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Eco-Trajectory Planning with Consideration of Queue along Congested Corridor for Hybrid Electric Vehicles

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Abstract

At signalized intersections, vehicle speed profile plays a vital role in determining fuel consumption and emissions. With advances of connected and automated vehicle technology, vehicles are able to receive predicted traffic information from the infrastructure in real-time to plan their trajectories in a fuel-efficient way. In this paper, an eco-driving model is developed for hybrid electric vehicles in a congested urban traffic environment. The vehicle queuing process is explicitly modeled by the shockwave profile model with consideration of vehicle deceleration and acceleration to provide a green window for eco-vehicle trajectory planning. A trigonometric speed profile is applied to minimize fuel consumption and maximize driving comfort with a low jerk. A hybrid electric vehicle fuel consumption model is built and calibrated with real vehicle data to evaluate the energy benefit of the eco-vehicles. Simulation results from a real-world corridor of six intersections show that the proposed eco-driving model can significantly reduce energy consumption by 8.7% on average and by 23.5% at maximum, without sacrificing mobility.

The transportation sector is one of the primary sources of emissions and fuel consumption. It produced 26% of the total greenhouse gas emissions in the U.S. in 2014, making it the second largest producer of greenhouse gases (*1*). Besides, with the rapid growth of oil consumption, the scarcity of fossil energy becomes more and more severe. Studies show that oil will be depleted in approximately 35 years with the current consumption rate (*2*). It is of vital importance to reduce fuel consumption and emissions, especially in urban areas. Alternative-fuel vehicles, as well as connected and automated vehicle (CAV) technology, are expected to be two effective methods.

Alternative-fuel vehicles, such as hybrid electric vehicles (HEVs) and electric vehicle (EVs), are considered as further directions of vehicle development. HEVs are powered by an internal combustion engine and an electric motor, whereas EVs are powered only by an electric motor. One reason that HEVs or EVs can save energy is that when the vehicle brakes, energy usually wasted can be used to generate electricity for the electric motor. Moreover, electric motors have inherently greater efficiency and do not waste energy while vehicles are decelerating or stopped.

Not only improving vehicle technology can help save fuels, but also the CAV technology can potentially provide more savings with vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communications. It is well known that given the same travel distance, different speed and acceleration profiles have a significant impact on fuel consumption and emissions (*3*). Typically, these types of driving behaviors targeting saving energy and reducing emissions are called eco-driving and the vehicles that have eco-driving capabilities are called eco-vehicles. By utilizing traffic information from traffic signals and other surrounding vehicles, eco-vehicles can adjust speed and acceleration dynamically to obtain a smoother trajectory, in which both fuel consumption and emissions can be reduced.

In this work, we propose a model to plan trajectories for HEVs, in a congested urban environment. It is

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assumed that the HEVs have communication capabilities (i.e., V2I) with Level 1 or higher automation level (i.e., longitudinal control). Information from both traffic signals and vehicle queues at the intersections are taken into account when planning the trajectory. The vehicle queuing process is modeled by the shockwave profile model (SPM) (*4*) in which different shockwaves are estimated and tracked to predict the queuing dynamics in the near future. A trigonometric speed profile is applied, and the trajectories of the HEVs are optimized with the objective to minimize fuel consumption with a low jerk. A hybrid electric vehicle (HEV) fuel consumption model is developed and calibrated to evaluate the eco-speed profile. Simulation results from a real-world road network show that the proposed eco-driving strategy can significantly save total energy consumption without compromising mobility performance.

The remaining of the paper is organized as follows: first, a brief review of current eco-driving research is presented. Next, an overview of the simulation framework is given and each component is then introduced in detail. Experiment results are presented with discussions. The final section concludes the paper and lays out further research directions.

Literature Review

In the literature, eco-driving at signalized intersections is usually referred to as eco-arrival and eco-departure (EAD). For a single intersection, Jiang et al. used Pontryagin's Minimum Principle (PMP) to solve an optimal control problem for eco-driving with a low penetration rate of CAVs (*5*). For multiple intersections, a corridor-level, sub-optimal eco-driving algorithm was introduced by De Nunzio et al. (*6*), using a weighted directed graph to determine the optimal path over the trip horizon along a signalized corridor. However, vehicle queues at the intersections are neglected in the optimization problem formulation, so the algorithm can only work under free-flow condition. It cannot handle the situations when intersections are congested. A multistage optimal control model was proposed to plan the trajectory for a signalized corridor in He et al. (*7*), with the consideration of both vehicle queue and traffic signals.

Some studies focus on controlling a single vehicle, whereas others extend to multiple vehicles with platooning. A dynamic eco-driving approach was developed by Barth et al. (*8*) for a single vehicle, assuming a trigonometric speed profile. The model not only minimizes fuel consumption but also considers jerk, corresponding to ride's comfort. However, vehicle queuing at intersections is not considered in this paper. Rakha and Kamalanathsharma developed an eco-driving model to determine whether a vehicle needs to slow down or pass the intersection with signal information (*9*), using microscopic fuel consumption models when conducting the optimization. However, when developing the solution algorithm, this study lacked consideration of queuing profile prediction, which is emphasized in this paper. A predictive intelligent driver model was introduced as the adaptive cruise control (ACC) controller in Xin et al. (*10*) for eco-driving, which was used to guide ACC-equipped CAV across intersections, considering the downstream queue discharging time. Kamal et al. designed a control system to measure relevant information about the roadway and traffic flow and to anticipate the state of the preceding vehicle to reduce fuel consumption (*11*).

Some studies investigated the impact of CAV market penetration rate on eco-driving. Sensitivity analysis of different penetration rates has been conducted in other research (*12*), which show the benefits of eco-driving in relation to fuel consumption at network level, even under 20% of connected vehicles. In Jiang et al. (*5*), the benefits remain significant when the penetration rate is higher than 40%.

