Final Report

Developing an ECO-Cooperative Adaptive Cruise Control System for Electric Vehicles

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16. Abstract

This study develops an Eco-Corporative Adaptive Cruise Control system (Eco-CACC) for battery electric vehicles (BEVs) in the vicinity of signalized intersections and investigates the network-level benefits of this system. The BEV Eco-CACC algorithms provide real-time energy-efficient speeds to connected automated EVs to optimize their travel through signalized intersections using Signal Phasing and Timing (SPaT) information received from traffic signal controllers and surrounding traffic information received from in-vehicle sensors. First, a basic BEV Eco-CACC algorithm was developed for a single intersection. After, an advanced algorithm called BEV Eco-CACC MS was developed with the consideration of impacts from queues and multiple intersections. The developed BEV Eco-CACC algorithms were implemented and tested using the INTEGRATION microscopic simulation software, considering different levels of market penetration rates, traffic conditions, signal timings, road grades, and vehicle types. The test results indicate that the energy-optimum solution for BEVs is different from that for internal combustion engine vehicles (ICEVs), thus demonstrating the need for vehicle-tailored optimum trajectories. The simulation tests demonstrate the BEV Eco-CACC MS produces up to 11% energy savings to pass multiple intersections. Lastly, the study conducts a stated choice experiment to unveil the inclination of drivers towards the Eco-CACC system and to calculate its potential market share. The results indicate that the Eco-CACC system can be very successful and that the overall attitude of individuals in favor of adopting of the system is capable of overturning the lack of private return on investment.

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1. Introduction

The United States is one of the prime consumers of petroleum in the world, burning more than 22% of the total petroleum refined on the planet. The transportation sector by itself consumes nearly three-quarters of the United States' total usage and is consequently ranked as the second largest carbon emitter in the country. Therefore, it is important to reduce petroleum consumption and make surface transportation more safe, efficient, and sustainable (R. K. Kamalanathsharma, 2014). Studies have shown that vehicle fuel consumption levels in the vicinity of signalized intersections are dramatically increased due to vehicle deceleration and acceleration maneuvers (Barth & Boriboonsomsin, 2008; H. Rakha, Ahn, & Trani, 2003). Over the past few decades, numerous studies have focused on changing traffic signal timings to optimize vehicle delay and fuel levels (Li, Li, Pang, Yang, & Tian, 2004; Stevanovic, Stevanovic, Zhang, & Batterman, 2009). In recent years, researchers have attempted to use connected vehicles and infrastructure technologies to develop eco-driving strategies when vehicles approach signalized intersections. Those eco-driving strategies aim to provide, in real-time, recommendations to individual drivers or vehicles so that vehicle maneuvers can be adjusted accordingly to reduce fuel consumption and emission levels (Barth & Boriboonsomsin, 2009; Saboohi & Farzaneh, 2008, 2009).

Most of the studies in this area are focused on developing eco-driving strategies for internal combustion engine vehicles (ICEVs). For example, Malakorn and Park proposed a cooperative adaptive cruise control system using Signal Phasing and Timing (SpaT) information to minimize the absolute acceleration levels of vehicles and reduce vehicle fuel consumption levels (Malakorn

& Park, 2010). Kamalanathsharma and Rakha developed a dynamic programming-based fuel-optimization strategy using recursive path-finding principles and evaluated the developed strategy using an agent-based modeling approach (R. Kamalanathsharma & Rakha, 2014). Asadi and Vahidi proposed a schedule optimization algorithm to allocate "green-windows" for vehicles to pass through a series of consecutive signalized intersections (Asadi & Vahidi, 2011).

In addition to the studies that focused on ICEVs, a few studies have investigated the eco-driving strategies for battery electric vehicles (BEVs) in the vicinity of signalized intersections. An eco-driving technique for BEVs was developed in (Miyatake, Kuriyama, & Takeda, 2011). The vehicle trajectory control problem was formulated as an optimization problem to minimize the summation of vehicle power. Bellman's dynamic programming algorithm was used to solve the optimal control problem. However, a simple energy model was used in this study by assuming that the recharge efficiency is a constant value. Another BEV eco-driving algorithm was proposed in (Zhang & Yao, 2015). However, the proposed energy consumption model was a statistical model based on limited collected data, thus the accuracy may not be good enough for the purpose of developing an optimal control strategy for dynamic vehicle maneuvers. Moreover, vehicle dynamics model was not considered in the constraints to compute acceleration level, so the optimal solution may be calculated using an unrealistic acceleration level. The same energy consumption model was used in (Qi, Barth, Wu, Boriboonsomsin, & Wang, 2018) to develop a connected eco-driving system for BEVs. A model predictive control scheme was used in the control system to force the vehicle to follow the optimal speed trajectory as close as possible. A field test with four participants showed an average of 22% energy savings for automated driving with the proposed eco-driving system. However, a 2012 Ford Escape with a hybrid engine was used in the field test, and this study assumed that this vehicle can represent the performance of an actual BEV.

The abovementioned studies of eco-driving strategies for BEVs have two main issues: (1) lack of a realistic energy consumption model to accurately compute the instantaneous energy consumption when EVs travel through signalized intersections; and (2) lack of a vehicle dynamics model to constrain vehicle acceleration maneuvers. In addition, although many eco-driving strategies for ICE and electric vehicles have been developed in previous studies, there is no comparison to demonstrate the differences in the energy-optimal solutions (e.g., BEVs versus ICEVs). In order to address these issues, this study develops a BEV eco-driving strategy, called the BEV Eco-Cooperative Adaptive Cruise Control (Eco-CACC) system, to compute real-time, energy-optimized vehicle trajectories considering vehicle dynamics constraints and using a realistic BEV energy consumption model. In this way, the energy-optimum program is formulated as an optimization problem with constraints, which is solved using a moving-horizon dynamic programming approach. A basic BEV Eco-CACC is firstly developed for a single intersection. Thereafter, an advanced algorithm called BEV Eco-CACC MS is developed with the consideration of impacts from queues and multiple intersections. The developed BEV Eco-CACC algorithms are implemented and tested using the INTEGRATION microscopic simulation software, considering different levels of market penetration rates, traffic conditions, signal timings, road grades, and vehicle types. The test results indicate that the energy-optimum solution for BEVs is different from that for ICEVs, thus demonstrating the need for vehicle-tailored optimum trajectories. The simulation tests demonstrate that the BEV Eco-CACC MS produces energy savings of up to 11% to pass multiple intersections. Lastly, the study conducts a stated choice experiment to determine the inclination of drivers towards the Eco-CACC system and to calculate its potential market share.

2. Develop Eco-CACC for BEVs

2.1 Definitions and Assumptions

When a vehicle approaches a signalized intersection, the vehicle may accelerate, decelerate, or cruise (maintain its current speed) depending on its speed, distance to the intersection, traffic signal indication, road grade, or headway distance (R. K. Kamalanathsharma, 2014). The Eco-CACC-I system was developed to compute and display a recommended real-time, energy-efficient speed profile to the driver, so that the vehicle can proceed through the signalized intersection while consuming minimum energy (Chen, Rakha, Almannaa, Loulizi, & El-Shawarby, 2017; H. A. Rakha et al., 2016). This recommended trajectory is subject to collision avoidance constraints with other vehicles and can be overridden as needed. Given that both upstream and downstream vehicle speed profiles are considered in the Eco-CACC-I system, a control region in the vicinity of signalized intersections should be defined. Considering the communication range of Dedicated Short Range Communication (DSRC) systems, the Eco-CACC-I is activated at a distance of d_{up} upstream of the intersection to a distance of d_{down} downstream of the intersection. Note that the distance is calculated from the vehicle location to the intersection stop line. The value of d_{down} is defined to ensure that the vehicle has enough downstream distance to accelerate from zero speed to the limit speed at a low throttle level (e.g., 0.3). This ensures that all computations are made along a fixed distance of travel.

Considering that the vehicle may or may not need to decelerate when approaching the traffic signal with no traffic-induced delays, two cases are considered to develop the Eco-CACC-I strategies as indicated below. More details of optimum speed profiles during various situations are discussed in (R. K. Kamalanathsharma, 2014; Xia, 2014).

- Case 1: Vehicle is able to traverse the intersection during the green indication without decelerating (either by maintaining a constant speed, or accelerating to a higher speed and then maintaining that speed).
- Case 2: Vehicle decelerates to a lower speed, and then maintains that speed while traversing the intersection during the green indication.

Figure 1 demonstrates the optimum speed profile for a vehicle traversing a signalized intersection in which the Eco-CACC-I system computes the optimum acceleration and deceleration levels. The sample speed profiles (initial speed u_1 and u_2) for case 1 are highlighted in blue, and the sample speed profile (initial speed u_3) for case 2 is represented in maroon. The road speed limit is denoted by u_f. Note that the samples in Figure 1 occur when the driver sees a red indication when the vehicle is at a distance d_{up} from the intersection stop line. The same classification of case 1 and 2 also exists for the green indication situation. To explain the proposed Eco-CACC-I algorithm, the initial red indication is assumed in the following sections for the purpose of simplicity.

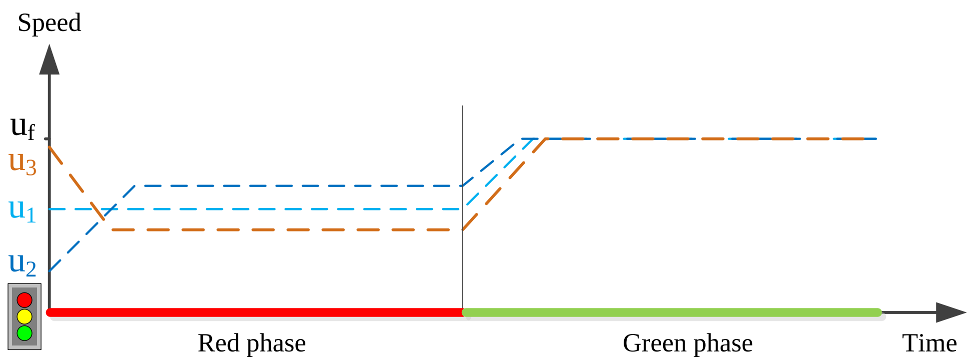


Figure 1: Samples of optimum speed profile when vehicle approaches a signalized intersection.

2.2 Vehicle Dynamics Model

The Eco-CACC system uses a vehicle dynamics model to compute vehicle acceleration behavior. Here, the vehicle acceleration follows the vehicle dynamics model developed in (Yu, Yang, & Yamaguchi, 2015). In this model, the acceleration value depends on vehicle speed and throttle level. Given that the throttle level is typically around 0.6 as obtained from field studies (R. K. Kamalanathsharma, 2014), a constant throttle level of 0.6 is assumed in the vehicle dynamics model to simplify the calculations in the Eco-CACC-I system for case 1. In case 2, the throttle level ranges between 0.1 and 1.0, and the optimum throttle level can be estimated by deriving the speed profile that results in the minimum energy consumption level. The vehicle dynamics model is summarized as

$$u(t+\Delta t) = u(t) + \frac{F(t) - R(t)}{m}\Delta t \tag{1}$$

$$F = \min\left(3600 f_p \beta \eta_D \frac{P_{max}}{u}, m_{ta} g \mu\right) \tag{2}$$

$$R = \frac{\rho}{25.92} \mathrm{C}_d \mathrm{C}_h \mathrm{A}_f u(t)^2 + mg\frac{c_{r0}}{1000}(c_{r1}u(t) + c_{r2}) + mgR_g \tag{3}$$

where F is the vehicle tractive effort; R represents the resultant of the resistance forces, including aerodynamic, rolling, and grade resistance forces; f_p is the driver throttle input [0,1] (unitless); β is the gear reduction factor (unitless), and this factor is set to 1.0 for light duty vehicles; 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 (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 time t (unitless).

2.3 Energy Consumption Model for BEVs

The Virginia Tech Comprehensive Power-based Electric Vehicle Energy Consumption Model (VT-CPEM) developed in (Fiori, Ahn, & Rakha, 2016) is used in the Eco-CACC system to compute instantaneous energy consumption levels for BEVs. The model is selected here for three main reasons: (1) speed is the only required input variable for this model, so this model is very easy to use to solve the proposed optimization problem; (2) the model has been validated and demonstrated to produce very good accuracy compared to empirical data; and (3) the model can be calibrated to a specific vehicle using publicly available data. The VT-CPEM is a quasi-steady backward highly-resolved power-based model, which only requires the instantaneous speed and the EV characteristics as input to compute the instantaneous power consumed. The VT-CPEM model is summarized in the following equations.

$$EC(t) = \int_0^t P_B(t) \cdot dt \tag{4}$$

$$P_B(t) = \begin{cases} \dfrac{P_W(t)}{\eta_D \cdot \eta_{EM} \cdot \eta_B} + P_A & \forall\, P_{Wheels}(t) \geq 0 \\ P_W(t) \cdot \eta_D \cdot \eta_{EM} \cdot \eta_B \cdot \eta_{rb}(t) + P_A & \forall\, P_{Wheels}(t) < 0 \end{cases} \tag{5}$$

$$P_W(t) = \big(ma(t) + R(t)\big) \cdot u(t) \tag{6}$$

$$\eta_{rb}(t) = \left[e^{\left(\frac{\lambda}{|a(t)|}\right)}\right]^{-1} \tag{7}$$

where EC represents the energy consumption from time 0 to t; P_W denotes the power at the wheels; P_B is the power consumed by (regenerated to) the electric motor; P_A is the power consumed by the auxiliary systems; η_D and η_{EM} are the driveline efficiency and the efficiency of the electric motor, respectively; η_B denotes the efficiency from battery to electric motor; η_{rb} represents the regenerative braking energy efficiency, which can be computed using Equation (7); the parameter λ has been calibrated (λ = 0.0411) in (Fiori et al., 2016) using empirical data described in (Gao, Chu, & Ehsani, 2007); $R(t)$ represents the resistance force computed in Equation (3).

2.4 BEV Eco-CACC Algorithms

Basic Algorithm

The basic algorithm is developed without the consideration of the impacts of queues and multiple intersections. Given that vehicles behave differently for the two cases described above, the Eco-CACC strategies are developed separately for cases 1 and 2.

Case 1 – In this case, the vehicle can traverse the signalized intersection without decelerating. In order to reach the maximum average speed to proceed through the intersection, the cruise speed during the red indication is defined by Equation (8). If u_c is equal to the vehicle's initial speed $u(t_0)$, then the vehicle can proceed at a constant speed upstream of the intersection. Otherwise, the vehicle should accelerate to u_c by following the vehicle dynamics model presented by Equations (1) through (3). Thereafter, when the signal indication turns green, the vehicle needs to follow the vehicle dynamics model and accelerate from the cruise speed u_c to the speed limit u_f until the vehicle travels a distance d_{down} downstream of the intersection.

$$u_c = min\left(\frac{d_{up}}{t_r}, u_f\right) \tag{8}$$

Case 2 – The vehicle's speed profile for this case is illustrated in Figure 2. Upstream of the intersection, the vehicle needs to slow down at a deceleration level a, then cruise at a speed u_c to traverse the intersection when the signal just turns green. Downstream of the intersection, the vehicle should accelerate from u_c to u_f, and then cruise at u_f. Since the deceleration level a upstream of the intersection and the throttle level f_p downstream of the intersection are the only unknown variables for this case, the optimum speed profile can be calculated by solving the optimization problem described below.

