Deeply Integrated Vehicle Dynamic and Powertrain Operation for Efficient Plug-in Hybrid Electric Bus

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ABSTRACT

The emerging connected and automated vehicle (CAV) technology has opened the door for developing innovative applications and systems to improve vehicle energy efficiency. While most of the recent research has been focused on optimizing vehicle dynamic (VD) and powertrain (PT) operation in isolation, there exists untapped potential to further improve vehicle fuel efficiency through a co-optimization of VD&PT control. In this paper, we develop an eco-operation solution for a plug-in hybrid electric bus (PHEB) which seamlessly integrates state-of-the-art CAV applications with advanced powertrain optimization strategies, aiming at improving vehicle energy efficiency and reducing tailpipe emissions. The proposed eco-operation system have 6 components, including traffic/signal timing information acquirement, information integration, scenario identification, powertrain, trajectory planning and a MATLAB/Simulink model for validation and fine-tuning. A deeply integrated vehicle dynamic and powertrain control algorithm is proposed in the paper to optimize the energy-efficiency. Based on the key logic of powertrain control strategy of PHEB, we develop a simplified PHEB powertrain model, and put it into our graph based optimization model as the edge cost to derive the optimal speed profile, which is further fine-tuned in the Simulink model. The proposed mode is validated in multiple numerical tests under Eco-Approach and Departure, Eco-Stop and Launch and Eco-Cruise scenarios, and shows significant performance (above 20%) in energy-saving.

KEYWORDS: Eco-Approach and Departure, Plug-in Hybrid Electric Bus, Connected Vehicles, Powertrain Control, Eco-Driving

INTRODUCTION AND MOTIVATION

The emerging connected and automated vehicle (CAV) technology has opened the door for developing innovative applications and systems to improve vehicle energy efficiency. Among all the CAV based applications, eco-driving at signalized intersection (i.e. Eco-Approach and Departure) is particularly promising for fuel saving and emission reduction in urban area, as drivers would effectively reduce stops and idling and avoid unnecessary acceleration and deceleration by receiving signal phase and timing (SPaT) information in advance (*1*). Connected eco-driving is also one of the most feasible pilot applications in the early stage of the Connected and Automated Vehicle (CAV) era, as it could show significant effect on fuel economy improvement under low penetration rate, even for a single vehicle that is communicable with the signal controller.

Early development and deployment of connected eco-driving technology mainly focused on vehicle dynamic control of passenger vehicles. Table 1 summarizes the connected eco-driving models model for intersection approach and departure. Those models are applied to different types of signals and facilities, and are developed using different algorithms. In general, rule-based models (e.g. (*2*), (*4*), and (*9*)) are efficient for computation and convenient for implementation, but may not find the best fuel-saving solution. Optimization-based methods (e.g. (*5*), (*6*), and (*7*)) have slightly higher performance in fuel saving and better flexibility in model extension, but may not have high enough computational efficiency for real time implementation. This computational efficiency issue can be solved by formulating the problem as a dynamic programming model (*6*). Table 1 also shows that all applications have good performance in energy saving, although different studies may have different test scenarios and different baseline driving strategies, which make the saving varying from 8 to 59%.

Table 1 Summary of connected eco-driving models

Authors and reference	Traffic signal	# of Inter-sections	Model description	Fuel saving
Sindhura et al. (*1*)	Fixed-time	Multiple	Acceleration rate minimization	12-14%
Li et al. (*2*)	Fixed-time	Single	Drivers make control based on alerts	8%
Asadi and Vahidi (*3*)	Fixed-time	Single	Predictive cruise control	59%
Barth et al. (*4*)	Fixed-time	Single	Trigonometric speed profiles	10-15%
Rakha et al. (*5*)	Fixed-time	Single	Fuel as the optimization objective	25%
Kamalanathsharma and Rakha (*6*)	Fixed-time	Single	Multi-stage dynamic programming	19%
De Nunzio et al. (*7*)	Fixed-time	Multiple	Pruning algorithms/ optimal control	10%
Mahler and Vahidi (*8*)	Probabilistic	Multiple	Predictive optimal velocity-planning	16%
Hao et al. (*9*)	Actuated	Single	Robust strategy for signal actuation	12%

Those applications show great energy-saving potential of connected eco-driving and guide the direction of future deployment. However, most connected eco-driving models have less emphasis on powertrain control, and use generic or simple model (e.g. tractive power optimization) to represent the powertrain characteristics. Recent studies pay more attention to the significance of powertrain in connected eco-driving research and developed powertrain-specific eco-driving model for energy optimization. Li and Peng developed a fuel consumption minimization strategy that was adaptive to the continuously variable transmission (CVT) of gasoline vehicles (*10*). Hu et al. proposed a dynamic/powertrain integrated control model for passenger vehicles that traveling mainly on freeways with rolling terrain to optimize the energy efficiency (*11*). Huang and Peng developed an algorithm to optimize vehicle speed trajectory over multiple signalized intersections with known traffic signal information using sequential convex optimization method (*12*). This paper adopted a simplified powertrain model which assumes powertrain efficiency factors are static and CVT keeps the engine operating long the best brake specific fuel consumption (BSFC) line. Jin et al. developed a power-based connected eco-driving controller for longitudinal control optimization, which is suitable to signalized intersections but takes relatively long computational time due to nonlinear integer programing *(13)*. Qi et al. designed and evaluated an integrated connected eco-driving assistance system for plug-in hybrid electric vehicles (PHEVs) (*14*). Two-subsystems, vehicle trajectory planning system and online energy management system, are optimized separately, and combined at the end to find the partial-optimal solution. Hao et al. developed a truck eco-approach and departure system based on SPaT message from signal controllers and road grade information along the path (*15*). This truck EAD model consisted of two levels: a powertrain-based fuel consumption estimation model and the graph-based optimal trajectory planning model. The powertrain model in this paper was designed for diesel engine with a 6-gear transmission, but it can be applied to other type of powertrains for energy consumption estimation.

In this paper, we aim to develop an eco-operation solution for a plug-in hybrid electric bus (PHEB) which seamlessly integrates state-of-the-art CAV applications with advanced powertrain optimization strategies, aiming at improving vehicle energy efficiency and reducing tailpipe emissions. The graph based trajectory planning algorithm in (*15*) is improved to adapt the PHEB powertrain. A deeply integrated vehicle dynamic and powertrain control model is proposed in the paper to optimize the energy-efficiency. The rest of this paper is organized as follows. In the next section, we introduce the project information, including application types and powertrain models for the PHEB. We then develop the integrated algorithm for vehicle dynamic and powertrain control, mainly using Eco-Approach and Departure as the example. In the numerical experiment section, we validate the proposed model using different applications and scenarios, followed by the conclusion marks.

EFFICIENT PLUG-IN HYBRID ELECTRIC BUSES

The CAV applications being developed for a PHEB in this project are illustrated in Figure 1. Besides Eco-Approach and Departure (EAD) application at signalized intersections, the proposed system also includes Eco-Stop and Launch (ESL) application which determines the most energy-efficient vehicle speed profile for decelerating to and accelerating from bus stops and stop signs, and Eco-Cruise (EC) application which identifies the most energy-efficient cruising speed for the bus based on look-ahead traffic and terrain (i.e., road grade) conditions, roadway speed limits, and vehicle performance characteristics.

