Final Report

Integrated Optimization of Vehicle Trajectories and Traffic Signal Timings: System Development and Testing

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16. Abstract

This research develops a two-layer optimization approach that provides energy-optimal control for vehicles and traffic signal controllers. The first layer optimizes the traffic signal timings to minimize the total energy consumption levels of approaching vehicles from upstream traffic. The traffic signal optimization can be easily implemented in real-time signal controllers, and it overcomes the issues in the traditional Webster's method of overestimating the cycle length when the traffic volume-to-capacity ratio exceeds 50 percent. The second layer optimizer is the vehicle speed controller, which calculates the optimal vehicle brake and throttle levels to minimize the energy consumption of individual vehicles. The A-star dynamic programming method is used to solve the formulated optimization problem in the second layer to expedite the speed computation so that the optimal vehicle trajectories can be computed in real time and easily implemented in a simulation software for testing. The proposed integrated controller is first tested on an isolated signalized intersection, and then on an arterial network with multiple intersections to investigate the performance of the proposed controller under various traffic demand levels. The test results demonstrate that the proposed integrated controller can greatly improve energy efficiency with fuel savings of up to 17.7%. It can also enhance traffic mobility by reducing traffic delays by up to a 47.2% and reducing vehicle stops by up to 24.8%. Moreover, the data collected from 70 participants in the driving simulator demonstrates that the proposed speed guidance system can reduce emissions by up to 20% in uphill scenarios and up to 7% in downhill scenarios. Lastly, different types of speed guidance options have been investigated in the simulator tests, and the color-coded option is the most favorable choice for participants.

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Abstract

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1. Introduction

The United States is one of the world's prime petroleum consumers, burning more than 20% of the planet's total refined petroleum. The surface transportation sector alone accounts for around 69% of the United States' total petroleum usage and 33% of the nation's CO_2 emissions (Administration, 2018). This presents the transportation sector with three important challenges: availability of fuel to drive vehicles, emissions of greenhouse gases, and vehicular crashes. It is, therefore, important to reduce petroleum consumption and greenhouse gas emissions to make surface transportation safer, more efficient, and more sustainable (Kamalanathsharma, 2014).

Studies have shown that stop-and-go traffic near signalized intersections can greatly increase traffic delays, energy consumption, and emission levels on arterial roads since vehicles are forced to stop ahead of traffic signals when encountering red indications, producing shock waves within the traffic stream (Barth & Boriboonsomsin, 2008; H. Rakha, Ahn, & Trani, 2003). Starting from the 1980s, many studies have focused on optimizing traffic signal timings using measured traffic data to improve the operation of arterial roads (Gartner, Assman, Lasaga, & Hou, 1991; B. Park, Messer, & Urbanik, 1999; Porche, Sampath, Sengupta, Chen, & Lafortune, 1996; Stevanovic, Stevanovic, Zhang, & Batterman, 2009). In the past decade, the advanced communication power in CVs ensures rapid information sharing, which enables researchers to develop eco-driving strategies to optimize vehicle trajectories in real-time according to signal phase and time (SPaT),This has the potential to greatly improve traffic mobility and reduce energy consumption and emissions (Almannaa, Chen, Rakha, Loulizi, & El-Shawarby, 2019; Hao Chen & Rakha, 2020; Hao Chen, Rakha, Loulizi, El-Shawarby, & Almannaa, 2016; H. Yang, Rakha, & Ala, 2017). Recently, a few studies have attempted to simultaneously optimize vehicle speeds and traffic signal timings to further improve transportation efficiency and fuel economy on arterial roads. For instance, an integrated optimization method was developed to optimize vehicle platoons and traffic signal timings using a mixed integer linear programming model (C. Yu, Feng, Liu, Ma, & Yang, 2018). However, this method uses some unrealistic assumptions, such as assuming all vehicles are homogeneous and lane changes are instantaneous, which limit the method's applicability. Therefore, a simplified simulation with one intersection was designed to validate the performance of the proposed method. In addition, another study developed a cooperative method of traffic signal and vehicle speed optimization at isolated intersections (Xu et al., 2018). This method entails a two-level controller – the first level calculates the optimal signal timing and vehicle arrival time to minimize total travel time; the second level optimizes the engine power and brake force to minimize the fuel consumption of individual vehicles. However, the proposed method assumes a 100% market penetration of CAVs, so it cannot be used for CVs that are controlled by human drivers. In addition, the optimization problem is solved using an enumeration method, which results in a heavy computational cost. Thereafter, a dynamic programming and shooting heuristic approach is proposed to optimize CAV trajectories and the traffic signal controller at the same time (Guo et al., 2019). A shooting heuristic algorithm was used to compute near-optimal vehicle trajectories to save computational costs. Numerical tests were conducted that demonstrated so that the proposed method outperforms adaptive signal control. Although the algorithm can be used with a mixture of CAVs and CVs, the developed controller only optimizes CAVs which can fully follow the speed control but does not provide optimized speed for CVs.

According to the aforementioned studies, optimizing both vehicle speed and signal timing is a promising method to improve transportation system efficiency and fuel economy on arterial roads. However, there are several issues in these studies. First, the developed methods are generally very complicated with high computational costs, and thus there is a need to develop a simpler approach with low computational cost so that it can be easily implemented in real-time applications. Second, existing studies only validated the developed methods either in numerical tests or simplified simulation tests with only one intersection. This is also because these methods are very complicated to implement into simulation software or field tests. So, there is a need to test the approach using microscopic traffic simulation software and validate the performances under various conditions, such as different traffic demand levels on the arterial network with multiple signalized intersections.

This study considers these issues in the previous literature to develop an integrated vehicle speed and traffic signal controller. In the proposed system, we develop a two-layer optimization approach that is computationally fast to provide energy-optimal control for vehicles and traffic signal controllers. These two optimizers will work in tandem by sharing information. The optimizer in the first layer computes the traffic signal timings to minimize the total energy consumption levels of approaching vehicles from upstream traffic. The traffic signal optimization can be easily implemented into the real-time signal controller, and it overcomes the issues in the traditional Webster's method of overestimating the cycle length when the traffic volume-to-capacity ratio exceeds 50 percent. The second layer optimizer is the vehicle speed controller which calculates the optimal vehicle brake and throttle levels to minimize the energy consumption of individual vehicles. The A-star dynamic programming is used to solve the formulated optimization problem in the second layer to expedite the computation speed so that the optimal vehicle trajectories can be computed in real time and easily implemented into simulation software for testing. The proposed integrated controller is first tested in an isolated signalized intersection. An arterial network with multiple intersections is then used to investigate the performance of the proposed controller under various traffic demands. The test results demonstrate that the proposed integrated controller outperforms other methods and produces the most savings in fuel consumption, traffic delay, and vehicle stop under various traffic demands. Lastly, we conducted driving simulator tests with 70 participants to investigate the impacts of speed guidance systems on driver behavior and greenhouse gas emissions. The test results demonstrate that the proposed speed guidance system can reduce emissions by up to 20% in uphill scenarios and up to 7% in downhill scenarios. Different types of speed guidance options have been compared in the simulator tests, and the color-coded option is the most favorable choice for participants.

2. Literature Review

Traffic congestion affects mobility, accessibility, and vehicle fuel consumption and emissions. Like intersections that are hot spots for stopping and starting, traffic congestion increases fuel consumption, which in turn contributes to the amount of emissions released by gasoline-powered vehicles. In this regard, many researchers have evaluated the impact of signal timings on fuel consumption (Coelho, Farias, & Rouphail, 2005; X. Li, Li, Pang, Yang, & Tian, 2004; Midenet, Boillot, & Pierrelée, 2004). These studies show that optimized signal timings decrease fuel consumption and vehicle emissions compared to nonoptimized timings. Optimizing signal timings – including the phasing scheme and sequence, cycle length, and offset – optimizes delay, queue length, fuel consumption, and emissions. Traffic signal timing can be classified into fixed time, actuated, responsive, or adaptive controls.

Since fixed-time control traffic signals stay fixed on the duration and phases’ order all the time and do not consider real-time traffic, they are suitable for stable and under-saturated traffic flow conditions (X. K. Yang, 2001). By comparison, an actuated control traffic signal takes into account traffic conditions using detectors installed at intersection approach stop lines that perceive the existence or absence of vehicles. Hence, actuated control traffic signals work better than fixed-time control traffic signals. However, they still don’t consider real-time optimization and may result in long network queues. Adaptive traffic signal control mitigates traffic congestion by changing signal timing parameters in response to real-time traffic conditions. These traffic signals apply detector inputs, historical trends, and predictive models to forecast vehicle arrivals at intersections and then use the forecasts to regulate the best gradual changes in cycle length, phase splits, and offsets to minimize delays and backups (French & French, 2006). For example, the Split Cycle Offset Optimization Tool (SCOOT) (Hunt, Robertson, Bretherton, & Winton, 1981) is a macroscopic model that reduces the number of vehicle stops and performs successfully in undersaturated traffic conditions. The Sydney Coordinated Adaptive Traffic System (SCATS) (Sims, 1981) works in a centralized, hierarchical model and assigns green times to the most significant requirement phases.

Other researchers have studied vehicle control fields and controls for vehicle engines, startup, and speed to improve fuel economy. One study (Hanyu Chen, Zuo, & Yuan, 2013) investigated an engine start/stop system control tactic that can automatically shut off an idling engine to lessen fuel consumption. Wang et al. proposed a startup support system at signalized intersections to improve transportation efficacy by decreasing delays (Wang et al., 2015). Li et al. established an eco-departure system that aims to optimize vehicle departure operations' speed trajectory at signalized intersections and reduce fuel consumption (S. E. Li, Xu, Huang, Cheng, & Peng, 2015).

Recent technology, such as connected automated vehicles (CAVs), has accelerated improvements in mobility, fuel economy, and urban traffic safety. CAVs, especially vehicle-to vehicle-(V2V) and vehicle-to-infrastructure (V2I) communications and vehicle automation, also provide new opportunities for traffic signal control and vehicle control at signalized intersections. Traffic signal controllers can obtain more exact location and motion information from approaching vehicles in real-time using V2I and V2V communications. Lee et al. obtained vehicles data from connected vehicles to evaluate the travel times used for arriving intersection control, which improves the total delay and average speed of vehicles compared to the actuated signal control (Lee, Park, & Yun, 2013). Priemer and Bernhard designed a decentralized adaptive traffic signal control technique that assessed queue length and traffic flow using the V2I data (Xu et al., 2018). Goodall et al. used simulation methods to predict queue length and delay after obtaining vehicle position and speed information via V2I, which was then used to optimize traffic signal timing (Goodall, Smith, & Park, 2013). According to the simulation results, this method improved traffic mobility compared to coordinated actuated signal control at different capacity levels. Zhao et al. established a V2I-based signal timing optimization system using vehicle fuel consumption features to improve vehicle fuel economy around the intersection (Zhao, Li, Wang, & Ban, 2015). Feng et al. presented a bi-level adaptive signal control algorithm using connected vehicle data to minimize vehicle delay and queue length (Feng, Head, Khoshmagham, & Zamanipour, 2015). The simulation results showed that the algorithm significantly reduced total delay under high CV penetration rates with the actuated control. The ability to acquire the exact vehicle motion information promotes accurate estimation of queue length, vehicle travel time, and vehicle fuel consumption for traffic signal control, which results in better signal control performance.

Thanks to V2I/V2V communications, an approaching vehicle can also obtain information about oncoming traffic signal phases and timing, as well as traffic conditions in real-time. Based on this type of communication, the vehicle's speed trajectory can be optimized and controlled to reduce fuel consumption and emissions. Such a vehicle control can be more easily deployed on CAVs since the recommended vehicle speed trajectory may be applied as part of the automation algorithm. Asadi and Vahidi proposed a predictive cruise control system at signalized intersections, considering the steady speed and minimal use of braking to get the green light and traverse the intersection without stopping (Asadi & Vahidi, 2010). Jin et al. suggested a power-based optimal longitudinal control for internal combustion engine vehicles that considered a brake-specific fuel consumption map, traffic signal information, and road grade to optimize the speed trajectory (Jin, Wu, Boriboonsomsin, & Barth, 2016). Wu et al. optimized the speed trajectory for electric vehicles on signalized arterials to reduce fuel consumption (Wu, He, Yu, Harmandayan, & Wang, 2015). Xu et al. used the branch and bound algorithm to optimize vehicle speed profiles in adjacent signalized intersections (Xu et al., 2018). He et al. assessed the traffic signal and queue length at intersections to present a multi-stage optimal control technique that optimizes vehicle speed (He, Liu, & Liu, 2015). HomChauduri et al. developed a speed optimization method for a group of connected vehicles using decentralized model predictive control, which proved to be an effective system in the vicinity of signalized intersections (HomChaudhuri, Vahidi, & Pisu, 2016).