A variety of solution algorithms have been proposed to plan the eco-vehicle trajectory. A dynamic programming (DP) algorithm has been developed by Miyatake et al. (*13*) for electric vehicles. Model predictive control (MPC) introduced in another research (*14*) reduced fuel consumption by up to 47% and carbon dioxide emission by up to 56% in a multi-intersection network, by minimizing the probability of stopping at the red light. It is assumed that all vehicles in the simulation are eco-vehicles controlled by MPC. Both analytical and numerical solutions have been discussed (*15*) to solve the fuel consumption minimization problem. The analytical methods work for simplified vehicle dynamics and fuel consumption models. The numerical methods can be applied to the non-linearity of the vehicle dynamics.

Methodology

In this section, we first give an overview of the simulation framework. Then each component of the system including queuing profile prediction, speed profile generation, and HEV fuel consumption model is introduced in detail.

Overall Simulation Framework

The overall simulation framework consists of three parts: VISSIM traffic simulator, Algorithm module, and Post Analysis module (Figure 1). VISSIM is a microscopic traffic simulation software developed by PTV. Vehicles in VISSIM can either follow internal car-following and lane-changing models or are controlled by user-defined

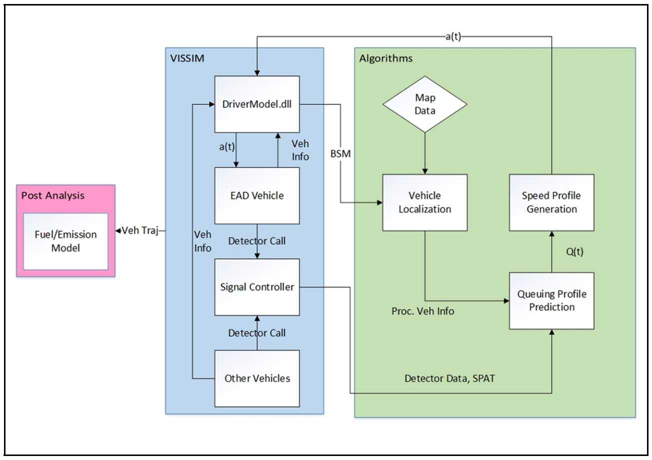

Figure 1. Overall simulation framework.

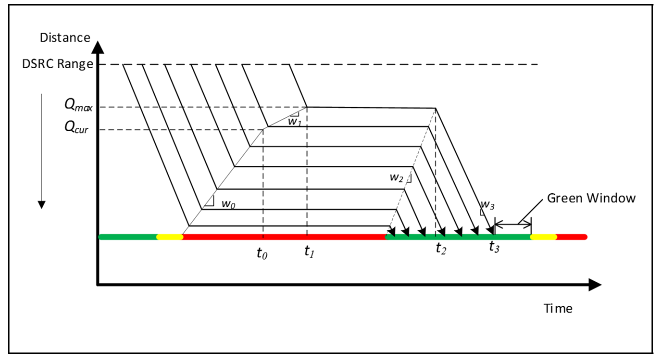

Figure 2. SPM-based queuing profile prediction.

API (*16*). VISSIM serves as the simulation platform and sends vehicle data (i.e., basic safety messages [BSMs]) and infrastructure data (i.e., detector data and signal phase and timing [SPaT] messages) to the Algorithm module, which generates suggested acceleration profile to control eco-vehicles in VISSIM using DriverModel.dll API. The Algorithm module includes Vehicle Localization algorithm, Queuing Profile Prediction algorithm, and Speed Profile Generation algorithm. After simulation runs, vehicle trajectories will be stored and used in Post Analysis module to calculate fuel consumption and emissions.

The Vehicle Localization algorithm processes vehicle trajectory data from BSMs, locates vehicles on the map and calculates related vehicle information such as approach, lane, estimated time of arrival (ETA) and requested signal phase. Combining with detector data and SPaT data, vehicle trajectories calculated from the Vehicle Localization algorithm serve as the input to the Queuing Profile Prediction algorithm. More details about the localization algorithm can be found in Feng (*17*). This framework can be applied to both CAVs with Level 1 or higher automation level and connected vehicles with a human–machine interface (HMI) to give drivers advisory speed.

Queuing Profile Prediction

The objective of queuing profile prediction is to make a real-time prediction of the vehicle queuing dynamics at the intersection and calculate a green window for the eco-vehicle's trajectory planning. Currently, the following assumptions are made to simplify the problem:

1. All vehicles are connected and broadcast BSMs.
2. Traffic signals operate under fixed timing plan.
3. Traffic demand is not oversaturated.

The SPM (*4*) is implemented to predict the queuing profile with the consideration of vehicle acceleration and deceleration process. The SPM tracks and estimates different types of shockwaves and their speeds at a signalized intersection and therefore the queuing dynamics can be constructed. The SPM is modified to make predictions of queuing dynamics instead of making estimations after the queue has been discharged. The entire queuing process within a signal cycle is shown in Figure 2. Four critical time points are defined:

t_0: Current time when the prediction is made.

t_1: Predicted time point that the maximum queue length $Q_{\max}$ is reached (stop time of the front vehicle).

t_2: Predicted time point that the end of the queue starts to move (launch time of the front vehicle).

t_3: Predicted time point that the end of the queue reaches the intersection (departure time of the front vehicle). This is also the start time of the green window.

Note that the front vehicle is defined as the immediate downstream vehicle of the eco-vehicle in the same lane. The end of the green window is considered to be the end of the green signal.