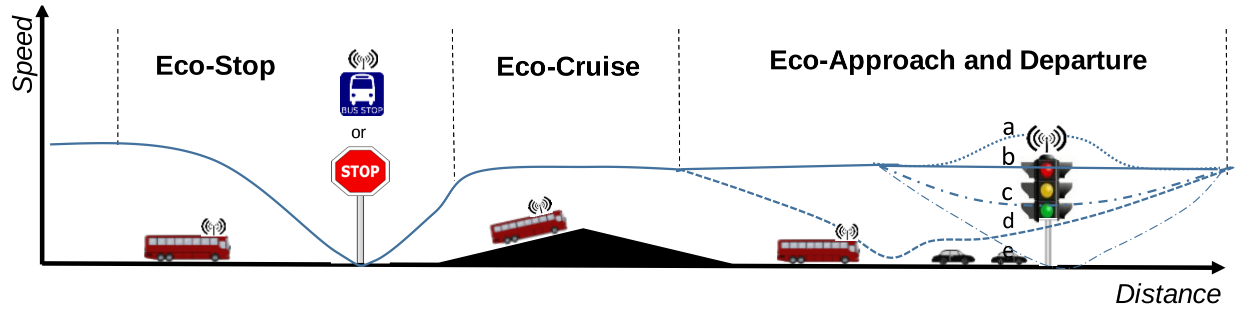
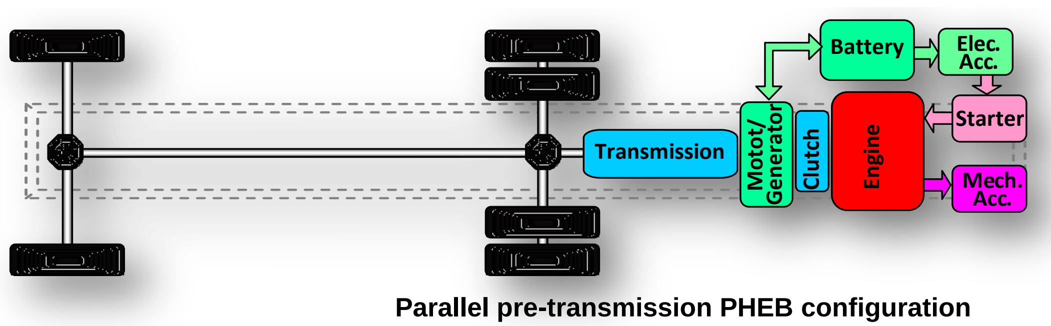
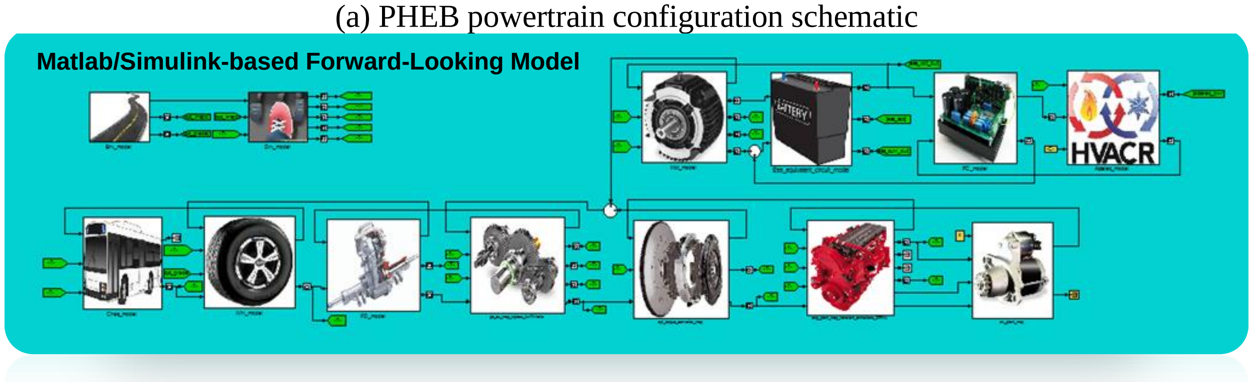


Figure 1. CAV applications being developed in this research

A Matlab/Simulink based PHEB model for a general pre-transmission parallel hybrid configuration was developed based on Oak Ridge National Laboratory components, data and Autonomie results as a part of the effort for an innovative vehicle-powertrain eco-operation system. Figure 2 shows the PHEB powertrain configuration and corresponding model framework. The key components considered in the PHEB powertrain model include chassis, wheel, final drive, transmission, clutch, engine, motor/inverter, battery, electrical accessories, and starter, as well as the driver model. In addition, there are also five control modules for engine, clutch, transmission, motor, battery and EV/Hybrid controller that manage key operating decisions during propulsion and braking.



(a) PHEB powertrain configuration schematic



(b) PHEB Matlab/Simulink model framework

Figure 2. Hybrid powertrain configuration and Matlab/Simulink model framework

INTEGRATED VEHICLE DYNAMIC AND POWERTRAIN CONTROL

In this section, we take Eco-Approach and Departure (EAD) as the example, to show the methods that deeply integrate the vehicle dynamic and powertrain control system of the study PHEB. Other applications, such as Eco-Stop and Launch and Eco-Cruise, can be considered as the reduced version of EAD which do not consider the signal timing constraints. One can define specific target states to accommodate those applications and scenarios.

System Architecture

The proposed PHEB eco-operation system have following components, as shown in Figure 3.