Eco-driving is a decision-making process that changes driving behavior to be more economically and ecologically friendly (Alam & McNabola, 2014). Such driving behavior applies to vehicles using eco-driving technology and affects cars’ compliance with environmental standards (Ando & Nishihori, 2011). Accordingly, several options regarding eco-driving have been proposed by car manufacturers, such as guiding the driver to change gears or adopt a moderate speed (Kim, Shin, Yoon, Bae, & Kim, 2011), heuristics trajectories (Kamal, Mukai, Murata, & Kawabe, 2010), and an eco-driving interface that is integrated with the dashboards of vehicles (Barth & Boriboonsomsin, 2009). Eco-driving involves accelerating moderately, anticipating traffic flow and signals to avoid sudden starts and stops, maintaining driving pace (using cruise control on the highway where appropriate), driving at or safely below the speed limit, and eliminating excessive idling (Barkenbus, 2010). The advantages of eco-driving go beyond emissions reductions; eco-driving reduces the cost of driving and offers concrete and well-known safety paybacks (Mensing, Bideaux, Trigui, Ribet, & Jeanneret, 2014).

Eco-driving can also be applied in diverse driving circumstances, including (a) free cruising uphill or downhill, (b) environmental compliance, and (c) stop-and-go traffic at signalized intersections. Because of the decrease in fuel consumption and, consequently, in CO2 emission, eco-driving is usually considered environmentally friendly. Eco-driving can reduce fuel consumption and, therefore, the carbon dioxide emissions of conventional internal combustion engines by 5% to 10%. Eco-driving attempts to change drivers' behavior through guidance, such as driving more smoothly to forestall changes in the traffic, shifting gears sooner, operating the vehicle within an optimum range of engine revolutions, avoiding jerky braking/acceleration, and avoiding traffic congestion (Pampel, Jamson, Hibberd, & Barnard, 2015).

Vehicle trajectory control aims to determine the vehicle speed profile that minimizes fuel consumption over a given time horizon, usually with various restrictions related to the specific route. It should be mentioned that vehicle speed is the primary function of vehicle performance, route characteristics, and traffic flows. Moreover, suitable gearing, together with the vehicle's speed, controlled the outline of fuel consumption. Effective vehicle trajectory control is considered to be the foundation of eco-driving, resulting in high energy efficacy and low emission of pollutants. The effect of driving style on fuel consumption is addressed in many studies that report fuel savings as a result of eco-driving systems (Saboohi & Farzaneh, 2009).

Because of the intersection’s role in increasing emissions, eco-driving issues have been examined at signalized intersections in urban traffic networks. In this study, it was presumed that the traffic light timings were known and available to vehicles via infrastructure-to-vehicle communication. This research minimized energy consumption while traveling through a sequence of signalized intersections by recommending optimal speeds to the driver so that they always caught a green light. The results showed that traffic congestion and idling time at signalized intersections are among the chief reasons for energy consumption. It is possible to decrease energy consumption by preventing a vehicle from coming to a full stop at intersections and advising cruising velocities to catch as many green lights as possible (Vagg et al., 2013).

Areas with traffic signals create increased delays because of idling at red lights. They also generate high fuel consumption and emissions due to the inherent accelerations and decelerations required. Several studies revealed a positive relationship between vehicle emissions, fuel consumption, and traffic signals (Andrieu & Saint Pierre, 2012; H. Yang, Rakha, & Ala, 2016). Using intelligent transportation technology to minimize delays can put more of the control burden on the vehicles themselves, with eco-driving strategies focusing on signalized arterials. For example, a traffic controller's signal phase and timing information can be communicated directly to individual cars to adjust their speed as they travel through a signalized corridor, minimizing idle time and acceleration. Eco-driving can provide optimal speed advice to the driver and promote safety by considering the current weather conditions, road grade, and other factors (Xia, Boriboonsomsin, & Barth, 2013). At lower speeds, vehicles spend more significant time on the roads and have a high fuel/distance value. At higher speeds, the engine needs to work harder to overcome aerodynamic resistance, and, consequently, the emissions are higher.

Since sudden stops are an issue with red lights, an innovative driving alert system was developed to provide traffic signal information that helps drivers avoid hard braking at intersections. Such a system defined a technique for assessing vehicle energy consumption and emissions at intersections and examined its potential advantages (M. Li, Boriboonsomsin, Wu, Zhang, & Barth, 2009). To minimize the emissions, an optimization-based control algorithm was formulated to use short-range radar and traffic signal information to predictively schedule an optimum speed trajectory for the vehicle (Asadi & Vahidi, 2010). The control objectives were defined as timely arrival at green lights with minimal braking, maintaining a safe distance between vehicles, and cruising at or near the set speed. Three example simulation case studies were presented to demonstrate the potential influence of the algorithm on fuel economy, emission levels, and trip time.

Previous studies confirmed that CAV-based traffic signal control is likely to improve transportation efficiency and fuel economy for all vehicles in the system. CAV-based vehicle speed optimization can also improve efficiency and reduce fuel use at the individual vehicle level, however. It is expected that combining signal timing and speed trajectory can further improve transportation efficiency and decrease fuel consumption. To accomplish this, the study in (S. E. Li et al., 2015) established a joint optimization method for traffic signal timing and vehicle speeds that decreased travel time in different traffic demands. However, they did not consider the fuel consumption of vehicles. In addition, the described vehicle speed optimization was rule-based, which may not lead to optimal speed trajectories. This study addresses previous limitations to integrating traffic signals and vehicle trajectory optimizations to reduce fuel consumption and emissions.

3. Integrated Control Strategies

The proposed integrated controller includes two layers of optimization for traffic signals and individual vehicles. The traffic signal controller optimizes the signal cycle length and timing according to the incoming traffic flow rate from the upstream links of the signalized intersection. The individual vehicle speed controller optimizes the vehicle trajectory using the data from traffic signals and surrounding vehicles through V2I and V2V communications. The integrated controller computes the optimized signal timing and vehicle trajectory to minimize the energy consumption of the entire traffic network. The details of the two-layer control strategies are provided below.

3.1 Traffic Signal Optimization

The traditional goal of optimizing traffic signal cycle length usually focuses on minimizing vehicle delay and increasing throughput at the intersection. The classic method is designed by British researcher F.V Webster, who developed an optimal cycle length formulation that approximates the signal timings necessary to minimize vehicle delay (Webster, 1958), as seen in Equation (1). This formulation has been used in traffic analysis for years and is still one of the prevailing methodologies used to determine the optimal cycle length for traffic signals.

$$C_{opt} = \frac{1.5L + 5}{1 - Y} \tag{1}$$

where,

C_{opt} = cycle length to minimize delay in seconds.

L = total lost time for cycle in seconds.

Y = sum of flow ratios for critical lane groups.

However, several studies have found that the optimal signal timing for minimizing delays is not necessarily identical to the timing plans that minimize energy consumption and emissions. For instance, the study in (Ma, Jin, & Lei, 2014) proposed and compared various traffic signal optimization methods using VISSIM and SUMO. The test results indicated that there are apparent trade-offs between the goal of mobility and sustainability. Moreover, researchers studied the emissions at isolated intersections and found that the goal of decreasing delays at intersections and reducing emissions is not simply equivalent (J.-Q. Li, Wu, & Zou, 2011). Delays at intersections will increase if the number of vehicle stops decrease, which will help reduce the pollution at intersections. In addition, the study in (Liao, 2013) considers a fuel-based signal optimization model, which describes the stochastic effects of vehicle movements that consume excess fuel. The proposed model was compared with the results from Webster's model, TRANSYT 7F, and Synchro, demonstrating the greatest efficiency among all the methods with fuel consumption reductions of up to 40%.

A recent study in (Calle Laguna, 2017) improved the traditional equation recommended by Webster by using the data obtained from microscopic traffic simulation software. The improved model, represented in Equation (2), has also outperformed Webster's equation to further reduce traffic delay, especially during higher traffic demand volumes. Since optimizing traffic signal to minimize traffic delay doesn't mean the fuel consumption is also minimized, another new formulation in Equation (3) is computed by optimizing the signal cycle length to minimize vehicle fuel consumption levels. In this way, the optimal cycle length can be obtained, thereafter the signal timings can be computed by considering the green time yields the critical lane traffic ratio (Urbanik et al., 2015). Eventually, the optimal signal timings can be computed according to the traffic flow rates from upstream links of the signalized intersections at each interval, e.g., five minutes.

$$C_{opt,delay} = \frac{0.33L + 8.56}{1 - Y} + 3.8 \tag{2}$$

$$C_{opt,fuel} = \frac{0.82L}{1 - Y} + 40 \tag{3}$$

3.2 Vehicle Trajectory Optimization

In this study, the vehicle trajectory is optimized by the connected eco-driving controller, named the Eco-Cooperative Adaptive Cruise Control at Intersections (Eco-CACC-I), previously developed in (Almannaa et al., 2019; Hao Chen & Rakha, 2020; Hao Chen et al., 2016; H. Yang et al., 2017) to compute real-time fuel consumption and the energy-optimized speed profile to assist vehicles traversing signalized intersections. The control region was defined as the distance upstream of the signalized intersection (d_{up}) to the distance downstream of the intersection (d_{down}) in which the Eco-CACC-I controller optimizes the speed profiles of vehicles approaching and leaving signalized intersections. Upon approaching a signalized intersection, the vehicle may accelerate, decelerate, or cruise (maintain a constant speed) based on several factors, such as vehicle speed, signal timing, phase, distance to the intersection, road grade, headway distance, etc. (Kamalanathsharma, 2014). We assumed no leading vehicle ahead of the subject vehicle so that we could compute the subject's energy-optimized vehicle trajectory without considering the impacts of other surrounding vehicles. The computed optimal speed was used as a variable speed limit, denoted as $v_e(t)$, which acts as one of the constraints on the subject vehicle's longitudinal motion. When a vehicle travels on the roadway, there are other constraints to be considered, including the allowed speed set by the vehicle dynamics model, steady-state car following mode, collision avoidance constraint, and roadway speed limit. All these constraints work together to control the vehicle speed. In this way, the proposed controller can also be used in a situation where the subject vehicle follows a leading vehicle, and the vehicle speed can be computed by $v(t) = min(v_1(t), v_2(t), v_3(t), v_4(t), v_e(t))$ using the following constraints:

- The maximum speed $v_1(t)$ allowed by the vehicle acceleration model for a given vehicle throttle position.
- The maximum speed $v_2(t)$ is constrained by the steady-state vehicle spacing in the simulation software.
- The speed limit of $v_3(t)$ to avoid a rear-end vehicle collision.
- The maximum speed $v_4(t)$ allowed on the road.

Within the control region, the vehicle's behavior can be categorized into one of two cases: (1) the vehicle can pass through the signalized intersection without decelerating or (2) the vehicle must decelerate to pass through the intersection. Given that vehicles drive in different manners for cases 1 and 2, the Eco-CACC-I control strategies were developed separately for the two cases.