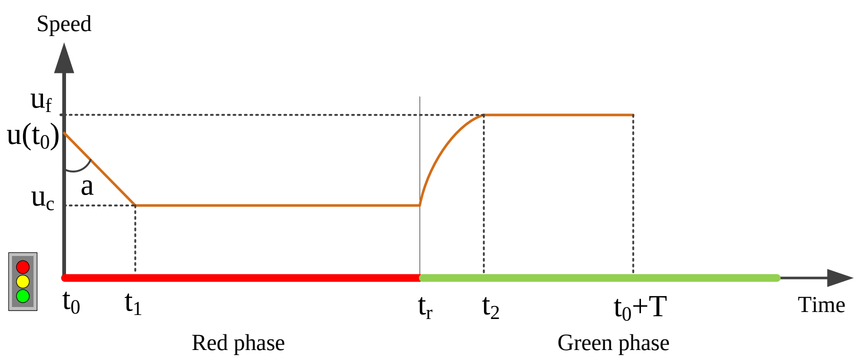


Figure 2: Optimum speed profile in case 2.

Assume a vehicle arrives at location d_{up} at time t_0 and passes d_{down} at time $t_0 + T$, and the cruise speed during the red indication is u_c, the objective function entails minimizing the total energy consumption level as:

$$min \int_{t_0}^{t_0+T} EC\big(u(t)\big) \cdot dt \tag{9}$$

where *EC(*)* denotes the energy consumption at instant *t* using Equations (4) through (7). The constraints can be constructed using the relationships between speed, acceleration, deceleration, and distance, as shown below:

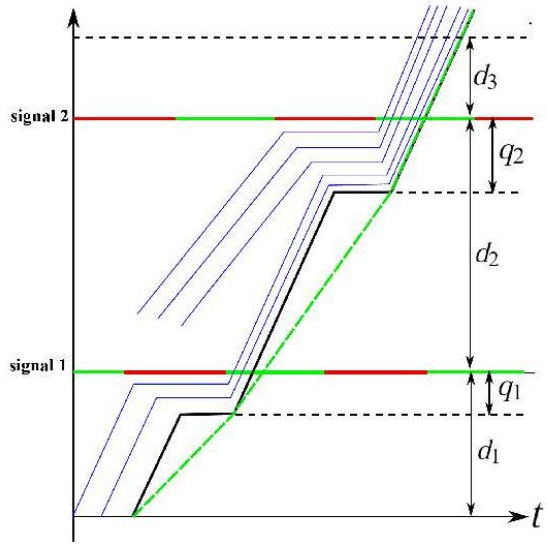
$$u(t):\begin{cases} u(t) = u(t_0) - at & t_0 \le t \le t_1 \\ u(t) = u_c & t_1 < t \le t_r \\ u(t+\Delta t) = u(t) + \dfrac{F(f_p) - R(u(t))}{m}\Delta t & t_r < t \le t_2 \\ u(t) = u_f & t_2 < t \le t_0 + T \end{cases} \tag{10}$$

$$\begin{gathered} u(t_0)\cdot t - \frac{1}{2}at^2 + u_c(t_r - t_1) = d_{up} \\ u_c = u(t_0) - a(t_1 - t_0) \\ \int_{t_r}^{t_2} u(t)\,dt + u_f(t_0 + T - t_2) = d_{down} \\ u(t_2) = u_f \\ 0 < a \le 5.9 \\ 0 \le f_p \le 1 \\ u_c > 0 \end{gathered} \tag{11}$$

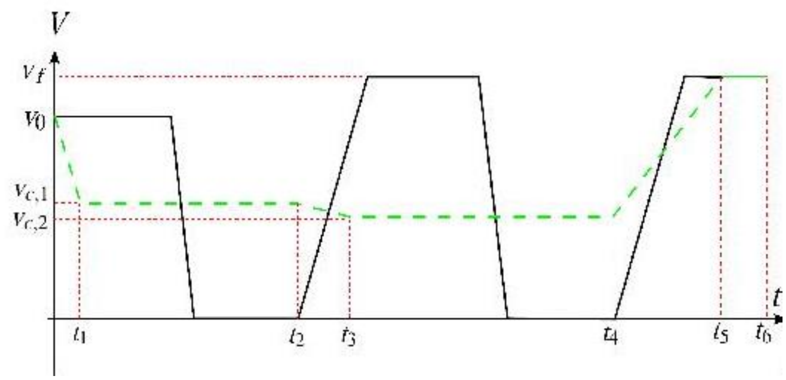
In Equation (10), the functions *F(*)* and *R(*)* represent the vehicle tractive effort and resistance force as computed by Equations (2) and (3), respectively. According to the relationships in Equations (10) and (11), the deceleration a and throttle level f_p are the only unknown variables. Note that the maximum deceleration level is limited to 5.9 m/s^2 (comfortable deceleration threshold felt by an average driver). In addition, the throttle level is set to range between 0 and 1. Dynamic programming (DP) is used to solve the problem by listing all the combinations of deceleration and throttle values and calculating the corresponding fuel consumption levels; the minimum calculated energy consumption gives the optimum parameters (Guan & Frey, 2013; R. K. Kamalanathsharma, 2014). Considering that the optimization solution needs to be computed at a rapid frequency (e.g., 10 Hz) for real-time applications, an A-star algorithm is used here to expedite the computational speed. The A-star algorithm is a path-finding algorithm 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 (R. K. Kamalanathsharma & Rakha, 2016). The deceleration speed and the throttle level are considered as constant values in the proposed A-star algorithm when computing the future cost. However, given that the optimal solution is recomputed every decisecond, the acceleration/deceleration level can also be updated every decisecond, thus producing a varying acceleration/deceleration maneuver.

Advanced Algorithm for Multiple Intersections

The previous developed BEV Eco-CACC algorithm only considers the impact of single signalized intersection to calculate an energy-optimized speed trajectory. However, the speed trajectory may not work effectively in minimizing energy consumption for multiple intersections. A previous study in (Yang, Almutairi, & Rakha, 2017) demonstrated the importance of considering the impact of multiple intersections in computing fuel-optimum speed profile for internal combustion engine (ICE) vehicles. Therefore, we extend the basic BEV Eco-CACC controller to multiple signalized intersections.



(a)



(b)

Figure 3: Vehicle equipped with BEV Eco-CACC controller passes two signalized intersections: (a) trajectories, (b) speed profiles.

Figure 3 presents the trajectories of vehicles passing two consecutive signalized intersections. The solid black line represents the trajectory of one vehicle experiencing two red lights without control (assume that the vehicle has infinite acceleration/deceleration rates). The vehicle is stopped ahead of both intersections by the red lights and the vehicle queues. After using the Eco-CACC multiple signalized-intersection (Eco-CACC MS) controller, the vehicle cruises to each intersection with a constant speed (represented by the dashed green line in Figure 3(a)). However, the assumption that the acceleration/deceleration rates of the equipped vehicle are infinite is not realistic. Figure 3(b) compares the speed profiles of the vehicle with (green line) and without (black line) the Eco-CACC MS controller, considering both acceleration and deceleration durations. Without using the controller, the vehicle has to stop completely at the first intersection. Between the two intersections, the vehicle first accelerates to the speed limit and then decelerates to 0 again. The stop-and-go behaviors and the long idling time waste a great deal of energy. However, the vehicle using the Eco-CACC MS controller decelerates to a speed $v_{c,1}$, and then cruises to the first intersection. Between the two intersections, it decelerates or accelerates from $v_{c,1}$ to $v_{c,2}$, and then cruises to the second intersection. Here, $v_{c,1}$ to $v_{c,2}$ are the cruise speeds to the first and second intersection, respectively. Once the queue at the second intersection is released, the vehicle accelerates to the speed limit. Compared to the base case without using the controller, both the vehicle trajectory and the speed profile with Eco-CACC MS are much smoother.

The objective of developing the Eco-CACC MS controller is to minimize the vehicle energy consumption level in the vicinity of the two intersections. In addition to the shape of the vehicle speed shown in Figure 3(b), the algorithm determines the optimum upstream acceleration/deceleration levels of the controlled speed profile. The mathematical formulation of the controller can be cast as

$$min \int_{t_0}^{t_6} EC\big(v(t)\big) \cdot dt \tag{12}$$

s.t.

$$v(a_1, a_2, a_3) = \begin{cases} v_0 \ + \ a_1 t & 0 < t \leq t_1 \\ v_{c,1} & t_1 < t \leq t_2 \\ v_{c,1} + a_2(t - t_2) & t_2 < \ t \leq t_3 \\ v_{c,2} & t_3 < t \leq t_4 \\ v_{c,2} + a_3(t - t_4) & t_4 < t \leq t_5 \\ v\_f & t_5 < t \leq t_6 \end{cases} \tag{13}$$

$$v_{c,1} = v_0 + a_1 \cdot \ t_1 \tag{14}$$

$$v_0 \cdot \ t_1 + \frac{1}{2} \ a_1 \ t_1^2 \ + \ v_{c,1} \ (t_2 - t_1) = d_1 - q_1 \tag{15}$$

$$t_2 = t_{g,1} + \frac{q_1}{w_1} \tag{16}$$

$$v_{c,2} = v_{c,1} + a_2 \cdot \ (t_3 - t_2) \tag{17}$$

$$v_{c,1}(t_3 - t_2) + \frac{1}{2} \ a_2 \ (t_3 - t_2)^2 + v_{c,2} \ (t_4 - t_3) \ = \ d_2 + q_1 - q_2 \tag{18}$$

$$t_4 = t_{g,2} + \frac{q_2}{w_2} \tag{19}$$

$$v_{c,2} + a_3 \ (t_5 - t_4) = v_f \tag{20}$$

$$v_{c,2}(t_5 - \ t_4) \ + \frac{1}{2} a_3 \ (t_5 - t_4)^2 \ + \ v_f \ (t_6 - t_5) = d_3 + q_2 \tag{21}$$

$$a_-^s \leq a_1 \leq a_+^s \tag{22}$$

$$a_-^s \leq \ a_2 \leq \ a_+^s \tag{23}$$

$$0 \leq \ a_3 \leq \ a_+^s \tag{24}$$

where

- $EC\big(v(t)\big)$: the vehicle energy consumption rate at any instant t computed using the VT-CPEM developed in (Fiori et al., 2016), see Equations (4~7);
- $v(t)$: the advisory speed limit for the equipped vehicle at time t;
- a_k: the acceleration/deceleration rates for the advisory speed limit, k = 1, 2, 3;
- v_0: the speed of the vehicle when it enters the upstream control segment of the first intersection;
- v_f: the road speed limit;
- d_1: the length of the upstream control segment of the first intersection;
- d_2: the distance between the two intersections;
- d_3: the length of the downstream control segment of the second intersection;
- $t_{g,1}$: the time instant that the indicator of the first signal turns to green;
- $t_{g,2}$: the time instant that the indicator of the second signal turns to green;
- t_k: the time instant defined in Figure 3(b);
- $v_{c,1}$: the cruise speed to approach the first intersection;
- $v_{c,2}$: the cruise speed to approach the second intersection;
- q_1: the queue length at the first immediate downstream intersection;
- q_2: the queue length at the second immediate downstream intersection;
- w_1: the queue dispersion speed at the first immediate downstream intersection;
- w_2: the queue dispersion speed at the second immediate downstream intersection;
- a_-^s: the saturation deceleration level;
- a_+^s: the saturation acceleration level.

Equation (13) demonstrates that given the traffic state—including queue lengths, the start and end times of the indicators of the two intersections, and the approaching speed of the controlled vehicles—the speed profile varies as a function of the acceleration/deceleration levels, (a_1, a_2, a_3). Equations (14~16) define that the equipped vehicle decelerates to $v_{c,1}$ and passes the first intersection just when the queue is released. Equations (17~19) determine that the vehicle passes the second intersection when the queue is released. Equations (20~21) show how the vehicle recovers its speed back up to the speed limit. The Eco-CACC MS controller searches for the three acceleration levels to minimize the energy consumption of the controlled vehicle over the entire control section. Note that in the proposed controller we only look ahead at two downstream intersections at a time.

3. Simulation Test

3.1 Test BEV Eco-CACC and Compare with ICEV Eco-CACC

A case study aimed to simulate the proposed basic Eco-CACC algorithm to investigate the impact of signal timing, speed limit, and road grade on the optimal solution. In addition, two electric vehicles (2015 Nissan Leaf and 2015 Tesla Model S) were considered in the simulation test to see if their different weight and engine power have an impact on the optimal solution. In order to compare and contrast BEV and ICEV optimal solutions, two ICEVs (2015 Honda Fit and 2015 Cadillac SRX) were used for the same simulation test.

Test Eco-CACC-I for BEVs

The simulated test road consisted of a single signalized intersection with a control length starting 200 meters upstream and ending 200 meters downstream of the intersection (total length of 400 meters). An automated connected vehicle, a 2015 Nissan Leaf equipped with the Eco-CACC system, was assumed to completely follow the optimal speed profile calculated by the Eco-CACC algorithm in that 400-meter distance. Combinations of speed limit (25, 30, 40, and 50 mph), green indication offset (15, 20, 25, and 30 seconds), and road grade (+3% and −3%) were tested. Given that the test results for the same vehicle for various speed limits were very similar, the test results of Nissan Leaf for a 25-mph speed limit are presented in Figure 4 and Figure 5.

Figure 4 shows the test results for a speed limit of 25 mph for different signal timings and road grade values. Each image in Figure 4 presents the sampling of numerous feasible solutions (speed profiles) for each combination of parameters. For instance, the right bottom image in Figure 4 includes 29 curves. Each curve represents a feasible solution (speed profile) when a vehicle traverses the intersection with a certain deceleration level (a_i) upstream of the intersection. The throttle level downstream of the intersection is the optimal throttle corresponding to the minimal energy consumption given the upstream deceleration level of a_i. Each feasible solution is plotted in a different color, and the optimal solution, which corresponds to the minimal energy consumption trajectory, is presented in a bold red color. It should be noted that all the images in the left column in Figure 4 show that the speed profile associated with the maximum deceleration level is the optimal solution for the uphill direction. Furthermore, all the images in the right column in Figure 4 show that the speed profile associated with the minimum deceleration level is the optimal solution for the downhill direction.

The corresponding energy consumption levels for each feasible solution (speed profile) are presented in Figure 5. Note that the solution index in the x-axis represents the 1st solution, 2nd solution, …, nth solution, ordered in ascending order by deceleration levels. All the images in the left column in Figure 5 show that the upstream trip regenerates minimum electric power, much less than the battery power consumed. In this case, the cruise speed is the most important factor in identifying the optimal solution since higher cruise speeds associated with higher deceleration levels result in less energy consumption for the entire trip. Consequently, the maximal deceleration level corresponds to the optimal solution for BEV driving in the uphill direction. All the images in the right column in Figure 5 illustrate that the upstream trip generates equal or slightly higher electric power than the battery power consumed during the downstream trip because of the gravity impact in the downhill direction. In this case, the deceleration level is the most important factor in identifying the optimal solution. Lower deceleration levels correspond to longer deceleration times and more regenerative electric power upstream of the intersection, which can result in lower energy consumption for the entire trip. Therefore, the minimal deceleration level corresponds to the optimal solution for BEV driving in the downhill direction.

Considering that the Nissan Leaf is a compact EV with only an 80-HP engine, a 2015 Tesla Model S with a much more powerful 283-HP engine was also tested to investigate the impact of engine size on the optimal control strategy. The same simulation was conducted assuming a connected and automated Tesla Model S is equipped with the Eco-CACC controller. The simulation results demonstrate very similar results to the Nissan Leaf with two main differences. Downstream of the intersection, the vehicle speed for Tesla can accelerate to the maximum allowed speed (speed limit) much faster in the downhill direction given that the Tesla Model S is more powerful than the Nissan Leaf. In addition, the energy consumption for the Tesla Model S is higher since it has more weight. However, the energy consumption curves across the solutions from minimal to maximal deceleration levels have the same trends, so the same optimal solution can be located for both vehicles. Given that the test results for the Nissan Leaf are already illustrated, the plots for Tesla are not presented here. According to the test results for the two BEVs, the optimal solutions for the downhill and uphill directions can be summarized as follows:

- Downhill direction: the optimal speed profile corresponds to the minimum deceleration level in the solution space.
    - Upstream – lower cruise speed produces longer braking times and more regenerative energy.
    - Downstream – lower cruise speed means the vehicle consumes more energy downstream; however, the benefit of energy regeneration upstream exceeds the additional needs for energy downstream.
- Uphill direction: the optimal speed profile corresponds to the maximum deceleration level in the solution space.
    - Upstream – different from the situation for the downhill direction given that the vehicle regenerates minimum energy by decelerating in the uphill direction.
    - Downstream – vehicle needs the maximum cruise speed while proceeding through the intersection, so that the downstream trip requires less energy.