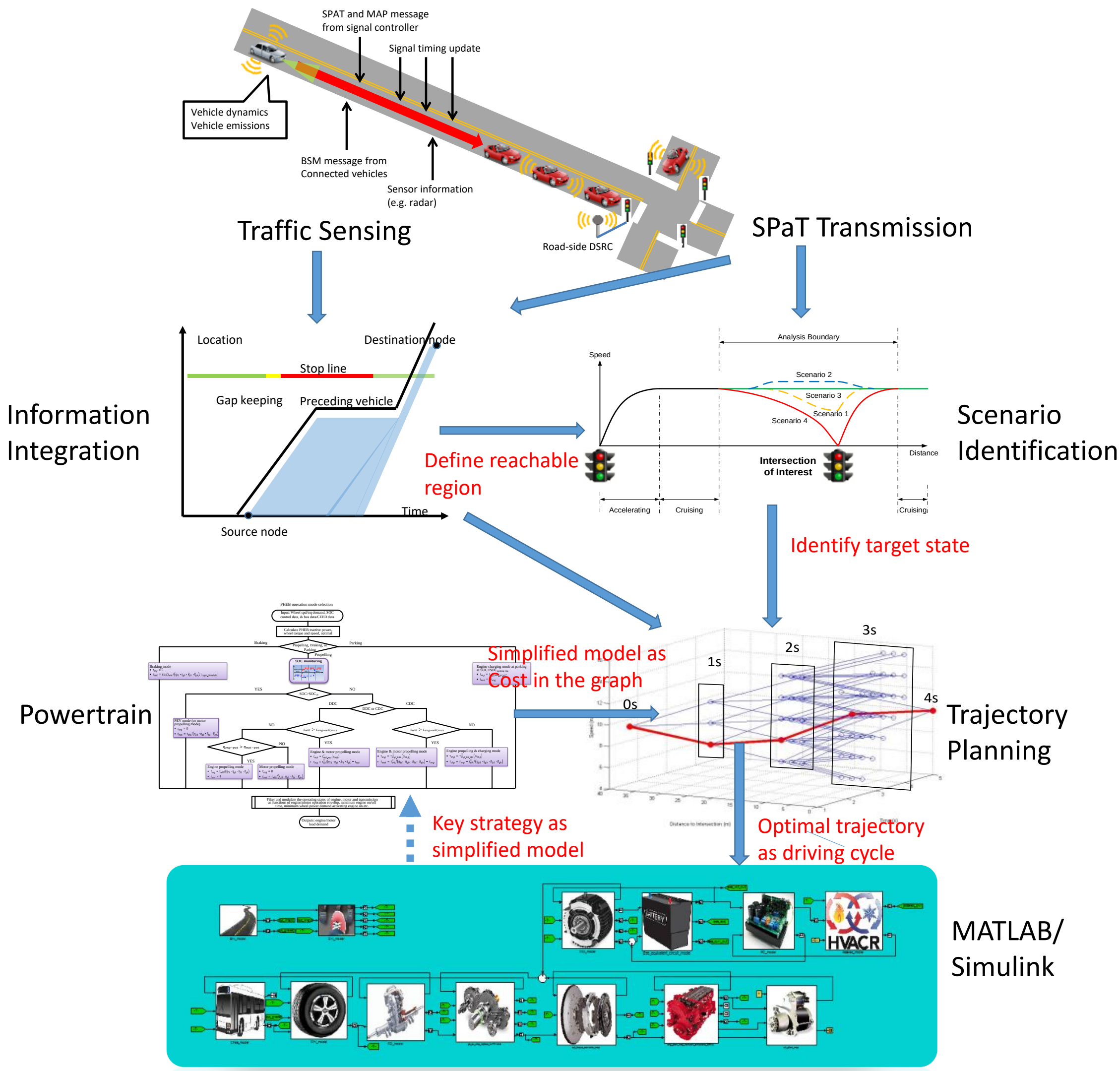


Figure 3 System architecture

<u>Information acquirement</u>, including traffic sensing and SPaT transmission. In this component, we collect all information from all available sources. For signal timing information, the system can get raw SPaT messages from either DSRC or 4G cellular network, and decode them into signal phase and count down data. For traffic information, the system synthesizes the data coming from infrastructure (e.g. loop detector and roadside radar), onboard sensors (e.g. automotive radar or camera), or communication devices from connected vehicles. Based on the traffic related data, we identify the current state of the preceding vehicle and predict its future states when approaching the intersection. If the preceding vehicle is not likely to be queued. Then we can forecast its future trajectory based on its current speed. If the preceding vehicle has joined the queue when detecting, we measure or estimate the location it queues, and predict the time it starts and the time it passes the intersection based on shockwave theory. If the vehicle have not joined the queue but is very likely to stop at queue at the intersection, we predict the time and location it joins the queue, and the time it starts or passes the intersection when the lights turns green. Those key state parameters will help envision the future trajectory of the vehicle based on some assumption of the vehicle dynamics, e.g. acceleration and deceleration rate. The predicted preceding vehicle's trajectory and the SPaT information will be sent to the information integration component for further processing.

Information integration. We translate the trajectory and signal data into the boundary values of the trajectory planning algorithm. As the study vehicle have to keep a safe distance away from the preceding vehicle, in the graph-based trajectory planning algorithm, a node is valid only if its distance to the intersection is greater than the distance of the preceding vehicle plus a safe distance. As the study vehicle cannot pass the intersection during the red time, any edge that connects two nodes at different sides of the intersection is invalid if the parent code is in the red time. Based on above rules we can define the reachable region of trajectory planning in the temporal-spatial domain, as shown in Figure 4. There are three typical cases for reachable region identification. If the vehicle can pass the intersection during the current green phase, no constraints are needed. The reachable region is then in a rhombus-shape. If the vehicle cannot keep the current speed to pass the intersection due to traffic signal and have to stop, the red time will provide a horizontal boundary. If there is a preceding vehicle, the reachable region is further shrank to keep a safe gap from that vehicle. In addition, the vehicle is only allowed to stop at the intersection if it is the first vehicle in the queue, or behind the preceding vehicle with a certain gap if it is not the first. A stop at any other location is not permitted according to common sense.

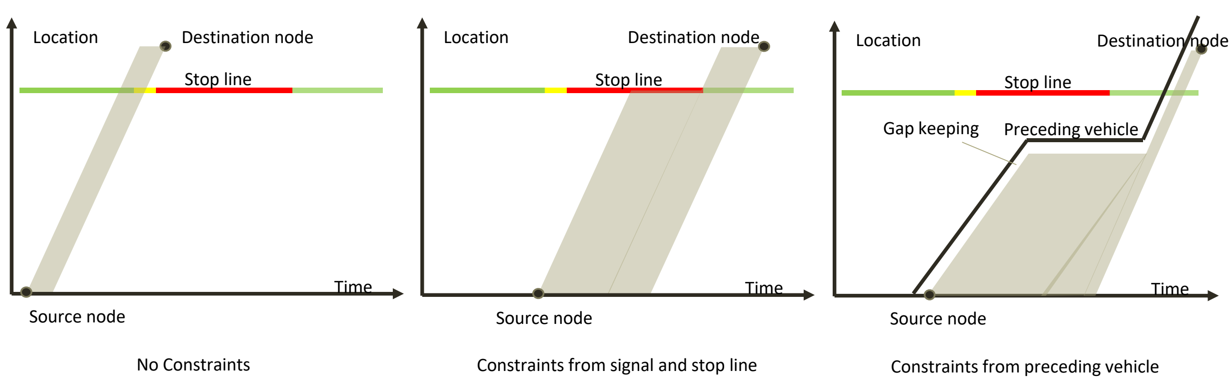


Figure 4 Three typical cases of reachable regions

Scenario identification. In this component, we aim to identify the target state of the vehicle based on its current state and signal timing information. In order to design an energy efficient trajectory while not sacrificing the travel time, we can set the target state as the final state of an uninformed driver who tries to pass the intersection as soon as possible (but still under traffic rules). Here the final state includes the location, time and speed when the vehicle is at the downstream of the stop line. Note that one can choose another target state for trajectory planning based on the user's need, the value of time/energy, and the following driving. For example, there may be some energy saving opportunity if we postpone the target departure time a little, but that mean delay in time and more chance of missing the green phase of the downstream intersection. As the focus of this paper is mainly on co-optimization of vehicle trajectory and powertrain, we will not discuss the different guidelines and strategies to identify the possible scenarios and target states in detail. To simplify the problem, we assume a reasonable target start is pre-determined before the integrated control.