Case 1 doesn't require the vehicle to decelerate to pass the signalized intersection. In this case, the cruise speed when the vehicle approaches a red light can be calculated by Equation (4) to maximize the average vehicle speed during the control region. When the vehicle enters the control region, it should adjust speed to u_c by following the vehicle dynamics model developed in (K. Yu, Yang, & Yamaguchi, 2015). After the traffic light turns from red to green, the vehicle accelerates from the speed u_c to the maximum allowed speed (speed limit u_f) by following the vehicle dynamics model until it leaves the control region.

$$u_c = min\left(\frac{d_{up}}{t_r}, u_f\right) \tag{4}$$

In case 2, the vehicle's energy-optimized speed profile is illustrated in Figure 1. After entering the control region, the vehicle with the initial speed of $u(t_0)$ needs to brake at the deceleration level denoted by a, then cruise at a constant speed of u_c to approach the signalized intersection. After passing the stop bar, the vehicle should increase speed to u_f per the vehicle dynamics model and then cruise at u_f until the vehicle leaves the control region. In this case, the only unknown variables are the upstream deceleration rate a and the downstream throttle f_p. The following optimization problem is formulated to compute the optimum vehicle speed profile associated with the least energy consumption.

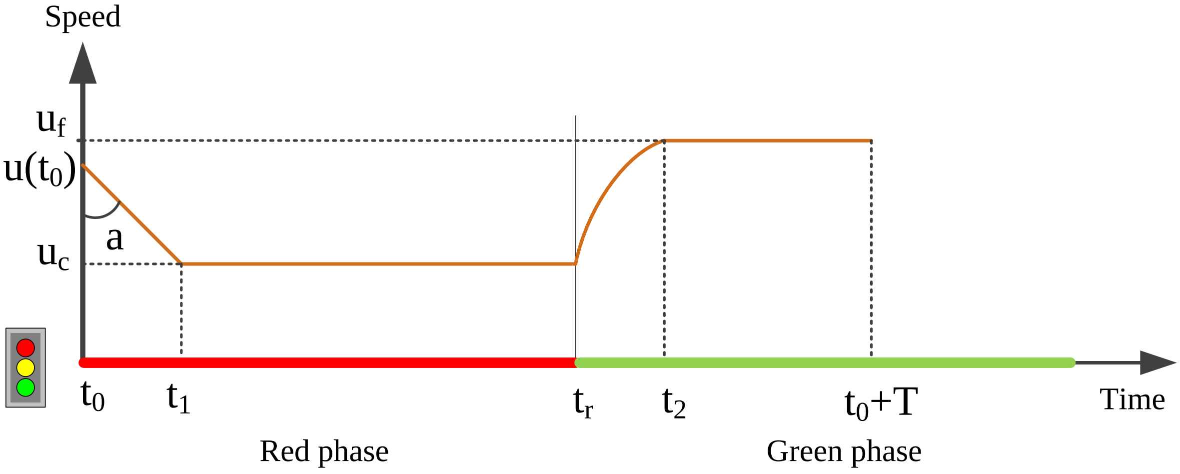


Figure 1: Vehicle optimum speed profile.

Assuming a vehicle enters the Eco-CACC-I control region at time t_0 and leaves the control region at time t_0+T, the objective function entails minimizing the total energy consumption as

$$min \int_{t_0}^{t_0+T} EC\big(u(t)\big) \cdot dt \tag{5}$$

where EC denotes the energy consumption at instant t. The energy models for internal combustion engine vehicles (ICEVs) are presented in Equations (8) ~ (9). The constraints to solve the optimization problem can be built according to the relationships between vehicle speed, location, and acceleration/deceleration as presented below:

$$
u(t):\begin{cases} u(t) = u(t_0) - at & t_0 \le t \le t_1 \\ u(t) = u_c & t_1 < t \le t_r \\ u(t+\Delta t) = u(t) + \dfrac{F\big(f_p\big) - R\big(u(t)\big)}{m}\Delta t & t_r < t \le t_2 \\ u(t) = u_f & t_2 < t \le t_0 + T \end{cases} \tag{6}
$$

$$
\begin{gathered}
u(t_0)\cdot t - \frac{1}{2}at^2 + u_c(t_r - t_1) = d_{up} \\
u_c = u(t_0) - a(t_1 - t_0) \\
\int_{t_r}^{t_2} u(t)\,dt + u_f(t_0 + T - t_2) = d_{down} \\
u(t_2) = u_f \\
a_{min} < a \le a_{max} \\
f_{min} \le f_p \le f_{max} \\
u_c > 0
\end{gathered} \tag{7}
$$

where $u(t)$ is the velocity at instant t; m is the vehicle mass; $a(t) = dv(t)/dt$ is the acceleration of the vehicle in [m/s^2] ($a(t)$ takes negative values when the vehicle decelerates); function F denotes vehicle tractive force, and function R represents all the resistance forces (aerodynamic, rolling, and grade resistance forces). Note that the maximum deceleration is limited by the comfortable threshold felt by average drivers (Kamalanathsharma, 2014). The throttle value f_p ranges between f_{min} and f_{max}. An A-star dynamic programming approach is used to solve the problem by constructing a graph of the solution space by discretizing the combinations of deceleration and throttle values and calculating the corresponding energy consumption levels; the minimum path through the graph computes the energy-efficient trajectory and optimum parameters (Guan & Frey, 2013; Kamalanathsharma, 2014).

The Virginia Tech Comprehensive Power-based Fuel Consumption Model (VT-CPFM) type 1 is selected in this study to estimate the instantaneous fuel consumption rate for ICEV (S. Park, Rakha, Ahn, & Moran, 2013). The VT-CPFM utilizes instantaneous power as an input variable and can be easily calibrated using publicly available fuel economy data (e.g., Environmental Protection Agency [EPA]-published city and highway gas mileage). Thus, the calibration of model parameters does not require gathering any vehicle-specific field data. The VT-CPFM is formulated as below.

$$
FC_{ICEV}(t) = \begin{cases} a_0 + a_1 P(t) + a_2 P(t)^2 & \forall\, P(t) \ge 0 \\ a_0 & \forall\, P(t) < 0 \end{cases} \tag{8}
$$

$$P(t) = \left(ma(t) + \ mg \ \cdot \frac{C_r}{1000}(c_1 u(t) + c_2) + \frac{1}{2}\rho_{Air} A_f C_D u^2(t) + mg\ \theta\right) u(t) \quad (9)$$

where $FC_{ICEV}(t)$ is the fuel consumption rate for ICEV; α_0, α_1 and α_2 are the model parameters that can be calibrated for a particular vehicle using public available vehicle specification information from the manufacturer, and the details of calibration steps can be found in (H. A. Rakha, Ahn, Moran, Saerens, & Van den Bulck, 2011); $P(t)$ is the instantaneous total power (kW); g [m/s^2] is the gravitational acceleration; θ is the road grade; C_r, c_1 and c_2 are the rolling resistance parameters that vary as a function of the road surface type, road condition, and vehicle tire type; ρ_{Air} [kg/m^3] is the air mass density; A_f[m^2] is the frontal area of the vehicle, and C_D is the aerodynamic drag coefficient of the vehicle (2015; 2013; 2015).

4. Simulation Tests

In order to test the performance of the proposed control strategies, we implement the controllers into the microscopic traffic simulation software and conduct two tests using an isolated signalized intersection and an arterial traffic network with multiple signalized intersections, respectively.

INTEGRATION is used as the simulation tool to simulate the traffic network in the case study. INTEGRATION is an integrated simulation and traffic assignment model that creates individual vehicle trip departures based on an aggregated time-varying O-D matrix. In consideration of traffic control devices and gap acceptance, INTEGRATION moves vehicles along the network in accordance with embedded preset traffic assignment models and the Rakha-Pasumarthy-Adjerid (RPA) car-following model. A more detailed description of INTEGRATION is provided in the literature (M. V. Aerde & Rakha, 2007a, 2007b).

4.1 Test the Proposed Integrated Controller on an Isolated Intersection

This test considers the simplest case of a single-lane signalized intersection to validate the performance of using the proposed controller. Figure 2 shows the setup of the intersection, the traffic stream parameters on the major road are 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 total simulation time is 60 minutes, and the traffic signal timing is optimized every 5 minutes. The vehicle speed is optimized within the control region: 200 meters upstream and 200 meters downstream of the intersection. Three levels of traffic demand volumes are considered in the test using the volume over capacity values of 0.1, 0.5, and 1, respectively. Five test scenarios described below are compared in the test.

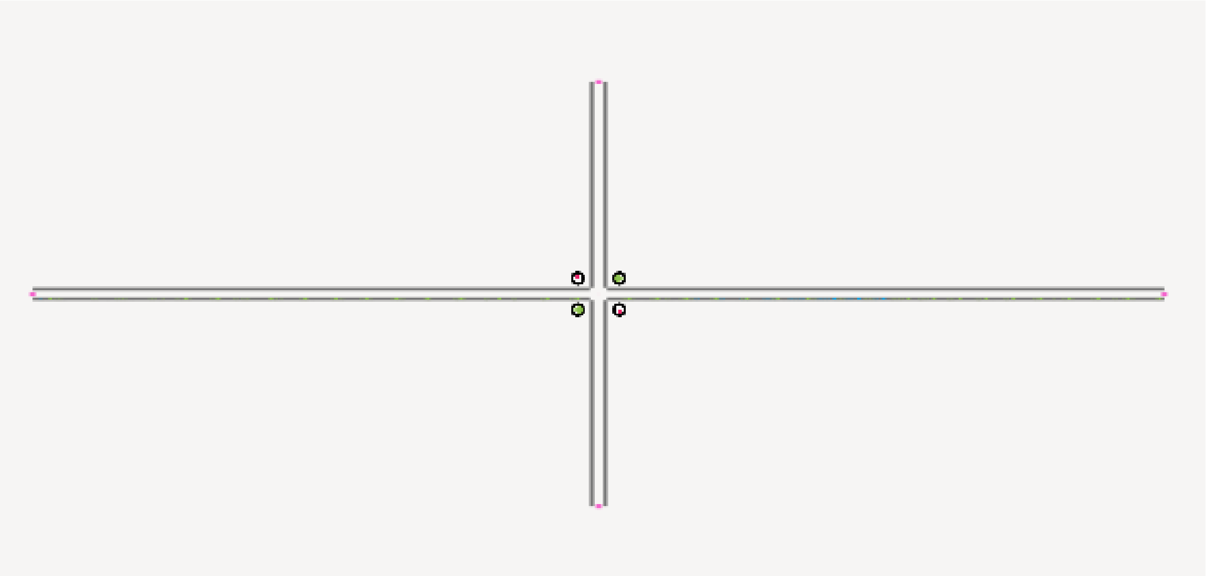


Figure 2: Test on an isolated signalized intersection.

- Scenario 1 (S1): Base
  This is the base scenario without signal optimization and vehicle speed control.

- Scenario 2 (S2): Signal Optimization – Webster
  The traffic signal is optimized using Webster's method as shown in Equation (1).

- Scenario 3 (S3): Signal Optimization – Delay
  The traffic signal is optimized using the modified method to minimize traffic delay as shown in Equation (2).

- Scenario 4 (S4): Signal Optimization – Fuel
  The traffic signal is optimized using the modified method to minimize fuel consumption as shown in Equation (3).

- Scenario 5 (S5): Integrated Controller (Signal Optimization – Fuel + Eco-CACC-I)
  The traffic signal is optimized using the modified method to minimize fuel consumption as shown in Equation (3), and vehicle speed is optimized using the Eco-CACC-I controller within the control region.

The test results of five scenarios under various traffic demands are summarized in Table 1. For uncongested traffic conditions, both modified signal optimization methods in S3 and S4 outperform Webster's method in S2 by producing more fuel savings. But the total delay in S4 is higher than S1~S3, which matches with findings in previous studies stating that the optimal signal timing for minimizing delays is not necessarily identical to the timing plans that aim at minimizing energy consumption and emissions. The proposed integrated controller in S5 produces the most fuel savings of 7.91% compared to the base scenario without any controller. However, it also produces an increased total delay of 3.55% compared to S1. Similar trends can be found in the medium and congested traffic conditions. For the medium traffic demand, the fuel consumption keeps reducing from S1 to S5. The integrated controller produces the most fuel savings of 7.12%, but the corresponding total delay is increased by 1.03% compared to S1. For congested traffic conditions, the integrated controller in S5 reduces fuel consumption by 6.52%, but it also greatly increases the traffic delay by 10.02% compared to S1. Overall, the test results demonstrate the proposed integrated controller can effectively reduce fuel consumption when vehicles transverse isolated signalized intersections.