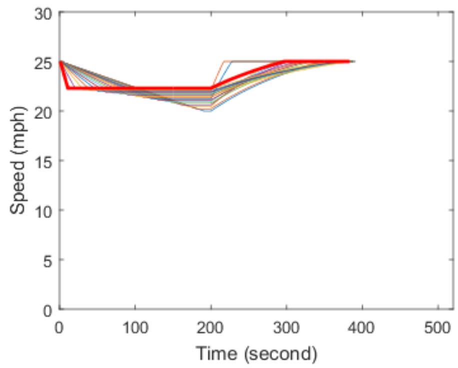
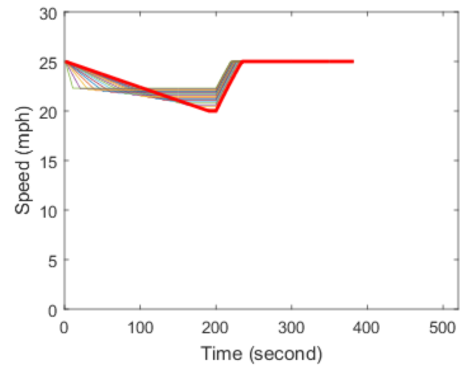
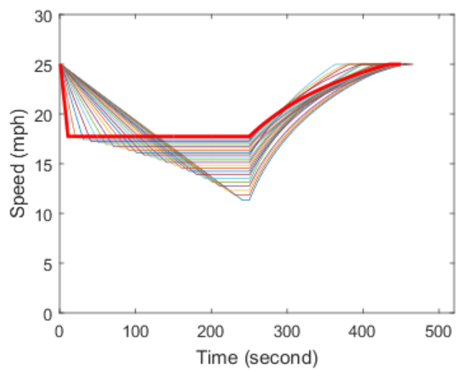
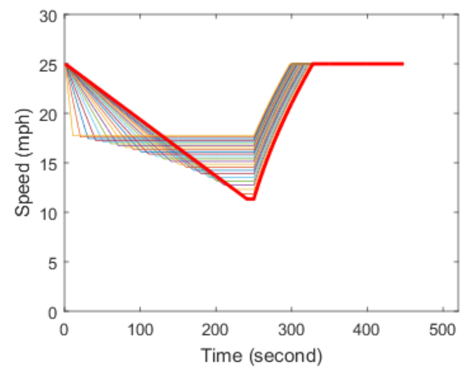
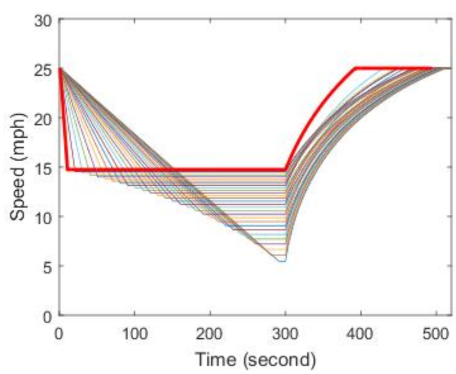
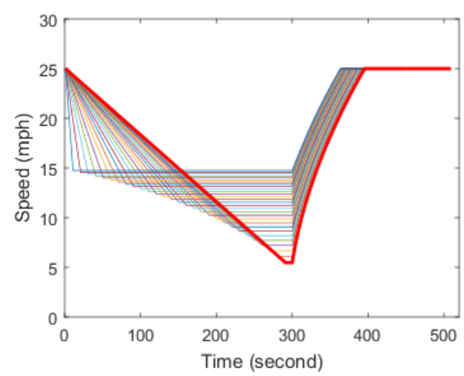
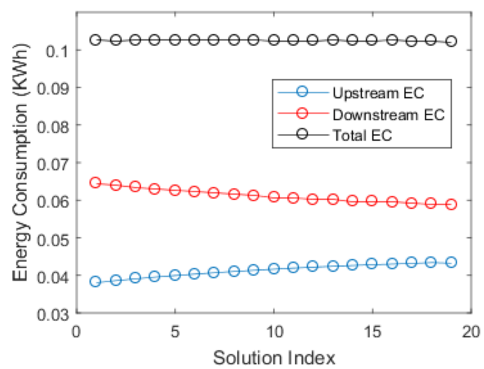
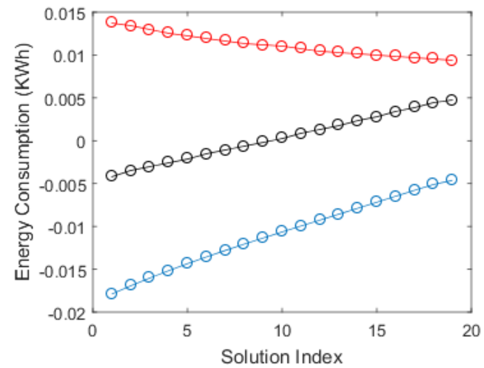
<table>
<tr><th>Speed Limit 25 mph</th><th>Uphill (3%)</th><th>Downhill (−3%)</th></tr>
<tr><td>20 Seconds Red Time</td><td></td><td></td></tr>
<tr><td>25 Seconds Red Time</td><td></td><td></td></tr>
<tr><td>30 Seconds Red Time</td><td></td><td></td></tr>
</table>

Figure 4: Nissan Leaf speed profile by BEV Eco-CACC for speed limit of 25 mph.

<table>
<tr><th>Speed Limit 25 mph</th><th>Uphill (3%)</th><th>Downhill (−3%)</th></tr>
<tr><td>20 Seconds Red Time</td><td>
</td><td>
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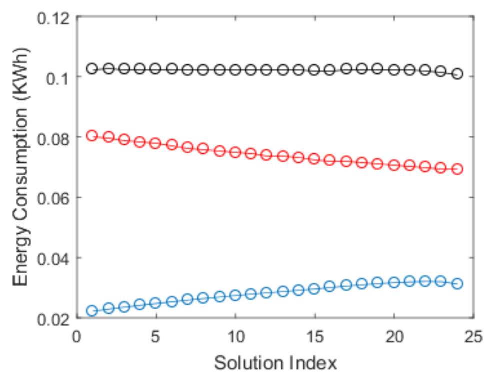
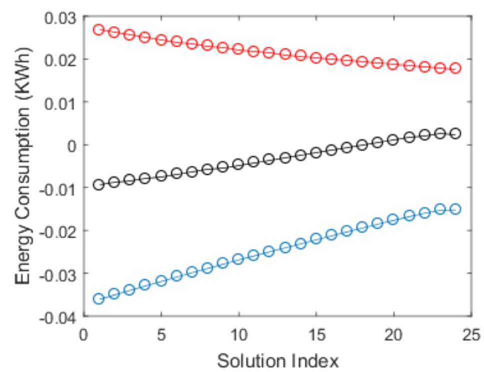
<tr><td>25 Seconds Red Time</td><td>
</td><td>
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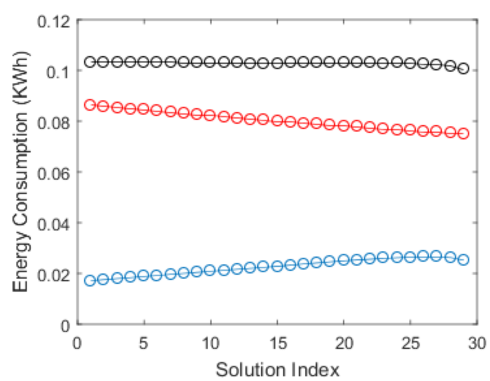
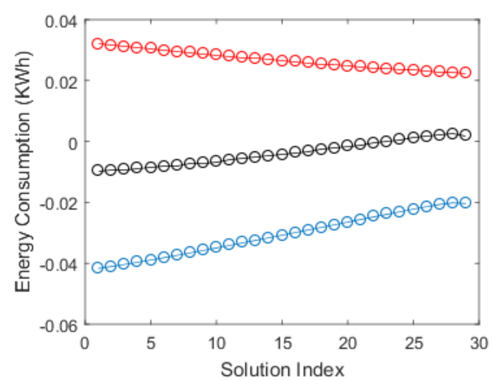
<tr><td>30 Seconds Red Time</td><td>
</td><td>
</td></tr>
</table>

Figure 5: Nissan Leaf BEV Eco-CACC energy consumption for speed limit of 25 mph.

Eco-CACC-I for ICEVs

The Eco-CACC for ICEVs previously developed in (Chen et al., 2017; Chen, Rakha, Loulizi, El-Shawarby, & Almannaa, 2016) is considered here for comparison with the Eco-CACC for BEVs. In this model, the optimization problem is formulated using Equations (9) through (11), and the same vehicle dynamics model shown in Equations (1) through (3) is used. Note that, the Virginia Tech Comprehensive Power-based Fuel Consumption Model (VT-CPFM-1) is used to replace the

BEV energy model in Equations (4) through (7). More details of the Eco-CACC controller for ICEVs can be found in (Chen et al., 2017; Chen et al., 2016).

The same simulation was conducted for a 2015 Honda Fit, which has similar engine power and weight to the 2015 Nissan Leaf. The test results are presented in Figure 6 and Figure 7.

Figure 6 shows the test results for a speed limit of 25 mph for different signal timings and roadway grades. All the images in the left column in Figure 5 demonstrate that the speed profile with deceleration level in the middle area (between the minimum and maximum values) is the optimal solution for the uphill direction. Furthermore, all the images in the right column in Figure 6 Figure 4: Nissan Leaf speed profile by BEV Eco-CACC for speed limit of 25 mph.demonstrate that the speed profile associated with the maximum deceleration level is the optimal solution for the downhill direction. The corresponding energy consumption levels for each feasible solution (speed profile) in the solution space are presented in Figure 6. Note that the solution index along the x-axis is also ranked and ordered in a descending manner based on the deceleration level. The energy consumption unit is “liters” for ICEVs. In addition, unlike BEVs that regenerate energy while braking, ICEVs always consume fuel during the trip. All the images in the left column in Figure 7 show that vehicle consumes more energy to reach a higher cruise speed in the uphill direction upstream of the intersection. However, higher cruise speeds result in less energy consumption downstream of the intersection. The optimal solution for ICEV driving in the uphill direction is somewhere in the mid-range, depending on the vehicle’s specifications and roadway grade. All the images in the right column in Figure 7 demonstrate that different deceleration levels do not change the ICEV’s energy consumption while traveling downhill, so higher cruise speeds consume the same fuel level upstream of the intersection. However, higher cruise speeds result in less energy consumption downstream of the intersection. In this case, the deceleration level is the most important factor to locate the optimal solution. Higher deceleration levels correspond to lower energy consumption for the downstream portion, while keeping the same amount of energy consumption for the upstream portion. Therefore, the maximal deceleration level corresponds to the optimal solution for ICEV driving in the downhill direction.

Considering that the Honda Fit is a compact gasoline vehicle with a 97-HP engine, a 2015 Cadillac SRX with a much more powerful 230-HP engine was also tested to verify if ICEV optimal solutions are general or engine specific. The same tests were conducted assuming a connected automated Cadillac SRX equipped with the Eco-CACC controller. The simulation results demonstrate that the test results for the two ICEVs are very similar. There are two differences. Downstream of the intersection, the Cadillac can accelerate to the maximum allowed speed (speed limit) faster in the downhill direction given that the Cadillac has more engine power compared to the Honda Fit. In addition, the energy consumption for the Cadillac is almost double that of the Honda Fit, given its large size. However, the energy consumption curves across the solutions from minimal to maximal deceleration levels show similar trends, demonstrating that the ICEV optimum strategies appear to be general. According to the test results for the two ICEVs, the optimal solutions produced by the Eco-CACC system for the downhill and uphill directions can be summarized as follows:

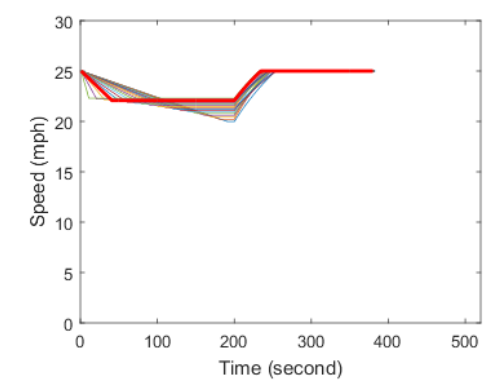
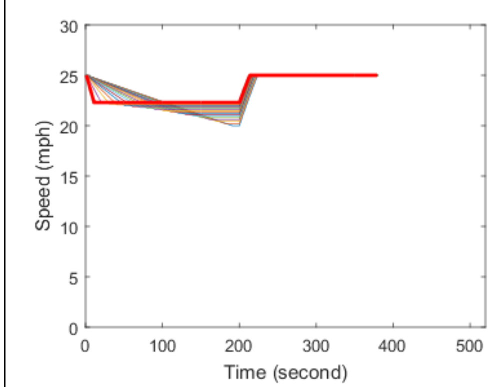
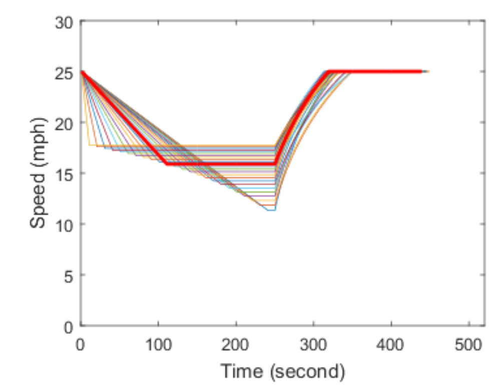
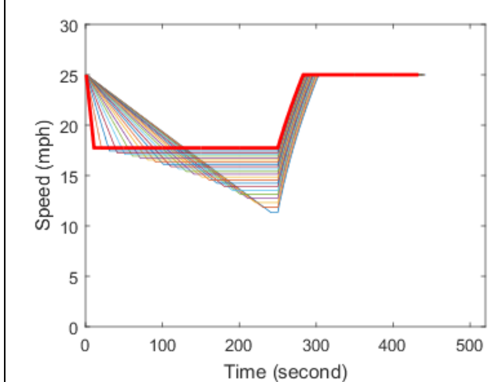
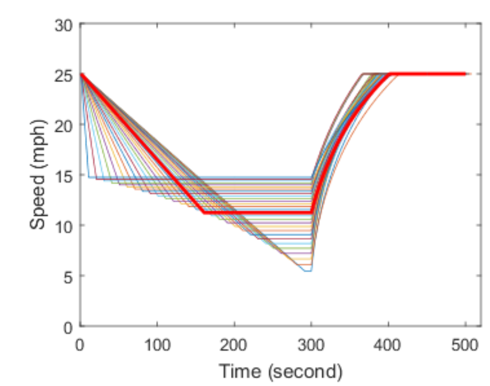
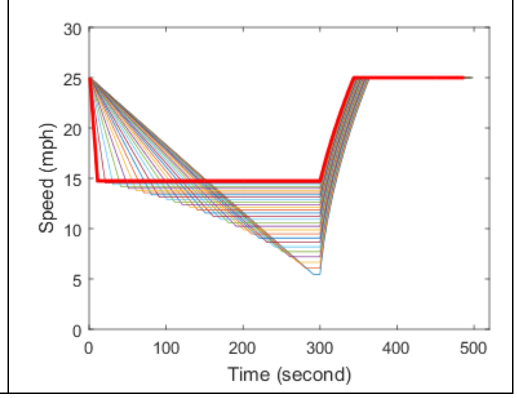
Speed Limit 25 mph	**Uphill (3%)**	**Downhill (−3%)**
20 Seconds Red Time		
25 Seconds Red Time		
30 Seconds Red Time		

Figure 6: Honda Fit speed profile by ICEV Eco-CACC for speed limit of 25 mph.

