Final Report

Optimum Connected Vehicle Speed Control on Signalized Roadways in Mixed Flow

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16. Abstract
Previous studies have shown that the optimal speed trajectories for vehicles with different engine types (e.g., gasoline versus electric vehicles) are very different under certain conditions. This study aims to solve this issue by developing a general speed control algorithm that calculates a compromised solution across different vehicle engine types while optimizing the entire mixed traffic flow in the network. The proposed algorithm optimizes vehicle trajectories for mixed traffic flow, including both internal combustion engine vehicles (ICEVs) and battery electric vehicles (BEVs). To investigate the performance of the proposed controller under various traffic demand levels, a case study was designed using a simulated arterial corridor with three signalized intersections. The algorithm for mixed flow was compared with the algorithms previously developed for each individual vehicle type to investigate the system-level performances. Test results demonstrate that the proposed controller for mixed flow outperforms the previously developed controllers for individual vehicle models by further reducing fuel consumption, battery energy, and traffic delay under various traffic demand levels. Lastly, the proposed algorithm was used to develop a speed guidance system that provides two options of output: 1) recommended speed value, and 2) color-coded speed guidance. The developed speed guidance system was coded into a DLL file by the Delphi coding program and can be directly used in driving simulators to test human responses to two options of driving guidance and their corresponding performances. The speed guidance system was implemented in the driving simulator, and participants are given a color-coded speed recommendation through the entire route in different scenarios. Participants' driving behaviors in various speed guidance scenarios are compared with those driving the same route without any speed guidance. Descriptive and statistical analyses including ANOVA, Post hoc Tukey and regressions are performed on the data obtained from 15 participants with various sociodemographic backgrounds. The study reveals that sociodemographic factors, such as gender and age, influence the effectiveness of the speed guidance system. Female drivers exhibit lower compliance with speed guidance, while older drivers face challenges in following the recommendations.

17. Key Words: vehicle speed control, trajectory optimization, signalized intersections, mixed flow, energy-optimized solution, connected and automated vehicles, driving simulator, microscopic traffic simulation.

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Abstract

Previous studies have shown that the optimal speed trajectories for vehicles with different engine types (e.g., gasoline versus electric vehicles) are very different under certain conditions. This study aims to solve this issue by developing a general speed control algorithm that calculates a compromised solution across different vehicle engine types while optimizing the entire mixed traffic flow in the network. The proposed algorithm optimizes vehicle trajectories for mixed traffic flow, including both internal combustion engine vehicles (ICEVs) and battery electric vehicles (BEVs). To investigate the performance of the proposed controller under various traffic demand levels, a case study was designed using a simulated arterial corridor with three signalized intersections. The algorithm for mixed flow was compared with the algorithms previously developed for each individual vehicle type to investigate the system-level performances. Test results demonstrate that the proposed controller for mixed flow outperforms the previously developed controllers for individual vehicle models by further reducing fuel consumption, battery energy, and traffic delay under various traffic demand levels. Lastly, the proposed algorithm was used to develop a speed guidance system that provides two options of output: 1) recommended speed value, and 2) color-coded speed guidance. The developed speed guidance system was coded into a DLL file by the Delphi coding program and can be directly used in driving simulators to test human responses to two options of driving guidance and their corresponding performances. This study utilizes a 3D driving simulator to investigate how drivers respond to and comply with speed guidance system, which provides real-time speed guidance for connected vehicles at signalized intersections throughout the entire route. Speed guidance system is implemented in the driving simulator, and participants are given a color-coded speed recommendation through the entire route in different scenarios. Participants' driving behaviors in various speed guidance scenarios are compared with those driving the same route without any speed guidance. Descriptive and statistical analyses including ANOVA, Post hoc Tukey and regressions are performed on the data obtained from 15 participants with various sociodemographic backgrounds. The drivers' behavior and adherence to the recommended speed guidance provided by the color-coded speed guidance system, were assessed. The study reveals that sociodemographic factors, such as gender and age, influence the effectiveness of the speed guidance system. Female drivers exhibit lower compliance with speed guidance, while older drivers face challenges in following the recommendations. In future research, extended testing will be conducted by using a large-scale traffic network to validate the system-level performances under different combinations of mixed flow (including ICEVs, BEVs, and hybrid electric vehicles - HEVs), various congestion levels, and different levels of market-penetration-rate of controlled vehicles.

1 INTRODUCTION

Urban areas are known for having high traffic volumes and emissions at signalized intersections. These areas cause frequent braking and accelerating and generate the longest periods of vehicle idling. Drivers often approach a green light at maximum speed and are forced to abruptly decelerate as the light changes. Drivers' limited knowledge about when the traffic signal will change thus leads to increased fuel consumption and longer travel times. Researchers have attempted to use connected vehicle and infrastructure technologies to develop eco-driving strategies aimed at optimizing vehicle speed. One of these strategies is the implementation of SCA, which aims to optimize the speed of connected vehicles by providing recommended trajectories in the presence of signalized intersections.

Many researchers have examined the influence of different speed optimization methods on driving behaviors. Previous studies on speed control can be broadly categorized into five main areas: those that explore the effects of speed control on reducing emissions, those investigating speed control in mixed traffic, those focusing on implementing speed control on Eco-driving, those related to CAVs, and systematic reviews. In order to reduce CO2 emissions from vehicle transport; however, more advanced fuel consumption models are increasingly needed.

Road freight transport systems are essential to economic development, but they also have adverse impacts on the environment and public health. Demir et al. conducted a review of 59 papers on green road freight transportation, and the results showed that the speed of travel is one of the most important factors in reducing fuel consumption (1). Unnecessary braking and acceleration increase the engine's energy consumption and leads to higher emissions. Wang et al. conducted a simulated study of two cruise control systems, a conventional cruise control system, and a Longitudinal control system. The authors optimized traffic signals according to real-time traffic flow, which allowed all of the CVs to form a “platoon” and hold a recommended speed while maintaining a safe distance from one another (2). The results indicated that the Longitudinal control system can reduce unnecessary braking and acceleration to reduce emissions. They also showed that the proposed model reduced stop time and coordinate phase stops by up to 53.69% and 41.15%, respectively. Moreover, the signal delays at the intersection for each vehicle declined by 13.19%, allowing the CVs to pass the intersection with no stops. In another study, Colon et al. created an integrated traffic microsimulation model to find the impact of autonomous vehicles on GHG emissions. Their results showed a 4% reduction in CO2 emissions (3). Building on previous research, Lu et al. developed a new speed control system to reduce fuel consumption and CO2 emissions (4). The authors designed different signal timing methods and achieved an 18% reduction in fuel consumption and a 9% decrease in travel time. Ahangari et al. introduced an eco-speed control system to investigate drivers' responses and emission reductions (5). The results showed that younger male drivers were more willing to follow the suggested speed. In addition, the eco-speed control system was found to reduce emissions by 9.1% compared to countdown timing systems. In another study, Gamage et al. the proposed Eco Speed Control algorithm eliminating idling in the presence of isolated signal intersections, allowing individual vehicles to obtain fuel-efficient driving paths. The proposed method resulted in an 18% reduction in fuel consumption and significantly reduced travel time (6). Chen et al. proposed another adapted speed controller designed for autonomous vehicles (7). The experimental results showed that the proposed method can effectively match the target speed. In another study, Xu et al. (8) proposed a double-layer, real-time speed optimization method to improve vehicle fuel consumption while passing several signalized intersections. The results showed that the proposed methods have the potential to improve fuel consumption and reduce travel time. The significant variability of fuel costs has led companies and governments to think about strategies to reduce energy consumption. Speed profiles, especially on urban roads with many signalized intersections, have a huge impact on fuel consumption. Lim et al. proposed a distance-based eco-driving scheme that optimizes speed for an entire route before departure and adapts to real-time traffic conditions during the drive. The method focuses on nearby heavy traffic regions for adaptation while maintaining the effectiveness of the optimized speed profile elsewhere. The scheme aims to improve fuel efficiency and vehicle performance through real-time adaptation and long-term optimization (9). In another research project, Nasri et al. sought to enhance the speeds and routes of autonomous delivery trucks. They conducted a comparative analysis of two linear models designed to minimize the expenses associated with emissions, fuel consumption, and travel durations. (10). The results demonstrated that stochastic modeling provided significantly greater value compared to the benefits derived from speed optimization. Chen et al. proposed a novel Energy Management (EM) method that optimizes two aspects of hybrid vehicles: fuel efficiency and battery durability (11). Khooban suggested a combination of a new fuzzy logic system and a non-integer controller for speed control in Hybrid Electric vehicles and achieved better results than previous studies (12). In another study, Liang et al. used a joint traffic signal optimization algorithm to reduce stop-and-go by implementing information from connected vehicles (CV) and speed guidance-enabled vehicles(SGVs) (13). The results showed 10% more efficiency in AVs compared to SGVs.

In one study, Lee et al. proposed a real-time intelligent speed optimization system for CAVs by combining a conventional speed optimization planner and reinforcement learning (14). The results showed that the proposed method reduces energy consumption and does not increase travel time when compared with conventional speed optimization planners. In another study, Cheng et al. developed an eco-driving assistance system that combines a fuel consumption model and a robust optimization model for vehicle fuel consumption optimization (15). The results obtained from vehicle experiments indicated that the proposed model performs efficiently. Kramer et al. proposed an optimization algorithm for speed and departure times to reduce pollution-routing problems (PRP) (16). The computational experiments showed up to 8.36% savings in operational costs. Pourmehrab et al. developed an Intelligent Intersection Control System (IICS) simulation for signal control optimization. The obtained results demonstrated a 38-52% reduction in average travel time when compared with conventional signal control (17). Shen et al. built an optimization algorithm to minimize fuel consumption and achieved a fuel savings of at least 8% in two different simulated highway environments (18). In another study, Talati et al. proposed a model that can determine the acceptable and safe speed range for self-driving vehicles with better latency and accuracy than traditional schemes (19). Xu et al. developed a model-free reinforcement learning approach for optimal speed control of gasoline engines (20). The simulation and experimental results showed that the learning mechanism is effective even when no model information is used in the learning algorithm. Lu et al. conducted a comprehensive study focusing on the impact of speed limit facilities on expressways. The study involved speed surveys, the development of an evaluation system, assessment of the speed control effect, and verification of the effectiveness of measures that aim to improve speed control. (21). The authors considered four types of speed limit control, including colored pavement, vibration markings, deceleration markings, and portal frames. The study's results show that the speed limit effect of portal frame is the best, and that deceleration markings were the least effective. In summary, these studies collectively demonstrate that speed optimization methods have the potential to improve energy efficiency, reduce travel time, and enhance overall performance in transportation systems.

The systematic review of 313 papers conducted by Asghari et al. indicated that factors like vehicle weight, speed, and travel time affect greenhouse emissions. They also presented a new classification of papers published on the green vehicle routing problem (Green-VRP) (22) and highlighted gaps in the research regarding conventional, electric, and hybrid vehicles. Moreover, the authors examined optimization techniques that can address the unique challenges of various engine types. The authors provided an overview of the existing research that has been done on the three major streams of the Green-VRP, which are internal combustion engine vehicles (ICEVs), alternative-fuel powered vehicles (AFVs), and hybrid electric vehicles (HEVs). The main purpose of this was to organize the existing literature and provide a reference point for future research into the new aspects of the Green-VRP. In another study, Vahidi et al. reviewed 198 papers to emphasize the CAVs' potential energy savings by conducting a literature review on eco-driving and applying the first principles of movement and optimal control theory (23). The results showed an increase in the energy efficiency of a group of CVs when they moved in a coordinated manner.