Table 1: Test results on isolated signalized intersection.

Uncongested (v/c=0.1)

Scenarios	FC (liter)	FC reduction	Delay (sec)	Delay reduction
S1	0.1012		11.4026	
S2	0.0979	-3.26%	10.8538	-4.81%
S3	0.0972	-3.95%	10.7853	-5.41%
S4	0.0955	-5.63%	11.524	1.06%
S5	0.0932	-7.91%	11.8076	3.55%

Medium (v/c=0.5)

Scenarios	FC (liter)	FC reduction	Delay (sec)	Delay reduction
S1	0.1054		12.8154	
S2	0.1021	-3.13%	12.3806	-3.39%
S3	0.1019	-3.32%	12.21379	-4.69%
S4	0.0998	-5.31%	12.319	-3.87%
S5	0.0979	-7.12%	12.9469	1.03%

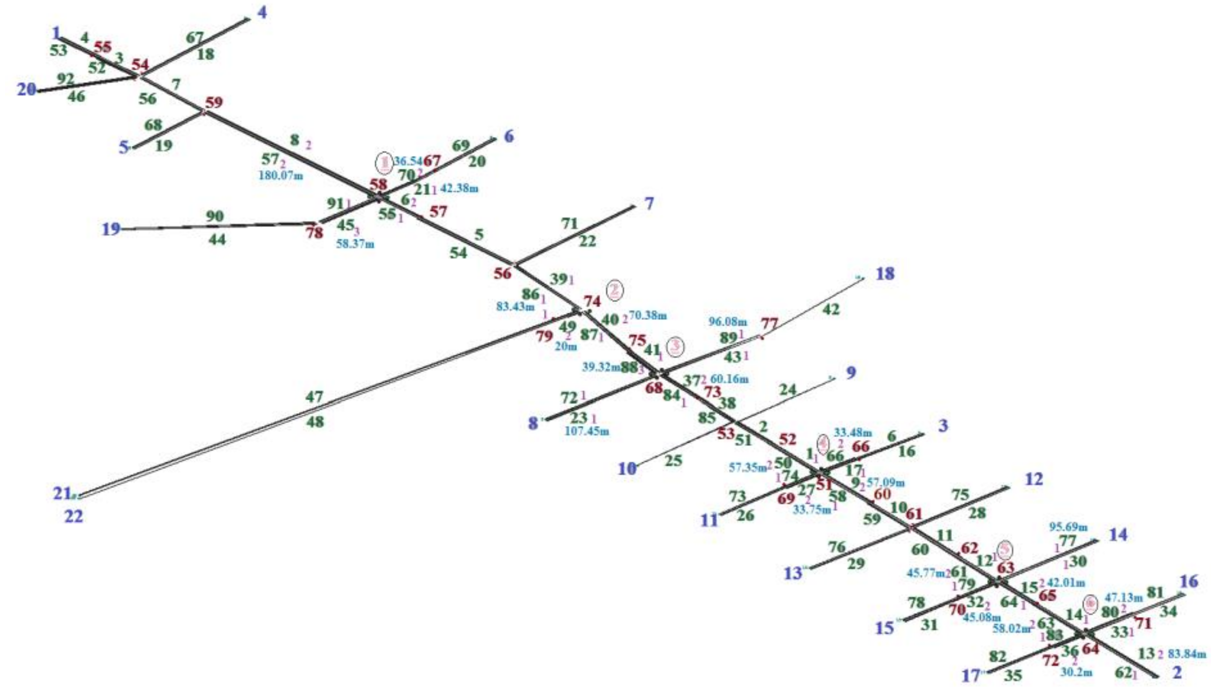
Congested (v/c=1)

Scenarios	FC (liter)	FC reduction	Delay (sec)	Delay reduction
S1	0.1089		32.7019	
S2	0.1056	-3.03%	32.4825	-0.67%
S3	0.1052	-3.40%	31.9564	-2.28%
S4	0.1032	-5.23%	32.2797	-1.29%
S5	0.1018	-6.52%	35.9777	10.02%

4.2 Test the Proposed Integrated Controller on an Arterial Traffic Network

The proposed integrated controller is further tested on an arterial network located in the heart of downtown Blacksburg, as shown in Figure 3. The O-D demand matrices were generated using QueesOD software (M. Aerde & Rakha, 2010) and were based on traffic counts collected during the afternoon peak period (4 ~ 6 pm) at 15 minutes intervals for the year 2012 (Abdelghaffar, Yang, & Rakha, 2017). The simulations were conducted using the following parameter values: free-flow speed of 40 km/h based on the roadway speed limit, speed-at-capacity of 29 km/h, jam density of 160 veh/km/lane, and saturation flow rate of 1800 veh/h/lane. In the simulation, vehicles were allowed to enter the links in the first 2 hours, and the simulation ran for an extra 15 minutes to guarantee that all vehicles exited the network. Three different traffic demand volumes are investigated during this test. 100% demand represents the O-D demand matrices calibrated by the field data during afternoon peak hours. Then we also consider 25% and 50% demand to investigate the performances of different controllers.

(a)



(b)

Figure 3: The arterial roadways in the city of Blacksburg, VA; (a) Google Images; (b) the simulated traffic network in the INTEGRATION software.

Table 2: Test results on arterial network.

<u>25% Demond</u>

Scenarios	FC (liter)	FC reduction	Delay (sec)	Delay reduction	Stops	Stops reduction
S1	0.0751		33.4		1.49	
S2	0.0688	-8.39%	22.7	-32.04%	2.08	39.60%
S3	0.0692	-7.86%	21.3	-36.23%	2.01	34.90%
S4	0.0675	-10.12%	23.2	-30.54%	2	34.23%
S5	0.0646	-13.98%	22.9	-31.44%	1.13	-24.16%

<u>50% Demond</u>

Scenarios	FC (liter)	FC reduction	Delay (sec)	Delay reduction	Stops	Stops reduction
S1	0.0757		34.6		1.53	

S2	0.0675	-10.83%	20.9	-39.60%	1.97	28.76%
S3	0.0681	-10.04%	20.1	-41.91%	1.94	26.80%
S4	0.0664	-12.29%	21.6	-37.57%	1.92	25.49%
S5	0.0643	-15.06%	20.9	-39.60%	1.15	-24.84%

100% Demond

Scenarios	FC (liter)	FC reduction	Delay (sec)	Delay reduction	Stops	Stops reduction
S1	0.0791		39		1.61	
S2	0.0671	-15.17%	19.4	-50.26%	1.86	15.53%
S3	0.0679	-14.16%	18.5	-52.56%	1.84	14.29%
S4	0.0668	-15.55%	20.9	-46.41%	1.82	13.04%
S5	0.0651	-17.70%	20.6	-47.18%	1.24	-22.98%

In this test, the same five different scenarios as described in the isolated intersection test are also considered. The test results of five scenarios under three traffic demand levels are summarized in Table 2. For 25% traffic demand, the delay-optimized method in S3 outperforms Webster’s method in S2 and the fuel-optimized method in S4 by producing the greatest reduction in delay at 36.23%. The fuel-optimized method in S4 outperforms Webster’s method in S2 and the delay optimized method in S3 by producing the most fuel savings at 10.12%. These findings are consistent with the test results in (Webster, 1958) and prove that Webster’s method represented in Equation (1) is indeed improved by the modified methods in Equations (2) and (3). However, the scenarios of S2, S3 and S4 result in more than a 34% increase in vehicle stops on the arterial network. Among all five scenarios, the integrated controller in S5 produces the greatest reduction in vehicle stops compared to S1 at 24.16%. S5 also produces the most fuel saving with13.98% among all five scenarios. The test results under 25% demand indicate that the integrated controller can greatly enhance traffic mobility with a31.44% reduction of total delay and a 24.16% reduction of vehicle stops, at the same time improving the energy efficiency with a 13.98% reduction in fuel consumption. Similar trends can be observed under 50% and 100% demand. In both cases, the integrated controller produces the most savings in fuel consumption and vehicle stops while significantly reducing traffic delay. Overall, the test results on the arterial network indicate that the proposed controller can greatly improve energy efficiency with 17.7% fuel savings and enhance traffic mobility with up to a 47.18% reduction in total delay and 24.84% reduction in vehicle stops.

5. Investigating the Impact of Speed Guidance on Driver Behavior using a Driving Simulator

This study aims to investigate the impacts of a speed guidance system on driver behavior and greenhouse gas emissions using a driving simulator. The speed guidance system uses the Eco-CACC-I algorithm previously developed in section 3.2 to compute the recommended speed to help drivers passing signalized intersections with reduced stop-and-go behaviors and greenhouse gas emissions.

5.1 Driving Simulator Setup

Figure 4: Driving simulator.

Figure 5: Snapshot of Driving Simulator Environment.

This study implements the speed guidance system (using the Eco-CACC-I algorithm developed in section 3.2) in a full-scale 3D driving simulator (DS) with VR-Design Studio software provided by the Forum8 Company (http://www.forum8.co.jp) to study drivers' behavior at signalized intersections in the presence of different types of Eco-Speed-Guidance (ESG). The hardware of the DS is like a real car, including a cockpit, ignition key, automatic transmission, acceleration and brake pedals, a steering wheel, a seat belt, wipers, a hazard button, and three surrounding monitors to provide a view of the surrounding environment and traffic (for forward and rear, right and left views) (demonstrated in Figure 4). The VR-Design Studio software can visualize the surrounding landscape with 3D buildings, vehicles, trees, etc., and allows the visual examination of alternative project options. It also animates the vehicle’s movements in the driving simulation. The software can create networks with real-world features such as traffic signals, road markings, and intersections. It is also possible to create different scenarios under various traffic and weather conditions and offer a realistic driving scene, as shown in Figure 5. The simulator system collects data related to the driver and vehicle's behavior, such as speed, acceleration, throttle, the vehicle's position, traffic signal color, and phase of the traffic signal at a rate per second. The driving simulator directly logs all the related data.

The flow chart of the Eco-CACC-I algorithm is illustrated in Figure 6. Using the Delphi programming language, we developed a code to connect the Eco-CACC-I algorithm and the real-time plug-in software from Forum8 company (3D V.R. & Visual Interactive Simulation). The Eco-CACC-I algorithm calculates the recommended speed based on vehicle speed, vehicle distance to the signalized intersection, remaining time for changing the signal phase, and the signal's current phase. The real-time plug-in provides real-time data such as the driver's vehicle's position and speed, the vehicle's distance to the intersection, traffic signal status, and the remaining time for changing the traffic signal phase through the TCP/IP port. The code listens to the TCP/IP port and obtains the data mentioned above every 0.1 seconds. The code also calls the Eco-CACC-I algorithm every 0.1 seconds and receives the recommended speed as demonstrated in Figure 7. Then, it converts the recommended speed to voice, text or a graphic/color command every 2 to 3 seconds 200 meters before and after the intersection, giving the subject driver the ability to react to the recommended speed.