Powertrain control and trajectory planning are two key components in the system. As discussed in the introduction, most fine-grained powertrain control algorithm are coded in MATLAB/Simulink based platform, such as Autonomie (*16*) and other customized models. For this PHEB project, a rule-based SOC control and engine/motor operation strategy is also designed in Simulink. It is difficult to put that Simulink model into the optimization loop directly, as it requires the full speed profile as the input driving cycle. It is therefore impossible to calculate "per second energy cost" based on the instant state. In addition, it takes very long computation time to go through the Simulink model for every possible trajectory to search for the optimal solution. A feasible alternative approach for deep algorithm integration is:

Step 1: Based on the key logic of powertrain control strategy, we develop a simplified PHEB powertrain model, and put it into our graph based optimization model as the edge cost to derive the theoretical optimal speed profile.

Step 2: The MATLAB/Simulink model takes that speed profile as the initial driving cycle, fine-tune it if it is not valid in engineering practice, and compute the powertrain parameters and energy consumption for the whole process under the optimal powertrain strategy.

Step 3 (optional): Repeat Step 1 and 2 iteratively to find the optimal solution with high validity and energy-efficiency. The number of iteration is mainly decided by real-time performance requirement.

In this way, Simulink is taken out of the optimization loop to avoid the huge computation time, and it is applied in Step 2 to ensure the solution is valid and effective in practice. The powertrain model is then included as a module of the graph based trajectory planning model and we can co-optimize both models at the same time. The whole process can be illustrated in the lower part of Figure 1. We use the right arrows to show Step 1, down arrow to show Step 2, and dashed up arrow to show the Step 3 which is optional.

In the following sections, we will describe the simplified PHEB powertrain model and graph based trajectory planning model in detail to show the deep integration of both operations.

Simplified PHEB powertrain model

For the study parallel pre-transmission PHEB, the supervisory control strategy considers three propulsion control processes: PHEB depletion charge (DC), discharge dominant control (DDC), and charging dominant control (CDC). As shown in Figure 5, when SOC is greater than the upper bound of the control range (SOC_{ub}), the control strategy selects the PHEB DC mode. After the SOC decreases below SOC_{ub}, the operation is in charge sustaining mode and the controller switches between the DDC and CDC processes each time the specified values of SOC_{ub} and SOC_{lb} are reached, ensuring safe and reliable battery operation. If SOC< SOC_{lb}, the control strategy adopts CDC.

Discharge dominant control (DDC): If the vehicle is under DDC mode, the PHEB can run in engine propulsion mode, motor propulsion mode, and combined engine and motor propulsion mode as show in Figure 5. The mode selection is based on wheel torque τ_{whl} and maximum engine torque $\tau_{eng-whl,max}$, as well as the estimate engine and motor efficiency $\eta_{eng-pwt}$ and $\eta_{mot-pwt}$ under certain speed.

We first formulate the equation to calculate wheel torque. Assume the velocity of the vehicle is v, the wheel speed is v/r_r, where r_r is the radius of the wheel, and the wheel torque demand is formulated as:

$$\tau_{whl} = r_r\left(ma + mg\sin\theta + \mu mg\cos\theta + \frac{1}{2}C_D\rho_a A v^2\right) \quad (1)$$

where m is the vehicle mass (kg), g is gravity constant, θ is the road grade (rad), μ is the rolling resistance coefficient, C_D is the drag coefficient, $\rho_a$is the air density (kg/m^3) and A is the vehicle frontal area (m^2).

If the wheel torque τ_{whl} is less than the maximum engine torque $\tau_{eng-whl,max}$, as shown in the bottom left of Figure 5, the vehicle need to determine whether an engine-only mode or a motor only mode is needed based on the efficiency of both modes at current state. Based on the Component energy efficiency database (CEED) based strategy and the parameters from Simulink model, we develop interpolation methods for efficiency factor computation and mode choice. Based on the mode selection result, if the PHEB is under engine propulsion mode, we compute the engine torque as follows

$$\tau_{eng} = \tau_{whl}/(\eta_{fd}\eta_{gb}R_{fd}R_{gb}) \quad (2)$$

where R_{gb} is the gear ratio, R_{fd} is the final drive ratio, η_{gb} and η_{fd} are the efficiency of gear box and final drive. The engine speed is then computed as Eqn (3). Based on the engine torque and speed, the fuel consumption rate can be then calculated using engine map.

$$\omega_{eng} = R_{fd}\,R_{gb}/r_r \cdot v \quad (3)$$

If the PHEB is under motor propulsion mode, the motor torque is calculated using the same formula as Eqn (2).

$$\tau_{mot} = \tau_{whl}/(\eta_{fd}\eta_{gb}R_{fd}R_{gb}) \quad (4)$$

$$\omega_{mot} = R_{fd}\,R_{gb}/r_r \cdot v$$

The battery power is then calculated based on the motor efficiency map. Note that if SOC is greater than SOC_{ub}, same motor propulsion mode model can be applied to the PHEB depletion charge mode.

If the wheel torque τ_{whl} is greater than the maximum engine torque $\tau_{eng-whl,max}$, the PHEB is under combined engine and motor propulsion mode. Based on the Simulink model, we can get the torque of motor and engine using following equations.

$$\tau_{mot} = \tau_{mot,max}(\omega_{mot})$$

$$\tau_{eng} = \frac{\tau_{whl}}{\eta_{fd}\eta_{gb}R_{fd}R_{gb}} - \tau_{mot} \quad (5)$$

<u>Charging dominant control (CDC):</u> if the vehicle is under CDC mode, the PHEB can run in engine propulsion while charging mode, and combined propulsion mode, depending on the relation between τ_{whl} and $\tau_{eng-whl,max}$.

As indicated in the bottom right of Figure 5, when engine propelling the vehicle while charging battery ($\tau_{whl} \leq \tau_{eng-whl,max}$), an interpolation function was applied to find the optimal engine torque $\tau_{eng,opt}(\omega_{eng})$under the current speed, so the residual power is assigned to the battery for charging. The motor (generator) torque for charging is

$$\tau_{mot,chg} = \tau_{eng,opt}(\omega_{eng}) - \frac{\tau_{whl}}{\eta_{fd}\eta_{gb}R_{fd}R_{gb}} \quad (6)$$

Under combined engine and motor propulsion mode ($\tau_{whl} > \tau_{eng-whl,max}$), Similar as Equation (5), we have

$$\tau_{eng} = \tau_{eng,max}(\omega_{eng})$$

$$\tau_{mot} = \frac{\tau_{whl}}{\eta_{fd}\eta_{gb}R_{fd}R_{gb}} - \tau_{eng} \quad (7)$$

<u>Regenerated Braking</u>: As the PHEB is capable of converting vehicle kinetic energy into a storable form of battery energy during braking, the regenerated braking power is formulated as

$$W_{reg} = \tau_{whl} \cdot \omega_{mot} \cdot \eta_{wh}\eta_{fd}\, \eta_{mot}\, \eta_{batt} \quad (8)$$

where η_{wh} is the wheel drive efficiency, η_{mot} is motor efficiency, and η_{batt} is battery efficiency.