Connected and Automated Vehicles (CAVs) are therefore effective way to reduce pollution and travel delay, as well as to save energy in the transportation system. CAVs provide a new computational framework for real-time control movements that maximize energy consumption and introduce other related benefits. From the point of view of control, CAVs can reduce traffic congestion and emissions, improve fuel efficiency, and increase passenger safety in different traffic scenarios.

Mahbub et al. provided a rigorous control framework for enabling platoon formations in mixed traffic conditions, which were simultaneously coordinated with both CAVs and human controlled vehicles (24). The results obtained from numerical analysis validated the proposed method. In another study, Garg et al. studied real traffic and communications data from a large-scale road network in Ireland to investigate the effect of CAVs on the efficiency of traffic (25). The results showed that CAVs significantly improve traffic efficiency in congested traffic scenarios. In other study, Ko et al. proposed speed harmonization and merge controls for CAVs and reduced fuel consumption by up to 20% compared to the merge control without speed harmonization (26). As signalized intersections have an important role in vehicle efficiency in urban areas, Xu et al. proposed a method for simultaneously controlling traffic signals and optimizing CAV speed to reduce CAVs' fuel consumption (27). The results obtained from the numerical experiment and simulation studies showed that the proposed method can improve the efficiency of transportation and vehicle fuel consumption in different traffic volumes. Tajalli et al. developed Distributed Optimization and Coordination Algorithms (DOCA) to find near-optimal solutions for CAVs speed optimization (28). The results indicated that travel time decreased by up to 14.8% and speed variation decreased by 9.7–13.4% across different demand patterns. In 2013, Nemeth et al. developed a cruise control system that utilizes predicted road and traffic information. The main contribution in this study was the incorporation of traffic light intersections in the speed design. In their design, an optimal speed trajectory was computed, considering factors such as longitudinal force, traveling time, and emissions. Simulation results confirmed that the controller reduces energy consumption near the actuators (29). In 2019, Seeber et al. addressed the issue of adhering to the prescribed speed tolerance while tracking the speed profile of an automotive test cycle for emission measurement. By applying an optimization-based iterative learning control scheme to the first third of the Worldwide Harmonized Light Vehicle Test Procedure (WLTP) test cycle, the study found a significant reduction in tolerance violations and pedal position changes (30).

In another study, Roy et al. proposed using traffic graphs to understand traffic behavior at intersections in developing countries with mixed traffic types and lane-less driving behavior. The study used a large dataset and showed that a spatio-temporal CNN-GRU network can identify congestion-prone behavior in different spatial regions of an intersection (31). Xu et al. presented a new speed control system for autonomous electric vehicles (AEVs) that combines deep reinforcement learning and robust control. The approach has a hierarchical architecture, with a deep maximum entropy proximal policy optimization algorithm used for decision-making and a linear matrix inequality controller used for motion control. Simulation experiments demonstrate the feasibility and effectiveness of the proposed approach, which shows an integrated performance with robustness to uncertainties and disturbances, driving smoothness, low fuel consumption, and good responsiveness (32). Veysi et al. proposed a stable fuzzy controller for an electric vehicle that ensures speed stabilization in the presence of disturbances and uncertainties. The controller is designed using the Takagi-Sugeno fuzzy model and parallel distributed compensation (PDC) fuzzy controller. Simulation results confirm the effectiveness of the proposed controller in stabilizing the EV speed with low computational load and power consumption (33). In the research conducted by Gamage et al. a Q-learning based vehicle speed control algorithm was proposed to minimize fuel consumption at an isolated signal intersection. The algorithm was trained and validated using a single-vehicle scenario under varying traffic signal and arrival speed conditions in the Aimsun microsimulation platform. Results show that the algorithm can reduce fuel consumption by 15.78% compared to a baseline scenario where speed control is disabled (34).

Wan et al. developed a Speed Advisory System (SAS) for connected vehicles to reduce fuel consumption. Their research found that implementing a fuel minimal driving strategy, alternating between acceleration, engine shut down, and constant speed, significantly improves fuel economy. SAS-equipped vehicles benefit themselves and other vehicles, with a slight compromise in traffic flow and travel time. The proposed suboptimal solution maintains drivability while increasing energy efficiency. SAS has the potential to harmonize traffic and decrease fuel consumption (*35*).

Studies have shown that traffic delays at signalized intersections on arterial roadways contribute to approximately 5%~10% of all traffic delays in the U.S., and the estimated cost of these delays is roughly $22.9 billion in urban areas (*36*). 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 (*37*, *38*). During the past decade, communications between vehicles (V2V) and between vehicles and infrastructure (V2I) provides additional data for researchers to develop control strategies to improve transportation system efficiency. These include eco-driving systems that optimize vehicle trajectories in the vicinity of signalized intersections, enhance mobility, and reduce vehicle fuel consumption and emissions. However, existing studies usually consider only one vehicle engine type to simplify roadway traffic conditions. There is a need to develop a general eco-driving strategy for mixed traffic flow by considering different vehicle powertrains.

In previous studies, an eco-driving system entitled Eco-CACC-I was developed for fuel-powered vehicles (*39–42*), and field tests were conducted to demonstrate that the system can efficiently reduce stop-and-go traffic and produce significant fuel and delay savings of 31% and 9%, respectively. Thereafter, the Eco-CACC-I algorithm was extended from ICEVs to BEVs (*40*) and HEVs (*43*). According to the findings of these studies, the optimal speed trajectories for vehicles with different engine types (e.g., gasoline versus electric vehicles) are very different under certain conditions. Therefore, it is necessary to develop a general speed control algorithm that calculates a solution that accommodates a mixed traffic with different vehicle engine types. In addition, one driving simulator study showed that a color display that prompts drivers to speed up or slowdown is a better design choice than directly providing a recommended speed to drivers (*5*). Therefore, it is necessary to consider this option when developing a speed control algorithm for mixed traffic flow to deliver simple driving instructions for drivers and compare it with the guidance speed.

This study aims to address these problems by developing a general eco-driving system that optimizes speed control for vehicles mixed with different engine types at signalized intersections. The proposed algorithm solely focuses on mixed traffic flow comprising ICEVs and BEVs to develop a general approach. Further testing of mixed traffic flow incorporating ICEVs, BEVs, and HEVs will be left to future research. The proposed vehicle controller has been implemented into the microscopic traffic simulation software (INTEGRATION) to validate the system-wide impacts of using the proposed system on traffic mobility and energy consumption under a mixed combination of vehicle types and various traffic conditions. A case study that models an arterial corridor with eight signalized intersections was used to investigate the performance of the proposed controller under various traffic demand levels. The test results demonstrate that the proposed controller for mixed flow traffic outperforms the vehicle speed controller for individual vehicle models and produces the most savings in fuel consumption, battery electric energy, and traffic delay. Lastly, the proposed algorithm is used to develop a speed guidance system providing two options of output: 1) recommended speed value, and 2) color-coded speed guidance. The developed speed guidance system is coded into a DLL file by the Delphi coding program and can be directly used in driving simulators to test the human responses to two options of driving guidance and the corresponding performances. This study utilizes an Eco Speed Guidance (ESG) system in a driving simulator to investigate its efficacy in optimizing speed control for vehicles with different engine types at signalized intersections. In the driving simulation phase, this study evaluates the effectiveness of color-coded speed recommendations provided to drivers when implementing ESG systems in vehicles. By utilizing a driving simulator, the research examines driver responses to the implementation of an in-vehicle ESG system that offers real-time speed guidance throughout the entire route. Specific objectives include assessing the percentage of drivers who adhere to the suggested speed guidance and those who successfully navigate intersections while the traffic signal is green, based on their reactions to the speed guidance system.

2 METHODOLOGY

This section first introduces the vehicle trajectory optimization algorithm for individual vehicle types, including ICEV and BEV. Thereafter, the optimal speed profiles for ICEV and BEV are analyzed and compared while considering the impacts of the speed limit and roadway grade. Based on the findings, a general vehicle speed controller is developed to optimize vehicle trajectory for a mixed flow including ICEVs and BEVs.

2.1 Vehicle Trajectory Optimization

In this study, vehicle trajectories are optimized using the Eco-Cooperative Adaptive Cruise Control at Intersections (Eco-CACC-I), connected eco-driving controller previously developed in (*39–42*) to assist vehicles traversing signalized intersections by computing real-time fuel consumption and the resulting energy-optimized speed profile. 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, headway distance, etc. (*44*). 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 of these constraints work together to control the vehicle's speed.

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 does not 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 (1) to maximize the average vehicle speed during the control region. When the vehicle enters the control region, it should adjust its speed to u_c by following the vehicle dynamics model developed in (*45*). 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.

$$u_c = min\left(\frac{d_{up}}{t_r}, u_f\right) \tag{1}$$

In case 2 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 entering the control region 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. The vehicle's energy-optimized speed profile is illustrated in Figure 1.

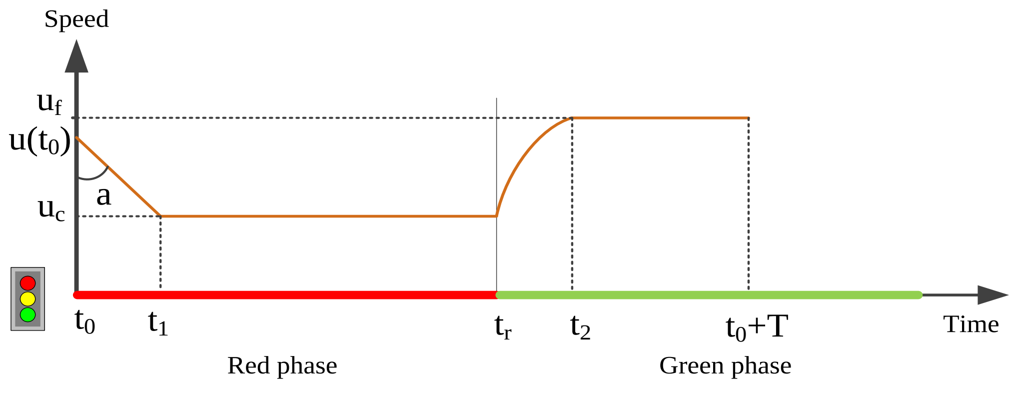


Figure 1: Vehicle optimum speed profile.

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

$$min \int_{t_0}^{t_0+T} EC\big(u(t)\big) \cdot dt \tag{2}$$

where *EC* denotes the energy consumption at instant *t*. The energy models for ICEV and BEV are presented in the next sections. The constraints to solve the optimization problem can be built according to the relationships between vehicle speed, location, and acceleration/deceleration as presented below:

$$u(t): \begin{cases} u(t) = u(t_0) - at & t_0 \le t \le t_1 \\ u(t) = u_c & t_1 < t \le t_r \\ u(t+\Delta t) = u(t) + \dfrac{F\big(f_p\big) - R\big(u(t)\big)}{m}\Delta t & t_r < t \le t_2 \\ u(t) = u_f & t_2 < t \le t_0 + T \end{cases} \tag{3}$$

$$\begin{gathered} u(t_0) \cdot t - \frac{1}{2}at^2 + u_c(t_r - t_1) = d_{up} \\ u_c = u(t_0) - a(t_1 - t_0) \\ \int_{t_r}^{t_2} u(t)\, dt + u_f(t_0 + T - t_2) = d_{down} \\ u(t_2) = u_f \\ a_{min} < a \le a_{max} \\ f_{min} \le f_p \le f_{max} \\ u_c > 0 \end{gathered} \tag{4}$$

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 resistance forces (aerodynamic, rolling, and grade resistance forces). Note that the maximum deceleration is limited by the comfortable threshold felt by average drivers (*44*). 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 (*44, 46*).