The primary purpose of the queuing profile prediction algorithm is to determine the start of the green window (t_3). Four different types of shockwaves are identified in Figure 2 to calculate t_3 step by step. w_0 is the queuing shockwave speed from red signal start until current time; w_1 is the predicted queuing shockwave speed until the maximum queue is reached; w_2 is the discharge shockwave speed; w_3 is the departure shockwave speed. t_3 is also the time point that the departure shockwave w_3 arrives at the intersection.

With the assumption of 100% penetration rate of connected vehicles, the current queue length Q_{cur} is known by checking each vehicle's speed and location from the BSMs. If the vehicle's speed is less than 5 mph, we consider it is in queuing state based on Highway Capacity Manual definition (*18*). To predict the time-point that the maximum queue length is reached, we consider the vehicle deceleration rate and the stopping distance of the front vehicle as

$$t_1 = \begin{cases} t_0 + \frac{v_l}{a_n} + \frac{d_{\text{stop}}^f - \frac{v_l^2}{2a_n}}{v_l} & \text{if } d_{\text{stop}}^f > \frac{v_l^2}{2a_n} \\ t_0 + \frac{2d_{\text{stop}}^f}{v_l} & \text{otherwise} \end{cases} \quad (1)$$

where
v_l = current speed of the front vehicle;
a_n = average vehicle deceleration rate, a constant parameter; and
d_{stop}^f = predicted stopping distance of the front vehicle, from its current position to its stop location, which can be calculated by the number of downstream vehicles multiplied by an average vehicle length.

When the signal turns to green, the discharge shock-wave speed w_2 is determined by the saturation flow rate, which is usually assumed to be a constant (e.g., 12 mph). As a result, critical time point t_2 can be predicted as

$$t_2 = t_g + Q_{\max}/w_2 \quad (2)$$

where t_g is the start time of the green signal.

The departure time t_3 is estimated based on t_2 assuming the last queuing vehicle accelerates to free-flow speed and then keeps constant speed until it passes the intersection. Based on the stopping location of the vehicle, t_3 can be calculated as

$$t_3 = \begin{cases} t_2 + \frac{v_f - v_l}{a_p} + \frac{d_l - \frac{v_f^2 - v_l^2}{2a_p}}{v_f} & \text{if } d_l > \frac{v_f^2 - v_l^2}{2a_p} \\ t_2 + \frac{-v_l + \sqrt{v_l^2 + 2a_p d_l}}{a_p} & \text{otherwise} \end{cases} \quad (3)$$

and

$$w_3 = \frac{Q_{\max}}{t_3 - t_2} \quad (4)$$

where a_p is the average vehicle acceleration rate.

The descriptions above provide a general approach to estimate the departure time t_3. However, the eco-vehicle may arrive at the intersection at any time with any number of downstream queuing vehicles. Vehicles downstream of the eco-vehicle may or may not stop based on current signal status and remaining timing of the signal phase. As a result, four different cases are identified as shown in Figure 3.

In case 1, the signal is red; there is no stopped vehicle at the downstream of the eco-vehicle. This case usually happens when the signal has just turned to red. Whether the eco-vehicle stops or not depends on whether its front vehicle can pass the stop bar when the green signal starts

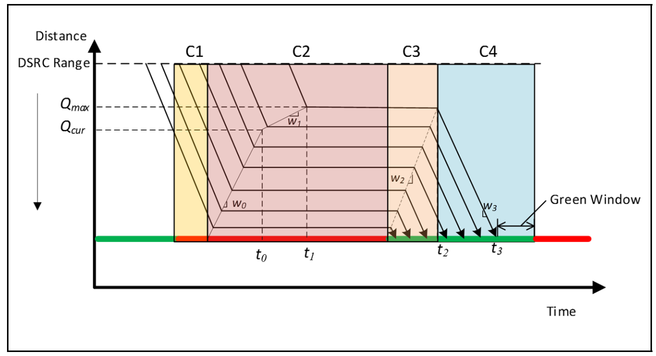

Figure 3. Four cases in queuing profile prediction.

(e.g., a very short red time). If the front vehicle stops, then case 1 turns to case 2.

In case 2, the signal is red, and there are stopped vehicles at the downstream of the eco-vehicle. This is the most common case when vehicles are waiting in the queue for the green light. The time of arrival at the end of the queue is compared with the time of discharge of the last vehicle in the queue, to determine whether the eco-vehicle stops or not.

In case 3, the signal is green, and there are stopped vehicles at the downstream of the eco-vehicle. It happens when an existing queue is dissipating. All stopped vehicles are discharging by saturation flow rate, and the approaching eco-vehicle is checked whether it joins the queue by comparing its arrival time with the discharge time of the last queuing vehicle.

In case 4, the signal is green, and there is no stopped vehicle at the downstream of the eco-vehicle in the same lane. Whether the eco-vehicle stops or not depends on whether its front vehicle can pass the stop bar before the red signal starts. The eco-vehicle stops if its front vehicle stops. Otherwise, the time of arrival at the stop bar is compared with the remaining time of the green signal.