For combined engine and motor propulsion mode and engine propelling the vehicle while charging mode, we also need to determine the weights of fuel consumption rate and battery discharging power (or charging power) to derive the cost of each edge in the trajectory planning. The impact of mode choice should be considered in a relatively long term, as the bus may be under operation for 8 hours before it has the chance to charge in the charging facility. Therefore, we estimate the weights based on the mileage that the unit fuel consumption or battery power can propel the bus under engine-only or motor only mode. The final cost is then the weighted sum of fuel consumption rate and battery power, with kW as the unit. The simplified PHEB powertrain model provide a direct link to connect vehicle dynamic state (speed, acceleration and road grade) to the energy consumption. This model is then integrated into the graph-based trajectory planning algorithm as the cost of each edge.

Trajectory Planning

As stated in the previous section, the trajectory planning algorithm synthesizes the traffic/signal boundary condition from information integration module, target states information from scenario identification module, and the energy cost from the powertrain module. We then develop a graph model to solve the trajectories planning problem with constraints on target travel time *T*, target distance X and target speed v_d. To formulate this graph model, we discretize the time and space into fixed time step Δt and distance grid Δx. The vehicle speed domain is therefore discretized with $\frac{\Delta x}{\Delta t}$ as the step. At each node of the proposed directed graph *G*=(*V*, *E*), we assign a unique 3-D coordinate (*t*, *x*, *v*) which describes the dynamic state of the vehicle, where $t \in (0, T]$ is the time (in second), $x \in [0, X]$ is the distance to the intersection (in meter) and $v \in [0, v_l]$ is the speed (in m/s), where v_l is the speed limit In this graph. As the study vehicle have to keep a safety distance x_{gap} from the location of the preceding vehicle x_{pre} (*t*) at certain time. We have

$$x(t) \geq x_{pre}(t) + x_{gap} \tag{9}$$

We also have *v*(*t*)>0 if $x(t) \geq x_{pre\_queue}$, as the vehicle is only allowed to stop right behind the queue position of preceding vehicle (or the stop line if there is no preceding vehicle). There is an edge from V_1 (t_1, x_1, v_1) to V_2 (t_2, x_2, v_2) if and only if following rules are satisfied:

1) Time at V_2 is consecutive with time at V_1: $t_2 = t_1 + \Delta t$;
2) Consistency on distance and speed: $x_2 = x_1 + v_1 \Delta t$
3) Acceleration constraint: $a_{min} \leq \frac{v_2 - v_1}{\Delta t} \leq a_{max}$, where a_{min} and a_{max} are the maximum deceleration rate and maximum acceleration rate for the study diesel truck respectively.
4) Signal constraint: if t_1 is in the red time, $x_1 \cdot x_2 > 0 \ or \ x_1 > 0, x_2 = 0$ to ensure there is no edge that connects two nodes at different side of the intersection if the parent code is in the red time.

Based on the PHEB powertrain model, we define the cost on edge $V_1 \rightarrow V_2$ as the weighted energy consumption during this state transition process. The road grade information is also integrated in the model (details in (*15*)). At this point, the energy consumption minimization problem is converted into a problem to find the shortest path from the source node V_s(*0*, *X*, v_s) to the destination node V_d (*T*, *0*, v_d) in the directed graph *G*=(*V*, *E*). The Dijkstra's algorithm (*17*) is then applied to solve this single-source shortest path problem.

The deep integration based trajectory optimization algorithm is then interfaced with the Matlab/Simulink platform for further trajectory fine-tuning and powertrain parameters and energy consumption computation. As shown in Figure 3, the three steps can repeat in a loop to improve the co-optimization performance, if the computation time allows.

NUMERICAL EXPERIMENT

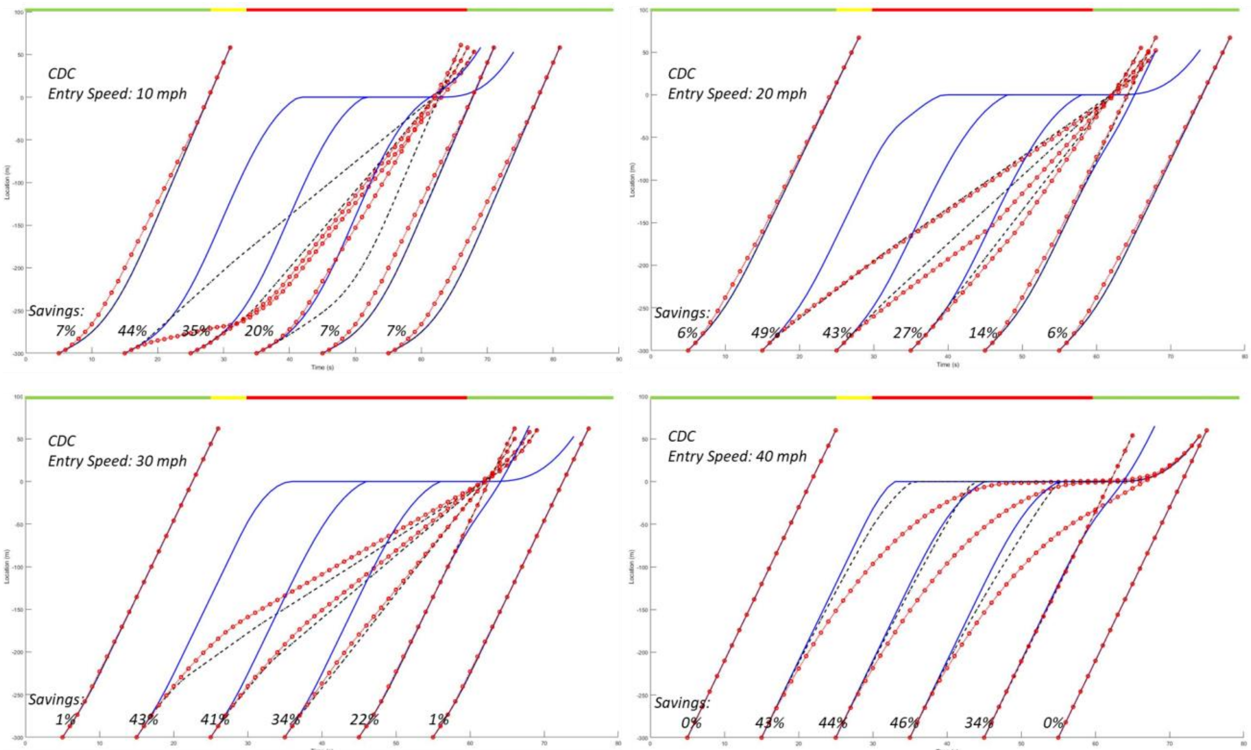
Eco-Approach and Departure

In this section, the developed VD/PT co-optimization algorithm is applied to simulate vehicle trajectories of a PHEB at a hypothetical signalized intersection with different entry times. The length of the study area is 300 m (i.e., from 300 m upstream of the intersection to the stop line). The speed limit is set to 40 mph. The time of the green phase is 27 s, the time for yellow is 3 s and the time for the red phase is 30 s. Six different entry times in a cycle are tested: the 5th second in green (G5), the 15th second in green (G15), the 25th second in green (G25), the 5th second in red (R5), the 15th second in red (R15), and the 25th second in red (R25). We also test multiple initial speeds from 10 mph to 40 mph, with 10 mph as the increment.