- Downhill direction: the optimal speed profile corresponds to the maximum deceleration level in the solution space.

    - Upstream – different deceleration levels do not change the ICEV's energy consumption during braking, so higher cruise speeds consume a similar amount of fuel.
    - Downstream – higher cruise speeds at the stop bar result in less energy consumption downstream.
- Uphill direction: the optimal speed profile corresponds to the maximum deceleration level in the solution space.
    - Upstream – Unlike the downhill direction, the vehicle consumes more energy to reach a higher cruise speed while traveling uphill.
    - Downstream – higher cruise speeds result in less energy consumption downstream. The optimal solution sits in the mid-range, depending on the vehicle's weight, engine power, and roadway slope.

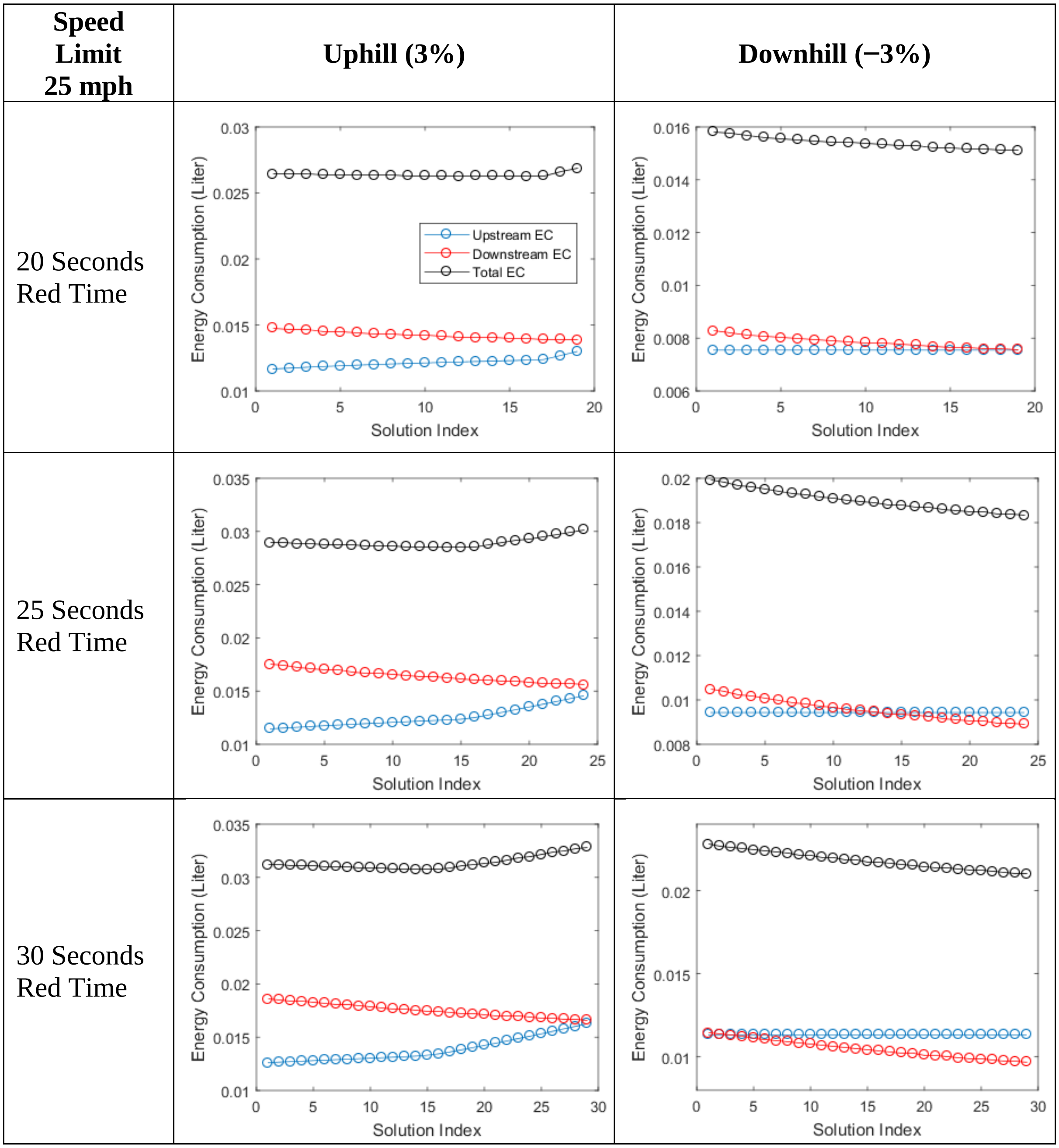


Figure 7: Honda Fit ICEV Eco-CACC fuel consumption for speed limit of 25 mph.

Test Results Analysis and Comparison

The test results indicate that the optimal solutions for BEVs and ICEVs are very different. The optimal solutions for BEVs and ICEVs are summarized in Table 1 for when a vehicle needs to decelerate upstream of an intersection. For downhill roadways, BEVs require longer deceleration times to accumulate more regenerative power to minimize the overall energy consumption in traversing the intersection. Alternatively, ICEVs need the opposite by using the maximum deceleration level (minimum deceleration time) to minimize the overall energy consumption. For uphill approaches, BEVs need to minimize the deceleration time for the vehicle to traverse the approach stop line at its maximum speed, saving energy downstream while accelerating back to the roadway speed limit. Alternatively, the optimum ICEV deceleration level is typically in the mid-range to minimize the overall energy consumption. The comparison results demonstrate that the energy-optimum solution for BEVs is different from that for ICEVs due to the fact that they consume energy differently. The findings in the case study also prove that previous studies that only consider the optimization of acceleration or deceleration and ignore the specific vehicle energy model may not correctly compute the energy-optimal eco-driving solutions for different types of vehicles.

Table 1: Optimal solutions for BEV and ICEV Eco-CACC systems when vehicle needs to decelerate to proceed through an intersection.

	BEV	**ICEV**
Uphill	Maximum deceleration	Mid-range deceleration
Downhill	Minimum deceleration	Maximum deceleration

3.2 Test Eco-CACC for Multiple Intersections

The system performance of the Eco-CACC MS controller was tested in the INTEGRATION software. A simulated traffic network with three signalized intersections as shown in Figure 8 was used in this test. The traffic stream parameters on the major road are a free-flow speed of 40 mph, a speed at capacity of 30 mph, a saturation flow rate of 1600 veh/h/lane, and a jam density of 160 veh/km/lane. The three signals (500 meters apart) have the same signal timing plan with a 60-second cycle length: 42-second phase length for the main street with 5 seconds yellow or all-red time for phase transition. The signal offsets are set to be 0 seconds. Note that the capacity of the main roadway is 987 veh/h/lane (1600 × (42-5)/60). Various traffic demand levels (100, 300, 500, 700, and 900 veh/h/lane) below the saturated flow were used during the test. Two types of vehicles (BEV and ICEV) were used in the test to validate the system performance under three scenarios: (1) basic case without Eco-CACC controller; (2) Eco-CACC for single signalized intersection (Eco-CACC 1S); and (3) Eco-CACC MS.

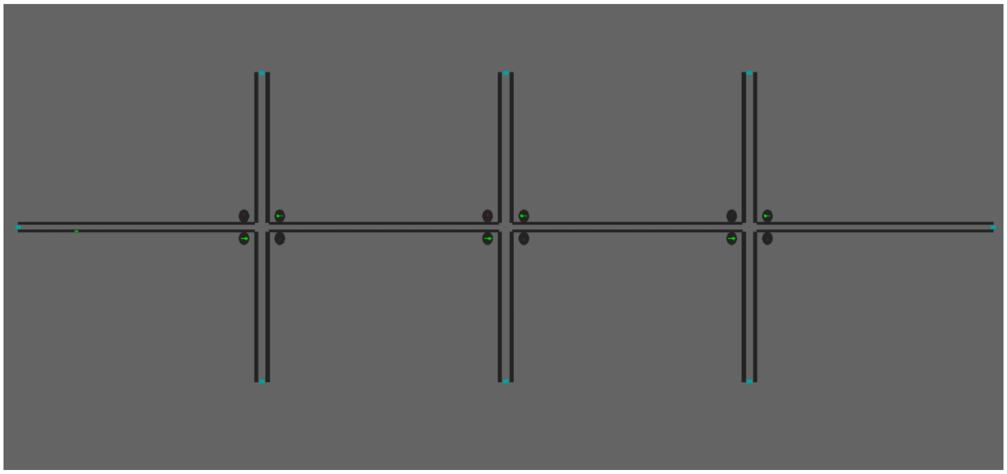


Figure 8: Test in a traffic network with three signalized intersections.

Test Eco-CACC-I Controller for ICEV

The test results of ICEVs equipped with the Eco-CACC controller are presented in Figure 9. The results demonstrate that the ICEV Eco-CACC controllers produce fuel savings for all demand levels compared to the basic case without the Eco-CACC controller. The average fuel savings by using the ICEV Eco-CACC 1S controller are 3.9%, 4.8%, 6.3%, 6.1%, and 5.9% for demand levels of 100, 300, 500, 700, and 900 veh/h/lane, respectively. The Eco-CACC MS controller further improves the average fuel savings by 10.6%, 11.1%, 11.8%, 11.4%, and 11.1% under the same demand levels. Note that the demand of 500 veh/h/lane results in the maximum fuel savings of 11.8% for the entire traffic network. The results demonstrate that the ICEV Eco-CACC MS controller produces average fuel savings of 11.2%, which outperforms the Eco-CACC 1S controller with 5.4% average fuel savings.

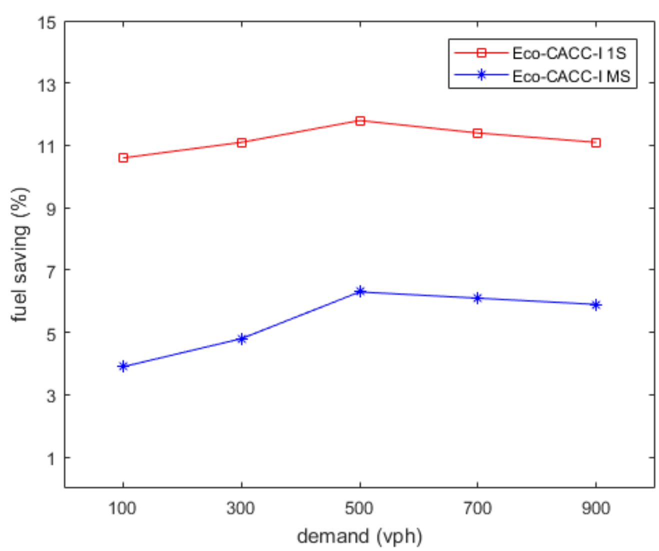


Figure 9: Test Eco-CACC controller for ICEV under various traffic demand levels.

Test Eco-CACC Controller for BEV

The test results of BEVs equipped with the Eco-CACC controllers are presented in Figure 10. The results demonstrate that the BEV Eco-CACC controllers produce energy savings for all demand levels compared to the basic case without the Eco-CACC controller. The average energy savings by using the BEV Eco-CACC 1S controller are 3.4%, 5.6%, 5.85%, 5.83%, and 5.82% for demand levels of 100, 300, 500, 700, and 900 veh/h/lane, respectively. The Eco-CACC MS controller further improves the average energy savings by 9.8%, 10.6%, 11%, 10.8%, and 10.6% under the same demand levels. Note that the demand of 500 veh/h/lane results in the maximum energy savings of 11% for the entire traffic network. The results demonstrate the BEV Eco-CACC MS controller produces average fuel savings of 10.6%, which outperforms the Eco-CACC 1S controller with 5.3% average energy savings.

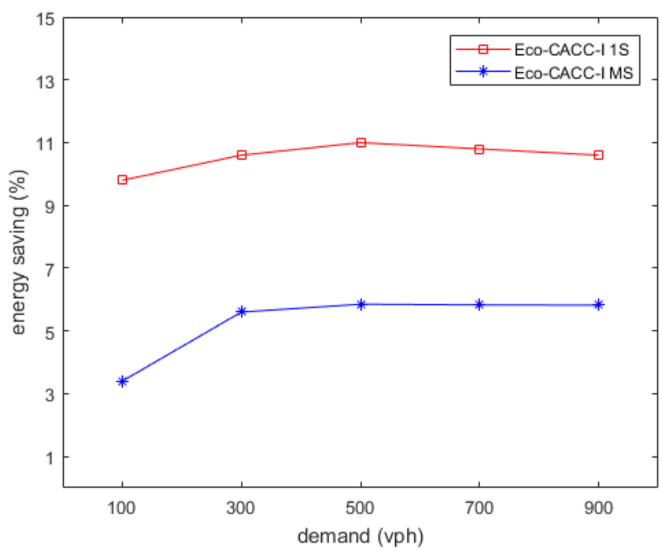


Figure 10: Test Eco-CACC controller for BEV under various traffic demand levels.

Sensitivity Analysis of BEV Eco-CACC MS

The previous section investigated the impact of traffic demand levels on the performance of the BEV Eco-CACC MS controller. We expand the sensitivity analysis in this section to test the impacts of phase splits and intersection spacing on the proposed controller. During the test, the same traffic network in Figure 8 with the traffic demand of 500 veh/h/lane is used.

A phase split ranging from 35% to 75% for the major road was considered to test the impact of different phase splits. Figure 11 presents the energy savings of using the BEV Eco-CACC MS controller as a function of the phase split. The figure demonstrates that the energy savings generally decrease with longer phase lengths. The longer phase length results in less chance of vehicles stopping at the signalized intersections, so there are fewer vehicles that can be optimized by the controller to improve energy savings.

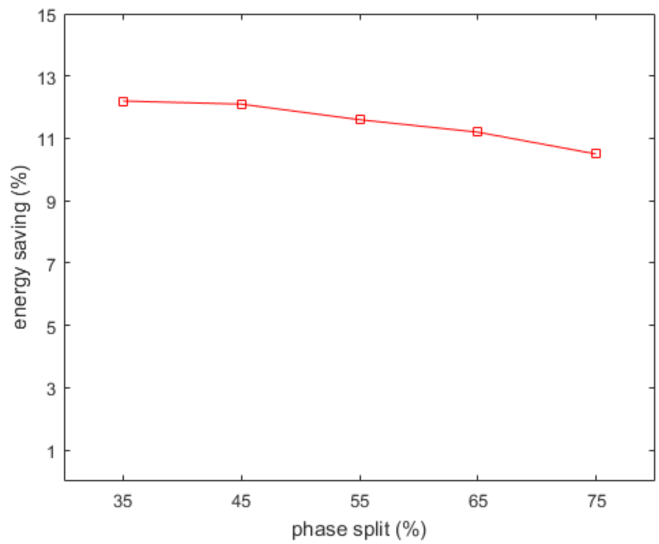


Figure 11: Test BEV Eco-CACC MS controller under various phase splits.

Intersection spacing ranging from 300 to 700 meters was considered to test the impact of different intersection spacings on the proposed controller. Figure 12 illustrates the energy savings of using the BEV Eco-CACC MS controller as a function of the intersection spacing. The figure demonstrates that the energy savings generally increase with longer intersection spacings. The longer intersection spacing means that equipped vehicles can be controlled for longer time, so the controller has the chance to provide a more energy-efficient speed profile to improve energy savings.