Speed Profile Generation

The objective of the Speed Profile Generation algorithm is to provide an eco-friendly vehicle trajectory. The planning horizon of the trajectory starts from the time point when the eco-vehicle enters the communication range until it arrives at the intersection. In an attempt to ensure a smooth trajectory and minimize the fuel consumption and emission with a low jerk, a trigonometric speed profile is applied from Barth et al. (*8*). Figure 4 shows two examples of the trigonometric speed profiles: one decelerating to a lower speed and one accelerating to a higher speed. In the figure, v_0 is the initial speed, and the area under the speed profile denotes the distance to stop bar d_{stop}. t_{arr} is the time of arrival at the intersection with $t_{\text{arr}} = t_3 + h$ where h is the saturation headway between

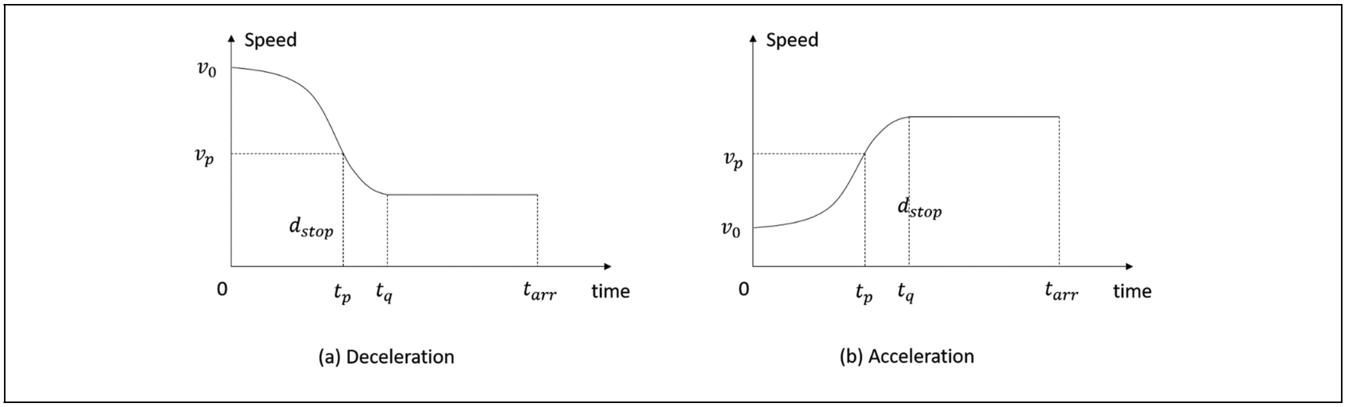

Figure 4. Trigonometric speed profiles.

two vehicles. At time point $t_p = \frac{\pi}{2m}$, the speed of the eco-vehicle reaches the average speed v_p, shown in Equation 5. After $t_q = \frac{\pi}{2m} + \frac{\pi}{2n}$, the speed doesn't change, and the vehicle will cruise to the stop bar. The speed profile for the acceleration process is shown in Equation 6. m and n are model parameters that reflect the maximum acceleration, maximum deceleration, and jerk. They determine the shape of the trigonometric speed profile to minimize fuel consumption by reaching the cruise segment as soon as possible. The detailed explanation of the choice of m and n can be found in Barth et al. (*8*). The deceleration process shares the same format as the acceleration process, with $v_r < 0$.

$$v_p = d_{\text{stop}}/t_{\text{arr}} \tag{5}$$

$$v = \begin{cases} v_p - v_r\cos(mt), t \in [0, t_p) \\ v_p - v_r\frac{m}{n}\cos[n(t + \frac{\pi}{2n} - t_p)], t \in [t_p, t_q) \\ v_p + v_r\frac{m}{n}, t \in [t_q, t_{\text{arr}}) \end{cases} \tag{6}$$

$$v_r = v_p - v_0 \tag{7}$$

Based on the different time-points that the eco-vehicle enters the communication range and corresponding queue status, the eco-vehicle may choose different speed profiles as shown in Figure 5. Four types of speed profiles are identified: slow down, speed up, cruise, and stop. The criteria that determine which type the eco-vehicle uses to plan the trajectory is shown in Figure 6. t^{queue} denotes the time when the eco-vehicle approaches the end of the queue with the current speed. If it is less than t_2 plus a 2-second buffer time, which means that the eco-vehicle arrives at the end of the queue before it starts dissipating, the eco-vehicle will plan to stop. Otherwise, the algorithm checks whether the time to stop bar with the current speed, t^{cr} falls into the green window Γ'. If so, the vehicle can cruise and pass. If not, it checks whether the green window intersects with $[t^e, t^{\text{cr}}]$, in which t^e is the earliest time the eco-vehicle can arrive at the intersection, by accelerating to the speed limit. If the eco-vehicle can accelerate and pass the intersection, it adopts a "speed up" speed profile. This scenario usually happens when the eco-vehicle is approaching the intersection at the end of the green phase. If acceleration is not feasible, the algorithm checks whether the green window intersects with $[t^l, t^{\text{cr}}]$, in which t^l is the latest time the vehicle can arrive at the intersection, by decelerating to the minimum cruise speed. If the intersecting interval is empty, the eco-vehicle applies the "stop" speed profile. Note that all "slow down," "speed up," and "stop" speed profiles are generated by the trigonometric profiles with different parameter settings. Technically, the eco-vehicle can always slow down to a very low speed and cross the intersection without stopping. However, a very low cruise speed may be disruptive to other traffic and cause frequent lane changing and cut-in behaviors. As a result, a minimum cruise speed is adopted as 70% of the speed limit. If the eco-vehicle cannot maintain the minimum cruise speed, it comes to a complete stop.

Although oversaturated traffic condition is not considered in this paper, the SPM can be extended to oversaturation cases (see Wu and Liu [*4*] for more details). However, the benefits of eco-driving will be limited under such circumstances. Because of constant cycle failures, all vehicles have to stop at least once to pass the intersection. There is little space for the Speed Profile Generation algorithm to plan a fuel-efficient vehicle trajectory.