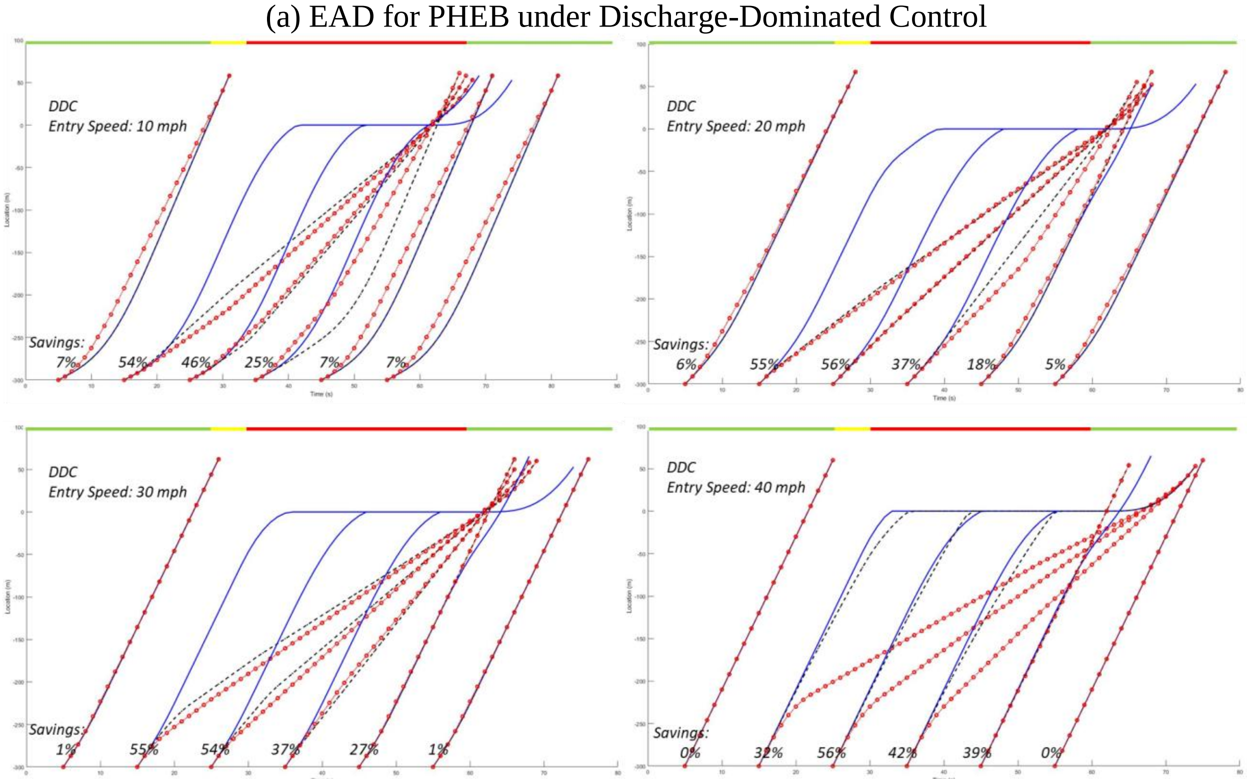
In Figure 7, we show PHEB trajectories for three Eco-Approach and Departure (EAD) cases. The blue solid lines represent the baseline trajectories for uninformed driver (without EAD). The black dashed lines represent the trajectories generated using the trigonometric EAD algorithm which was widely applied in previous studies (*4*, *9*). The red dotted lines and circles represent the trajectories generated using the integrated control algorithm developed in this paper. We also show the signal phases using their corresponding colors. Note that in each subfigure, we overlay the trajectories of the PHEB under six different entry time scenarios (i.e., G5, G15, G25, R5, R15, and R25). The energy savings reported along the x-axis correspond to the six entry time scenarios. These are the energy savings of the newly developed EAD algorithm as compared to the baseline case of uninformed driver without EAD.

Figure 7 (a) shows the comparison of PHEB trajectories during CDC mode when the PHEB mainly relies on power from the engine. Under CDC operation, the newly developed EAD algorithm results in an average energy savings of 26% when compared with the baseline PHEB with uninformed driver. The new EAD algorithm also results in an average of 10% less energy consumption than the trigonometric EAD algorithm. Figure 7(b) shows the comparison of PHEB trajectories during DDC mode. The newly developed EAD algorithm results in an average energy savings of 31% when compared with the baseline PHEB with uninformed driver. The new EAD algorithm also results in an average of 10% less energy consumption than the trigonometric EAD algorithm.

For both CDC and DDC mode, the proposed methods show significant energy saving benefit for almost all scenarios. Specifically, when the vehicle approaches the intersection area at the beginning of the red phase, the energy saving is over 40% for CDC and 50% for DDC. If the vehicle can pass the intersection directly in the green time without any delay, the improvement on energy is not as significant because there is not too much opportunity for trajectory optimization in this case.



(a) EAD for PHEB under Discharge-Dominated Control



(b) EAD for PHEB under Charge-Dominated Control

Figure 7. Trajectories and energy saving of proposed EAD model

We then take the optimal trajectory as the input driving cycle and applied it to the MATLAB/Simulink model for powertrain-parameters and energy consumption fine-tuning. Table 2 shows the fuel and battery consumption for PHEB under both CDC and DDC mode. Comparing with baseline method and trigonometric method, the proposed method shows significant energy saving benefits in this table.

Table 2 (a) Fuel and Battery consumption for PHEB under Charge-Dominated Control

Entry Speed	**10 mph**		**20 mph**		**30 mph**		**40 mph**	
Consumption (- if Charging)	Fuel (g)	Battery (kwh)	Fuel (g)	Battery (kwh)	Fuel (g)	Battery (kwh)	Fuel (g)	Battery (kwh)
Baseline	0.20	0.21	0.15	0.13	0.13	0.07	0.11	-0.06
Old EAD	0.20	0.04	0.20	-0.20	0.17	-0.26	0.09	-0.04
New EAD	0.22	-0.15	0.17	-0.17	0.15	-0.22	0.08	-0.17

Table 2 (b) Fuel and Battery consumption for PHEB under Discharge-Dominated Control

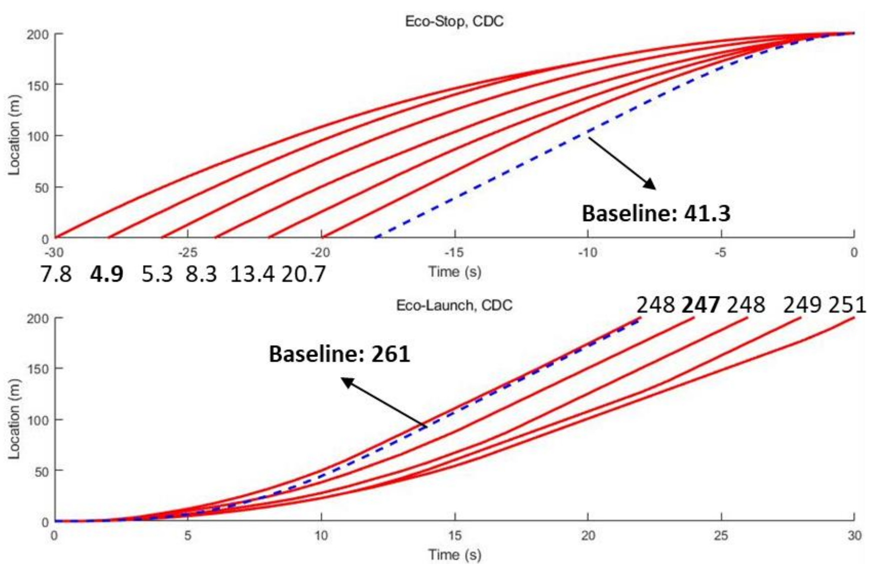
Entry Speed	**10 mph**		**20 mph**		**30 mph**		**40 mph**	
Consumption (- if Charging)	Fuel (g)	Battery (kwh)	Fuel (g)	Battery (kwh)	Fuel (g)	Battery (kwh)	Fuel (g)	Battery (kwh)
Baseline	0.12	0.52	0.10	0.29	0.08	0.22	0.06	0.08
Old EAD	0.10	0.49	0.07	0.33	0.06	0.22	0.05	0.09
New EAD	0.06	0.50	0.06	0.32	0.05	0.21	0.04	0.09