2.2 Energy Consumption Models for ICEVs

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 ICEVs (*47*). 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 shown below.

$$FC_{ICEV}(t) = \begin{cases} a_0 + a_1 P(t) + a_2 P(t)^2 & \forall\, P(t) \geq 0 \\ a_0 & \forall\, P(t) < 0 \end{cases} \tag{5}$$

$$P(t) = \left(ma(t) + \ mg \ \cdot \frac{C_r}{1000}(c_1 u(t) + c_2) + \frac{1}{2}\rho_{Air} A_f C_D u^2(t) + mg\,\theta \right) u(t) \tag{6}$$

where $FC_{ICEV}(t)$ is the fuel consumption rate for ICEVs; α_0, α_1 and α_2 are the model parameters that can be calibrated for a particular vehicle using publicly available vehicle specification information from the manufacturer, and the details of calibration steps can be found in (*48*); *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).

2.3 Energy Consumption Model for BEVs

The Comprehensive Power-based Electric Vehicle Energy Consumption Model (CPEM) developed by (*49*) is used in the Eco-CACC-I system to compute instantaneous energy consumption levels for BEVs. The 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 CPEM model is summarized by the following equations.

$$EC(t) = \int_0^t P_{Battery}(t) \cdot dt \tag{7}$$

$$P_{Battery}(t) = \left(P_{Wheels}(t) \cdot \frac{\eta_{rb}(t)}{\eta_D \cdot \eta_{EM}} + P_A \right) \cdot \frac{1}{\eta_B} \tag{8}$$

$$P_{Wheels}(t) = \big(ma(t) + R(t)\big) \cdot u(t) \tag{9}$$

$$\eta_{rb}(t) = \begin{cases} 1 & \forall\, P_{Wheels}(t) \geq 0 \\ \left[e^{\left(\frac{\lambda}{|a(t)|}\right)} \right]^{-1} & \forall\, P_{Wheels}(t) < 0 \end{cases} \tag{10}$$

Where EC represents the energy consumption from time 0 to t; $P_{Battery}$ is the power consumed by (regenerated to) 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 electric motor, respectively; η_D denotes the efficiency from battery to electric motor; η_{rb} represents the regenerative braking energy efficiency, which can be computed using Equation (10); and the parameter λ has been calibrated (λ = 0.0411) in (*49*) using the empirical data described in (*50*).

2.4 Optimal Vehicle Trajectory for ICEV and BEV

This section aims to compare the optimal vehicle trajectory for an ICEV and a BEV by considering the impacts of signal timing, speed limit and road grade. Different combinations of these variables may change the optimal solution of the speed control algorithm. The 2015 Nissan Leaf EV is selected for testing considering it is one of the most popular EVs available on the market. In order to compare the optimal solutions for BEV and ICE vehicles, an ICEV - 2015 Honda Fit is selected since it has a similar engine power and weight as the Nissan Leaf.

The test road consists of a single signalized intersection with a control length that starts 200 meters upstream and ends 200 meters downstream of the intersection (a total length of 400 meters). The automated connected vehicle equipped with the Eco-CACC-I system follows the optimal speed profile calculated by the Eco-CACC-I algorithm within the abovementioned 400-meter distance. The combinations of speed limit (25, 30, 40, 50 mph), green indication offset (15, 20, 25, 30 seconds), and road grade (uphill 3% and downhill -3%) are tested. The test results show that speed profiles with deceleration levels in the middle area (between the minimum and maximum values) are the optimal solution for the uphill roadway. Besides, the speed profiles associated with the maximum deceleration level are the optimal solution for the downhill roadway.

The same tests are conducted using a 2015 Nissan Leaf, a BEV which has a similar engine power and weight as the 2015 Honda Fit. The test results demonstrate that the speed profile associated with the maximum deceleration level is the optimal solution for the uphill direction. Besides, the speed profile associated with the minimum deceleration level is the optimal solution for the downhill direction.

2.5 Vehicle Trajectory Optimization for Mixed Flow

The differences in optimal vehicle trajectory between ICEVs and BEVs are related to their distinct vehicle maneuvers and deceleration levels. The resulting differences in speed can generate traffic shockwaves, leading to increased traffic and safety hazards. To overcome this issue, it is necessary to develop a method that reduces the differences in vehicle maneuvers between ICEVs and BEVs, resulting in a more uniform traffic flow. Here, we propose a new approach to finding the optimal vehicle trajectory by selecting the middle level of deceleration from all candidate levels that satisfy the constraints in Equations (2) and (3). As this approach does not rely on energy consumption models for specific vehicle engines, we use it for mixed flow traffic to produce similar vehicle maneuvers for ICEVs and BEVs by using the middle level of deceleration.

2.6 Case Study

In order to test the performance of the proposed control strategies, we implemented the vehicle speed controllers in microscopic traffic simulation software and assessed system level performance in an arterial corridor with three signalized intersections.

INTEGRATION was the software used 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. INTEGRATION moves vehicles along the network in accordance with embedded preset traffic assignment models and the Rakha-Pasumarthy-Adjerid (RPA) car-following model while considering traffic control devices and gap acceptance. A more detailed description of INTEGRATION is provided in the literature (*51*).

2.7 Simulation Setup

This test aims to compare the system-level network performances of the proposed controller for mixed flow traffic and the individual controllers for specific vehicle types (including ICEV and BEV). Figure 2 shows the layout of the arterial corridor with three signalized intersections. The distance between any two neighboring intersections is 500 meters. The traffic stream parameters are a free flow speed of 40 mph, a speed at a 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 75 minutes, the vehicles (OD pairs) are generated for the first 60 minutes and the last 15 minutes are used to clear out all vehicles moving inside the network. The cycle length for each signal is 60 seconds, and the offset value for each signal is set to zero. The traffic signal timings of through traffic in the main direction are 30 seconds, 3 seconds, and 27 seconds for green, yellow, and red, respectively. The entire arterial corridor is within the control region for vehicle trajectory optimization. Three levels of traffic demand volumes are considered in the test using the volume over capacity values of 0.1, 0.5, and 0.85, respectively. Here, we consider the same percentage of ICEVs (2018 Toyota Camry LE 2.5) and BEVs (2013 Nissan Leaf) in the mixed traffic flow. Three test scenarios are compared in the test. Scenario 1 is the base case without vehicle speed control. Vehicle speed control for an individual vehicle model is implemented for each vehicle in scenario 2. The proposed vehicle speed control for mixed flow is used in scenario 3.

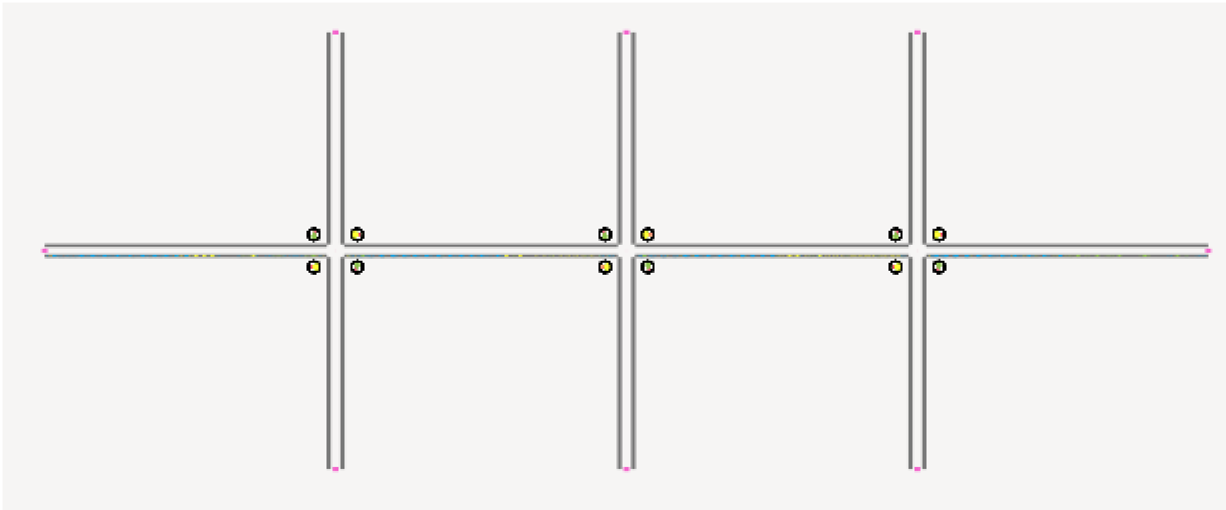


Figure 2: Test on an arterial corridor.

2.8 Test Results

The comparison plots of fuel, battery energy, traffic delay, and vehicle stops in three scenarios under three different levels of traffic conditions (uncongested, medium, and congested) are presented in Figures 3 through 6. Figure 3 and Figure 5 indicate that both controllers in S2 and S3 can effectively reduce fuel consumption and traffic delay under various traffic demand levels compared with the base case in S1. The maximum saving can be observed in uncongested traffic with a v/c value of 0.1. The controllers in S2 and S3 produce 7.3% and 9.2% fuel savings, with 8.9% and 8.1% reduction in traffic delay, respectively. Figure 4 and Figure 6 clearly demonstrate that both controllers in S2 and S3 can effectively reduce battery energy consumption and vehicle stops by an average of 30~40 percent under any traffic conditions compared with the base case in S1. Overall, the test results demonstrate the proposed vehicle trajectory optimization for mixed flow can effectively reduce fuel consumption, battery energy, traffic delay, and vehicle stops under various traffic demand levels when vehicles transverse arterial corridors with signalized intersections.

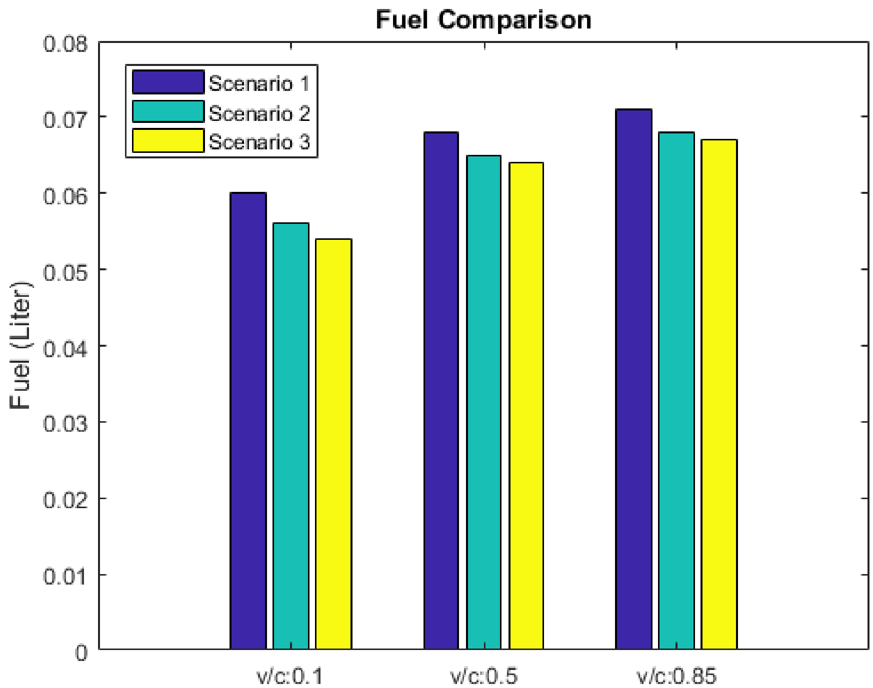


Figure 3: The comparison of fuel consumption by three scenarios under various traffic demand levels.