HEV Fuel Consumption Model

In this subsection, a vehicle level HEV simulation model is introduced for the fuel consumption evaluation. The HEV simulation model is configured with Toyota Hybrid System (THS) and contains an engine thermal/fuel model, a battery state of charge (SOC) model, an electric motor model, a vehicle longitudinal model and a driver model. A rule-based power-split controller is applied to regulate the powertrain operation according

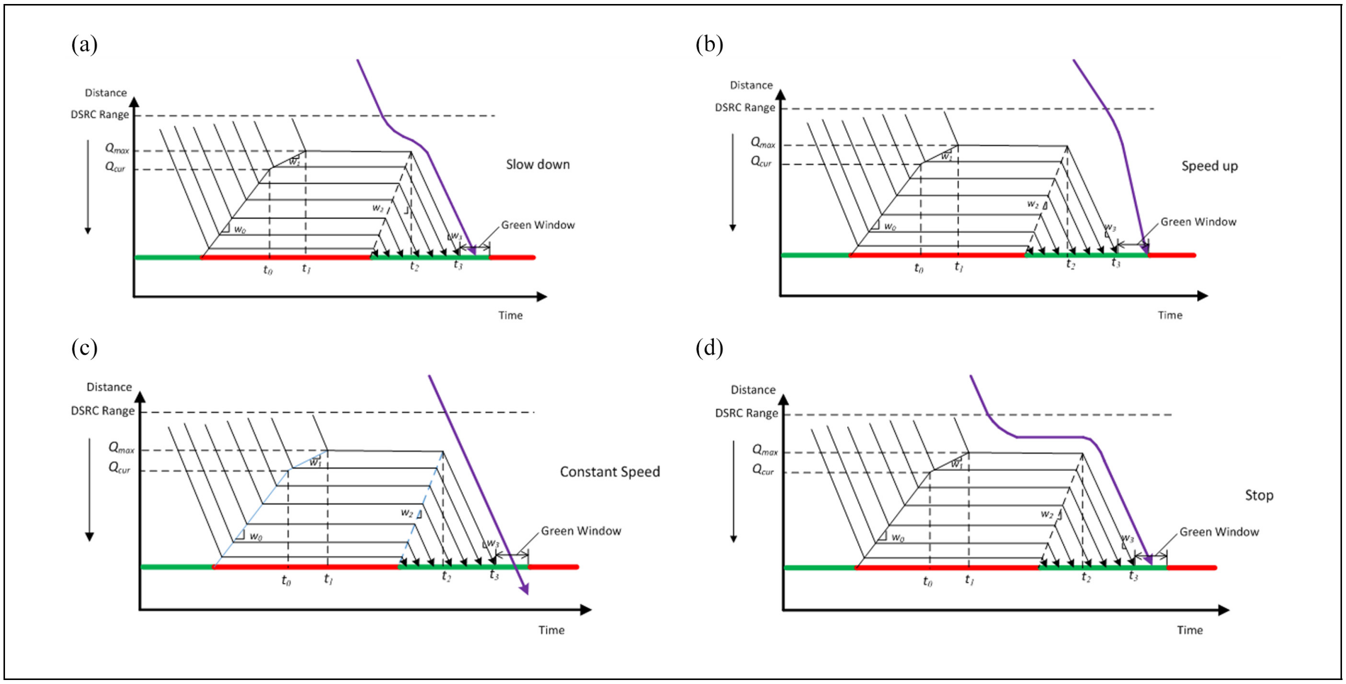

Figure 5. Trajectory planning scenarios: (*a*) slow down; (*b*) speed up; (*c*) cruise; and (*d*) stop.

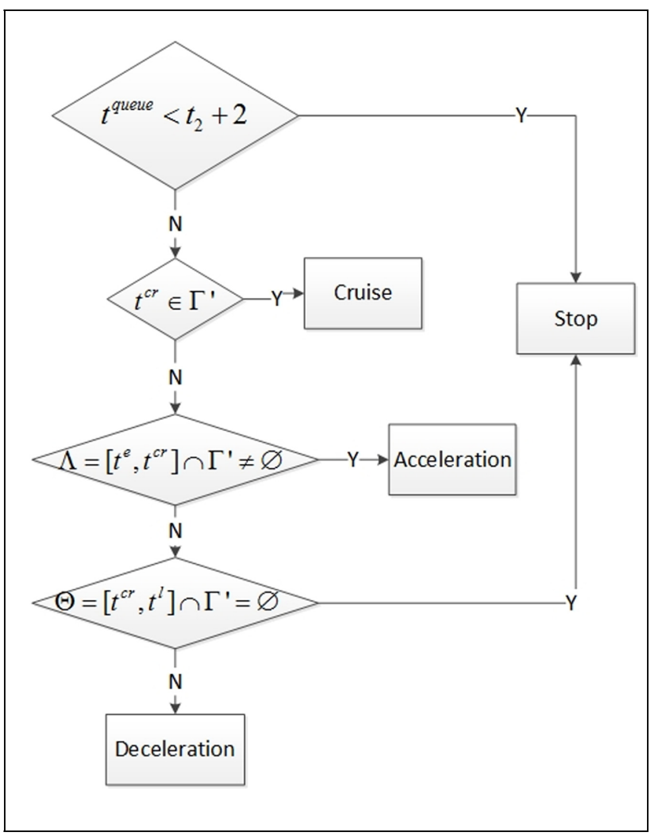

Figure 6. Trajectory planning scenario determination process.

to the driver demand. In this paper, we only focus on modeling energy-related components which are the battery model and fuel consumption model. For more details on the entire vehicle model, please refer to other papers (*19, 20*).

For the electric path, the governing equation of the battery dynamics is given as

$$\dot{SOC} = -\frac{U_{oc} - \sqrt{U_{oc}^2 - 4R_{int}P_{batt}}}{2R_{int}C_{batt}}, \tag{8}$$

where
$\dot{SOC}$ = state of the charge,
P_{batt} = battery power,
C_{batt} = battery capacity,
U_{oc} = open circuit voltage, and
R_{int} = internal resistance.
Both $U_{oc} = f_1(SOC)$ and $R_{int} = f_2(SOC)$ are functions of SOC and calibrated by real data.

