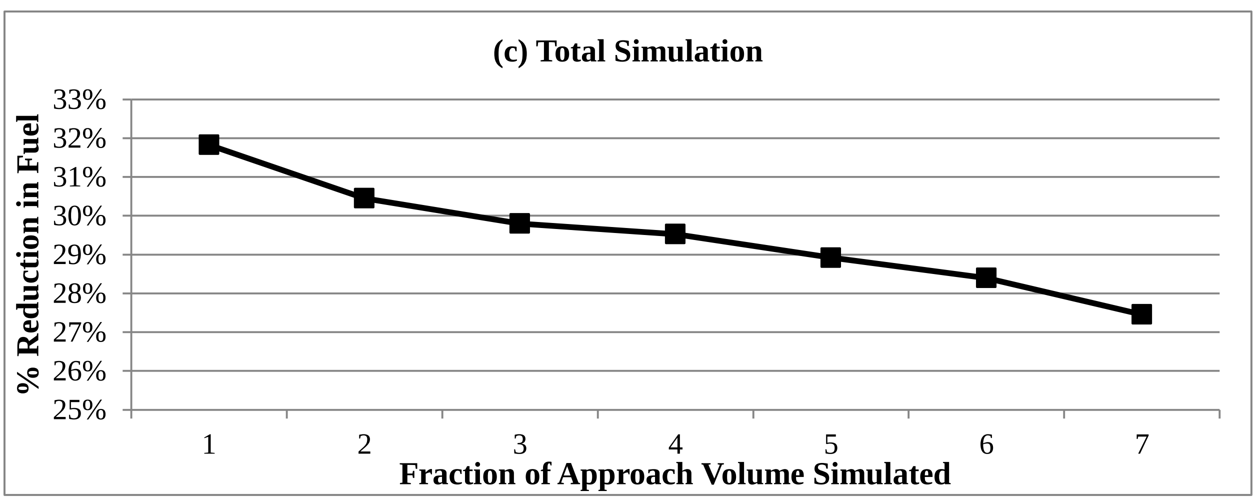


Figure 14: Percentage reduction in fuel consumption for different approaches.

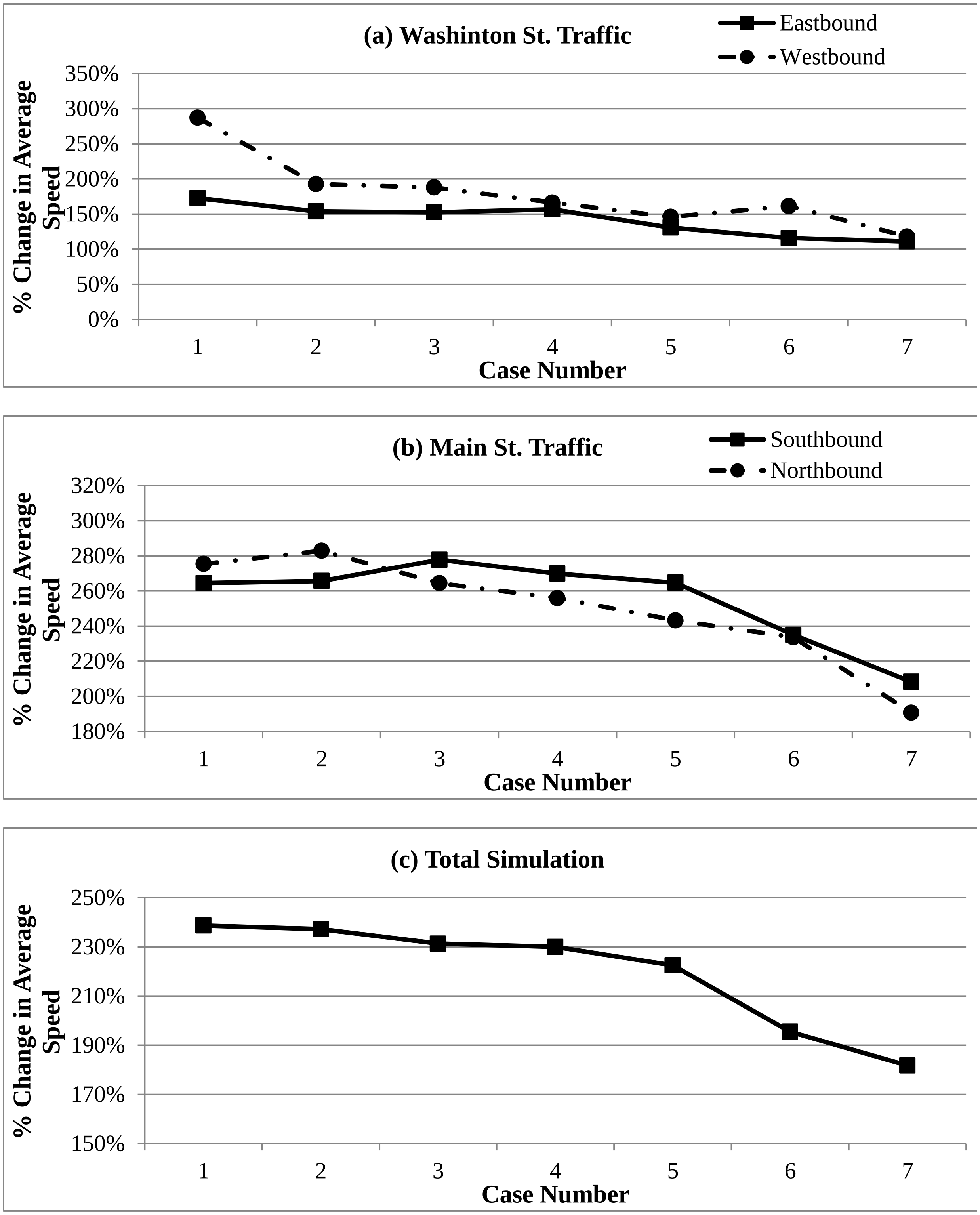


Figure 15: Percentage change in average travel speed (point-point) for different approaches.

Figure 15 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 15(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 15(b) for the major street were comparable in both directions. Figure 15(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.

FINDINGS; CONCLUSIONS; RECOMMENDATIONS

The research presented in this report 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 was modeled, tested and evaluated in multiple simulation environments. The report also 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. The *Algorithm Development* chapter described in brief how the algorithm is modeled to include multiple constraints that are prescribed by advanced signal information, vehicular and roadway parameters.

The report also analyzes vehicle-specific modeling of ESC 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 Eco-Speed Control 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 ESC 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.

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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) C	EPA Estimate (mpg) H	Max. Power (kW)	VT-CPFM 1 Parameters 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: PUBLICATIONS AND PRESENTATIONS RESULTING FROM THIS PROJECT

Kamalanathsharma R., Rakha H. and Yang H. (2015), "Network-wide Impacts of Vehicle Eco-Speed Control in the Vicinity of Traffic Signalized Intersections," To be presented at the 94th Transportation Research Board Annual Meeting, Washington DC, January 11-15, CD-ROM [Paper # 15-4290].

Kamalanathsharma R., and Rakha H. (2014), "Agent-based Simulation of Eco Speed-Controlled Vehicles at Signalized Intersections," Accepted to Transportation Research Record – Journal of the Transportation Research Board, Washington DC, [# 14-1028].