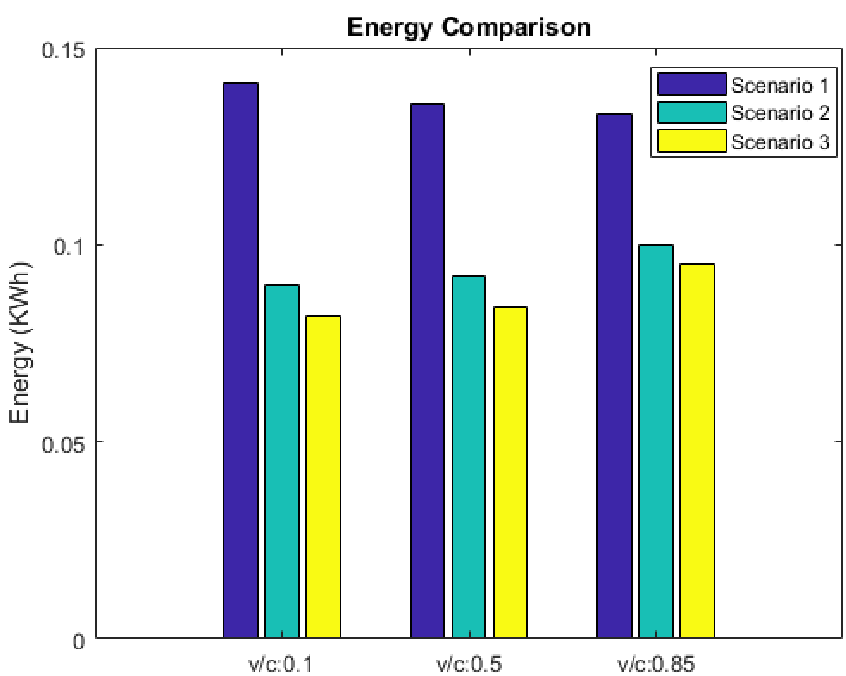


Figure 4: The comparison of battery energy consumption by three scenarios under various

traffic demand levels.

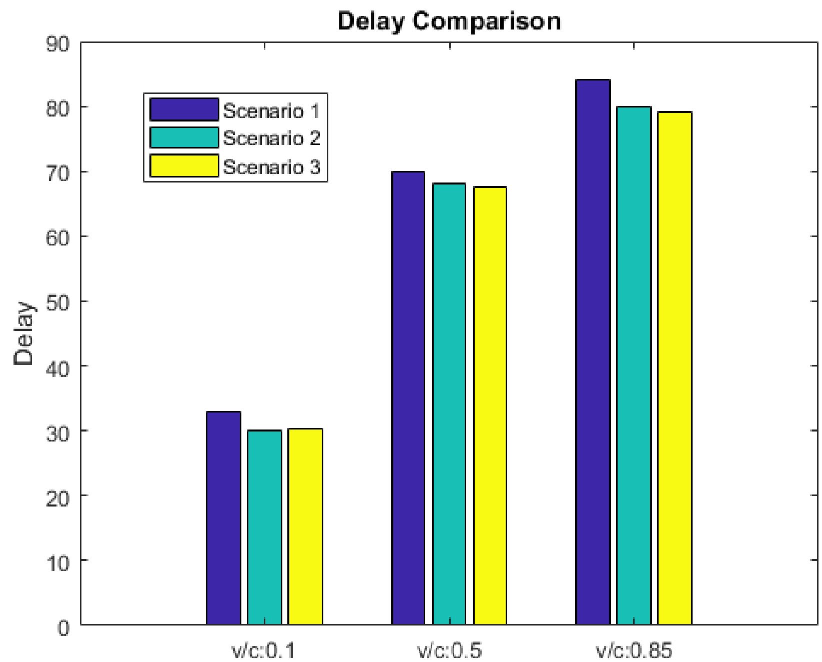


Figure 5: The comparison of traffic delay by three scenarios under various traffic demand levels.

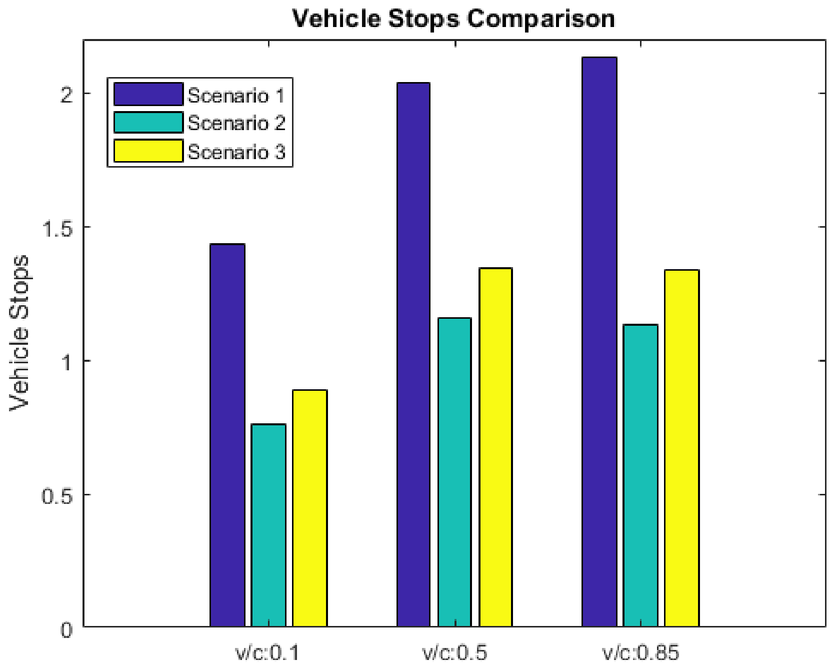


Figure 6: The comparison of vehicle-stop by three scenarios under various traffic demand levels.

2.9 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 using a driving simulator. The speed guidance system uses the vehicle trajectory optimization method developed in section 2.3 to compute the recommended speed and help drivers pass signalized intersections with reduced stop-and-go behaviors.

2.9.1 Setup Test Environment in Driving Simulator

Figure 7: Driving simulator.

This study implements the speed guidance system (using the Eco-CACC-I algorithm developed in section 2.3) 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 Eco-Speed-Guidance (ESG) system. 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, rear, right, and left views) (demonstrated in Figure 7). 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. The simulator system collects data related to the vehicle and driver'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 related data.

To investigate drivers' behavior, we designed a road segment consisting of eight signalized intersections and implemented four different scenarios to account for various weather conditions. Table 1 and Figure 8 provides an overview of these scenarios.

Scenario 1, referred to as the base scenario, served as the benchmark in that no specific information was provided to participants. It allowed us to assess their driving behavior in the presence of the eight signalized intersections without any speed guidance. Scenarios 2-4 included recommended speeds for various weather scenarios: sunny weather, rainy weather, and nighttime driving, respectively. These recommended speeds aimed to enable participants to pass through the signalized intersections smoothly without the need to come to a complete stop, provided they followed the Recommended Speed.

Table 1: Simulated Scenarios' Description

Scenario	**Visibility**	**Num of Lanes**	**Grade**	**Num of Intersections**
Scenario1-Base Scenario	Sunny weather	1 Lane	0	8
Scenario 2-ESG	Sunny weather	1 Lane	0	8
Scenario 3-ESG	Rainy weather	1 Lane	0	8
Scenario 4-ESG	Nighttime	1 Lane	0	8

To isolate the effects of the ESG system and evaluate its impact on driver compliance behavior, the road segment consisted of only one lane in each direction. This configuration allowed us to analyze the direct influence of the ESG system on driver behavior without other factors affecting the results. By developing these distinct scenarios and examining participants' responses within each weather condition, we aimed to gain insights into the influence of the ESG system on driver behavior and compliance at signalized intersections.

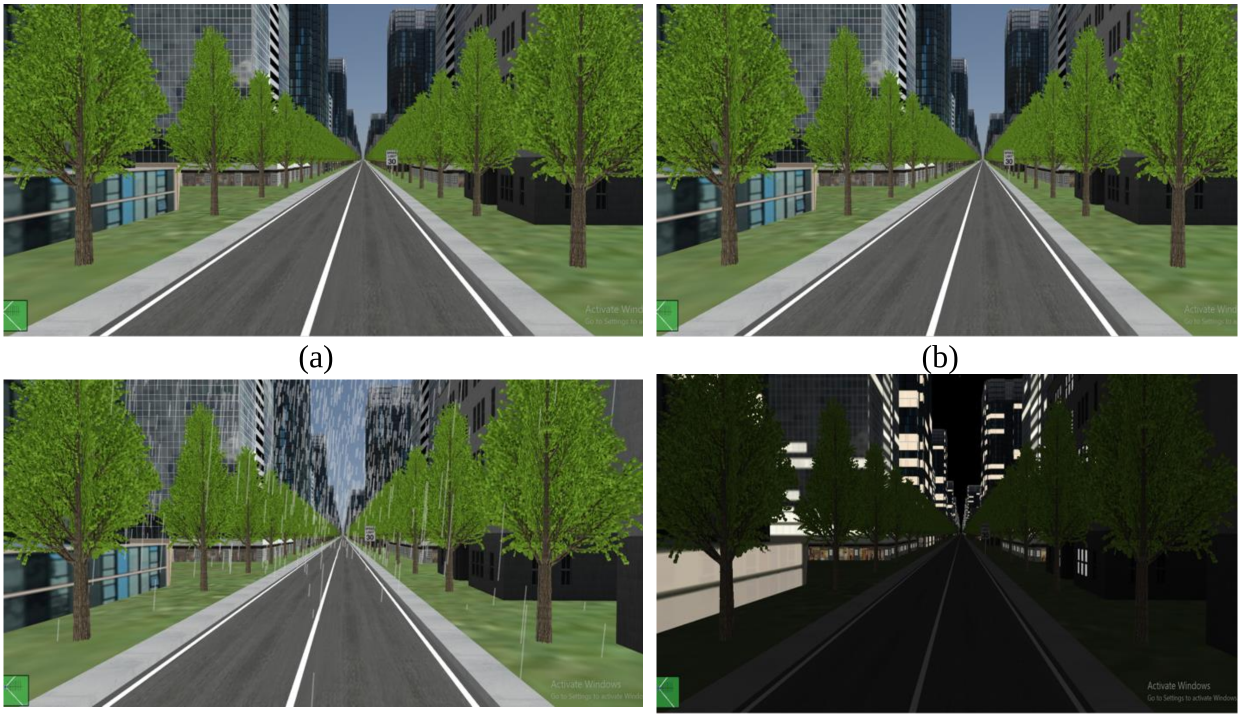


Figure 8: Snapshot of Scenarios; a)Scenario 1 (Without ESG – Sunny Weather), b)Scenario 2 (With ESG - Sunny Weather), c)Scenario 3 (With ESG - Rainy Weather), d)Scenario 4 (With ESG – Night Vision).

2.9.2 Develop Speed Guidance System in Driving Simulator

To test the performance of the speed guidance system in a corridor with multiple traffic signals, an arterial corridor with eight signalized intersections is simulated in the driving simulator environment. The distances between two neighboring intersections from left to right are 400, 300, 500, 400, 300, 500, 400 meters. This arterial corridor is also simulated and tested using the microscopic simulation software, INTEGRATION, to validate the performance of the speed controller for ICEVs and BEVs. In the simulation test, the traffic stream parameters are a free-flow speed of 40 mph, a speed at a 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 75 minutes, the vehicles (OD pairs) are generated for the first 60 minutes and the last 15 minutes are used to clear out all vehicles moving inside of the network. The cycle length and phase splits of all intersections are 60 seconds and 50%, respectively, and the offsets of all signals are set as 0. The overall energy reductions for ICEVs and BEVs are about 3~10% and 10~30% respectively in the arterial network under various traffic demand levels. The test results from simulation software can be compared with the test results from driving simulator later.