The battery power is calculated from

$$P_{batt} = T_m \omega_m \eta_m - T_g \omega_g \eta_g, \tag{9}$$

where
T_m = motor torque,
T_g = generator torque,
ω_m = motor speed,
ω_g = generator speed,
η_m and η_g = efficiency parameters which are based on look-up tables obtained from AUTONOMIE (*21*).

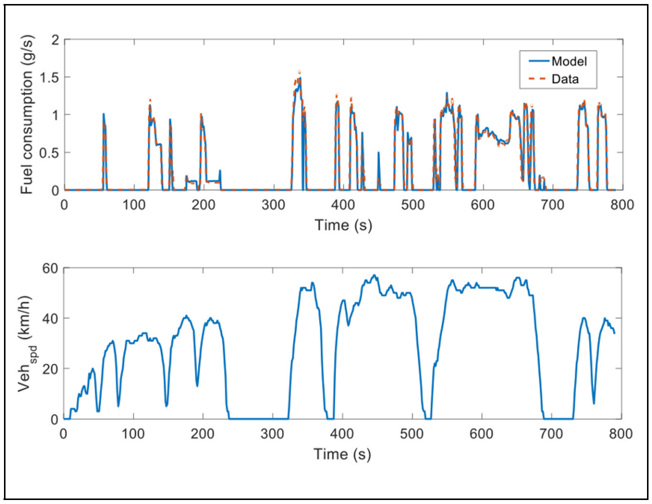

Figure 7. Fuel consumption validation of the HEV model.

The battery SOC is validated against the real testing data of a Prius 2017.

For calculating the fuel consumption, the engine is modeled as a quasi-static system where the effective engine torque T_e and the engine speed ω_e are the input variables while the fuel flow rate m_f is the output variable. Thermal influence on the fuel consumption is also considered when the engine coolant temperature varies. Thus, the fuel consumption of the engine is calculated by

$$\dot{m}_f = f_{fuel,\,map}(\omega_e, T_e) f_{cl,\,map}(T_{cl}), \tag{10}$$

where $f_{fuel,\,map}(\omega_e, T_e)$ denotes the standard fuel flow rate by a look-up table and $f_{cl,\,map}(T_{cl})$ denotes the sensitivity parameter depending on engine coolant temperature T_{cl}. The fuel consumption model is validated against a Prius 2017 testing vehicle through a local driving cycle in Ann Arbor, Michigan as shown in Figure 7. The red dotted curve is the fuel consumption from the real vehicle and the blue curve is fuel consumption generated from the model with the same speed profile, which is a good match to the real data.

The HEV draws power from both engine and battery. As a result, the actual energy consumed (E_{act}) is used as the performance index in the evaluation scenarios

$$E_{act} = LHV_{gas} {}^* m_f + \Delta E_{batt}/\eta_{sys} \tag{11}$$

$$\Delta E_{batt} = \left(S\dot{O}C_{st} - S\dot{O}C_{end}\right)^* E_{batt} \tag{12}$$

where

E_{act} is the actual energy consumed in MJ;
LHV_{gas} is the lower heat value of gasoline in MJ/kg;
m_f is the fuel consumption in kg;
ΔE_{batt} is the change of battery energy in MJ

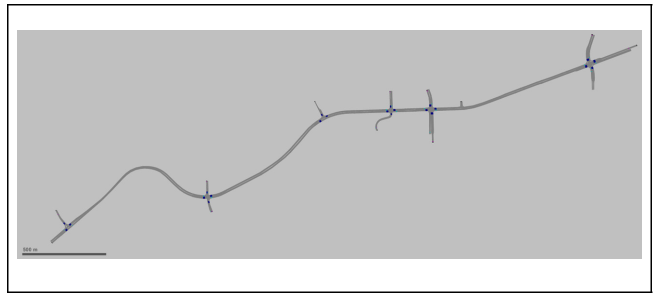

Figure 8. VISSIM simulation model of Plymouth Rd.

$S\dot{O}C_{st}$ is the state of charge at the beginning of the trip in percentage
$S\dot{O}C_{end}$ is the state of charge at the end of the trip in percentage
E_{batt} is the total battery energy in MJ
η_{sys} is a battery coefficient

Simulation Analysis

Experimental Setup

A VISSIM simulation model is built for a six-intersection corridor at Plymouth Rd, Ann Arbor as shown in Figure 8. The stretch of the Plymouth Rd is about 2.2 mi and has two lanes for each direction which is one of the busiest commuting routes, serving US23 to the North campus of the University of Michigan and downtown Ann Arbor. Some crossing roadways are major arterials which carry a large volume of traffic and others are side streets with less traffic demand. The road geometries are calibrated with the satellite maps from Google Earth.

The VISSIM model is calibrated with data collected from two sources: video data and the naturalistic driving data (NDD) from the Safety Pilot Model Deployment (SPMD) project (*22*). The video data were collected from each intersection simultaneously at afternoon peak hour (4:00–5:00 p.m.). The video data contain vehicle volumes at each movement, turning ratios at each approach and signal phasing and timing data. The SPMD data is used to calibrate the acceleration profiles to match actual driving behaviors. In total, 2,593 acceleration events along Plymouth corridor were extracted and the mean acceleration values under different speeds are calculated and set as the desired acceleration rate in VISSIM. The reason calibrated acceleration profiles are used is that different driving behaviors have a significant impact on the fuel consumption.