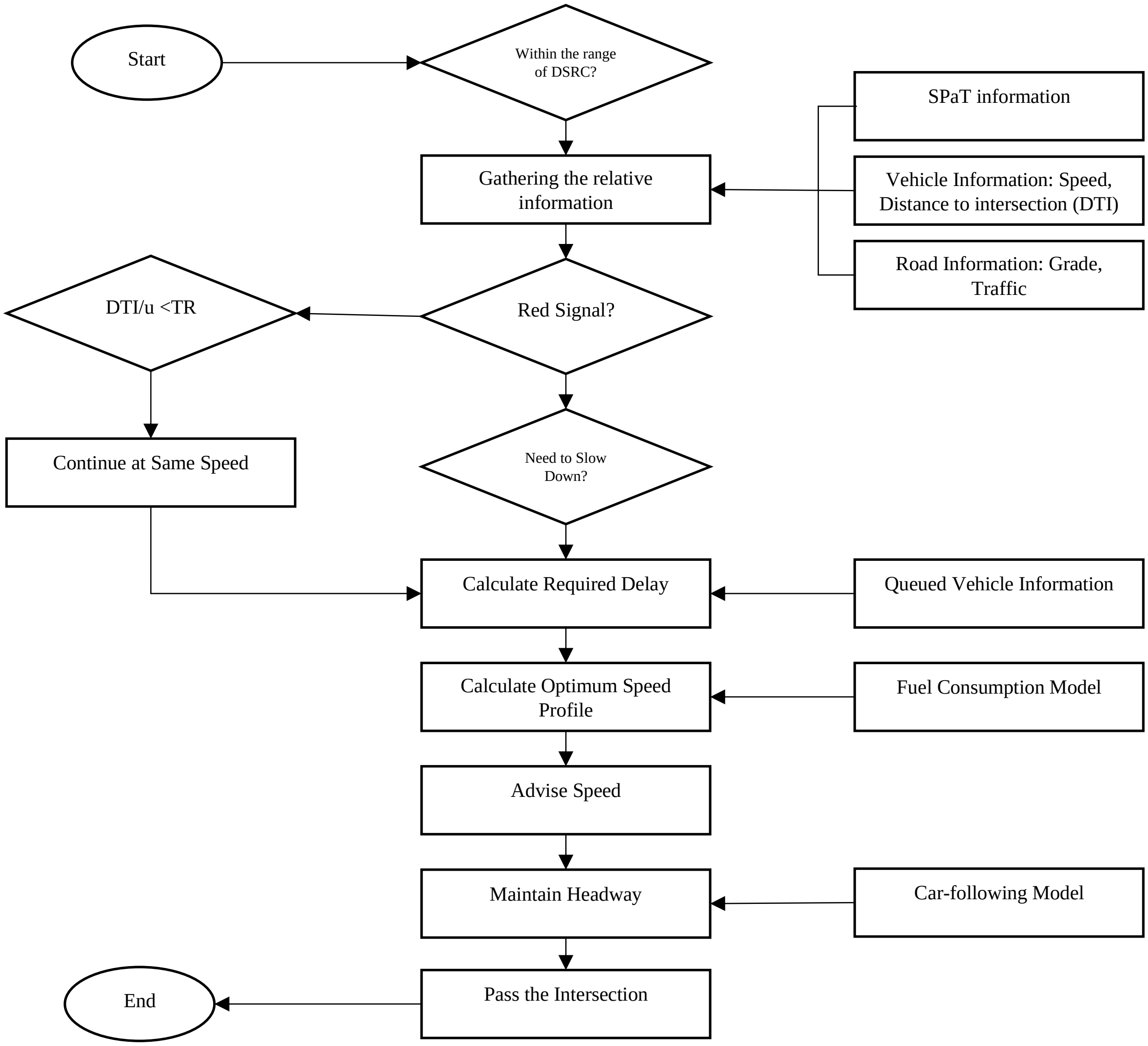


Figure 6: The flow chart of speed guidance calculation.

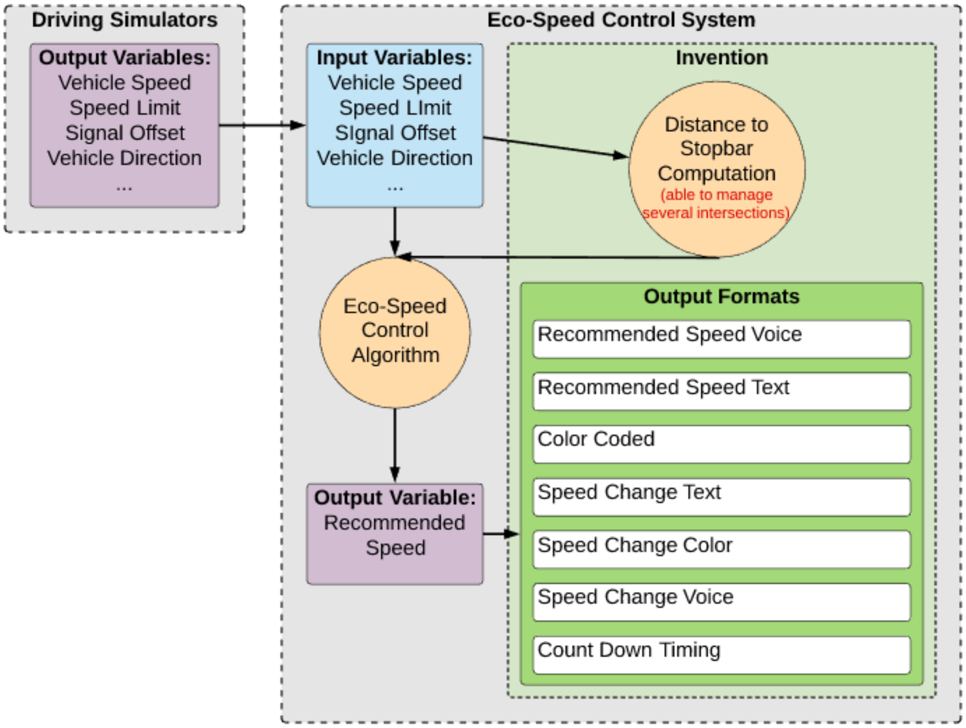


Figure 7: Connecting the speed guidance system and the driving simulator

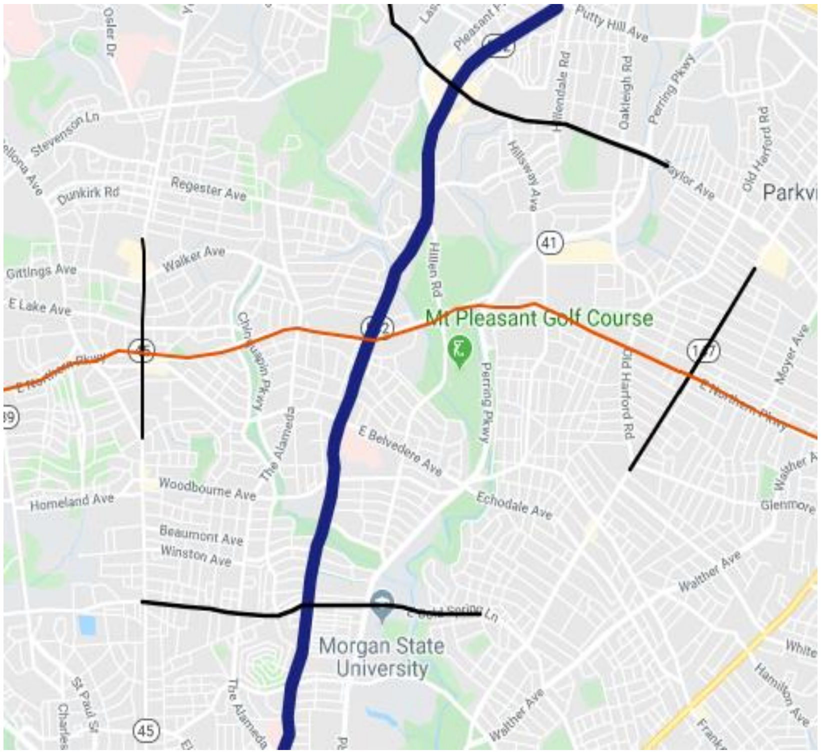
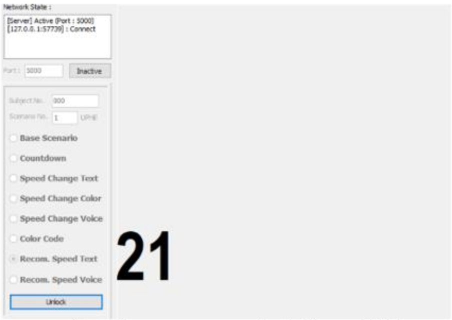


Figure 8: The layout of the study area.

Table 3: Simulated scenarios.

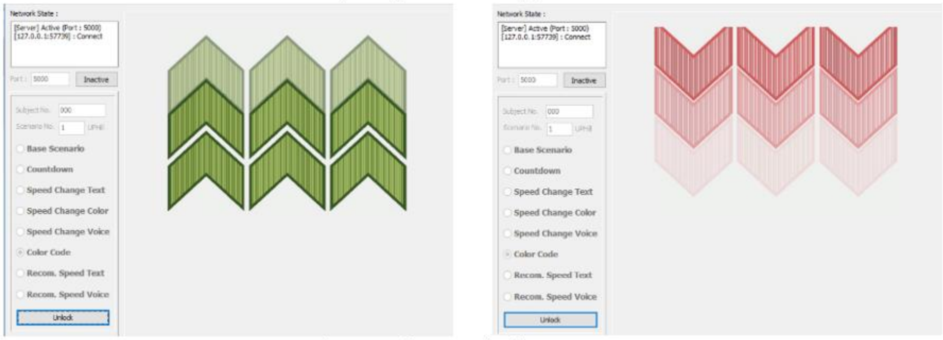
Scenario	Information Type	Traffic Type	Road Condition	Number of Lanes	Grade
1	Base Scenario	Mild Traffic	Uphill	3 Lanes	0.03
2	Base Scenario	No Traffic	Uphill	1 Lane	0.03
3	Base Scenario	Mild Traffic	Downhill	3 Lanes	-0.03
4	Base Scenario	No Traffic	Downhill	1 Lane	-0.03
5	Recommended Speed-Voice	Mild Traffic	Uphill	3 Lanes	0.03
6	Recommended Speed-Voice	No Traffic	Uphill	1 Lane	0.03
7	Recommended Speed-Text	No Traffic	Uphill	1 Lane	0.03
8	Color Code	No Traffic	Uphill	1 Lane	0.03
9	Speed Change-Text	No Traffic	Uphill	1 Lane	0.03
10	Speed Change-Voice	No Traffic	Uphill	1 Lane	0.03
11	Speed Change-Color	No Traffic	Uphill	1 Lane	0.03
12	Recommended Speed-Voice	Mild Traffic	Downhill	3 Lanes	-0.03
13	Recommended Speed-Voice	No Traffic	Downhill	1 Lane	-0.03
14	Countdown	Mild Traffic	Uphill	3 Lanes	0.03
15	Countdown	No Traffic	Uphill	1 Lane	0.03
16	Countdown	No Traffic	Downhill	1 Lane	-0.03
17	Countdown	Mild Traffic	Downhill	3 Lanes	-0.03

The study area is a medium-size road network in the Baltimore metropolitan area which consists of three signalized intersections, as shown in Figure 8, with seventeen scenarios (described in Table 3) of different road characteristics, traffic conditions, and ESG to investigate drivers' behavior and CO^2 emissions reduction. The participants started driving in a Base scenario with no guidance to compare that driving behavior with other types of ESG. Participants then drove different ESG scenarios on the road network, which included three intersections with uneven roads (uphill and downhill). ESG was provided to drivers 200 meters before and 200 meters after each intersection in each scenario.

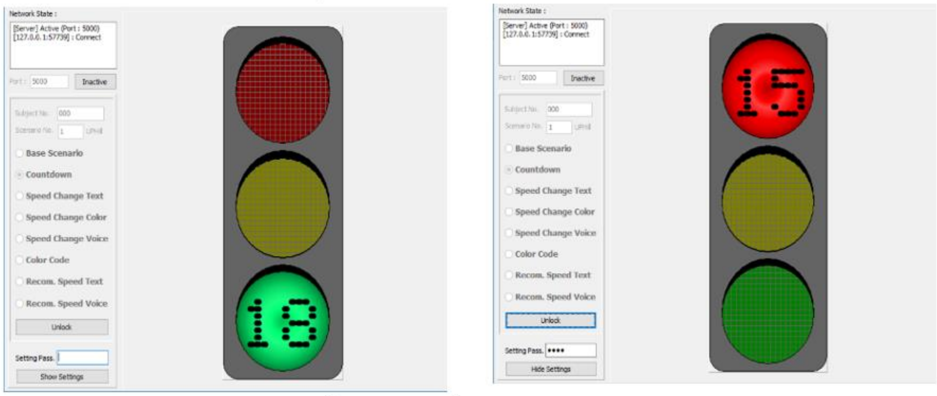


a) Recommended Speed Text

b) Speed Change Color



c) Color Coded



d) Countdown

Figure 9: Different Types of Speed Guidance.