The proposed vehicle trajectory optimization for mixed flow in section 2.1 is used to develop a speed guidance system in the driving simulator environment. An EcoDrive DLL file generates a speed guidance system using the Delphi programming language. In the driving simulator test, the test vehicle is connected to the speed guidance system through the DLL file. The vehicle's speed, location, signal phase, and timing are transferred into the DLL file in real-time to compute the speed guidance. Two types of speed guidance options are designed for algorithm: 1) recommended speed value; and 2) color-coded speed guidance ("1" speed up, "-1" speed down, "0" maintain current speed). In the driving simulation test, color-coded speed guidance was considered.

The participants began driving in the base scenario, which served as a point of comparison for their driving behavior in relation to the other scenarios. Subsequently, participants experienced various scenarios with ESG provided throughout the entire network, including all eight intersections. In each scenario, participants received "Speed Guidance" through a color code system. In the Speed Guidance scenarios, a "Green Arrow" indicated the need to accelerate, while a "Red Arrow" signaled the need to decelerate (Figure 9). Participants were instructed to drive at a constant speed limit of 30 mph and adjust their speed according to the information provided via ESG to pass through the signalized intersections without stopping. The objective of the study was to assess the 'participants' ability to follow the ESG.

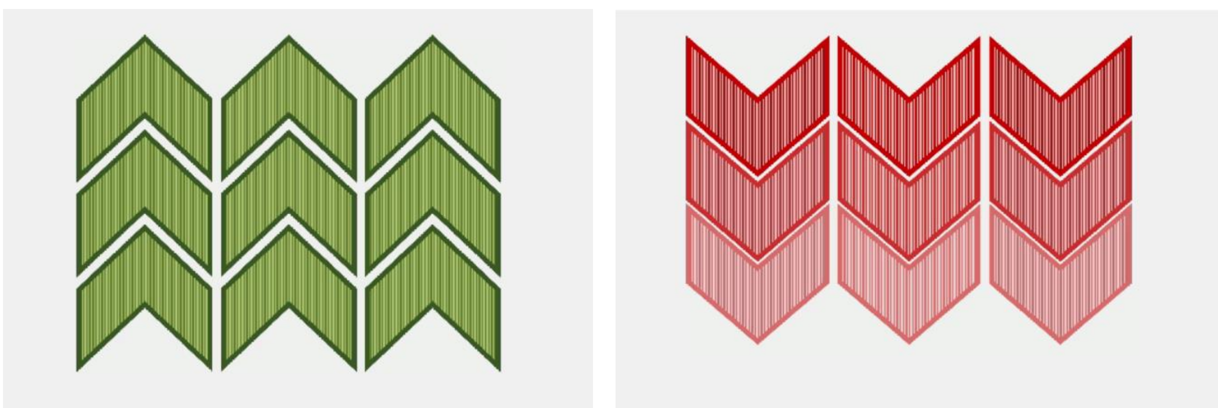


Figure 9: Color code type of eco speed guidance

Before conducting the study, we obtained approval from the Institutional Review Board (IRB) to ensure compliance with ethical guidelines. To recruit participants, we employed various methods, including distributing flyers within the Morgan State University (MSU) campus and sending email invitations. A total of 15 participants from MSU were recruited for the driving experiments. The email and flyer's invitations provided detailed information about the study, including the study requirements, contact information, and an explanation of the monetary compensation offered for participating in the simulator-based driving experiments. Prospective participants underwent a screening process to assess their eligibility, and those who met the criteria were scheduled for the simulator sessions. To be eligible for participation, individuals were required to possess a valid driver's license. Participants received compensation of $10 per hour for their involvement in the study, reflecting their time spent driving in the simulator environment.

In the driving simulator, a speed limit of 30 mph was implemented for all participants. They were instructed to maintain a speed of 30 mph and adjust their speed in response to the ESG provided in Scenarios 2-4, aiming to pass through the signalized intersections without coming to a stop. The primary objective of the study was to assess participants' ability to follow the ESG rather than their willingness to do so. Before starting the driving experiments, participants were informed about the importance of following the ESG during the investigation to successfully navigate the intersections without stopping. However, there was no mandatory instruction compelling them to strictly follow the guidance. While some participants were able to promptly follow the provided ESG, others required more time to adjust their speed and align with the speed guidance. All participants completed each of the four scenarios outlined in Table 1, which included scenarios without any information (Base) and with ESG in a random order to eliminate the learning effect.

To gather additional information, participants were asked to complete two survey questionnaires: a pre-driving survey and a post-driving survey. The pre-driving survey collected demographic information such as age, gender, ethnicity or race, employment status, educational status, income level, household size (Table 2), and familiarity with "Eco Speed Guidance/Eco Driving Guidance" (Figure 10). Participants completed the pre-driving survey before engaging in the driving simulator experience. Following the driving experiment, the post-driving survey was administered to gather feedback on their driving experience in the different scenarios (Figure 11).

Table 2: Participants' Sociodemographic Characteristics

Variable	**Categories**	**Frequency**	**Percent**
Gender	Female	7	46.7
	Male	8	53.3
Age	18-25	4	26.7
	26-35	4	26.7
	36-45	5	33.3
	46-55	2	13.3
Educational Status	Undergraduate	4	26.7
	Graduate	7	46.7
	Postgraduate	4	26.7
Work Status	Part-time	4	26.7
	Full-time	11	73.3
Income	Less than $20 k	1	6.7
	$20k-$30k	4	26.7
	$30k-$50k	0	0
	$50k-$75k	4	26.7
	$75k-$100k	3	20
	More than $100k	3	20
Household size	only me	5	33.3
	2	4	26.7

	3	3	20
	4 or more	3	20
Race or Ethnicity	African American	5	33.3
	White	9	60
	Asian	1	6.7

Descriptive statistics were gathered from the data obtained through the Pre-Driving Survey questionnaire, which provided insights into the characteristics of the fifteen participants who participated in the driving experience. Among the participants, 53.3% were male, and 46.7% were female. The age range of the participants spanned from 18 to 55 years old, with 33.3% falling within the age group of 36 to 45 years (Table 2).

3 ANALYSIS AND RESULTS

3.1 Compliance Rate

Many studies use statistical analysis to develop policies to improve traffic safety, investigate and forecast travel behavior, and pinpoint deficiencies in transportation policy (*52–56*). A statistical analysis was conducted to evaluate the percentage of drivers who successfully **passed** intersections based on **following** the ESG, as well as to assess the effectiveness of the ESG under different weather conditions affecting visibility. This suggests a preference for **following** the ESG when visibility is reduced during nighttime conditions, highlighting the effectiveness of the ESG in such circumstances. To take into consideration the inherent challenge of **following** the ESG accurately, the authors defined compliance as a participant's speed being within 5 mph of the recommended speed (i.e., recommended speed +/- 5 mph). If participants pass more than seven intersections based on their adherence to the ESG, we consider that they have successfully passed the intersections for the purpose of this analysis. The criterion for **passing** intersections in this study is defined as successfully **passing** at least seven out of the eight intersections by **following** the ESG without stopping at red lights.

Table 3 presents the outcomes of an experiment examining the impact of ESG on participants' behavior while passing through intersections under different weather conditions. In Scenario 1 (Without ESG - Sunny Weather) the result shows none of the participants were able to **pass** more than seven intersections. For this scenario the average number of intersections successfully **passed** by all participants was only 4.9%. Additionally, in Scenario 2 (With ESG – Sunny Weather), a high percentage (73%) of participants **followed** the guidance, leading to 73% of them successfully **passing** more than seven intersections. The average number of intersections **passed** by all participants significantly increased to 6.9%, showcasing the substantial improvement achieved with the implementation of ESG. Moreover, in Scenario 3 (With ESG – Rainy Weather), a similar percentage (73%) **followed** the guidance. However, the success rate in **passing** more than seven intersections slightly decreased to 60% compared to the sunny weather scenario. For this scenario the average number of intersections **passed** by all participants was 6.8%. In Scenario 4 (With ESG – Night Vision) the result shows an even higher percentage (80%) of participants **followed** the guidance. However, the success rate in **passing** more than seven intersections dropped to 40%, representing the lowest success rate among the presented scenarios. The average number of intersections **passed** by all participants in this scenario was 6.3%. Overall, the highest average number of **passing** intersections was observed in Scenario 2 (With ESG - Sunny Weather), showcasing the effectiveness of ESG in enhancing intersection navigation. Conversely, Scenario 1 (Without ESG - Sunny Weather) demonstrated the lowest average success rate, underscoring the significance of ESG in promoting safer and more efficient traffic flow.

Table 3: Percentage of All Participants Who Follow ESG and Passed Intersections

Scenario	**Follow ESG**	**Passing >= 7 Intersections**	**Avg Passing**
Scenario 1 (Without ESG – Sunny Weather)	Without ESG	0%	4.9
Scenario 2 (With ESG – Sunny Weather)	73%	73%	6.9
Scenario 3 (With ESG– Rainy Weather)	73%	60%	6.8
Scenario 4 (With ESG – Night Vision)	80%	40%	6.3

3.2 ANOVA

3.2.1 Following Eco Speed Guidance and Passing Intersections Analysis

An analysis of variance (ANOVA) was used to determine the proportion of drivers who **follow** the ESG and **passed** intersections based on different scenarios. Table 4 presents the findings of a study evaluating participants' adherence to ESG in three different scenarios. In the "**Following Percentage**" column, the "**Rate**" column shows the percentage of participants **following** ESG across scenarios for each category. In Scenario 2 (With ESG - Sunny Weather) and Scenario 3 (With ESG - Rainy Weather), younger participants aged 18-35 demonstrated a higher **following** rate to ESG compared to those above 36. However, in Scenario 4 (With ESG - Night), participants aged 26-45 displayed a higher **following** rate of ESG among other age groups. Consistently across all three scenarios, male participants and participants with a graduate education level demonstrated higher **following** rate compared to others.

In the "**Passing Intersection Percentage**" column, the "**Rate**" column shows the percentage of participants who **passed** more than seven intersections across scenarios for each category. In Scenario 2 (With ESG - Sunny Weather) and Scenario 3 (With ESG - Rainy Weather), younger participants aged 18-35 and participants with graduate level demonstrated higher **passing** rate compared to others. However, in Scenario 4 (With ESG - Night), participants aged 36-45 displayed a higher **passing** rate among other age groups. In all education subcategories, participants showed similar performance of **passing** rate within each category. Consistently across all three scenarios, female participants demonstrated higher **passing** rate compared to others. The

ANOVA results show there is no significancy different between **passing** intersection and **following** ESG among different scenarios.