The vehicle volumes and turning ratios collected at each intersection are used as the input to calibrate the VISSIM model. To quantitatively evaluate the accuracy of the calibration, the Geoffrey E. Havers

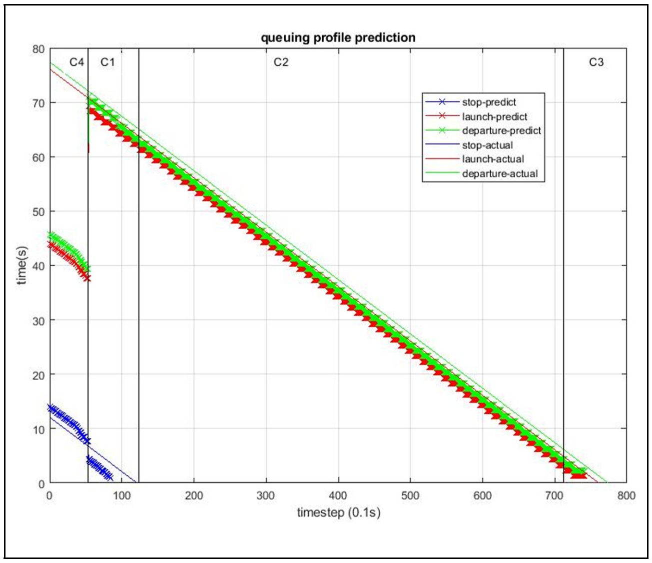

Figure 9. Queuing profile prediction.

(GEH) value of each movement is calculated. The GEH value is defined as

$$\mathrm{GEH} = \sqrt{\frac{(Vol_{\mathrm{sim}} - Vol_{\mathrm{real}})^2}{(Vol_{\mathrm{sim}} + Vol_{\mathrm{real}})/2}} \tag{13}$$

A general rule to determine whether a simulation network is well calibrated is that the GEH values for more than 85% of the traffic volumes at selected movements are less than 5 (*23*). A total number of 61 movements along the corridor are identified. Simulation results show that 58 out of 61 movements (95.1%) have the GEH value less than 5, which indicates a well-calibrated network.

Results and Discussion

Queuing Profile Prediction. Figure 9 shows the results of the queuing profile prediction of the four cases, as discussed in the methodology section. In this experiment, there is one downstream vehicle ahead of the eco-vehicle. The lines without crosses are true values, and the lines with crosses are predictions. The blue (crossed) lines denote the true (predicted) stop time of the front vehicle (t_1), and the red (crossed) lines denote the true (predicted) launch time of the front vehicle (t_2). The true (predicted) departure time of the front vehicle (t_3) goes with the green (crossed) lines. The horizontal axis is the simulation steps (every 0.1 s) and the vertical axis is the simulation time. As a result, the true values are 45° diagonal lines. When the true values reach zero on the vertical axis, it means the front vehicle stops/launches/leaves at this time point. The vertical differences between the crossed lines and solid lines are the prediction errors. Note that the prediction is made every 0.1 s. The predictions of launch time (t_2) and leave time (t_3) are pretty accurate except for case 4. In case 4, when the signal is green and no vehicle stops downstream of the eco-vehicle, the SPaT data only provide the remaining time of the current green phase. The duration of the upcoming red signal is unknown, which leads to the inaccuracy of the prediction. After the signal turns to red, the prediction becomes accurate, which is case 1. After the front vehicle stops, the queue has been formed, as in case 2. After the signal turns to green, the queue starts dissipating, which is case 3. The small fluctuations of prediction of stop time (in blue) in case 4 and case 1 are caused by the constant vehicle deceleration value assumption.

Evaluation Scenarios. The evaluation scenarios are designed to test the algorithms in the network with different traffic conditions and signal timings. Figure 10 shows a sample speed profile with trajectory planning (in blue) and without trajectory planning (in red) under the same traffic condition. VISSIM's internal driving model with calibrated acceleration profile is used as the baseline. It can be seen from the figure that through trajectory planning, the eco-vehicle can greatly reduce speed fluctuation both in the free-flow condition and when approaching intersections, although in this case, the number of stops is the same. Table 1 confirms that in total 11.59% energy is saved because of trajectory planning using the HEV fuel consumption model.

To further validate the performance of the algorithms, a total number of 50 eco-vehicles are generated using different random seeds and compared with the baseline. Figure 11 shows the distribution of total energy reduction among all vehicles. The maximum energy saving is about 23.5%, and average energy saving is about 8.7%. Figure 12 shows the distribution of travel time differences among all vehicles with or without eco trajectory planning. The average travel time with eco trajectory planning is about 442.5 s whereas the average travel time without eco trajectory planning is about 442.3 s. The results indicate that the proposed algorithms are able to save energy while maintaining mobility performance. It is noticed that in some cases the travel time difference can reach 15–20%. That is because of the different speed profiles that the eco-vehicle may adopt. For example, if the vehicle is under eco trajectory planning, it may choose the "speed up" profile and pass the intersection, while without eco trajectory planning, the vehicle may stop and wait for the red signal for an entire cycle.

Conclusions

This study proposed an eco-driving model to plan the trajectory for HEVs at signalized intersections. The SPM was applied to predict the queuing profile and calculate

Table 1. Energy Comparison Sample Speed Profile

	Fuel (kg)	SOC begin	SOC end	Total energy (MJ)	Reduction (%)
With Planning	0.1446	0.6	0.5824	6.528	11.59
Without Planning	0.1591	0.6	0.5655	7.384	N/A

Note: MJ = megajoule; SOC = state of charge; N/A = not available.