In the above-mentioned ESG area at each intersection, the participants were given the "Recommended Speed" or "Speed Change" via Voice, Text, and Graphic/Color. In Recommended

Speed scenarios, an exact speed like “28 mph” was provided, while in Speed Change scenarios, participants were prompted with statements like "Increase Speed," "Decrease Speed," and "No Change." Participants were supposed to drive at a speed limit of 30 mph and change their speed in response to the information provided via ESG (except in the base scenario) to go through the signalized intersection without stopping. One goal of this part of the study is to measure the ability of drivers to follow the ESG.

The seventeen scenarios include no information as a benchmark, and then providing either Recommended Speed or Speed Change (Increase or Decrease or No Change) via Voice , Text, and Graphic/Color. Different types of speed guidance options are illustrated in Figure 9. We differentiated between results obtained when traveling uphill and downhill (due to differences in emission), and reuslts obtained in no traffic and mild traffic as demonstrated in Table 3.

5.2 Participants

After Institutional Review Board approval, 70 participants were recruited from Morgan State University and the Baltimore metro area via the dissemination of flyers to drive in different scenarios described in Table 3. The flyer’s content included contact information, a summary of the requirements for the study and an explanation of the monetary compensation for driving the simulator. Subsequently, prospective participants were screened for a valid driver’s license and scheduled to drive in the simulator environment.

Descriptive statistics of the participants were obtained from Pre-Driving Survey questionnaire data. .About 41.4% of participants were male, and 58.6% were female. The participants' age ranged between 18 to 65 years old; 32.9% of them were between 18 and 25 years old. The details of the participants’ socioeconomic characteristics are summarized in Table 4.

Table 4: Participants' Socioeconomic Characteristics.

Variables		Frequency	Percent
Gender	Female	41	58.6
	Male	29	41.4
Age	18 to 25	23	32.9
	26 to 35	20	28.6
	36 to 45	8	11.4
	46 to 55	10	14.3
	56 to 65	9	12.8
Level of Education	High School or Less	13	18.6
	College Student	7	10.0
	Associate Degree	4	5.7
	Bachelor's Degree	17	24.3
	Graduate Degree	26	37.1
	Professional Degree	3	4.3
Employment Status	Unemployed	11	15.7
	Employed Part-time	19	27.1
	Employed Full time	40	57.2
Annual Household Income	Less than $20K	20	28.6
	$20K to $30K	9	12.9
	$30 to $50K	10	14.3
	$50 to $75K	13	18.6
	$75 to $100K	5	7.1
	More than $100K	13	18.5
Household Size	1	24	34.3
	2	28	40.0
	3	10	14.3
	4 and more	4	11.4

5.3 Driving Simulator Test Results

To find the percentage of drivers who follow the different types of ESG – including “Recommended Speed-Text,” “Recommended Speed-Voice,” “Speed Change-Text,” “Speed Change-Voice,” “Speed Change-Color,” and “Color Coded” – in each of the three simulated intersections, several ANOVA analyses were conducted. The Following Percentages were calculated based on the Vehicle Speed Direction and the ESG Direction by considering ‘1’ for an increase in speed, ‘-1’ for a decrease in speed and ‘0’ for no change. The results of uphill scenarios (Table 5) show that more than 50% of participants followed the ESG, with the highest Following Percentage of 76% belonging to “Speed Change-Color” scenarios. In comparison, 53% of the participants followed the Speed Change-Voice scenarios. The results of the downhill scenarios in Table 5 show that 61% of the participants follow the speed in “Recommended Speed-Voice” scenarios at the first intersection. The percentage of those following the Recommended Speed Voice in the second and third intersections is higher than the first intersection with 63% and 66% respectively.

Table 5: Following percentage by Uphill and Downhill Scenarios.

Uphill Scenarios					
Scenarios	**Following Percentage**			**F**	**Sig.**
	First Intersection	**Second Intersection**	**Third Intersection**		
Recommended Speed-Text	60%	57%	54%	4.23	0.000
Recommended Speed-Voice	53%	61%	57%		
Speed Change-Text	67%	70%	63%		
Speed Change-Voice	67%	68%	65%		
Speed Change-Color	76%	69%	67%		
Color Coded	69%	68%	65%		
Downhill Scenarios					
Scenarios	**Following Percentage**			**F**	**Sig.**
	First Intersection	**Second Intersection**	**Third Intersection**		
Recommended Speed-Voice	61%	63%	66%	4.23	0.000

To find whether emissions were reduced compared to the Base scenario (uphill, no traffic, one lane) due to ESG, we performed several ANOVA analyses. The results of uphill scenarios (Table 6) demonstrate a significant reduction in emissions in all ESG scenarios compared to the Base scenario. The greatest reduction in emissions (7%) occurred in the “Speed-Change-Color” scenario. The results of downhill scenarios (Table 7) also demonstrate a significant reduction in emissions, with a 0.3% decrease in the “Recommended Speed-Voice” scenario and a 2% decrease in the “Countdown” scenario compared to the Base scenarios.

Table 6: Descriptive and ANOVA Result of Emissions by Uphill Scenarios.

Scenario Type	**Emissions (g/s)**			**F**	**Sig.**
	Fist Intersection	**Second Intersection**	**Third Intersection**		
Base Scenario	128868.2	125579.1	125992.2	4.23	0.00
Recommended Speed-Text	124922.5	124615.8	120632.6		
Recommended Speed-Voice	125428.8	123782.5	122647.0		
Speed Change-Text	120369.5	118878.7	119043.8		
Speed Change-Voice	122650.4	121977.7	124431.8		
Speed Change-Color	119395.0	120011.6	119841.6		
Color Coded	122210.6	121347.4	121692.9		
Countdown	132816.3	122794.7	122636.4		

Table 7: Descriptive and ANOVA Result of Emissions by Downhill Scenarios.

Scenario Type	**Emissions (g/s)**			**F**	**Sig.**
	Fist Intersection	**Second Intersection**	**Third Intersection**		
Base Scenario	128101.5	124941.9	125560.6	1.964	0.002
Recommended Speed-Voice	127730.2	120790.5	120985.9		
Countdown	126148.1	118786.2	122072.1		

Table 8 shows significant emission reductions in the ESG scenarios and the Countdown scenarios compared to the Base scenarios. Each ANOVA analysis shows the Base scenario's emissions level compression, the ESG scenario, and each intersection's Countdown separately.

Table 8: Descriptive and ANOVA Result of Emissions by Scenarios (No Traffic, Uphill, one lane).

Color-Coded Scenario, Base Scenario, and Countdown Scenario							
Dependent Variable		**Scenario Types**	**Mean**	**Std. Deviation**	**N**	**F**	**Sig.**
Emissions	**First Intersection**	**Base Scenario**	148545.2	203504.8	133	1.985	0.066
		Color Coded	119395	3006.7	70		
		Countdown	121585.9	20189.9	136		
	Second Intersection	**Base Scenario**	126450.4	32942.3	133		
		Color Coded	120011.6	3331.7	70		
		Countdown	122127.302	22702.6	136		
	Third Intersection	**Base Scenario**	126635.4	32853.9	133		
		Color Coded	119841.6	3035.9	70		
		Countdown	120869.6	15523.9	136		
Recommended Speed-Text Scenario, Base Scenario, and Count down Scenario							
Dependent Variable		**Scenario Types**	**Mean**	**Std. Deviation**	**N**	**F**	**Sig.**
Emissions	**First Intersection**	**Base Scenario**	148545.2	203504.8	133	1.854	0.086
		Recommended Speed-Text	124922.5	24425.8	70		
		Count down	121585.852	20189.9	136		
	Second Intersection	**Base Scenario**	126450.4	32942.3	133		
		Recommended Speed-Text	124615.8	39209.1	70		
		Count down	122127.3	22702.6	136		
	Third Intersection	**Base Scenario**	126635.4	32853.9	133		
		Recommended Speed-Text	120632.6	14071.9	70		
		Count down	120869.6	15523.9	136		
Speed Change-Text Scenario, Base Scenario, and Countdown Scenario							
Dependent Variable		**Scenario Types**	**Mean**	**Std. Deviation**	**N**	**F**	**Sig.**
Emissions	**First Intersection**	**Base Scenario**	148545.2	203504.8	133	2.129	0.048
		Speed Change-Text	120369.5	2906.2	70		
		Countdown	121585.9	20189.9	136		
	Second Intersection	**Base Scenario**	126450.4	32942.3	133		
		Speed Change-Text	118878.7	3105.981	70		
		Countdown	122127.3	22702.616	136		
	Third Intersection	**Base Scenario**	126635.4	32853.89	133		
		Speed Change-Text	119043.8	2525.694	70		
		Countdown	120869.6	15523.898	136		

To find variables that affect the participants' following behavior, a Generalized Linear Model (GLM) analysis was performed. The Following Percentage, which represents how often a participant adjusts their speed based on ESG, is considered the dependent variable in the model. Socioeconomic variables, the type of ESG, the grade of the road, and traffic conditions are considered independent variables. Among all independent variables in the model, the type of ESG, grade of the road, traffic condition, age and gender significantly impacted the Following Percentage.

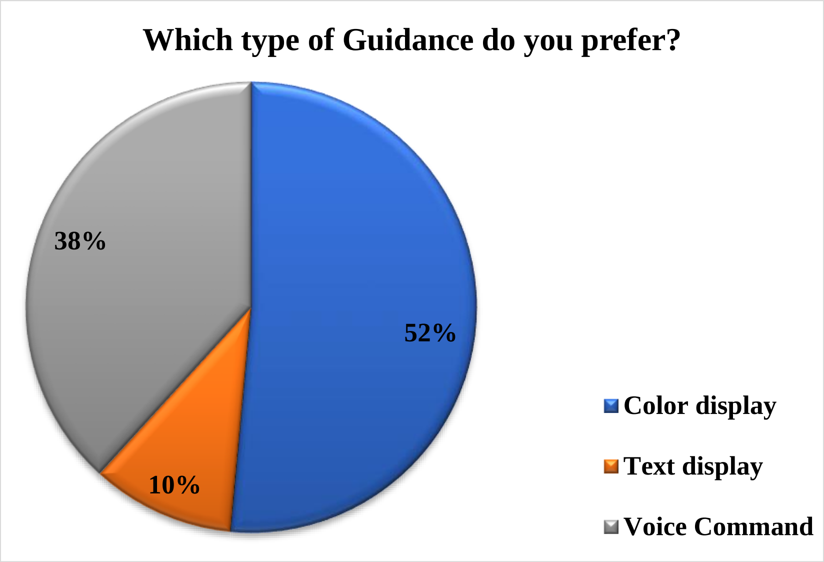
Table 9: Compliance Model.