Table 4: ANOVA Results for Following ESG and Passing Intersection

Scenario Name	**Variable**	**Category**	**Following ESG**			**Passing Intersection**		
			Percent	**F**	**Sig.**	**Percent**	**F**	**Sig.**
Scenario 2 (With ESG – Sunny Weather)	**Age**	**18-25**	36%	0.11	0.89	27%	1.75	0.19
		26-35	36%			27%		
		36-45	18%			18%		
		46-55	9%			18%		
	Gender	**Male**	55%			45%		
		Female	45%			55%		
	Education	**Undergrad**	36%			27%		
		Graduate	55%			55%		
		Postgraduate	9%			18%		
Scenario 3 (With ESG – Rainy Weather)	**Age**	**18-25**	36%			33%		
		26-35	36%			33%		
		36-45	18%			22%		
		46-55	9%			11%		
	Gender	**Male**	55%			33%		
		Female	45%			67%		
	Education	**Undergrad**	36%			33%		
		Graduate	55%			44%		
		Postgraduate	9%			22%		
Scenario 4 (With ESG – Night Vision)	**Age**	**18-25**	25%			33%		
		26-35	33%			0		
		36-45	33%			50%		
		46-55	8%			17%		
	Gender	**Male**	58%			33%		
		Female	42%			67%		
	Education	**Undergrad**	25%			33%		
		Graduate	50%			33%		
		Postgraduate	25%			33%		

3.3 Regression Analysis

3.3.1 Following ESG and Passing Intersections for All Three Scenarios

To identify the relationship between the ESG **following** percentage and **passing** intersection as a dependent variable and the sociodemographic of participants as independent variables, binary logistic regression analyses were performed on dataset. As shown in Table 5, the regression results for the **following** ESG and **passing** intersections as dependent variables with age, gender, and education as independent variables in all three scenarios, are as follows:

Table 5: Regression Results for Following ESG and Passing Intersections

Scenario	**Variable**	**Coefficient**	**Standard Error**	**Sig.**
Following ESG	**age**	-3.1254	1.475	0.034
	gender	2.2261	1.396	0.111
	education	-4.6858	1.804	0.009
Passing Intersections	**age**	0.5187	0.574	0.366
	gender	-1.6142	0.755	0.033
	education	0.2010	0.803	0.802

According to Table 5, there is a negative relationship between age and the **following** of ESG; younger drivers tend to **follow** ESG more than older drivers. Furthermore, there is a negative relationship between education and **following** ESG; drivers with an undergraduate degree are more likely to **follow** ESG. It is important to note that the statistical significance of the coefficients is determined by the p-values. A p-value that is less than the critical value (0.05) indicates a statistically significant effect. In this case, age and education have statistically significant effects on the likelihood of **following** the recommended speed. Moreover, binary logistic regression analysis was performed on the combined data to determine the relationship between the proportion of participants who pass at least seven intersections while the traffic light is green and the 'participants' sociodemographic characteristics as independent variables. According to the findings presented in Table 5, there is a negative relationship between gender and the likelihood of **passing** at least seven intersections while the traffic signal is green. Female drivers are more likely to surpass this threshold compared to male drivers.

3.4 Survey Analysis

3.4.1 Pre-Survey

In the pre-survey, the result of the question "Are you familiar with 'Speed-Control Guidance/Eco Driving Guidance?" provides insight into participants' familiarity and knowledge about speed-control guidance or eco-driving guidance. The graph shows the distribution of responses among the participants:

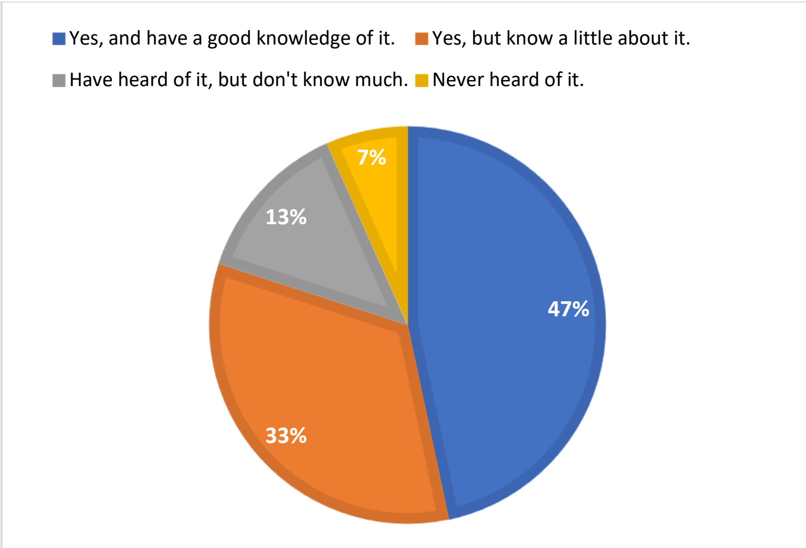
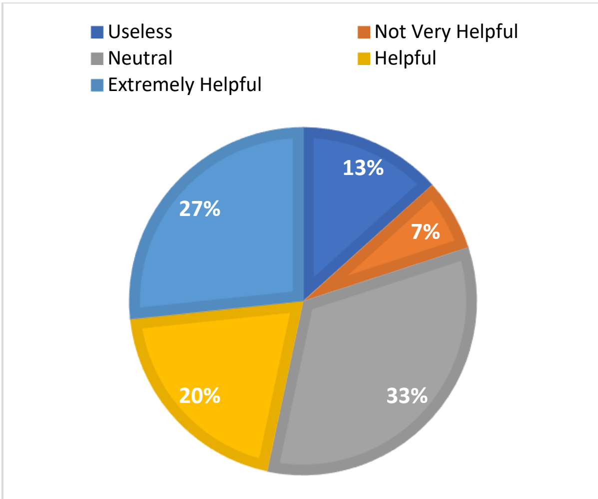


Figure 10: Familiarity rate of Speed Control Guidance/ECO Driving Guidance

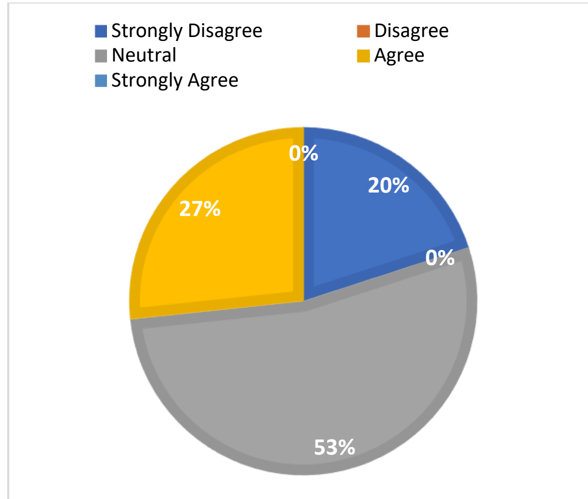
Figure 10 indicated that 47% of the participants responded "Yes" and showed that they have a good knowledge of speed-control guidance/eco-driving guidance. Moreover, 33% of the participants responded "Yes" and mentioned that they know only a little about speed-control guidance/eco-driving guidance. Additionally, 13% of the participants responded that they have heard about speed-control guidance/eco-driving guidance but do not know much about it. On the other hand, 7% of the participants stated that they had never heard of speed-control guidance/eco-driving guidance.

3.4.2 Post Survey

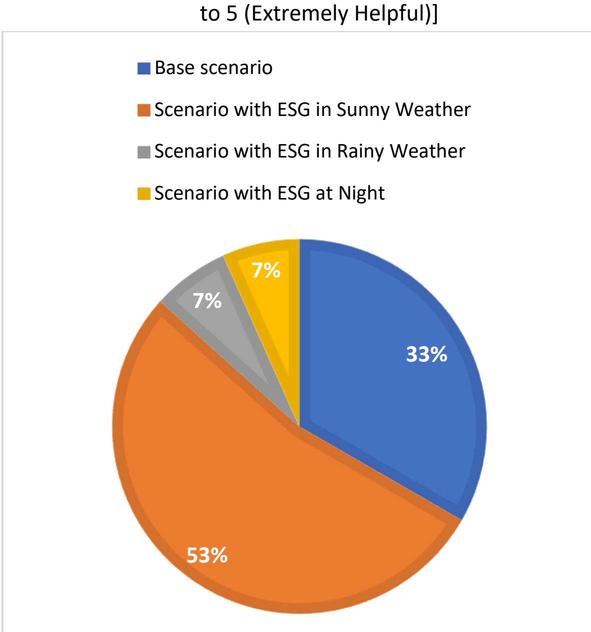
The following figures show the descriptive analysis of post-driving surveys. Figure 11 (a) shows participants' perceptions and opinions regarding the usefulness of ESG. The results reveal that 13% of participants found it useless, 7% expressed it as unhelpful, and approximately 33% had a neutral stance. In comparison, 20% of participants found the ESG to be helpful, while 27% found it extremely helpful. Figure 11 (b) shows the easiness of **following** the ESG, and that 20% of participants strongly disagreed, indicating that they found it challenging or even impossible to **follow** the speed guidance. Interestingly, no participants disagreed or strongly agreed, suggesting a lack of consensus on the matter. Approximately 53% of participants expressed a neutral stance, while 27% of participants agreed that it was easy to **follow** the speed guidance. This subset of participants found it manageable to comply with the speed guidance.



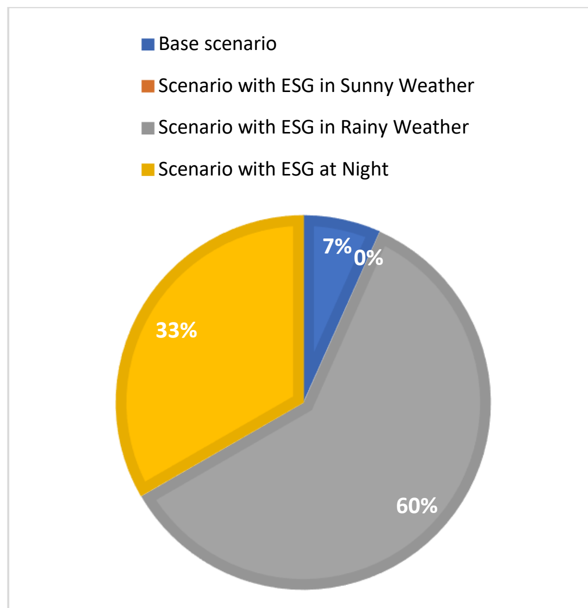
a) Rate the usefulness of the speed information you were provided? [On a scale of 1 (Useless) to 5 (Extremely Helpful)]



b) It was easy to follow the speed guidance. [On a scale of 1 (Strongly Disagree) to 5 (StronglyAgree)



c) Which scenario do you prefer the best?



a) Driving in which scenario was more challenging for you?

Figure 11: a) Usefulness of ESG b) Easiness of following ESG c) Preference of Type of Scenarios d) Comparison of Perceived Driving Challenge Between Scenarios

Figure 11 (c) displays the preferences of participants regarding the four different scenarios. Among the participants, 33% preferred scenario with no information provided, which represents the base scenario without any ESG for its autonomy and control. A majority of 53% of participants expressed a preference for scenario with ESG in sunny weather. The guidance system provided benefits such as maintaining a consistent speed and reducing the need for manual speed adjustments. A smaller percentage of participants, 7% each, preferred scenario with ESG in rainy weather and scenario with ESG at night. This indicates that some participants found the presence of ESG beneficial even in challenging weather conditions or during nighttime driving. Figure 11 (d) indicates that only 7% of participants found scenario with no information provided most challenging, indicating driving without ESG in sunny weather was more challenging for a small portion of the participants. None of the participants selected scenario with ESG in sunny weather as the most challenging, suggesting ESG in sunny weather made the driving experience less challenging. In contrast, a significant majority of participants, 60%, reported that scenario with ESG in rainy weather was the most challenging. This suggests that driving with ESG in rainy weather posed a higher level of difficulty for most of the participants. Additionally, 33% of participants found scenario with ESG at night, involving ESG during nighttime driving, to be the most challenging. These findings demonstrate that rainy weather conditions and nighttime driving presented notable challenges for a considerable number of participants. On the other hand, ESG in sunny weather alleviates perceived challenges.

Taken together, the findings obtained from Figure 11 (c) and Figure 11 (d) highlight the significant influence of weather conditions, particularly visibility, on participants' preferences and perceived challenges in driving scenarios. Sunny weather with good visibility, combined with ESG, was generally preferred, and mitigated perceived difficulties. On the other hand, rainy weather, and nighttime driving, characterized by reduced visibility, posed challenges that even the presence of guidance systems could not fully overcome.

4 DISCUSSION

Previous studies have extensively investigated methods for optimizing speed control to mitigate emissions, categorizing them based on emission reduction effects, speed control in mixed traffic, eco-driving implementation, and the relationship to CAVs. In line with previous findings, our study indicated that male participants exhibit a greater tendency to **follow** ESG, while older drivers face challenges.