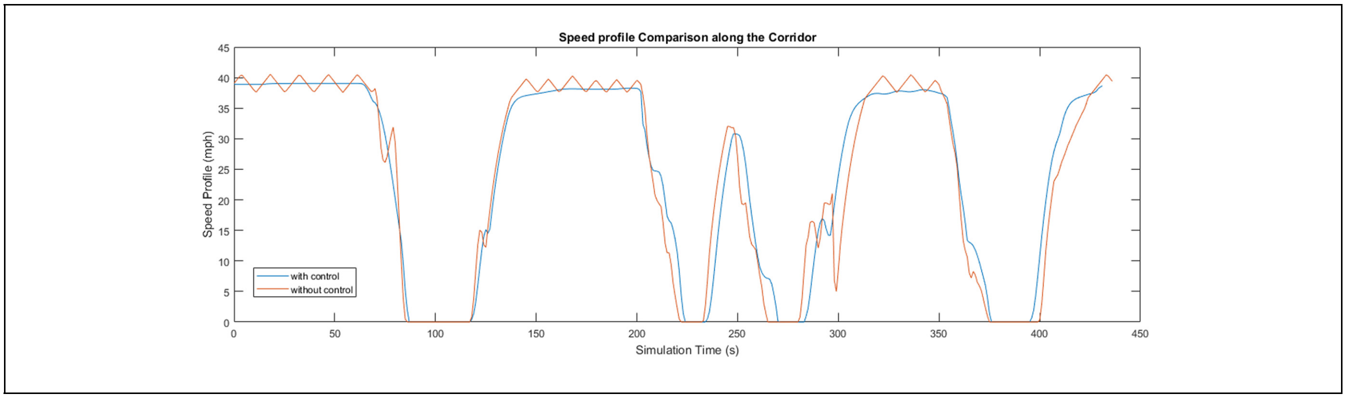

Figure 10. Speed profile comparison along the corridor.

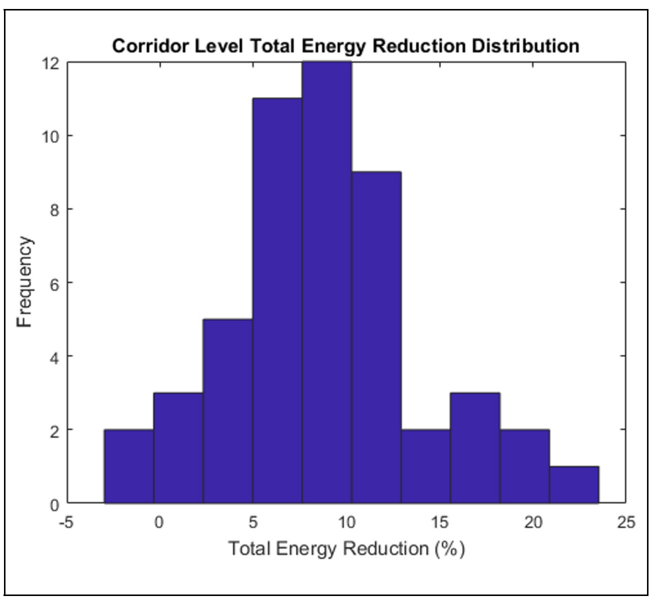

Figure 11. Distribution of energy reduction.

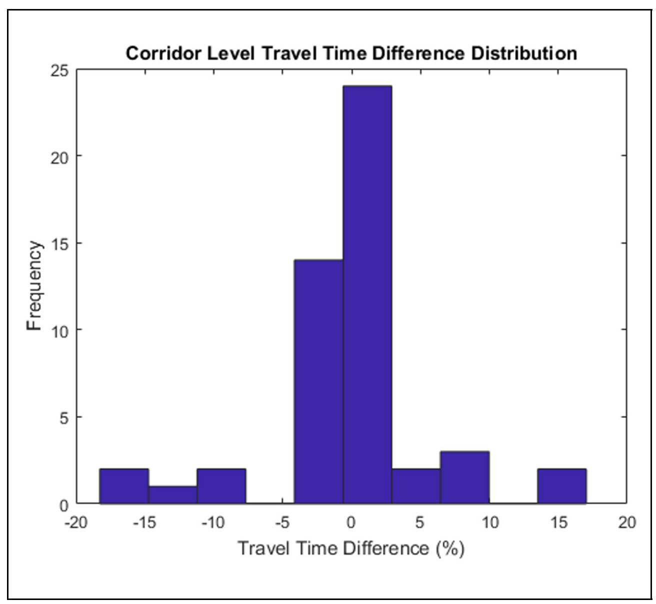

Figure 12. Distribution of travel time difference.

green windows for eco-vehicles. Given traffic signal and vehicle queue information, the vehicle speed trajectory was optimized in a trigonometric form, to minimize the fuel consumption. An HEV fuel consumption model was developed and calibrated to evaluate the vehicle speed profile. Results from a six-intersection corridor simulation model showed that the maximum energy saving can reach 23.5% and the average saving is about 8.7%. Meanwhile, the travel time of the eco-vehicle along the corridor remains similar.

There are a few directions worth investigating in future work. The queuing profile prediction algorithm needs to be modified for a lower penetration rate of CAV environment, in which data from infrastructure-based sensors need to be added. Oversaturated traffic conditions can also be considered with a focus on evaluating the benefits of eco-driving under such conditions. Currently, lane-changing behavior is not modeled, which should be added, especially when the eco-vehicle needs to make turns. Finally, driver acceptance of the new technology and changes in driving behaviors is another interesting research topic.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: YF, DZ, JS; data collection: ZY, XG; analysis and interpretation of results: ZY, XG, YF; draft manuscript preparation: ZY, XG, DZ, JS, YF. All authors reviewed the results and approved the final version of the manuscript.

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The views presented in this paper are those of the authors alone.