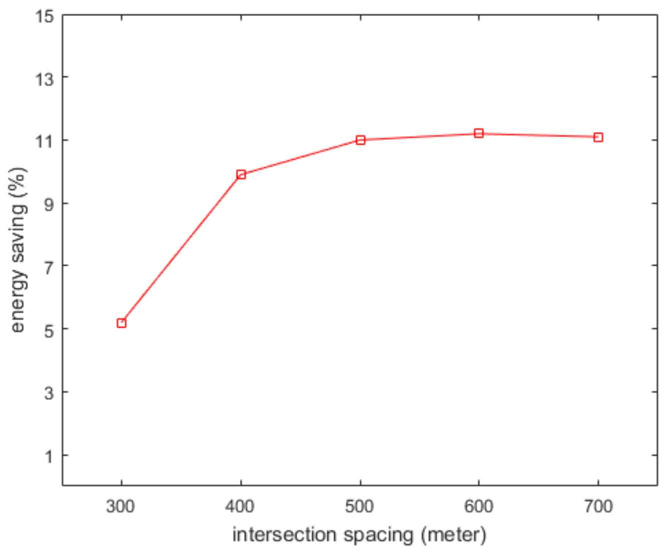


Figure 12: Test BEV Eco-CACC MS controller under various intersection spacings.

4. Adoption of Eco-CACC for ICEVs and BEVs

4.1 Problem Statement

The manufacture and purchase of efficient vehicles is probably one of the measures that may have the greatest impact on fuel economy. However, the complete renewal of the fleet is a process that will take place over the long term. The growing presence of EVs on the roads is another potential source of environmental improvement, but their introduction will be a gradual process until technological advancements allow them to reach a critical mass. One easy option to implement, but probably not given enough importance, is the modification of driving style. Moving from an aggressive driving style to a calmer one, as the prototypes of current self-driving cars bear witness, is one of the most direct actions for achieving significant reductions in greenhouse gas emissions. More genteel driving habits are known as eco-driving, which consists of moderating acceleration and braking, avoiding starts and stops, and anticipating signals (Ando et al., 2010); i.e., a slow but steady approach to driving that also results in better safety.

Although adopting this behavior can clearly be done by oneself, technology has a major role to play, such as vehicle-to-infrastructure (V2I) connectivity, which allows the driver/vehicle to have real-time information on the road conditions and traffic. With the help of this type of communication, De Vlieger et al. (2000) developed an algorithm to allocate signal phases in real-time in order to optimize vehicle delay and queue lengths. Ando et al. (2010) went a step further, modeling a signal control algorithm for intersections used by conventional, connected, and automated vehicles. The algorithm finds both optimal departure sequence and optimal trajectory. Another algorithm applied to signal phasing and timing is Eco-CACC, developed by Kamalanathsharma (2014). Thanks to V2I communication within the vicinity of signalized traffic intersections, the system computes and recommends in real-time a fuel-efficient speed profile with the purpose of minimizing fuel consumption when the vehicle is passing through the intersection. A proof-of-concept of the Eco-CACC system was tested in real environment trials (Chen et al., 2016), demonstrating its applicability and showing promising results in fuel and travel time savings. Those experiments led to further controlled field evaluation of its effectiveness (Almannaa et al., 2019), evidencing the superiority of the automatic control (up to 31% fuel savings when driving downhill) over human control (19%). However, these latter experiments were carried out in closed facilities in conditions under total control and without interaction with other vehicles. This system has also been evaluated in more complex traffic conditions through software simulations. Specifically, queue effects, multiple intersections, and interaction of Eco-CACC and non-Eco-CACC vehicles have been studied in Almutairi (2017) and Yang et al. (2017). The system has recently been expanded to BEVs, and the simulation test results demonstrated that the energy-optimum solution for BEVs is different from that for gasoline-powered vehicles, thus demonstrating the need for vehicle-tailored optimum trajectories (Chen et al., 2019).

These promising results increase interest in knowing the determinants of adopting this new cruise-control feature and its potential market penetration. However, modeling its adoption is difficult as there is no reference market, not even similar markets with which to compare or extrapolate sales. In the same way, there is literally no information about consumer preferences for a new technology that has not been implemented yet. Stated choice experiments (SCEs) and discrete choice models (DCMs) provide a methodological framework to shed light on the matter (Louviere & He nsher (1983) and Louviere & Woodworth (1983) for the former; Cook & Nachtrheim (1980), Hensher et al. (2005), Louviere et al. (2000), Train (2009) for the latter). SCEs allow for data collection on alternatives that do not yet exist to obtain information on consumer preferences. A number of recent works follow this approach in the context of new technologies. For instance, Krueger et al. (2019) performed an SCE in order to investigate changes in the valuation of travel time due to the presence of autonomous vehicles. Their empirical results suggest that no changes should be expected. Cherchi (2017) used SCEs to measure the effect of social conformity in the preferences for EVs, including these social aspects in the choice tasks as additional attributes. (Anders Fjendbo Jensen et al., 2013) investigated how the experience affects the preferences of individuals towards EVs, conducting a two-wave SCE where data were collected before and after the respondents experienced an EV for three months. Cirillo et al. (2017) analyzed household future preferences for gasoline, hybrid, and electric vehicles in a dynamic marketplace. Gkartzonikas & Gkritza (2019) carried out a comprehensive review of studies that use SCEs, although only in the context of autonomous vehicles.

On the other hand, DCMs make use of the SCE's disaggregated data to determine the influence of the alternatives' characteristics on the probability of choosing them. Examples of their use are abundant; some applications to simulate market shares in different countries can be found in Axsen & Wolinetz (2018), Haaf et al. (2016), and Tanaka et al. (2014), which also offers an interesting summary of stated preference studies on EVs as an extension of the studies carried out by Horne et al. (2005) and Hidrue et al. (2011).

This work combines all the elements described above by designing SCEs specifically created for the case of the Eco-CACC to collect data on the inclination of consumers to purchase gasoline-powered and electric-powered vehicles equipped with this technology. These data served to estimate DCMs to determine if the characteristics of the Eco-CACC are sufficient to stimulate the demand of vehicles equipped with this system and predict its market share. Interestingly, our results show that the results of a pure cost-benefit analysis based on relative prices (i.e., the cost of adopting the Eco-CACC vs. its associated fuel savings) are only favorable for the gasoline car, but not for the EV. Yet, for the EV, a preference for environmentally friendly economic consumption and a favorable attitude towards the early adoption of new products more drive the purchasing decision, resulting in an actual increase of the market share. Hence, our results show that people willing to buy EVs are likely to pay the premium of adopting the Eco-CACC regardless of its negative monetary cost-benefit outcome based on the improvement it brings in terms of environmental efficiency. From our results, we conclude that these individuals, besides acquiring an EV, are also willing to internalize the externalities (i.e., damage or social cost) associated with polluting emissions.

This is a remarkable result with critical implications for infrastructure policy and industrial development. Until environmental concerns took center stage, adaptive traffic control systems (ATCS) were mainly oriented towards reducing congestion times, saving energy costs, and increasing safety. Key performance indicators of government-sponsored ATCS routinely report the change in these indicators. An example is the Meadowlands Adaptive Signal System for Traffic Reduction (MASSTR) in New Jersey, based on the Sydney Coordinated Adaptive Traffic System (SCATS). Once expanded to its final area, this system will serve more than 3 million vehicles each day. Currently, the emphasis is placed on the reduction of emissions, and planners estimate savings in gasoline consumption of more than 1.2 million gallons per year and greenhouse gas emission of more than 11,000 tons per year, NJEAS (2016). SCATS is a traffic management strategy in which traffic signal timing adapts based on actual traffic demand. This is accomplished using an ATCS consisting of both hardware and software. In 2010, the implementation of SCATS was estimated at approximately $28,800 per mile per year by the United States Department of Transportation (U.S. DOT).[1] Although ATCS have been deployed in numerous metropolitan areas, this represents a sizable investment, which would need to be enhanced to include V2I technologies such as those required by Eco-CACC. Unless individuals are willing to adopt V2I features, the resources invested by federal and state agencies would be useless. By evaluating the potential market penetration of Eco-CACC, we provide public officials with insights on adoption trends that will help to devise efficient regulations. For example, if buying the Eco-CACC for EVs is less attractive from a cost-benefit perspective because the savings it yields are lower than for

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[1] Calculated as ((total cost/number of years)*number of signals within corridor/length of corridor in miles). Total costs are divided into initial investments plus maintenance. See the Cost Database in the website of the Intelligent Transportation Systems Joint Program Office: https://www.itscosts.its.dot.gov/its/itsbcllwebpage.nsf/krhomepage

gasoline vehicles, then it may not be worth it to adapt the ATCS infrastructure in congested cities where gasoline vehicles are increasingly banned (as is currently happening in many European countries). Yet, if individuals are ultimately willing to adopt the technology given their preferences, then these investments will have the expected returns in terms of emission reductions.[2]

From the perspective of industry, the results of this study are informative as they indicate willingness to pay for the Eco-CACC system. This is relevant for manufacturers, from the engineering department that needs to embed the hardware (sensors, wiring, etc.) and software (compliance with ITS standards) in current designs, to the marketing department that may target the sale of the system individually or bundled with additional connection and autonomous features. If the willingness to adopt ECO-CACC is conditional on the choice of vehicle, EV or gasoline, then the accompanying features need to be customized since they are targeted to different markets (e.g., arterial vs. highway use). In short, this study informs industry stakeholders about the desirability of Eco-CACC from a consumer choice perspective, providing insights on their willingness to adopt it, along with its individual market segment penetration.

4.2 Methodology for Eco-CACC Adaption

The energy savings provided by following the optimal speed profile from the Eco-CACC system have been evaluated in several experiments. Some of them were carried out in real facilities without traffic, whilst more complex traffic conditions were simulated through software. For the field tests, a gasoline-powered 2014 Cadillac SRX was used. It was equipped with V2I communication, Differential Global Positioning System, a real-time data acquisition system, and a laptop with software to control the trips and road scenarios. Through the V2I communication unit, the vehicle received the data on the upcoming signal phases. This information, along with the distance and speed, was used by the Eco-CACC algorithm to compute the fuel-efficient speed profile. Although this is the only vehicle that has been used in a real situation, many simulation tests with different types of gasoline vehicles were conducted, and their results were in accordance with the field tests: an overall average reduction of fuel between 8% and 15%. Other simulations were also carried out for battery EVs, which yielded savings around 10.5% in arterial roads, on average. Therefore, real and simulated tests for both gasoline and EVs coincide in the range of 8% to 15% energy savings.

On the other hand, it is particularly relevant that the Eco-CACC system is only activated in the vicinity of signalized intersections. This is important in relation to the information shown to users in the SCE scenarios. Since the driving time in the vicinity of signals may only be a small part of the total driving time and depend on where users drive, it would not be accurate to inform

[2] Eventually, regardless of individuals' attitude and industry concerns, regulatory agencies could make the installation of the Eco-CACC compulsory, just as they enforce emissions standards for on-road vehicles and engines. For example, EPA regulations for the U.S. can be accessed at https://www.epa.gov/regulations-emissions-vehicles-and-engines/regulations-onroad-vehicles-and-engines.

consumers of the 8% to 15% general savings. To limit this problem, the survey asked about the type of road that the respondent usually drives (arterial, highway, or equally both). If the user drives mainly in arterial roads, where there are more traffic lights, the total savings were reduced by 25%, for a range of 6% to 11.25%. On the contrary, if the user drives mainly in highways, where there are fewer traffic lights, the savings were reduced by 75%, which means a range of 2% to 3.75%. For the third option, the savings were reduced by 50%. These assumptions provided the respondents with a more realistic perception of the savings that they could actually obtain. However, sometimes a percentage may not influence an individual's decision, as they may not compute the actual savings in dollars. Therefore, in addition to the percentage, the monetary equivalence of the fuel savings was also shown in the choice tasks based on predefined energy costs and the annual miles travelled declared, which were also asked in a previous section of the questionnaire.

Finally, it was important define the price of the Eco-CACC system in order to identify the potential trade-offs between price and savings. In this regard, the system installed in the vehicle used for the field tests was a prototype that cost more than the vehicle itself. However, following similar price schedules in adaptive cruise control features, it is estimated that once this technology is fully developed it will increase the price of the vehicle in the range of $1,000 to $2,000 dollars since it will be just an enhancement to current cruise control technology.

Stated Choice Experiment

The purpose of an SCE is to determine the influence of the characteristics of a set of alternatives on the probability of choosing them. A study of this type normally consists of an individual making a choice in a hypothetical scenario in which different levels of the attributes are presented. Given the difficulty (economic or technical) of counting with a high number of individuals, it is common practice to make the respondent face a number of these choice situations and pool the responses.

In order to develop the design of the experiment it is necessary to define (1) the alternatives, their attributes, and their levels; (2) the type of design; and (3) the underlying DCM to be estimated once the data are collected. This study was interested in identifying the key elements of the adoption of Eco-CACC and its market share in both gasoline vehicles and EVs. This required two different logical branches in the survey. Depending on the type of vehicle that interviewees are considering for their next purchase, they are directed to the corresponding branch, as detailed in the following section. These elements are summarized in Table 2.

Table 2: Alternatives, attributes, and model.

	Gasoline Branch	Electric Branch
Alternatives	Gasoline Gasoline + Eco-CACC None	Electric Electric + Eco-CACC None
Attributes	Price Fuel savings Propulsion cost Annual propulsion costs	Price Fuel savings Propulsion cost Annual propulsion costs
Design	Efficient with Bayesian priors	
Model	Multinomial Logit/Mixed Logit	

Price, fuel savings, and propulsion costs vary among individuals and choice situations. The price for the alternative including the Eco-CACC is set higher than the one that does not include it. The annual propulsion cost is shown to provide a better understanding of how much the savings are. It is calculated based on the propulsion cost per mile and the savings of the scenario, and on the annual mileage previously declared by the interviewee. A third alternative, *None*, was provided as an opt-out choice for users who would not buy any of the vehicles, considering their characteristics. Other attributes were evaluated in a preliminary phase. For instance, in the case of electric cars, there may be several relevant features to consider, such as charging time or range. However, since this work focuses on Eco-CACC and not on the vehicles themselves, their inclusion was discarded. Regarding the cruise system, we considered including the effect of audio alerts, which were used in previous field tests. That is, instead of the car adjusting its speed when receiving the signal data, the system provided the information to the drivers through audio, who adjusted the speed themselves However, the final version of Eco-CACC will be totally automated, with no audio alerts, and therefore there was no point in considering it.

Attribute levels are the main decision element. Thus, they must be carefully defined in the design phase. In this case, the levels of fuel savings displayed in the scenarios come from the tests mentioned above. The price and propulsion cost come from real information obtained from the market. At this point, the fundamental question is how to distribute the levels of the attributes throughout all the choice tasks that will appear in the questionnaire. This is not a trivial matter and requires a great deal of preliminary work. The number of attributes, their levels, and the number of alternatives exponentially increase the combinations needed for a correct design. On the one hand, the number of levels itself must be the minimum that provides a reasonable variability of the attributes. On the other hand, the values must be realistic since they will constitute the input for the user to make a choice. In this case, prices were taken from a medium-sized vehicle for reference. The fuel savings were determined from the field and simulation tests.

Finally, we opted for an efficient design, which aims to produce data that generates parameter estimates with standard errors that are as small as possible.[3] However, the asymptotic variance-covariance (AVC) matrix cannot be known (because the objective of the experiment is, precisely, to estimate these parameters) and, therefore, cannot be minimized. Nevertheless, if some prior information about the parameters is available from the literature or other studies, the AVC can be determined. There is always some uncertainty about the priors since they may correspond to the true parameters or not. In order to take into account this uncertainty, it is possible to define a distribution of the value of each prior instead of using a single point estimate, an approach called Bayesian efficient design. In the case of this work, we relied on the literature (Cherchi, 2017) and previous research experience to define Bayesian priors for price, distributed uniformly between −0.447 and −0.26. Table 3 summarizes the levels for all attributes that are combined in the mathematical design in order to create a number of unique choice tasks. The vehicle prices in the EV branch are set higher than in the gasoline. In both cases, the price of the alternative that counts with the cruise control system is increased by $1,000, $1,500, or $2,000. The percentage of fuel savings for each scenario are either 8%, 11%, or 15%, but that is adjusted by the type of roads mainly driven by the individual, as indicated in the previous section. Finally, the savings that the Eco-CACC provides in terms of fuel savings is computed to show the savings in dollars.