Variable	**β**	**Standard Error**	**Significance**
Constant	0.741	0.014	0.000
Type of Information Dissemination			
Color Code	0.005	0.016	0.757
Recommended Speed Text	-0.097	0.016	0.000
Recommended Speed Voice	-0.073	0.014	0.000
Speed Change Text	-0.003	0.016	0.875
Speed Change Color	0.038	0.016	0.017
Countdown	-0.087	0.014	0.000
Speed Change Voice	Reference Category		
Grade of the Road			
Downhill	0.023	0.007	0.000
Uphill	Reference Category		
Traffic Condition			
Mild Traffic	-0.017	0.007	0.008
No Traffic	Reference Category		
Gender			
Female	-0.015	0.006	0.011
Male	Reference Category		
Age Group			
18 to 25	-0.047	0.018	0.023
26 to 35	-0.029	0.009	0.002
36 to 45	-0.006	0.011	0.626
46 to 55	-0.023	0.011	0.030
56 to 65	Reference Category		
Dependent Variable: Following Percentage **Likelihood Ratio Chi-Square:** 312.262 **Log-Likelihood:** 1370.698			

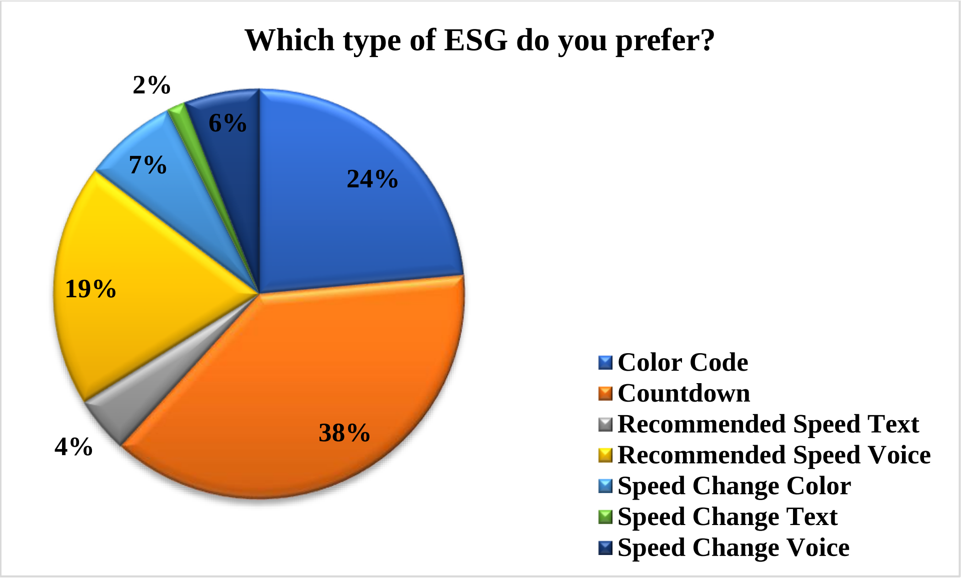
The results of the model (Table 9) show that the Following Percentage in "Recommended Speed-Text" and "Recommended Speed-Voice" is significantly less than the following percentage in "Speed Change-Voice" (as a reference category). The Following Percentage of "Speed Change-

Color" is significantly not only more than "Speed Change-Voice," but also more than the other types of ESG. The Speed Change guidance was found to be better than Recommended Speed guidance, and the Color guidance was found to be better than Voice or Text guidance, meaning that "Speed Change-Color" is the best type of guidance. The Following Percentage in downhill scenarios was significantly higher than in uphill scenarios. By comparison, the Following Percentage in mild traffic was significantly less than in scenarios with no traffic, as expected. The results also showed that males followed ESG more than females, and that older participants (ages 56-65) followed ESG more successfully than younger ones. Such a result might be related to a tendency among younger drivers to drive faster, making it more difficult to follow the speed advisory.

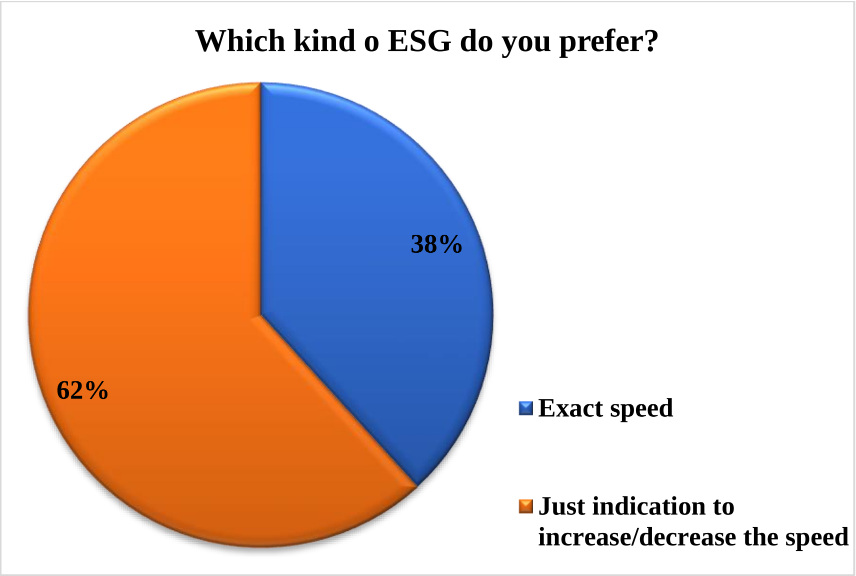
The post-survey results are summarized in Figure 10. Figure 10 (a) shows that more than 50% of participants prefer Color display to Text or Voice, and Figure 10 (b) shows that only 2% of participants prefer Speed Change-Text and 4% prefer Recommended-Speed Text among the other ESG types. , demonstrating that text display is not an effective way of ESG. Figure 10 (c) shows that more than 60% prefer Speed-Change guidance to Recommended Speed guidance. Such results are aligned with participants' observed driving behavior, wherein the Following Percentage of Speed-Change guidance was higher than that of Recommended Speed guidance. Regarding distraction behavior, Figure 10 (d) shows that 16% of participants did not get distracted at all when receiving ESG while driving, 12% got distracted slightly, 26% stated that they were somewhat distracted, 37% were very distracted and 9% of participants found ESG extremely distractive.



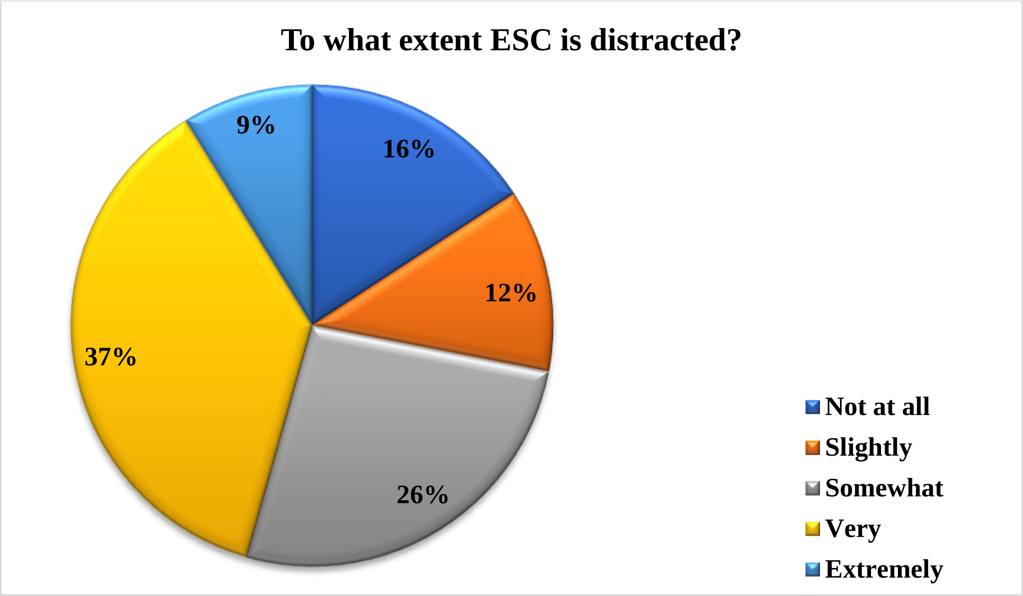
(a)


Which type of ESG do you prefer?
2%
6%
7%
24%
19%
4%
38%
Color Code
Countdown
Recommended Speed Text
Recommended Speed Voice
Speed Change Color
Speed Change Text
Speed Change Voice

(b)


Which kind o ESG do you prefer?
38%
62%
Exact speed
Just indication to increase/decrease the speed

(c)



(d)

Figure 10: Survey results: (a) preference of guidance; (b) preference of ESG; (c) preference of the type of ESG; (d) distraction rate of ESC.

In summary, the driving simulator test proves that developed vehicle speed guidance systems that provide speed advisories to drivers using V2I and V2V communications can effectively improve traffic mobility and reduce vehicle energy consumption and emission levels. The results also demonstrate that participants can follow directions for recommended speed changes with several different display types, such as text, voice and graphic/color (demonstrated in Figure 9). The display type with the highest Following Percentage was the speed change-color scenario at 76%, which featured green up arrows to recommend an increase in speed and red down arrows to recommend a decrease in speed. Recommended speed-voice, with just 53% of drivers following it, was the least successful among the types of displays. The results also confirm the effectiveness of ESC in emission reduction, with up to 20% reduction related to uphill scenarios and up to 7% in downhill scenarios. Women and younger drivers complied with speed guidance less than male and older drivers.

6. Conclusions

Recent studies show that optimizing both vehicle speed and signal timing is a promising method to improve transportation system efficiency and fuel economy on arterial roads. However, the developed methods are generally very complicated with high computational costs. On the other hand, existing studies validated the developed methods either in numerical tests or simplified simulation tests with only one intersection. So, there is a need to test these methods using microscopic traffic simulation software and validate their performance under various conditions on an arterial network with multiple signalized intersections. To solve those issues, this paper develops a two-layer optimization approach that provides energy-optimal control for vehicles and traffic signal controllers. The optimizer in the first layer computes the traffic signal timings to minimize the total energy consumption levels of approaching vehicles from upstream traffic. The traffic signal optimization can be easily implemented into the real-time signal controller, and it overcomes the issues in the traditional Webster's method of overestimating the cycle length when the traffic volume-to-capacity ratio exceeds 50 percent. The second layer optimizer is the vehicle speed controller which calculates the optimal vehicle brake and throttle levels to minimize the energy consumption of individual vehicles. The A-star dynamic programming is used to solve the formulated optimization problem in the second layer to expedite the computation speed so that the optimal vehicle trajectories can be computed in real-time and implemented into simulation software for testing. The proposed integrated controller is first tested in an isolated signalized intersection, and then an arterial network with multiple intersections is used to investigate the performance of the proposed controller under various traffic demands. The test results demonstrate that the proposed integrated controller can greatly improve energy efficiency with up to 17.7% fuel savings, at the same time enhancing the traffic mobility by reducing total delay by 47.18% and vehicle stops by 24.84%. Lastly, we conducted driving simulator tests with 70 participants to investigate the impacts of speed guidance systems on driver behavior and greenhouse gas emissions. The test results demonstrate that the proposed speed guidance system can reduce emissions by up to 20% in uphill scenarios and up to 7% in downhill scenarios. Different types of speed guidance options have been compared in the simulator tests, and the color-coded option is the most favorable choice for participants. More tests on city-level traffic networks will be considered in future work. We will also consider expanding the integrated control strategies to different vehicle types such as battery electric and hybrid electric vehicles.

7. References

Abdelghaffar, H. M., Yang, H., & Rakha, H. A. (2017). *Developing a de-centralized cycle-free nash bargaining arterial traffic signal controller.* Paper presented at the 2017 5th IEEE International Conference on Models and Technologies for Intelligent Transportation Systems (MT-ITS).

Administration, U. S. E. I. (2018). Oil: crude and petroleum products explained. Retrieved from https://www.eia.gov/energyexplained/oil-and-petroleum-products/use-of-oil.php

Aerde, M., & Rakha, H. A. (2010). QUEENSOD Rel. 2.10—User's Guide: Estimating Origin—Destination Traffic Demands from Link Flow Counts. *Tech. Rep.*

Aerde, M. V., & Rakha, H. (2007a). *INTEGRATION © Release 2.30 for Windows: User's Guide – Volume I: Fundamental Model Features*. M. Van Aerde & Assoc., Ltd., Blacksburg.

Aerde, M. V., & Rakha, H. (2007b). *INTEGRATION © Release 2.30 for Windows: User's Guide – Volume II: Advanced Model Features*. M. Van Aerde & Assoc., Ltd., Blacksburg.

Alam, M. S., & McNabola, A. (2014). A critical review and assessment of Eco-Driving policy & technology: Benefits & limitations. *Transport Policy, 35*, 42-49.

Almannaa, M. H., Chen, H., Rakha, H. A., Loulizi, A., & El-Shawarby, I. (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*, 244-262.

Ando, R., & Nishihori, Y. (2011). How does driving behavior change when following an eco-driving car? *Procedia-Social and Behavioral Sciences, 20*, 577-587.

Andrieu, C., & Saint Pierre, G. (2012). Comparing effects of eco-driving training and simple advices on driving behavior. *Procedia-Social and Behavioral Sciences, 54*, 211-220.

Asadi, B., & Vahidi, A. (2010). Predictive cruise control: Utilizing upcoming traffic signal information for improving fuel economy and reducing trip time. *IEEE transactions on control systems technology, 19*(3), 707-714.