Eco-Stop and Launch

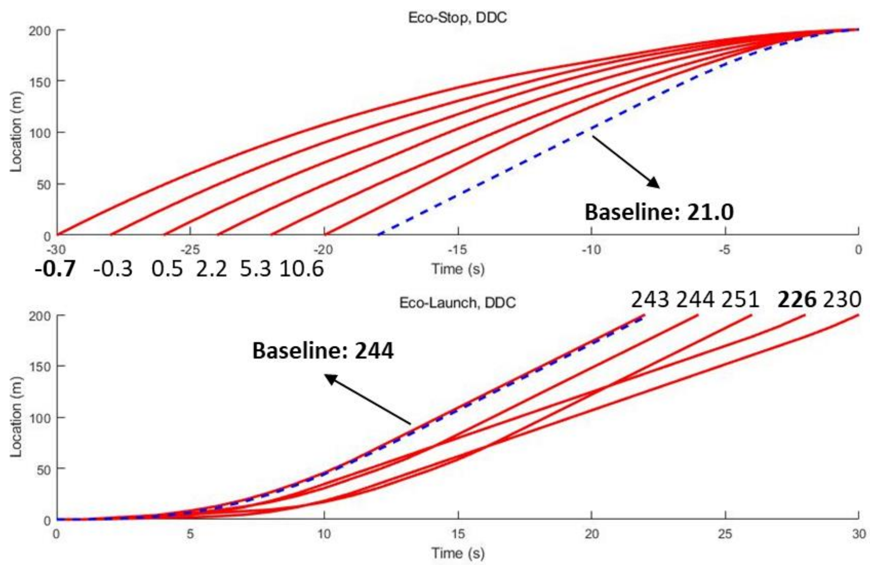
The Eco-Stop and Launch (ESL) application can be considered as a special case of EAD. It is similar to the stop scenario in EAD, but instead of stopping at a traffic light, the PHEB is to stop at a bus stop or a stop sign. To test the eco-stop process, we assume the initial distance to the bus stop (or stop sign) to be 200 m, and the entry speed to be 30 mph. We then use the new EAD algorithm to construct the most energy-efficient deceleration trajectories for different time durations. A similar approach is applied to the eco-launch process to determine the most energy-efficient acceleration trajectories when accelerating from a stop.

Figure 8(a) shows the results of the eco-stop and eco-launch processes in CDC operation. In the top figure, we label the total energy consumption (in kJ) of the deceleration process below the optimal trajectories (red solid curves) for different deceleration durations from 20 s to 30 s with a 2 s increment. It shows that if the PHEB takes 28 s to traverse the 200 m distance to a full stop at the destination, the total energy consumption would be lowest at 4.9 kJ. That is 88% less than the baseline method, which is derived from the previously developed trigonometric model. In the bottom figure, we note the total energy consumption of the acceleration process above the optimal trajectories for different acceleration durations. The PHEB would consume the least fuel consumption of 247 kJ if it takes 22 s to traverse the 200 m distance to get to the final speed of 30 mph. This eco-launch acceleration profile achieves 5% fuel savings when compared with the baseline model. Figure 8(a) also shows other options for eco-stop and launch for the different deceleration/acceleration durations. It is observed that the total energy consumption has a convex relationship with the deceleration/acceleration duration. Thus, the globally optimal trajectory with respect to total fuel consumption and time can be found. Note that if the PHEB needs to save time in order to catch up with the schedule, it may choose a faster stop and launch profile at the expense of energy efficiency.

Figure 8(b) shows the results of the eco-stop and eco-launch processes in DDC operation. During the eco-stop process, the PHEB may gain additional energy from regenerated braking if it decelerates slowly to a stop. The net energy savings as compared to the baseline range from 10 kJ (50%) to for the deceleration duration of 20 s to 22 kJ (103%) for the deceleration duration of 30 s. Note that the total energy consumption has a monotonic relationship with the deceleration duration—the shorter the duration, the more total energy consumption. Thus, the selection of the stop and launch profile will depend more on the time constraint and practicality. During the eco-launch process, the energy consumption is not as sensitive to how the PHEB accelerates within the same amount of acceleration duration. The baseline and the fastest optimal trajectories would both take 22 s and consume 261 and 248 kJ, respectively. A slower acceleration of 24 s would save 14 kJ or 5%.



(a) Eco-Stop and Launch under CDC mode



(b) Eco-Stop and Launch under DDC mode
Figure 8. Trajectories of Eco-Stop and Launch

Eco-Cruise

The Eco-Cruise (EC) application can be considered as another special case of EAD. It is similar to the constant speed scenario of EAD in Figure 1, but in addition to cruising through a signalized intersection, it can also be applied to cruising in midblock or between stops. As cruising does not involve deceleration and acceleration, the key aspect to address with respect to energy consumption is the impact of road grade. For any cruising speed, an optimal vehicle trajectory can be designed for a specific terrain.

Figure 9 shows examples in which the PHEB enters a road segment with the distance of 260 m at the speed of 13 m/s under CDC operation mode. If the road segment is on a flat terrain, the optimal solution is to simply cruise at 13 m/s for 20 s. However, if the road segment is on a rolling terrain, then the PHEB needs to adjust the cruising speed in response to the road grade in order to minimize the energy consumption. As shown in Figure 10, the EC application suggests different speed profiles for different types of terrain. In the CDC mode, for a crest vertical curve with 5% uphill in the first half and 5% downhill in the second half, the optimal speed profile suggested by EC (represented by the blue solid curve) saves 8.6% fuel as compared with the baseline with a constant speed. The optimal speed profile is an M-shaped curve with the minimum at the peak point of the crest vertical curve. For a sag vertical curve with 5% downhill in the first half and 5% uphill in the second half, the optimal speed profile suggested by EC (represented by the red dotted curve) saves 17% fuel. The optimal speed profile is a W-shaped curve with the maximum at the bottom of the sag vertical curve.