Table 3: Levels of attributes and priors for both branches.

	Gasoline/Electric	**Gasoline/Electric + Eco-CACC**
Price ($) Uniformly distributed [−0.447, −0.26]	22,500/30,000 25,000/32,500 27,500/35,000	Price + 1,000 / 1,500 / 2,000
Fuel Savings (%)[1]	0	8, 11, 15
Annual Propulsion Cost ($)	Propulsion cost * Annual miles	(Propulsion cost * Annual miles) * (1 − Fuel savings)

[1] Figures adjusted by type of road mainly driven (75% for arterial roads, 25% for highways, 50% for both).

The algorithm used to compute the mathematical design provides unique combinations of these attributes, which are mapped into the survey in order to produce a choice task to display to the user, as Figure 13 illustrates.

[3] Performed with the Ngene software for experiment design (ChoiceMetrics, 2014).

	Electric Vehicle	Electric Vehicle + Eco-CACC
Price	$32,500	$33,000
Fuel Savings	-	11.25%
Propulsion Cost Annual expected cost given the miles declared	$0.03 $900	$0.03 $799

Which one woudl you choose?

- I would buy the EV
- I would buy the EV with Eco-CACC
- I wouldn't buy any of them

Figure 13: Choice task for an individual who declared driving mainly on arterial roads and the next purchase will be an EV.

Since this design considers two types of vehicles and three type of roads, it comprises 12 utility functions, organized in two main logic branches (gas/electric), which are later subdivided into three others (by type of road). These particularities add several layers of complexity to the design and to the questionnaire coding but provide scenarios closer to reality. With respect to the choice situations, we defined 36 of them, divided into four blocks. Therefore, each respondent faced nine different scenarios to respond to. That allowed for attribute level balance, which ensures that the parameters can be estimated on the whole range of levels.

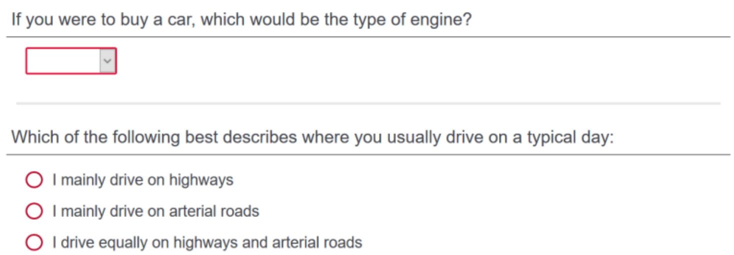
4.3 Questionnaire

The survey was built following the experimental design discussed above. The questionnaire consisted of the four sections described below, each containing a number of questions that serve a specific purpose. The population of interest was American individuals older than 18 with a driver's license.

Preliminary Questions

There were two questions in this section, shown in Figure 14. The first referred to power source of the next vehicle that the interviewee is willing to purchase. If *Gasoline* was selected, the interviewee was directed to the logic branch corresponding to gasoline vehicles, where choice tasks were presented in which the attributes shown refer to gasoline vehicles. Selecting *Electric, Hybrid* or *Other*, the interviewee was directed to the EV logic branch. The second question asked about the roads the interviewee drives on a typical day. The options were *Arterial, Highways, or Equally both.* The fuel savings shown in the scenarios were adjusted by this response as detailed above.

It is noteworthy that no specific information about EVs was provided at this point. This is due to the fact that the pilot data showed percentages of choice (68% gasoline) reasonably similar to those either observed or predicted in other studies (Anders F. Jensen et al., (2014), Dagsvik et al. (2002), Ewing & Sarigöllü, (2000), Hidrue et al. (2011), Hoen & Koetse, (2014)) Therefore, we assumed that individuals were already informed and discarded the inclusion of descriptive text explaining the characteristics of the EV in subsequent waves of data collection. This way we kept the questioning burden to a minimum while focusing on Eco-CACC.


If you were to buy a car, which would be the type of engine?

Which of the following best describes where you usually drive on a typical day:

I mainly drive on highways

I mainly drive on arterial roads

I drive equally on highways and arterial roads

Figure 14: Preliminary questions.

Car Ownership

This set of questions aimed to identify the vehicles owned in the household, and if the next purchase will be an additional vehicle or a replacement. Information about the new vehicle was also asked since the propulsion cost shown in the choice tasks were calculated using the annual mileage identified here, which is the main purpose of this section. Nevertheless, these data might also be useful to understand the potential choices of the alternative with Eco-CACC made later in the scenarios. Table 4 shows the information extracted from the questions, as well as their levels.

Table 4: Variables and levels of car ownership.

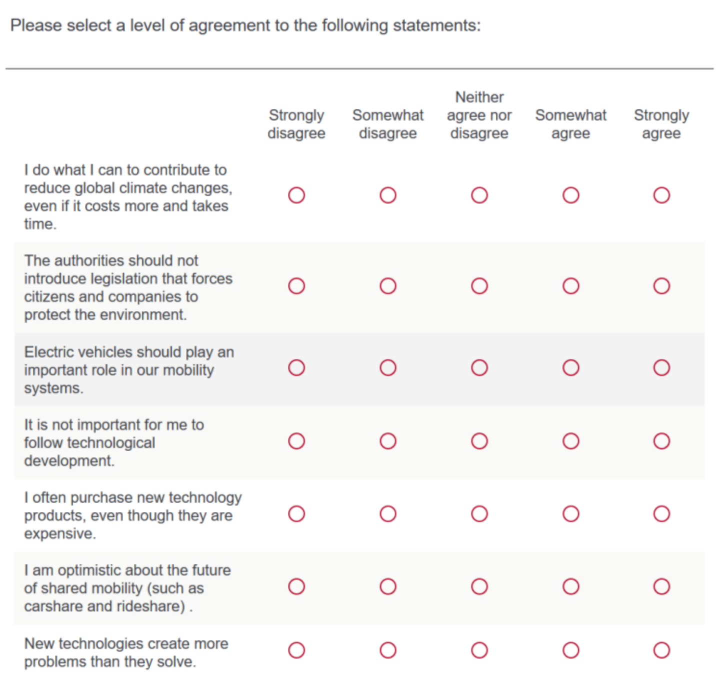
Variable	Levels
Number of vehicles in household	0, 1, 2, 3, 4, 5
Category	Small (Convertible, Sedan, Coupe) Mid-size (Crossover, Wagon, Van, SUV) Large (Truck)
Year of purchase Date	'Before 2019' to 2019
Year of manufacture	'Before 2019' to 2019
For each car:	
Engine	Gas, Diesel, Hybrid, EV, Other
Who drives	Me, Spouse, Both, Other
Main use	Work, Leisure, Both
Next purchase will replace or additional	Yes (which one)/ No

Stated Choice Experiment

After reading some information about the cruise system, the user was redirected to the survey branch corresponding to the responses made previously on power source and roads. Then a choice task that provides a series of characteristics for the alternatives was displayed, similar to that of Figure 13. The user evaluated the scenario and chose one of them. In this case, for the Gasoline branch the alternatives were Gasoline, Gasoline + Eco-CACC, and None. For the EV branch, the choices were Electric Vehicle, Electric Vehicle + Eco-CACC, and None. This process was repeated nine times, with the user facing a different choice task each time.

Socioeconomics and Attitude towards EVs

This section had two parts. The first gathered general sociodemographic information. The second presented a question (Figure 15) in which it was necessary to select a level of agreement to attitudinal statements. These statements pertained to three different categories (unknown to the respondent): environmental concern, technology innovation, and pro-EV. A score was assigned to each response following a Likert scale ranging from −2 (*strongly disagree*) to 2 (*strongly agree*). Then the scores of the same category were added in order to create an overall representative score for that attitude.



Please select a level of agreement to the following statements:

	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
I do what I can to contribute to reduce global climate changes, even if it costs more and takes time.	○	○	○	○	○
The authorities should not introduce legislation that forces citizens and companies to protect the environment.	○	○	○	○	○
Electric vehicles should play an important role in our mobility systems.	○	○	○	○	○
It is not important for me to follow technological development.	○	○	○	○	○
I often purchase new technology products, even though they are expensive.	○	○	○	○	○
I am optimistic about the future of shared mobility (such as carshare and rideshare) .	○	○	○	○	○
New technologies create more problems than they solve.	○	○	○	○	○

Figure 15: Attitudinal questions.

5. Survey Results

5.1 Data Analysis

The main statistics of the distribution of the 2,853 samples collected can be found in the appendix. The percentage of individuals working for the government was high, which in this case is consistent since this survey was taken in the State of Maryland, which "surrounds" Washington, D.C., a center of public jobs. Also, some of the counties of this state are among the wealthiest in the United States, which justifies the high maxima of individual and household incomes. On the other hand, 68.15% of the interviewees stated that the next vehicle they would buy would be powered by gasoline. Therefore, this percentage of users was directed to the gasoline branch; the remaining 31.85% were directed to the electric one, where they faced scenarios with information on their preferred type of propulsion. Regarding the roads driven, 20.81% mainly drove arterial roads, 19.23% mainly drove highways, and 59.94% equally drove both.

Table 5: Percentage of choice by branch and type of road driven.

Branch / Choice	Gasoline			Electric Vehicle (EV)		
	Arterial	Highway	Both	Arterial	Highway	Both
No Eco-CACC	41.00%	55.60%	49.10%	27.80%	40.90%	20.80%
Eco-CACC	44.20%	41.00%	41.90%	55.60%	54.50%	67.90%
None	14.80%	3.40%	9.00%	16.70%	4.50%	11.30%

Table 5 shows the percentage of each alternative by branch and type of road driven by the user. For the gasoline engine, the alternative with Eco-CACC was the most selected by individuals who mainly drive arterial roads. For EVs, Eco-CACC technology was chosen the most in all road categories.

5.2 Methodological Approach and Model Specification

We started the analysis of the cruise control system choices with a multinomial logit (MNL) model to set a baseline against which to compare more complex specifications, such as multinomial mixed logit (MML). MML overcomes the limitations of MNL by allowing random taste variation, substitution patterns, and the capture of the effect of multiple choices made by the same individual (panel structure). These capabilities are especially convenient for the case at hand, as users responded to nine different scenarios in which two alternatives, substitutes to each other to some extent, were presented.

Based on the Random Utility Models paradigm (Marschak, 1974) and following (Train, 2009), the utility obtained by an individual n when choosing the alternative j pertaining to a set J is:

$$U_{nj} = \beta_n' x_{nj} + \mu_n' z_{nj} + \varepsilon_{nj} \tag{25}$$

where x_{nj} and z_{nj} are observed attributes of alternative j, β_n' is a vector of coefficients that can be defined as fixed or random, μ_n' is a vector of random terms with zero mean, and ε_{nj} is independent and identically Gumbel distributed. If β'_{n} is random and varies over decision makers representing taste variation, it does with density $f(\beta)$, which is a function of parameters θ. The second part of the utility, $\mu'_n z_{nj} + \varepsilon_{nj}$, can be correlated among alternatives depending on the specification of z_{nj}, to form specifications analogous to, for instance, nested logit (Hackbarth & Madlener, 2013). In the logit model, z_{nj} is zero, so that there is no correlation, resulting in the Irrelevance of Independent Alternatives (IIA) property.

Conditional on β, the probability that a person makes a sequence of choices $i = \{i_1, \dots, i_T\}$ is:

$$L_{ni}(\beta) = \prod_{t=1}^{T} \left(\frac{e^{\beta'_n x_{ni_t t}}}{\sum_j e^{\beta'_n x_{ni_j t}}} \right) \tag{26}$$

and the inconditional probability is the integral of this product over all values of β:

$$P_{ni} = \int L_{ni}(\beta) f(\beta) d\beta \tag{27}$$

This probability needs to be simulated taken draws from the distribution. Then the logit formula in Equation (26) is calculated for each I, and its product is taken. This process is repeated a number of times and the results are averaged.

In our models, we did not define a particular substitution pattern; on the contrary, we just included an error component structure, which was enough to dramatically improve their goodness of fit and to find coherent estimates. We also considered several attributes as random, lognormally, and normally distributed, in order to capture taste variation, but with little success. These efforts are reported in the following two subsections, one for each branch of the survey. As a general comment, all the attributes were found significant in the Gasoline case but not in the EV case. The possible reasons are described below.

Gasoline Branch

Table 6: Model estimations for the gasoline branch.

	Model 1		Model 2		Model 3		Model 4	
	Estimate	**t-ratio**	**Estimate**	**t-ratio**	**Estimate**	**t-ratio**	**Estimate**	**t-ratio**
ASC_GAS	1.518***	5.38	3.913***	6.47	3.406***	7.6	3.399***	8.35
ASC_GASSYS	2.594***	5.45	4.105***	6.55	3.543***	5.77	3.303***	5.81
System Cost	-0.219***	-3.29	-0.313***	-3.27				
System Cost (mean)					-0.86***	-3.43	-0.839***	-3.5
System Cost (sd)					-1.461***	-3.61	-1.474***	-7.98
Fuel Savings	-0.053	-0.45	0.501***	3.58				
Fuel Savings (mean)					0.233***	3.27	0.223***	3.14
Fuel Savings (sd)					0.391***	8.84	0.38***	7.02
Technology Inclined att.							0.388	1.66
Environmental Concerned att.							0.3628***	3.62
EC_GAS			-2.983***	-4.55	3.017***	7.43	2.633***	8.17
EC_GASSYS			-2.055***	-4.94	-0.276	-1.39	0.29***	2.28
EC_NONE			-2.91***	-6.49	2.112***	7.21	2.37***	8.39
LL(fi l)	-1807.96		-1124.35		-1103.04		-1093.85	
Adj.Rho-square (0)	0.1516		0.4703		0.4793		0.4827	
AIC	3623.92		2262.71		2224.09		2209.72	
BIC	3646.21		2301.72		2274.24		2271.02	

*significant at 10%, ** significant at 5%, ***significant at 1%

Table 6 presents the results for all models estimated using the case scenarios for which users stated that a gasoline vehicle would be their next purchase. This includes all type of roads. We started with a standard MNL model (Model 1), including all the attributes of the alternatives. In this case, the effect of fuel savings is not significant and has the opposite sign. Therefore, following the approach described above, MML models with error components and panel effect were estimated (Models 2 to 4). Adding error components (Model 2) immediately improves the estimation significantly (Rho-square = 0.47) and finds correct signs for the attributes. Nevertheless, exploring the existence of taste heterogeneity yields even better results. Model 3 considers the coefficients of the system cost and the fuel savings that it provides as random (normally distributed). Both the mean and the standard deviation are highly significant, justifying this approach. Estimates that include socioeconomic variables beyond Model 3 were attempted. However, none of these variables contributed to a better adjustment of the data, except those related to the individual's attitudes towards technology and the environment (Model 4). Likelihood ratio tests confirm these improvements. On the other hand, Models 3 and 4 yield a willingness-to-pay of $270 ($0.233/0.86 * \$1{,}000$) and $265 ($0.223/0.839 * \$1{,}000$) for 1% of savings, respectively, which seems reasonable given that a vehicle is a durable good. It is worth to mention that other specifications were also estimated, such as the combination of error components, random coefficients, and systematic heterogeneity among type of roads. However, none of those provided better results than Model 4.