In this study, we focused on the effectiveness of ESG and participants' tendency to **follow** ESG and **pass** more than seven intersections while the traffic signal was green. The ANOVA and regression analysis were performed to evaluate driver's behavior in different scenarios. It can be inferred from our study that sociodemographic factors contribute to the effectiveness of ESG. The results indicate that female drivers exhibit lower compliance with speed guidance compared to male drivers. Surprisingly, despite their lower compliance, female drivers outperform male drivers in **passing** more than seven intersections. Furthermore, older drivers face challenges in **following** the ESG, highlighting the need for improved methods of disseminating information to facilitate better adherence among this demographic. Conversely, participants with a graduate degree exhibit superior performance in both **following** speed guidance and **passing** intersections, underscoring the positive influence of higher education on driving behavior. These findings shed light on the unique characteristics and challenges faced by different driver groups, emphasizing the importance of considering individual differences in road safety and traffic management strategies. Upon analyzing the survey's responses, it was revealed that approximately 47% of participants expressed the usefulness of a speed advisory, while a similar percentage stated that **following** the recommended speed was an easy task for them. These insights shed light on the perceptions and experiences of participants regarding the ESG's speed-related features.

The contribution of this study is as follows: Firstly, this study utilizes statistical analysis to identify potential relationships between different scenarios. Secondly, it examines the relationships between visibility, tendency to follow ESG, and success in passing more than seven intersections.

5 SUMMARY AND CONCLUSION

Previous studies have shown that the optimal speed trajectories for vehicles with different engine types (e.g., gasoline versus electric vehicles) are very different under certain conditions. This study aimed to address these problems by developing a general eco-driving system that optimizes speed control for vehicles with different engine types at signalized intersections. The proposed algorithm solely focuses on mixed traffic flows comprised of ICEVs and BEVs to develop a general approach. The proposed vehicle controller was implemented into microscopic traffic simulation software (INTEGRATION) to validate the system-wide impacts of using the proposed system on traffic mobility and energy consumption under a mixed combination of vehicle types and various traffic conditions. A case study that models an arterial corridor with three signalized intersections was used to investigate the performance of the proposed controller under various traffic demand levels. The test results demonstrate that the proposed controller for mixed flow traffic outperforms the vehicle speed controller for individual vehicle models and produces the most savings in fuel consumption, battery electric energy, and traffic delay. Lastly, the proposed algorithm is used to develop a speed guidance system providing two options of output: 1) recommended speed value, and 2) color-coded speed guidance. The developed speed guidance system is coded into a DLL file by the Delphi coding program and can be directly used in driving simulators to test human responses to two options of driving guidance and the corresponding performances. This study utilized a full-scale driving simulator to assess drivers' performance to **follow** and comply with ESG in different weather and visibility conditions. This study investigated the impact of ESG on successfully **passing** at least seven out of eight intersections without needing to stop at red signal. The primary achievement of this study was determining the effectiveness of ESG for multiple intersections, which remained activated from the beginning of the road until the completion of the scenario. A sample of 15 participants took part in driving simulator experiments in different scenarios. To evaluate drivers' performance to **follow** ESG, four scenarios were designed with different visibility.

The results of the scenario with ESG that takes place under sunny weather conditions with good visibility indicate that male drivers tended to **follow** the ESG more than female drivers but had lower success in **passing** seven intersections. Furthermore, the study reveals that younger participants showed better adherence to **follow** speed recommendations. Additionally, graduates and full-time participants exhibit a higher tendency to **follow** speed guidance and demonstrate a higher success rate in **passing** at least seven intersections. Notably, participants with an income range between $20,000 and $30,000 display a higher propensity to **follow** ESG, and those with an income range between $20,000 to $75,000 achieve a higher success rate in **passing** more than seven intersections. The results of the scenario with ESG that was designed for rainy weather conditions with low visibility show that the probability of **following** ESG is higher in male drivers than female drivers but has lower success in **passing** more than seven intersections without stopping behind the intersections. The younger age group, people with a graduate degree, and participants with full-time jobs performed better. Participants with a lower income were successful in **following** ESG. Consequently, lower-income participants and those with an income ranging between $75,000 to $100,000 passed more than seven intersections based on the decision to **follow** ESG. The results of the nighttime vision scenario with low visibility indicated that male drivers **followed** ESG better than female drivers but had a lower success rate in **passing** more than seven intersections. The results also showed that middle-aged groups performed better to **follow** the ESG, and only 36-to-45-year-old participants can better pass more than seven intersections. Individuals with full-time jobs and graduates level complied with speed guidance and could better pass intersections while the traffic signal was green. Additionally, participants with an income range between $20,000 to $75,000 were more successful in **following** the ESG. On the other hand, those with all income ranges, excluding $50,000 to $75,000, can pass seven intersections without stopping at the intersection. Overall, the presence of ESG has a positive impact on participants' behavior, leading to a higher percentage of them **passing** more than seven intersections. However, the effectiveness of ESG may vary depending on weather conditions, with higher success rates observed in sunny and rainy weather compared to night conditions. Although the developed approach should be compatible with HEVs, further testing of mixed traffic flow incorporating ICEVs, BEVs, and HEVs will be considered in future research. We will also consider expanding the simulation test to include a large-scale traffic network and validate system-level performances under different combinations of mixed flow traffic, various traffic demand levels, and different rates of the market penetration of controlled vehicles.

One limitation observed in this study which is common to all driving simulator studies is that the simulator experience differs from real-world driving. To improve the reliability of conclusions concerning the effectiveness of the ESG, it is advised to implement color-coded speed recommendations in real-world driving scenarios.

Additionally, this study focused solely on straight roads, neglecting scenarios involving right or left turns. To draw more comprehensive conclusions regarding the effectiveness of the color-code ESG design, future research should encompass various scenarios with both right and left turns at intersections. This will enable a more accurate assessment of driver behavior under different turning conditions, providing a more robust evaluation of the color-code ESG design's efficacy. Furthermore, one limitation of the current simulator used in this study is the absence of actuated traffic lights. As potential research for future studies, incorporating actuated traffic lights into the simulator could address this limitation and enhance the simulation's realism and applicability.

Authors Year	Goal	Data	Methodology	Results
Demir et al.(*1*) (2014)	• Review on green road freight transportation	59 papers	• Literature Review • Descriptive Statistics	• Most studies focused on vehicle load and speed • Showed an importance of travel at a speed that helps to reduce fuel consumption
Wang et al. (*2*) (2019)	• optimize traffic signal according to the real-time traffic flow • All CVs form a platoon to maintain the best space and run at the recommended speed	The proposed model tested on simulations of road network imitating the real world.	• Join Control Model • To evaluate the performance of the proposed model, VISSIM/MATLAB simulation used • To verify the feasibility of the model, classical MAXBAND model selected	• The proposed model reduced the stop time and stops of coordinate phase by up to 53.69% and 41.15%. The signal delays at the intersection for each vehicle reduced by 13.19%. • The CV passed the intersection with no stops.
Conlon et al.(*3*) (2019)	• Find Greenhouse Gas Emission Impact of Autonomous Vehicle Introduction in an Urban Network	Used the Chicago downtown network and CMAP's regional origin-destination trip table as the baseline	• An integrated traffic microsimulation and emission model	• AVs show potential to reduce total CO2 emissions at a network scale, approaching 4% reduction at full autonomy
Lu et al.(*4*) (2019)	• A speed control system at successive signalized intersections under connected vehicles environment is proposed for reducing fuel consumption and CO2 emissions.	A real-time simulation framework result	• Use a kinematic wave model • Choose different signal timing plan to examine the effectiveness of our speed control algorithm.	• The proposed speed control method could reduce fuel consumption by more than 18% and travel time by 9% in medium density traffic flow—the most effective in the study.
Ahangari et al.(*5*) (2019)	• Using a driving simulator to investigate drivers' response and compliance to Eco-speed control systems in the vicinity of a signalized intersection and the effectiveness of such a system in reducing emissions.	58 participants	• Descriptive and statistical analyses including Generalized Linear Models (GLM) and t-tests	• Men and younger drivers are more likely to follow the recommended speed. • The emissions calculations indicate that an Eco-speed control system decreases the emissions level 9.1% more than countdown timing systems do

				• The emissions level is lower in the countdown timing system compared to conventional traffic signals.
Gamage et al.(*6*) (2016)	• To presents a novel eco-speed control algorithm to assist fuel-efficient driving at signalized intersections. The proposed algorithm employs Q-learning, a self-learning intelligent agent to optimize the driving speed to minimise the resulting fuel consumption.	----	• AIMSUN microscopic simulation.	• The eco-speed control algorithm demonstrates that the fuel consumption can be reduced up to 18% and a significant reduction in the vehicle idling time as well.
Chen et al.(*7*) (2019)	• To propose an adaptive speed controller for the electromagnetic direct drive vehicle robot driver to achieve the accurate tracking of desired speed.	Experiments are conducted using a Ford FOCUS car.	• Experimental result	• The proposed control method can accurately track the target speed and adhere to changes in speed caused by interferences under different test conditions. It also has small mileage deviation
Xu et al. (*8*) (2019)	• To improve fuel economy, a double-layer speed optimization method with real-time computation that considers traffic signal information collected via vehicle-to-infrastructure communication and traffic conditions was proposed	Conduct numerous field tests using a test bed and an experimental vehicle platform.	• In the first layer, a Dijkstra algorithm is used to optimize the average ecospeed between adjacent intersections with full-horizon traffic signal information. In the second layer, an optimal control method to plan a real-time speed profile with average speed constraints was used	• By computing optimal solutions in real time, the proposed double-layer speed optimization method has the potential to improve fuel economy and decrease trip time.
Lim et al.(*9*) (2017)	• To propose a distance-based eco-driving method using a two-stage hierarchy for long-term optimization with local adaptation	Simulation test	• Quadratic programming method	• The QP method is applied to simplify the time intervals of each distance step and cost function.

Nasri et al.(*10*) (2018)	• To reduce the cost of emissions, fuel consumption and travel time among of Autonomous trucks (Ats) by optimizing the routes and the speeds	Computational experiment	• Compare the two linear models: the discrete speed and discrete recourse model, and the discrete speed and continuous recourse model.	• The discretized recourse model, yielding an average cost reduction of 4.95%. • The continuous recourse model yielded average cost savings of 7.48%.
Chen et al.(*11*) (2019)	• To propose a strategy that simultaneously finds the optimal driving speed with the energy source power split for the drive mission specified in terms of the road geometry and travel time.	Simulation test	• An indirect optimal control method Comparative results	• It simultaneously solves the optimal speed profile and the power split in terms of fuel efficiency • Increase the performance of battery durability for a hybrid vehicle
Khooban et.al(*12*) (2019)	• To proposes a new fuzzy Proportional Derivative + Integral (PD+I) controller based on a non-integer system for the robust speed control of highly nonlinear hybrid electric vehicles	• Experimental Data • The Supplemental Federal Test Procedure	• To prove the effectiveness of the suggested novel smart controller, a valid comparison is conducted between the results of the proposed method and recent studies on the same topic like the Model Predictive Control and the conventional online fuzzy PD+I (OFPD+ I) controllers.	• The proposed controller can track a desired reference signal with lower deviation • The performance of the suggested method is more robust in comparison with the prior-art controllers for all the case studies
Liang et al.(*13*) (2019)	• Using connected vehicle (CV) information to identify optimum signal timing and phasing plans while also providing speed guidance to both autonomous (AVs) • Using human driven speed guidance-enabled vehicles (SGVs) to minimize total number of stopping maneuvers.	Simulation test	• A joint traffic signal optimization algorithm • Both realistic acceleration/deceleration behaviors and human drivers' reaction times are explicitly considered in the speed guidance design process.	• Average delay and number of stops decrease with higher CV penetration rate. The number of stops decreases as the ratio of both AVs and SGVs increases. While AVs are about 10% more efficient than SGVs, human-driven vehicles still provide a benefit even when they do not fully comply with speed guidance information
Lee et al.(*14*) (2021)	• Combine a conventional speed optimization planner and reinforcement learning to propose a real-time intelligent	• Considered intersection-approaching scenarios where there is one traffic	• A deep reinforcement learning (DRL) algorithm that can learn the optimal policy through iteratively interacting	• Results show that the learned optimal policy enables the proposed intelligent speed optimization planner to properly adjust the