Barkenbus, J. N. (2010). Eco-driving: An overlooked climate change initiative. *Energy policy, 38*(2), 762-769.

Barth, M., & Boriboonsomsin, K. (2008). Real-world carbon dioxide impacts of traffic congestion. *Transportation Research Record: Journal of the Transportation Research Board*(2058), 163-171.

Barth, M., & Boriboonsomsin, K. (2009). Energy and emissions impacts of a freeway-based dynamic eco-driving system. *Transportation Research Part D: Transport and Environment, 14*(6), 400-410.

Calle Laguna, A. J. (2017). *Isolated Traffic Signal Optimization Considering Delay, Energy, and Environmental Impacts.* Virginia Tech.

Chen, H., & Rakha, H. A. (2020). Battery Electric Vehicle Eco-Cooperative Adaptive Cruise Control in the Vicinity of Signalized Intersections. *Energies, 13*(10), 2433.

Chen, H., Rakha, H. A., Loulizi, A., El-Shawarby, I., & Almannaa, M. H. (2016). Development and Preliminary Field Testing of an In-Vehicle Eco-Speed Control System in the Vicinity of Signalized Intersections. *IFAC-PapersOnLine, 49*(3), 249-254.

Chen, H., Zuo, C., & Yuan, Y. (2013). *Control strategy research of engine smart start/stop system for a micro car* (0148-7191). Retrieved from

Coelho, M. C., Farias, T. L., & Rouphail, N. M. (2005). Impact of speed control traffic signals on pollutant emissions. *Transportation Research Part D: Transport and Environment, 10*(4), 323-340.

De Gennaro, M., Paffumi, E., Martini, G., Manfredi, U., Vianelli, S., Ortenzi, F., & Genovese, A. (2015). Experimental Test Campaign on a Battery Electric Vehicle: Laboratory Test Results (Part 1). *SAE International Journal of Alternative Powertrains, 4*(2015-01-1167), 100-114.

Department of Energy (DOE). (2013). Advanced Vehicle Testing Activity (AVTA) of the Idaho Nation Laboratory (INL). Retrieved from http://avt.inel.gov/pdf/fsev/fact2013nissanleaf.pdf

Feng, Y., Head, K. L., Khoshmagham, S., & Zamanipour, M. (2015). A real-time adaptive signal control in a connected vehicle environment. *Transportation Research Part C: Emerging Technologies, 55*, 460-473.

French, L. J., & French, M. S. (2006). *Benefits of signal timing optimization and its to corridor operations*. Retrieved from

Gartner, N. H., Assman, S. F., Lasaga, F., & Hou, D. L. (1991). A multi-band approach to arterial traffic signal optimization. *Transportation Research Part B: Methodological, 25*(1), 55-74.

Goodall, N. J., Smith, B. L., & Park, B. (2013). Traffic signal control with connected vehicles. *Transportation Research Record, 2381*(1), 65-72.

Guan, T., & Frey, C. W. (2013). *Predictive fuel efficiency optimization using traffic light timings and fuel consumption model.* Paper presented at the Intelligent Transportation Systems-(ITSC), 2013 16th International IEEE Conference on.

Guo, Y., Ma, J., Xiong, C., Li, X., Zhou, F., & Hao, W. (2019). Joint optimization of vehicle trajectories and intersection controllers with connected automated vehicles: Combined dynamic programming and shooting heuristic approach. *Transportation Research Part C: Emerging Technologies, 98*, 54-72.

He, X., Liu, H. X., & Liu, X. (2015). Optimal vehicle speed trajectory on a signalized arterial with consideration of queue. *Transportation Research Part C: Emerging Technologies, 61*, 106-120.

HomChaudhuri, B., Vahidi, A., & Pisu, P. (2016). Fast model predictive control-based fuel efficient control strategy for a group of connected vehicles in urban road conditions. *IEEE transactions on control systems technology, 25*(2), 760-767.

Hunt, P., Robertson, D., Bretherton, R., & Winton, R. (1981). *SCOOT-a traffic responsive method of coordinating signals* (0266-7045). Retrieved from

Jin, Q., Wu, G., Boriboonsomsin, K., & Barth, M. J. (2016). Power-based optimal longitudinal control for a connected eco-driving system. *IEEE Transactions on Intelligent Transportation Systems, 17*(10), 2900-2910.

Kamal, M. A. S., Mukai, M., Murata, J., & Kawabe, T. (2010). *On board eco-driving system for varying road-traffic environments using model predictive control.* Paper presented at the 2010 IEEE International Conference on Control Applications.

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

Kim, S. Y., Shin, D. J., Yoon, H. J., Bae, H. C., & Kim, D. S. (2011). *Development of eco-driving guide system* (0148-7191). Retrieved from

Lee, J., Park, B., & Yun, I. (2013). Cumulative travel-time responsive real-time intersection control algorithm in the connected vehicle environment. *Journal of transportation engineering, 139*(10), 1020-1029.

Li, J.-Q., Wu, G., & Zou, N. (2011). Investigation of the impacts of signal timing on vehicle emissions at an isolated intersection. *Transportation Research Part D: Transport and Environment, 16*(5), 409-414. doi:http://dx.doi.org/10.1016/j.trd.2011.03.004

Li, M., Boriboonsomsin, K., Wu, G., Zhang, W.-B., & Barth, M. (2009). Traffic energy and emission reductions at signalized intersections: a study of the benefits of advanced driver information. *International Journal of Intelligent Transportation Systems Research, 7*(1), 49-58.

Li, S. E., Xu, S., Huang, X., Cheng, B., & Peng, H. (2015). Eco-departure of connected vehicles with V2X communication at signalized intersections. *IEEE Transactions on Vehicular technology, 64*(12), 5439-5449.

Li, X., Li, G., Pang, S.-S., Yang, X., & Tian, J. (2004). Signal timing of intersections using integrated optimization of traffic quality, emissions and fuel consumption: a note. *Transportation Research Part D: Transport and Environment, 9*(5), 401-407.

Liao, T.-Y. (2013). A fuel-based signal optimization model. *Transportation Research Part D: Transport and Environment, 23*(1), 1-8.

Ma, X., Jin, J., & Lei, W. (2014). Multi-criteria analysis of optimal signal plans using microscopic traffic models. *Transportation Research Part D: Transport and Environment, 32*(0), 1-14. doi:http://dx.doi.org/10.1016/j.trd.2014.06.013

Mensing, F., Bideaux, E., Trigui, R., Ribet, J., & Jeanneret, B. (2014). Eco-driving: An economic or ecologic driving style? *Transportation Research Part C: Emerging Technologies, 38*, 110-121.

Midenet, S., Boillot, F., & Pierrelée, J.-C. (2004). Signalized intersection with real-time adaptive control: on-field assessment of CO2 and pollutant emission reduction. *Transportation Research Part D: Transport and Environment, 9*(1), 29-47.

Nissan Leaf. (2015). Nissan Leaf Characteristiscs. Retrieved from http://www.nissanusa.com/electric-cars/leaf/

Pampel, S. M., Jamson, S. L., Hibberd, D. L., & Barnard, Y. (2015). How I reduce fuel consumption: An experimental study on mental models of eco-driving. *Transportation Research Part C: Emerging Technologies, 58*, 669-680.

Park, B., Messer, C. J., & Urbanik, T. (1999). Traffic signal optimization program for oversaturated conditions: genetic algorithm approach. *Transportation Research Record, 1683*(1), 133-142.

Park, S., Rakha, H., Ahn, K., & Moran, K. (2013). Virginia tech comprehensive power-based fuel consumption model (VT-CPFM): model validation and calibration considerations. *International Journal of Transportation Science and Technology, 2*(4), 317-336.

Porche, I., Sampath, M., Sengupta, R., Chen, Y.-L., & Lafortune, S. (1996). *A decentralized scheme for real-time optimization of traffic signals.* Paper presented at the Proceeding of the 1996 IEEE International Conference on Control Applications IEEE International Conference on Control Applications held together with IEEE International Symposium on Intelligent Contro.

Rakha, H., Ahn, K., & Trani, A. (2003). Comparison of MOBILE5a, MOBILE6, VT-MICRO, and CMEM models for estimating hot-stabilized light-duty gasoline vehicle emissions. *Canadian Journal of Civil Engineering, 30*(6), 1010-1021.

Rakha, H. A., Ahn, K., Moran, K., Saerens, B., & Van den Bulck, E. (2011). Virginia tech comprehensive power-based fuel consumption model: model development and testing. *Transportation Research Part D: Transport and Environment, 16*(7), 492-503.

Saboohi, Y., & Farzaneh, H. (2009). Model for developing an eco-driving strategy of a passenger vehicle based on the least fuel consumption. *Applied Energy, 86*(10), 1925-1932.

Sims, A. (1981). *Scat the sydney co-ordinated adaptive traffic system.* Paper presented at the Symposium on computer control of transport 1981: Preprints of papers.

Stevanovic, A., Stevanovic, J., Zhang, K., & Batterman, S. (2009). Optimizing traffic control to reduce fuel consumption and vehicular emissions: Integrated approach with VISSIM, CMEM, and VISGAOST. *Transportation Research Record, 2128*(1), 105-113.

Urbanik, T., Tanaka, A., Lozner, B., Lindstrom, E., Lee, K., Quayle, S., . . . Gettman, D. (2015). *Signal timing manual* (Vol. 1): Transportation Research Board Washington, DC.

Vagg, C., Brace, C. J., Hari, D., Akehurst, S., Poxon, J., & Ash, L. (2013). Development and field trial of a driver assistance system to encourage eco-driving in light commercial vehicle fleets. *IEEE Transactions on Intelligent Transportation Systems, 14*(2), 796-805.

Wang, J., Bian, Y., Xu, B., Qin, H., Hu, M., & Huang, B. (2015). V2I-based startup assistance system at signalized intersections. *Advances in Mechanical Engineering, 7*(8), 1687814015600667.

Webster, F. V. (1958). *Traffic signal settings*. Retrieved from

Wu, X., He, X., Yu, G., Harmandayan, A., & Wang, Y. (2015). Energy-optimal speed control for electric vehicles on signalized arterials. *IEEE Transactions on Intelligent Transportation Systems, 16*(5), 2786-2796.

Xia, H., Boriboonsomsin, K., & Barth, M. (2013). Dynamic eco-driving for signalized arterial corridors and its indirect network-wide energy/emissions benefits. *Journal of Intelligent Transportation Systems, 17*(1), 31-41.

Xu, B., Ban, X. J., Bian, Y., Li, W., Wang, J., Li, S. E., & Li, K. (2018). Cooperative method of traffic signal optimization and speed control of connected vehicles at isolated intersections. *IEEE Transactions on Intelligent Transportation Systems, 20*(4), 1390-1403.

Yang, H., Rakha, H., & Ala, M. V. (2016). Eco-cooperative adaptive cruise control at signalized intersections considering queue effects. *IEEE Transactions on Intelligent Transportation Systems, 18*(6), 1575-1585.

Yang, H., Rakha, H., & Ala, M. V. (2017). Eco-cooperative adaptive cruise control at signalized intersections considering queue effects. *IEEE Transactions on Intelligent Transportation Systems, 18*(6), 1575-1585.

Yang, X. K. (2001). Comparison among computer packages in providing timing plans for Iowa arterial in Lawrence, Kansas. *Journal of transportation engineering, 127*(4), 311-318.

Yu, C., Feng, Y., Liu, H. X., Ma, W., & Yang, X. (2018). Integrated optimization of traffic signals and vehicle trajectories at isolated urban intersections. *Transportation Research Part B: Methodological, 112*, 89-112.

Yu, K., Yang, J., & Yamaguchi, D. (2015). Model predictive control for hybrid vehicle ecological driving using traffic signal and road slope information. *Control theory and technology, 13*(1), 17-28.

Zhao, J., Li, W., Wang, J., & Ban, X. (2015). Dynamic traffic signal timing optimization strategy incorporating various vehicle fuel consumption characteristics. *IEEE Transactions on Vehicular technology, 65*(6), 3874-3887.