EV Branch

Table 7 presents the results for all models estimated using the case scenarios for users who would buy an EV for their next purchase. This includes all types of roads. The procedure followed was similar to that for gasoline vehicles, estimating an MNL model (Model 1) first. Although in this case the sign of the coefficients was consistent, we replicated the model specifications of the gasoline case based on their good performance. Model 2 adds an error component, resulting in a dramatic improvement in the goodness of fit. Model 3 is an attempt to improve estimation by considering taste heterogeneity, but it seems not to be present in the case of drivers willing to purchase an EV. Finally, Model 4 adds the only socioeconomic variable that helps to improve the performance, which is the positive attitude towards new technologies, alternative specific in this case. Likelihood ratios among models confirm the improvements.

Although the consistent non-significance of the cost and fuel savings coefficients among models may seem like a negative result, it is quite illuminating. The main reason for that is probably the low cost of propulsion. That is, the price of electricity per mile traveled is actually very low. This makes the savings provided by Eco-CACC very little, even in its more beneficial range. At the same time, since the cost of the cruise system is between $1,000 and $2,000, it is very unlikely that the users perceive a trade-off between cost and benefits. In other words, the energy is inexpensive, and the savings represent at most 11.5% of that small annual amount. For a hypothetical case of an individual driving 20,000 miles a year, and considering a propulsion cost of 5 cents, that would mean savings of $112.5 over the entire life of the vehicle in a best-case scenario. For a technology that may cost $2,000, it is clear that the user simply does not see a benefit. Note that this is also the case even for models that do not control for the users' attitude towards the environment and new technologies, whose effect could have been captured in the rest of the models by *Fuel Savings*, reflecting the adoption decision. Besides the undisputed lack of return on investment of the ECO-CACC system in terms of fuel savings, an additional underlying cause may be the unfamiliarity of sampled drivers with ATCS, which have not been deployed in the State of Maryland.[4] Consequently, since the distance range of EVs is limited, drivers anticipate that they will not take advantage of the Eco-CACC in their area since signalized intersections are not capable of incorporating this technology. That is why state and federal agencies should make

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[4] The only ATCS close to Washington, D.C., located in Arlington, VA, and based on the SCOOT system covering 200 intersections, has been decommissioned–see http://latom.eng.fau.edu/research-reports/. A list of current and previously existing ATCS, including deployments in phase 3, can be consulted in USDOT (2018: 36-38). A total of 224 adoptions are reported.

further efforts to deploy the system across metropolitan areas to encourage the adoption smart cruise control systems based on V2I technology.

Table 7: Model estimations for the electric branch.

	Model 1		Model 2		Model 3		Model 4	
	Estimate	**t-ratio**	**Estimate**	**t-ratio**	**Estimate**	**t-ratio**	**Estimate**	**t-ratio**
ASC_EV	0.895***	3.44	3.049***	4.25**	2.678***	2.23	2.642***	4.07
ASC_EVSYS	1.697***	2.81	4.436***	4.33	4.436***	4.33	4.102***	4.23
System Cost	-0.0128	-0.15	-0.083	-0.7			-0.081	-0.68
System Cost (mean)					-0.042	-0.34		
System Cost (sd)					0.352**	2.04		
Fuel Savings	0.0465	0.32	0.156	0.95			0.166	1.03
Fuel Savings (mean)					0.214	0.9		
Fuel Savings (sd)					-0.307	-1.59		
Technology Inclined att. EV							0.409***	2.8
Technology Inclined att. EV + Eco-CACC							0.3729***	2.64
SIGMA_EV			1.472***	4.65	1.644***	4.18	-1.805***	-4.01
SIGMA_EVSYS			-1.512***	-4.78	0.025	0.03	-1.276**	-2.47
SIGMA_NONE			3.739***	6.03	3.35***	1.84	3.168***	5.77
LL(fi l)	-803.09		-597.53		-597.53		-593.84	
Adj.Rho-square (0)	0.1918		0.394		0.394		0.396	
AIC	1614.19		1209.07		1209.07		1205.68	
BIC	1633.44		1242.76		1242.76		1248.99	

*significant at 10%, ** significant at 5%, ***significant at 1%

5.2 Market Shares

Reliable predictions of the market share of a new product are strategic for industry (Calfee, 1985). Also, they can also be essential for public agencies since product adoption rates may impact regulation (Mabit & Fosgerau, 2011). With a full set of alternative specific constants, the advantage of multinomial logit regression is that it allows recovering the market shares of the alternatives at the sample level. However, this may not be case for MML, and it is certainly not the case if we want to know the shares in data subsets. Therefore, to calculate these market shares we rely on the model with the best estimators and goodness of fit, which is Model 4 for both gasoline and EVs. Table 8 presents the actual and predicted choices for both branches, for each type of road subset, as well as overall. The *t*-ratios and *p*-values show if the difference between actual and predicted choices is significant. For a better understanding, it is indicated when the model significantly over- or underestimates.

Table 8: Actual and predicted choices, gasoline and EV.

	Gas	Gas + Eco-CACC	None	EV	EV + Eco-CACC	None
All						
Times chosen (data)	822	942	180	240	571	98
Times chosen (prediction)	837.98	951.99	154.02	237.54	573	97.85
Diff (prediction-data)	15.98	9.99	-25.97	-2.45	2.59	-0.14
t-ratio	0.747	0.468	-2.19	-0.18	0.17	-0.01
p-value	0.455	0.64	0.02‡	0.85	0.85	0.98
Arterial group						
Times chosen (data)	191	177	64	45	90	27
Times chosen (prediction)	188.61	208.26	35.12	41.3	103.25	17.44
Diff (prediction-data)	-2.38	31.26	-28.87	-3.69	13.25	-9.56
t-ratio	-0.235	3.088	-5.1	-0.66	2.17	-2.44
p-value	0.81	0†	0‡	0.5	0.03†	0.014‡
Highway group						
Times chosen (data)	144	195	12	81	108	9
Times chosen (prediction)	153.65	169.18	28.15	51.57	122.86	23.56
Diff (prediction-data)	9.65	-25.81	16.15	-29.42	14.86	14.56
t-ratio	1.05	-2.82	3.18	-4.78	2.18	3.23
p-value	0.29†	0‡	0†	0†	0.02†	0†
Both group						
Times chosen (data)	487	570	104	114	373	62
Times chosen (prediction)	495.71	574.54	90.74	144.67	347.47	56.85
Diff (prediction-data)	8.71	4.54	-13.25	30.67	-25.52	-5.14
t-ratio	0.52	0.27	-1.45	2.98	-2.26	-0.731
p-value	0.59	0.78	0.14	0†	0.02‡	0.46

†Model significantly overestimates, ‡ Model significantly underestimates

The models predict accurately, in general terms, the overall market shares of the three alternatives in both branches, except for the case of the *None of them* alternative in the gasoline branch, which is underestimated. When the shares are calculated by type of road driven, the alternatives with Eco-CACC are significantly overestimated for the drivers of arterial roads but underestimated for gasoline and overestimated for EV highway drivers. In the case of users that drive equally on arterial roads and highways, the choice of EV + Eco-CACC is also underestimated by the model.

Table 9: Market shares predicted by selected models, gasoline and EV.

	Gas	Gas + Eco-CACC	None	EV	EV + Eco-CACC	None
All						
Market share (data)	42.28%	48.46%	9.26%	26.40%	62.82%	10.78%
Market share (prediction)	43.11%	48.97%	7.92%	26.13%	63.04%	10.76%
Arterial group						
Market share (data)	44.21%	40.97%	14.81%	27.78%	55.56%	16.67%
Market share (prediction)	43.66%	48.21%	8.13%	25.49%	63.73%	10.77%
Highway group						
Market share (data)	41.03%	55.56%	3.42%	40.91%	54.55%	4.55%
Market share (prediction)	43.77%	48.20%	8.02%	26.05%	62.05%	11.90%
Both group						
Market share (data)	41.95%	49.10%	8.96%	20.77%	67.94%	11.29%
Market share (prediction)	42.70%	49.49%	7.82%	26.35%	63.29%	10.36%

Table 9 shows the conversion of the above figures to market shares. The prediction for vehicles that incorporate the Eco-CACC system is, overall, 48.46% for gasoline cars and 62.82% for EVs. These proportions are maintained for the different sub-groups of drivers, no matter the type of engine. It is interesting that, while the market shares of the alternatives with and without the system are similar in the case of gasoline vehicles, the first more than doubles the second for the electric case, and yet the specific cost-benefit variables of the system are not relevant for that choice. This leads to the conclusion that users' decisions are mainly based on the strong influence of their attitude towards new technologies as well as on random heterogeneity. As previously anticipated, the predisposition of individuals buying EVs towards new environmentally friendly technologies, such as the Eco-CACC, makes them adopt the system regardless of its lack of return on investment. Resorting to the classic taxonomy of Rogers (1962), we would consider individuals buying EVs as innovators or early adopters; i.e., people who by nature can afford and are excited by the possibilities that new technologies have to offer to improve environmental efficiency. Coupled with the higher cost of the EV, they do not mind investing in a cruise-control feature whose high price is also a barrier to its widespread adoption. This suggests that those adopting Eco-CACC would be wealthier, a socioeconomic characteristic that correlates with reasonably high levels of education and social status. Our results, however, do not concur with this stereotype in full. As shown in the appendix, we see that both individual and household average incomes are smaller for the EV branch than for the gasoline branch. In particular, the average income in households buying EVs is $69,542 versus $78,033 for the gasoline car. However, it is observed that EV buyers are indeed have more education than buyers of gas vehicles; i.e., educational degrees above high school are consistently higher in the EV branch.

5.3 Discussion

The objective of this section is to evaluate the potential market penetration of the Eco-CACC system. The results are key for the successful market penetration of connected and self-driving cars relying on V2I systems, which would require the commitment of government agencies in the form of infrastructure investments and of car manufacturers, who would have to adapt their production and commercial practices.

To determine the market share, a Stated Choice Experiment was designed, considering the particularities of the Eco-CACC system, the performance that field and simulated tests yielded, and known methodologies already tested in the literature and other previous research. For the survey and data collection, the design has been divided into two branches, gasoline and electric, in order to discern the possibly different decision-making processes of those potential consumers. The reason is that both types of vehicles belong to clearly differentiated market segments, whose characteristics are steadily growing apart. For both branches, an efficient design was executed, predefining the Eco-CACC attributes and their levels. With the data collected, several multinomial logit and mixed multinomial logit formulations were tested to achieve the best fit to the data and, therefore, to have a reliable base from which to calculate market shares.

In the case of gasoline vehicles, both the additional cost of the system and the fuel savings were significant. This means that drivers perceive a trade-off between the cost of the Eco-CACC and the savings that it provides. This is not the case for the EVs. This is a consistent result in all models, and the reason is the low cost of propulsion. The price of electricity per mile traveled is reduced and, therefore, the savings, in absolute amount, are reduced as well. Although the percentage may seem interesting, by explicitly showing the annual savings its effect is diluted so the expected cost-benefit analysis plays against the adoption decision. In short, cost-benefit analyses yield results against adopting the Eco-CACC because savings are not high enough to compensate for the cost of the system. Moreover, the system is activated only around signalized intersections. Since the share of driving time when that occurs is currently limited to certain areas in the case of the gasoline car and none for EVs in the State of Maryland (based on ATCS deployment and the limited range of EVs), the fact that the willingness to adopt Eco-CACC is low should come as no surprise.

This last result is key for infrastructure planning purposes. Eco-CACC is more cost-effective in urban, arterial areas. As more cities worldwide discourage ICEVs from urban cores, owners of gasoline vehicles will be disinclined to adopt Eco-CACC, as their driving will mainly be on highways. To the contrary, the use of EVs is being increasingly promoted in urban areas through environmentally friendly regulations (e.g., tax breaks, free parking, etc.), where the private benefits of adopting the Eco-CACC are dubious. Thus, agencies face the dilemma of investing in ATCS, which would encourage the adoption of V2I systems, but demand would not follow, rendering this investment useless. However, the positive attitude of EV buyers towards new technologies resulting in higher environmental efficiency dominates the adoption choice despite the adverse cost-benefit result. As a result, quite unexpectedly, the market shares for the Eco-CACC-equipped EV are the highest across both branches. This is a reassuring result for government agencies, as it implies that the deployments of ATCS enhanced with V2I technology will be matched by demand. Also, being contamination an externality, these agencies (as social planners) could regulate its adoption as part a future package of safety and environmental features to be mandatory in connected cars. Knowing the positive attitude of consumers towards Eco-CACC, which translates into high market shares, this regulation should not face general opposition.

As for industry, it seems that the push for autonomous cars is not waiting for ATCS investments. Car manufactures are using different types of active and passive sensors to deploy their self-driving vehicles, but they are not actively seeking partnerships with public officials. Hence the installation of Eco-CACC is not currently a priority for them. If it were to be adopted, it would be eventually bundled in packages allowing vehicle-to-vehicle and V2I communications. Our results show that while they might not be particularly eager to offer the system in EVs, if they were to look at consumers' willingness to pay at the pure cost-benefit level, their attitude might shift favorably towards the adoption of features such as Eco-CACC. This is consistent with observed long-run trends in the industry that will result in the transition away from of internal combustion vehicles.

If concerted action between public agencies and car manufacturers is taken, the implementation of the Eco-CACC system can be very successful. The overall attitude of individuals in favor of adopting of the system is capable of overturning the lack of private return on investment. Of course, lower prices for the cruise system would result in even higher adoption rates. If Eco-CACC can be implemented at a lesser cost, the benefits may be more evident for users. But again, our models already predict remarkable market shares for the alternatives that include Eco-CACC technology: 49% for gasoline cars and 63% for EVs.

We conclude with the caveat that finding reliable estimations of market share is a complicated process, especially in this case. Eco-CACC is a disruptive technology for which no prior information exists in terms of the willingness to adopt it, which implies an inherent uncertainty. However, following the previous literature on similar cases, we believe that the SCE approach coupled with multinomial regression analysis represents an appropriate tool to model this uncertainty and obtain relevant conclusions regarding the future adoption of this technology. Possible extensions of this study that would increase the robustness of the results might consist of exploring aggregated diffusion models, like those initiated by Bass (1969) and extended by other authors such as Weerahandi & Dalal (1992) and Jun & Kim (2011), who combine Bass diffusion models with multinomial logits, aiming to capture simultaneously both the diffusion and replacement processes.

6. Conclusions

This study develops an Eco-CACC system for BEVs to compute real-time energy-optimized vehicle trajectories considering vehicle dynamics constraints and using a realistic BEV energy consumption model. In this way, the energy-optimum program is formulated as an optimization problem with constraints, which is solved using a moving-horizon dynamic programming approach. The developed BEV Eco-CACC system considers the impacts of queues and multiple signalized intersections and then investigates the network-level benefits of this system.

First, a basic BEV Eco-CACC algorithm was developed for a single intersection. Thereafter, an advanced algorithm called BEV Eco-CACC MS was developed with the consideration of impacts from queues and multiple intersections. The developed BEV Eco-CACC algorithms were implemented and tested using the INTEGRATION microscopic simulation software, considering different levels of market penetration rates, traffic conditions, signal timings, road grades, and vehicle types. The test results indicate that the energy-optimum solution for BEVs is different from ICEVs, thus demonstrating the need for vehicle-tailored optimum trajectories. The simulation tests demonstrate that the BEV Eco-CACC MS produces up to 11% of energy savings to pass multiple intersections.

Lastly, the study conducted an SCE to unveil the inclination of drivers towards the Eco-CACC system and to calculate its potential market share. The results indicate that the implementation of the Eco-CACC system can be very successful and the overall attitude of individuals in favor of adopting of the system is capable of overturning the lack of private return on investment.

7. References

R. K. Kamalanathsharma, "Eco-Driving in the Vicinity of Roadway Intersections - Algorithmic Development, Modeling, and Testing," Doctor of Philosophy, Virginia Polytechnic Institute and State University, 2014.