	speed optimization planner for connected and automated vehicles	light with different signal phase and timing setup.	with different driving scenarios without increasing the limited connectivity and sensing range.	parameters in a piecewise constant manner, leading to additional energy savings without increasing total travel time compared to the conventional speed optimization planner.
Cheng et al.(*15*) (2013)	• To combine a precise fuel consumption model with a robust optimization module. develop an eco-driving assistance system	Vehicle Variables	• A dynamic programming technique • Experimental test	• The accuracy of the model is improved through piecewise modeling technique
Kramer et al.(*16*) (2015)	• To investigate the resolution of difficult vehicle routing variants with speed and departure time optimization.	• The method tested on the instances of Demir et al. (2012) and Kramer et al. (2015), containing between 10 and 200 customers	• A simple polynomial algorithm • Computational experiments	• The experimental results with this heuristic showed that delayed departure times from the depot can lead to very significant savings: up to 8.36% operational costs for the considered benchmark sets.
Pourmehrab et al. (*17*) (2017)	• To develop and simulate an Intelligent Intersection Control System (IICS) that can optimize signal control with AV trajectories in an undersaturated traffic flow of AV and conventional vehicles	• 3000 simulation experiments.	• Simulation experiment. • Simulations in VISSIM	• Comparison of the algorithm to operations with conventional actuated control shows 38 – 52% reduction in average travel time compared to conventional signal control.
Shen et al.(*18*) (2018)	• To built optimization algorithm to calculate trajectories of powertrain control, as well as vehicle speed, that minimizes fuel consumption in a computationally efficient manner.	• Simulation test on two different real-world highways.	• optimization algorithm • Pontryagin's minimum principle (PMP)	• Simulation results show that the proposed optimization algorithm achieves a relative fuel saving of at least 8% compared to the baseline
Talati et al.(*19*) (2021)	• To propose a model which can determine the acceptable and safe speed range for the self-driving vehicle	• Data from a camera sensor that captures video streams or images of the street	• Comparative analysis • Speed controller analysis	• The proposed scheme is more latency and accurate than traditional schemes.

		• Sensors such as Lidar be employed to transmit the data		
Xu et al.(*20*) (2021)	• To develop a completely model-free reinforcement learning approach for optimal speed control of gasoline engines.	• A 4-cylinder gasoline engine is used for validating the proposed scheme and observing the dynamical behavior of the engine system	• Simulation and Experimental result	• The learning mechanism is effective even when no model information is used in the learning algorithm
Lu et al.(*21*) (2016)	• A comparative study on speed control effect of speed limit facilities on the expressway based on speed surveys, development of evaluation system, evaluation of speed control effect and verification on the speed control effect of improving measures.	• The Beijing-Hong Kong-Macao expressway was selected as a sample site for on-site speed surveys. The speed of cars and large size vehicles were collected.	• Comparative Study	• The speed limit effect of portal frame is the best, and the speed limit effect of deceleration marking is the worst.
Asghari et al.(*22*) (2020)	• organization of recent literature to provide a reference point for future research on new aspects of Green-VRPs.	• 313 papers	• Systematic Literature Review	• The majority of PRPs examined vehicle weight, speed, and travel time as effective factors on greenhouse emissions.
Vahidi et al.(*23*) (2018)	• To emphasize the potential of CAV energy saving based on the first principles of movement, optimal control theory and a review of the literature on eco-driving	• 198 Papers	• Literature Review	• Automation helps vehicles adjust their movements more accurately in advance of future events including slow traffic, traffic signal, movement of other vehicles, and save energy. • Increase energy efficiency of a group of vehicles by moving in a coordinated manner.
Mahbub et al.(*24*) (2021)	• To investigate the interaction between CAV and human-driven vehicle (HDV) dynamics, and provide a rigorous control framework that enables platoon	• Considered a CAV followed by one or multiple HDVs traveling in a single-lane roadway	• numerical analysis	• Presented a framework for platoon formation under a mixed traffic environment where a leading CAV derives and implements its control

	formation with the HDVs by only controlling the CAVs within the network.			input to force the following HDVs to form a platoon • Numerical example showed he validate of proposed research
Garg et al.(*25*) (2021)	• To investigates the impact of CAVs on traffic efficiency in realistic communication and road network scenarios	• A large-scale road network in Ireland with real traffic data	• IDM car-following model • The field-tested CACC and ACC models • SUMO is used for modeling the lane changing behavior	• Results show that CAVs can significantly improve traffic efficiency in congested traffic scenarios at high penetration rates. • Simulation results showed that high penetration rates of CAVs provide significant improvement in traffic performance
Ko et al.(*26*) (2020)	• To propose speed harmonization and merge control, taking advantage of CAVs to alleviate traffic congestion at a highway bottleneck area.	• Simulation test	• The CAVs decide which CAV to pass first in each lane using the trained Q-network without communication among them. • Reinforcement learning algorithm called deep Q network to train behaviors of CAVs.	• The proposed approach improves the mixed traffic flow by increasing the throughput up to 30% and reducing the fuel consumption up to 20%, when compared to the late merge control without speed harmonization.
Xu et al.(*27*) (2019)	• Implement Cooperative Method of Traffic Signal Optimization and Speed Control of Connected Vehicles at Isolated Intersections and improve transportation efficiency and decrease CAV fuel consumption.	• Simulation Studies • Numerical Experiment	• The former calculates the optimal traffic signal timing and vehicles' arrival time to minimize the total travel time of all vehicles; the latter optimizes the engine power and brake force to minimize the fuel consumption of individual vehicles. The enumeration method and the pseudo spectral method are applied in roadside and onboard optimization, respectively.	• The cooperative method can effectively adjust the traffic signal timing according to the real-time traffic condition and simultaneously produce optimal vehicle trajectory/speed profiles, which results in the improved transportation efficiency and vehicle fuel economy.
Tajalli et al.(*28*) (2018)	• To develop distributed optimization and coordination algorithms suitable for Dynamic Speed Optimization (DSO)	• Tested the developed methodology in networks with eight, twenty, and	• Scalable and real-time algorithm	• The developed methodology reduced the travel time by up to 14.8% and speed variation by 9.7–

	problem that can find near-optimal solutions in real-time and are scalable to transportation networks of various sizes.	forty intersections under four different demand patterns.		13.4% over different demand patterns compared to a no-speed harmonization strategy.
Nemeth et al.(*29*) (2013)	• To design vehicle speed based on signals obtained from the road and traffic to save energy and reduce fuel consumption while not significantly increasing travel time	• Used a simulator to compare two cruise control systems	• Longitudinal control system	• Reduce unnecessary stop-and-go traffic, thereby reducing emissions. • About 17% saved in longitudinal force compared to the conventional cruise control system.
Seeber et al.(*30*) (2019)	• Using a learning scheme to solve the problem of tracking the prescribed speed profile.	• Road-to-Rig (R2R) test bed of the company KS Engineers was used	• Experimental test	• After very few iterations, both tolerance violations and sudden changes of the pedal position are eliminated, yielding significantly improved driving behavior
Roy et al.(*31*) (2020)	• To propose a way to understand the traffic state of smaller spatial regions at intersections using traffic graphs.	• Introduced a large dataset called EyeonTraffic (EoT) containing 3 hours of aerial videos collected at 3 busy intersections in Ahmedabad, India	• Train a spatio-temporal deep network	• Their experiments on the EoT dataset show that the traffic graphs can help in correctly identifying congestion-prone behavior in different spatial regions of an intersection.
Xu et al. (*32*) (2021)	• To proposes a robust optimal speed control approach based on hierarchical architecture for AEV	• Simulations of the proposed longitudinal decision-making DMEPPO method and the LMI robust speed tracking method	• Combining deep reinforcement learning (DRL) and robust control. • Simulation experiment	• The proposed robust optimal speed control scheme based on hierarchical architecture for AEV is feasible and effective
Xu et al.(*57*) (2017)	• To propose a horizontal alignment design method for mountain highways that considers the typical driving patterns when human drivers select their target trajectory and speed.	• Provided five direction control patterns and four speed control patterns to designers	• Mathematical programming method. • Propose a new alignment design method which can take into account typical handling patterns (driving styles) of	• The proposed method is especially suitable for the horizontal alignment design of low/medium speed highways that traverse rugged terrain.

			human drivers and pay special attention to dangerous driving behaviors.	
Veysi et al.(*33*) (2020)	• To propose controller evaluates the stabilization of the EV speed with robust disturbance rejection approach throughout both transient and steady states and in the presence of external disturbances and parametric uncertainties.	• EV's battery voltage, as control input, and EV speed, as system output, are constrained. • Simulations in five steps are conducted on an EV equipped with a brushed direct current (BDC) motor as a case study in MATLAB simulation environment.	• A stable fuzzy controller in the form of linear matrix inequalities (LMIs) • Takagi–Sugeno (T-S) fuzzy model and the parallel distributed compensation (PDC) fuzzy controller.	• The simulation results obtained from MATLAB and the Real Time Digital Simulation (RTDS) confirm the energy-efficient and robust performance of the proposed controller in quick stabilization of the EV speed in the presence of all structured and unstructured uncertainties.
Gamage et al.(*34*) (2016)	• To propose a Q-learning based vehicle speed control algorithm to minimize the fuel consumption in the vicinity of an isolated signal intersection.	• Simulation test	• Q-learning (a self-learning) speed control algorithm • Using the Aimsun microsimulation platform • A comprehensive parametric analysis	• The algorithm can reduce the vehicle's fuel consumption by 15.78% by adopting the suggested driving speeds.
Wan et al.(*35*) (2016)	• Connected Vehicles (CV) equipped with a Speed Advisory System (SAS) can obtain and utilize upcoming traffic signal information to manage their speed in advance, lower fuel consumption, and improve ride comfort by reducing idling at red lights.	• 21 carefully arranged microsimulation case studies, that connected vehicles equipped with a speed advisory system	• Used the microscopic traffic simulation tool Paramics which is able to simulate a large number of vehicles in a complex traffic network.	• SAS-equipped vehicles not only improve their own fuel economy, but also benefit other conventional vehicles and the fleet fuel consumption decreases with the increment of percentage of SAS-equipped vehicles.
Wu et al.(*58*) (2013)	• Using 10-year crash data from 28 intersections in Nebraska to estimate a random parameters negative binomial	• 10-year crash data from 28 intersections in Nebraska	• A random parameters negative binomial model and a nested logit model	• Speed-limit reductions in conjunction with signal-warning flashers appear to be an effective safety countermeasure, but only clearly so if the speed-limit reduction is at least 10 mph.

	model of crash frequency and a nested logit model of crash-injury severity.			
Dhamaniya et al.(*59*) (2013)	• To develop the speed prediction model for different categories of vehicles, which is required to predict the actual speed for such traffic conditions for better planning and design of the roadway system	• Field data were collected on different sections of urban arterials in New Delhi, Jaipur and Chandigarh by video recording method.	• Statistical Analysis	• These speeds were found to be in good agreement with observed speeds in the field. • The t-test also indicated that there was no significant difference between predicted speeds and observed speed data. • These equations are useful in predicting the speed of a vehicle at a given volume or composition of traffic stream which is crucial in estimation of Passenger Car Unit (PCU) factors.

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