M. Barth and K. Boriboonsomsin, "Real-world carbon dioxide impacts of traffic congestion," Transportation Research Record: Journal of the Transportation Research Board, pp. 163-171, 2008.

H. Rakha, K. Ahn, and A. Trani, "Comparison of MOBILE5a, MOBILE6, VT-MICRO, and CMEM models for estimating hot-stabilized light-duty gasoline vehicle emissions," Canadian Journal of Civil Engineering, vol. 30, pp. 1010-1021, 2003.

X. Li, G. Li, S.-S. Pang, X. Yang, and J. Tian, "Signal timing of intersections using integrated optimization of traffic quality, emissions and fuel consumption: a note," Transportation Research Part D: Transport and Environment, vol. 9, pp. 401-407, 2004.

A. Stevanovic, J. Stevanovic, K. Zhang, and S. Batterman, "Optimizing traffic control to reduce fuel consumption and vehicular emissions: Integrated approach with VISSIM, CMEM, and VISGAOST," Transportation Research Record: Journal of the transportation research board, pp. 105-113, 2009.

Y. Saboohi and H. Farzaneh, "Model for optimizing energy efficiency through controlling speed and gear ratio," Energy Efficiency, vol. 1, pp. 65-76, 2008.

Y. Saboohi and H. Farzaneh, "Model for developing an eco-driving strategy of a passenger vehicle based on the least fuel consumption," Applied Energy, vol. 86, pp. 1925-1932, 2009.

M. Barth and K. Boriboonsomsin, "Energy and emissions impacts of a freeway-based dynamic eco-driving system," Transportation Research Part D: Transport and Environment, vol. 14, pp. 400-410, 2009.

K. J. Malakorn and B. Park, "Assessment of mobility, energy, and environment impacts of IntelliDrive-based Cooperative Adaptive Cruise Control and Intelligent Traffic Signal control," in Sustainable Systems and Technology (ISSST), 2010 IEEE International Symposium on, 2010, pp. 1-6.

R. Kamalanathsharma and H. Rakha, "Agent-Based Simulation of Ecospeed-Controlled Vehicles at Signalized Intersections," Transportation Research Record: Journal of the Transportation Research Board, pp. 1-12, 2014.

B. Asadi and A. Vahidi, "Predictive cruise control: Utilizing upcoming traffic signal information for improving fuel economy and reducing trip time," Control Systems Technology, IEEE Transactions on, vol. 19, pp. 707-714, 2011.

M. Miyatake, M. Kuriyama, and Y. Takeda, "Theoretical study on eco-driving technique for an electric vehicle considering traffic signals," in Power Electronics and Drive Systems (PEDS), 2011 IEEE Ninth International Conference on, 2011, pp. 733-738.

R. Zhang and E. Yao, "Eco-driving at signalised intersections for electric vehicles," IET Intelligent Transport Systems, vol. 9, pp. 488-497, 2015.

X. Qi, M. J. Barth, G. Wu, K. Boriboonsomsin, and P. Wang, "Energy Impact of Connected Eco-driving on Electric Vehicles," in Road Vehicle Automation 4, ed: Springer, 2018, pp. 97-111.

Almannaa, Mohammed Hamad, Hao Chen, Hesham A. Rakha, Amara Loulizi, and Ihab El-Shawarby. 2019. “Field Implementation and Testing of an Automated Eco-Cooperative Adaptive Cruise Control System in the Vicinity of Signalized Intersections.” Transportation Research Part D: Transport and Environment 67 (February): 244–62. https://doi.org/10.1016/j.trd.2018.11.019.

Almutairi, Fawaz. 2017. “Eco-Cooperative Adaptive Cruise Control at Multiple Signalized Intersections.” Thesis, Virginia Tech. https://vtechworks.lib.vt.edu/handle/10919/84351.

Ando, Ryosuke, Yasuhide Nishihori, and Daisuke Ochi. 2010. “Development of a System to Promote Eco-Driving and Safe-Driving.” In Smart Spaces and Next Generation Wired/Wireless Networking, edited by Sergey Balandin, Roman Dunaytsev, and Yevgeni Koucheryavy, 207–18. Lecture Notes in Computer Science. Berlin, Heidelberg: Springer. https://doi.org/10.1007/978-3-642-14891-0_19.

Axsen, Jonn, and Michael Wolinetz. 2018. “Reaching 30% Plug-in Vehicle Sales by 2030: Modeling Incentive and Sales Mandate Strategies in Canada.” Transportation Research Part D: Transport and Environment 65 (December): 596–617. https://doi.org/10.1016/j.trd.2018.09.012.

Bass, Frank M. 1969. “A New Product Growth for Model Consumer Durables.” Management Science 15 (5): 215–27. https://doi.org/10.1287/mnsc.15.5.215.

Calfee, John E. 1985. “Estimating the Demand for Electric Automobiles Using Fully Disaggregated Probabilistic Choice Analysis.” Transportation Research Part B: Methodological, Special Issue Economic Models of Automobile Demand, 19 (4): 287–301. https://doi.org/10.1016/0191-2615(85)90037-2.

Chen, Hao, Hesham A. Rakha, Amara Loulizi, Ihab El-Shawarby, and Mohammed H. Almannaa. 2016. “Development and Preliminary Field Testing of an In-Vehicle Eco-Speed Control System in the Vicinity of Signalized Intersections.” IFAC-PapersOnLine 49 (3): 249–54. https://doi.org/10.1016/j.ifacol.2016.07.042.

Chen, Hao, and Hesham A. Rakha. 2019. "Developing a Traffic Signal Eco-Cooperative Adaptive Cruise Control System for Battery Electric Vehicles," in 96th Annual Meeting Transportation Research Board, Washington D.C.

Cherchi, Elisabetta. 2017. “A Stated Choice Experiment to Measure the Effect of Informational and Normative Conformity in the Preference for Electric Vehicles.” Transportation Research Part A: Policy and Practice 100 (June): 88–104. https://doi.org/10.1016/j.tra.2017.04.009.

ChoiceMetrics. 2014. “Ngene 1.1.2 User Manual & Reference Guide”.

Cirillo, Cinzia, Yan Liu, and Michael Maness. 2017. “A Time-Dependent Stated Preference Approach to Measuring Vehicle Type Preferences and Market Elasticity of Conventional and Green Vehicles.” Transportation Research Part A: Policy and Practice 100 (June): 294–310. https://doi.org/10.1016/j.tra.2017.04.028.

Cook, R. Dennis, and Christopher J. Nachtrheim. 1980. “A Comparison of Algorithms for Constructing Exact D-Optimal Designs.” Technometrics 22 (3): 315–24. https://doi.org/10.1080/00401706.1980.10486162.

Dagsvik, John K, Tom Wennemo, Dag G Wetterwald, and Rolf Aaberge. 2002. “Potential Demand for Alternative Fuel Vehicles.” Transportation Research Part B: Methodological 36 (4): 361–84. https://doi.org/10.1016/S0965-8564(01)00013-1.

De Vlieger, I, D De Keukeleere, and J. G Kretzschmar. 2000. “Environmental Effects of Driving Behaviour and Congestion Related to Passenger Cars.” Atmospheric Environment 34 (27): 4649–55. https://doi.org/10.1016/S1352-2310(00)00217-X.

Ewing, Gordon, and Emine Sarigöllü. 2000. “Assessing Consumer Preferences for Clean-Fuel Vehicles: A Discrete Choice Experiment.” Journal of Public Policy & Marketing 19 (1): 106–18. https://doi.org/10.1509/jppm.19.1.106.16946.

Feng, Yiheng, K. Larry Head, Shayan Khoshmagham, and Mehdi Zamanipour. 2015. “A Real-Time Adaptive Signal Control in a Connected Vehicle Environment.” Transportation Research Part C: Emerging Technologies, Engineering and Applied Sciences Optimization (OPT-i) - Professor Matthew G. Karlaftis Memorial Issue, 55 (June): 460–73. https://doi.org/10.1016/j.trc.2015.01.007.

Gkartzonikas, Christos, and Konstantina Gkritza. 2019. “What Have We Learned? A Review of Stated Preference and Choice Studies on Autonomous Vehicles.” Transportation Research Part C: Emerging Technologies 98 (January): 323–37. https://doi.org/10.1016/j.trc.2018.12.003.

Haaf, C. Grace, W. Ross Morrow, Inês M. L. Azevedo, Elea McDonnell Feit, and Jeremy J. Michalek. 2016. “Forecasting Light-Duty Vehicle Demand Using Alternative-Specific Constants for Endogeneity Correction versus Calibration.” Transportation Research Part B: Methodological 84 (February): 182–210. https://doi.org/10.1016/j.trb.2015.11.012.

Hackbarth, André, and Reinhard Madlener. 2013. “Consumer Preferences for Alternative Fuel Vehicles: A Discrete Choice Analysis.” Transportation Research Part D: Transport and Environment 25 (December): 5–17. https://doi.org/10.1016/j.trd.2013.07.002.

Harwood, Leslie C. n.d. “CONNECTED VEHICLE/INFRASTRUCTURE UNIVERSITY TRANSPORTATION CENTER (CVI-UTC),” 45.

Hensher, David A., John M. Rose, and William H. Greene. 2005. Applied Choice Analysis: A Primer. Cambridge University Press.

Hidrue, Michael K., George R. Parsons, Willett Kempton, and Meryl P. Gardner. 2011. “Willingness to Pay for Electric Vehicles and Their Attributes.” Resource and Energy Economics 33 (3): 686–705. https://doi.org/10.1016/j.reseneeco.2011.02.002.

Hoen, Anco, and Mark J. Koetse. 2014. “A Choice Experiment on Alternative Fuel Vehicle Preferences of Private Car Owners in the Netherlands.” Transportation Research Part A: Policy and Practice 61 (March): 199–215. https://doi.org/10.1016/j.tra.2014.01.008.

Horne, Matt, Mark Jaccard, and Ken Tiedemann. 2005. “Improving Behavioral Realism in Hybrid Energy-Economy Models Using Discrete Choice Studies of Personal Transportation Decisions.” Energy Economics 27 (1): 59–77. https://doi.org/10.1016/j.eneco.2004.11.003.

Jensen, Anders F., Elisabetta Cherchi, and Juan de Dios Ortúzar. 2014. “A Long Panel Survey to Elicit Variation in Preferences and Attitudes in the Choice of Electric Vehicles.” Transportation 41 (5): 973–93. https://doi.org/10.1007/s11116-014-9517-6.

Jensen, Anders Fjendbo, Elisabetta Cherchi, and Stefan Lindhard Mabit. 2013. "On the Stability of Preferences and Attitudes before and after Experiencing an Electric Vehicle." Transportation Research Part D: Transport and Environment 25 (December): 24–32. https://doi.org/10.1016/j.trd.2013.07.006.

Jun, Duk Bin, and Jung il Kim. 2011. "A Choice-Based Multi-Product Diffusion Model Incorporating Replacement Demand." Technological Forecasting and Social Change 78 (4): 674–89. https://doi.org/10.1016/j.techfore.2010.10.012.

Kamalanathsharma, Raj Kishore. 2014. "Eco-Driving in the Vicinity of Roadway Intersections - Algorithmic Development, Modeling and Testing," May. https://vtechworks.lib.vt.edu/handle/10919/56987.

Krueger, Rico, Taha H. Rashidi, and Vinayak V. Dixit. 2019. "Autonomous Driving and Residential Location Preferences: Evidence from a Stated Choice Survey." Transportation Research Part C: Emerging Technologies 108 (November): 255–68. https://doi.org/10.1016/j.trc.2019.09.018.

Louviere, Jordan J., and David A. Hensher. 1983. "Using Discrete Choice Models with Experimental Design Data to Forecast Consumer Demand for a Unique Cultural Event." Journal of Consumer Research 10 (3): 348–61. https://doi.org/10.1086/208974.

Louviere, Jordan J., David A. Hensher, and Joffre D. Swait. 2000. Stated Choice Methods: Analysis and Applications. Cambridge University Press.

Louviere, Jordan J., and George Woodworth. 1983. "Design and Analysis of Simulated Consumer Choice or Allocation Experiments: An Approach Based on Aggregate Data." Journal of Marketing Research 20 (4): 350–67. https://doi.org/10.1177/002224378302000403.

Mabit, Stefan L., and Mogens Fosgerau. 2011. "Demand for Alternative-Fuel Vehicles When Registration Taxes Are High." Transportation Research Part D: Transport and Environment 16 (3): 225–31. https://doi.org/10.1016/j.trd.2010.11.001.

Marschak, Jacob. 1974. "Binary-Choice Constraints and Random Utility Indicators (1960)." In Economic Information, Decision, and Prediction: Selected Essays: Volume I Part I Economics of Decision, edited by Jacob Marschak, 218–39. Theory and Decision Library. Dordrecht: Springer Netherlands. https://doi.org/10.1007/978-94-010-9276-0_9.

NJSAS (2016), Meadowlands Adaptive Signal System for Traffic Reduction. Fact sheet, New Jersey Sports & Exposition Authority, New Jersey.

Tanaka, Makoto, Takanori Ida, Kayo Murakami, and Lee Friedman. 2014. "Consumers' Willingness to Pay for Alternative Fuel Vehicles: A Comparative Discrete Choice Analysis between the US and Japan." Transportation Research Part A: Policy and Practice 70 (December): 194–209. https://doi.org/10.1016/j.tra.2014.10.019.

Rogers, Everett M. 1962. Diffusion of Innovations. Free Press of Glencoe, Macmillan Company.

Train, Kenneth E. 2009. Discrete Choice Methods with Simulation. Cambridge University Press.

USDOT (2018). Adaptive Signal Control. Final Report 2018. Publication No. FHWA-HRT-17-007. FHWA Research and Technology Evaluation. Federal Highway Administration, Washington, D.C.: U.S. Department of Transportation.

Weerahandi, S., and S. R. Dalal. 1992. "A Choice-Based Approach to the Diffusion of a Service: Forecasting Fax Penetration by Market Segments." Marketing Science 11 (1): 39–53. https://doi.org/10.1287/mksc.11.1.39.

Yang, Hao, Hesham Rakha, and Mani Venkat Ala. 2017. "Eco-Cooperative Adaptive Cruise Control at Signalized Intersections Considering Queue Effects." IEEE Transactions on Intelligent Transportation Systems 18 (6): 1575–85. https://doi.org/10.1109/TITS.2016.2613740.

8. Appendix

	Overall	Gasoline	Electric (EV)
Age			
Min	18	18	18
Max	78	78	72
Ave	38	38	38
Gender			
Female	70.32%	71.25%	68.31%
Married			
Yes	42.89%	43.96%	40.59%
Employment status			
Government full time	5.99%	4.63%	9.79%
Government part time	0.63%	0.93%	0.00%
Private full time	52.03%	55.53%	44.55%
Private part time	7.88%	6.48%	10.89%
Self-empolyed	6.62%	5.09%	9.90%
Retired	9.46%	10.64%	6.93%
Student	4.10%	2.78%	6.93%
Unemployed	9.15%	9.25%	8.91%
Other	4.10%	4.63%	2.97%
Education degree			
Less than high school	1.26%	1.39%	0.99%
High school	19.87%	21.75%	15.84%
Graduate or professional degree	17.66%	12.03%	20.79%
Bachelor's degree	22.70%	23.60%	29.70%
Some college	38.47%	41.18%	32.67%
Individual gross income			
Min	0	0	1,000
Max	300,000	300,000	180,000
Ave	52,364	52,756	51,525
Household gross income			
Min	1,000	1,000	1,000
Max	800,000	800,000	300,000
Ave	75,327	78,033	69,542
% Income living expenses*			
Min	2	1	6
Max	99	99	99
Ave	56.52%	55.96%	57.71%

*Income share spent in Housing, Healthcare, Insurance, Food and Education