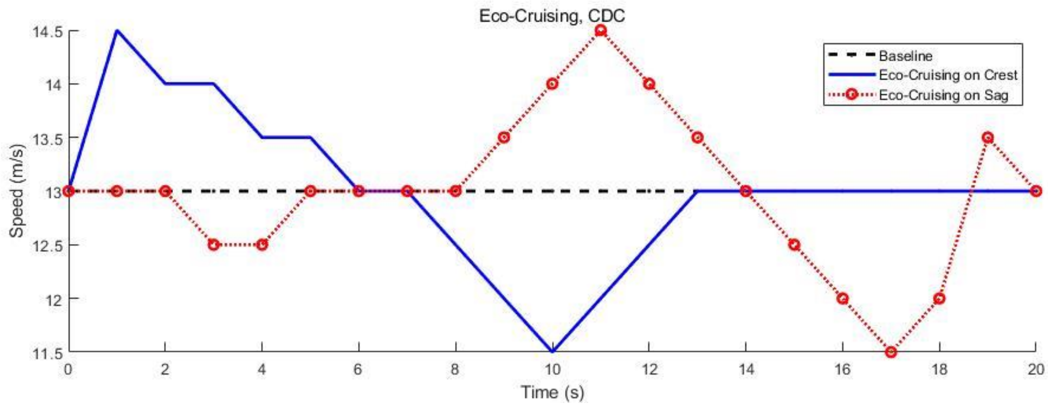


Figure 9. Eco-Cruise under CDC mode

CONCLUSIONS

In this paper, we developed an integrated vehicle dynamic and powertrain control model to support the eco-operation solution for a plug-in hybrid electric bus (PHEB) and improve the vehicle energy efficiency and reducing tailpipe emissions. The proposed eco-operation system have 6 components, including traffic/signal timing information acquirement, information integration, scenario identification, powertrain, trajectory planning and a MATLAB/Simulink model for validation and fine-tuning. Based on the key logic of powertrain control strategy of PHEB, we develop a simplified PHEB powertrain model, and put it into the graph based optimization model as the edge cost to derive the theoretical optimal speed profile. The MATLAB/Simulink model takes that speed profile as the initial driving cycle, fine-tune it if it is not valid in engineering practice, and compute the powertrain parameters and energy consumption for the whole process under the optimal powertrain strategy. The proposed mode is validated in multiple numerical tests under EAD, ESL and EC scenarios, and shows significant performance in energy-saving, e.g. 26%-31 in EAD, 5%~103% in ESL, and 9%~17% in EC. Meanwhile, the proposed algorithm is computational efficient due to the dynamic programming concept when formulating the problem, which is beneficial in real world implementation. Directions for future research can be summarized as follows:

(1) We are now working on implementation of the proposed model in both microsimulation (e.g. VISSIM) and Dyno-In-The-Loop testbed, so that more realistic and reliable data will be collected and analyzed to validate and improve the model.

(2) The proposed model is applicable to other types of vehicles and powertrains, such as light-duty and heavy-duty vehicle, EVs and PHEVs, by replacing the current powertrain module with other models. More features of other powertrains can be evaluated in the proposed framework.

(3) In the real world traffic, the acquisition of traffic information is constrained by the communication and sensing range, and the timing of actuated signals also has high uncertainty. It is a great challenge to design a robust speed profile that would adapt the dynamic and uncertain downstream traffic and signal conditions. As a future work, a Partially Observed Markov Decision

Process (POMDP) based approach is therefore developed to provide a proactive approach rather than a passive way to adapt to the dynamic uncertainty.

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REFERENCE

[1] S. Mandava, K. Boriboonsomsin and M. Barth, "Arterial velocity planning based on traffic signal information under light traffic conditions," *12th International IEEE Conference on Intelligent Transportation Systems*, St. Louis, MO, 2009, pp. 1-6.

[2] M. Li, K. Boriboonsomsin, G. Wu, W. Zhang, and M. J. Barth, "Traffic Energy and Emission Reductions at Signalized Intersections: A Study of the Benefits of Advanced Driver Information", *International Journal of ITS Research*, 2009.

[3] B. Asadi, and A. Vahidi, "Predictive Use of Traffic Signal State for Fuel Saving". *12th IFAC Symposium on Transportation Systems Redondo Beach*, CA, USA, September 2009.

[4] M. J. Barth., S. Mandava, K. Boriboonsomsin, and H. Xia, "Dynamic ECO-driving for arterial corridors". *Integrated and Sustainable Transportation System (FISTS), 2011 IEEE Forum on*, pp.182-188, June 29 2011-July 1 2011.

[5] H. Rakha, R. K. Kamalanathsharma, "Eco-driving at Signalized Intersections Using V2I Communication". The 14th IEEE Conference on Intelligent Transportation Systems (ITSC), Washington, D.C., USA. October 5 – 7, 2011

[6] R. K. Kamalanathsharma, and H. Rakha, "Multi-stage dynamic programming algorithm for eco-speed control at traffic signalized intersections". In 16th International IEEE Conference on Intelligent Transportation Systems, IEEE, pp. 2094–2099., 2013.

[7] G. De Nunzio, C. C. de Wit, P. Moulin, D. Di Domenico, "Eco-Driving in Urban Traffic Networks using Traffic Signal Information". The 52nd IEEE Conference on Decision and Control, Florence, Italy, December 2013

[8] G. Mahler and A. Vahidi, "An Optimal Velocity-Planning Scheme for Vehicle Energy Efficiency Through Probabilistic Prediction of Traffic-Signal Timing". Intelligent Transportation Systems, IEEE Transactions on, vol. 15, pp. 2516-2523, 2014.

[9] P. Hao, G. Wu, K. Boriboonsomsin, M. Barth. "Developing a Framework of Eco-Approach and Departure Application for Actuated Signal Control". IEEE on Intelligent Vehicles Symposium, Seoul, Korea. June, 2015

[10] S. Li and H. Peng, "Strategies to minimize the fuel consumption of passenger cars during car-following scenarios", Proceedings of the *Institution of Mechanical Engineers, Part D: Journal of Automobile Engineering*, Vol 226, Issue 3, pp. 419 – 429, 2012.

[11] J. Hu, Y. Shao, Z. Sun, & J. Bared, "Integrated vehicle and powertrain optimization for passenger vehicles with vehicle-infrastructure communication", *Transportation Research Part C* 79 (2017) 85–102, 2017.

[12] X. Huang, H. Peng, "Speed Trajectory Planning at Signalized Intersections with Sequential Convex Optimization", Proceedings of the 2017 American Control Conference, Seattle, WA, USA, 2017.

[13] Q. Jin, G. Wu, K. Boriboonsomsin and M. J. Barth, "Power-Based Optimal Longitudinal Control for a Connected Eco-Driving System" , *IEEE Transactions on Intelligent Transportation Systems*, vol. 17, no. 10, pp. 2900-2910, Oct. 2016.

[14] X. Qi, G. Wu, P. Hao, K. Boriboonsomsin and M. J. Barth, "Integrated-Connected Eco-Driving System for PHEVs With Co-Optimization of Vehicle Dynamics and Powertrain Operations", *IEEE Transactions on Intelligent Vehicles*, vol. 2, no. 1, pp. 2-13, March 2017.

[15] P. Hao, K. Boriboonsomsin, C. Wang, G. Wu, and M. Barth. "Connected eco-approach and departure (EAD) system for diesel trucks". Proceedings of the 97th Annual Meeting of Transportation Research Board, Washington, DC. 2018.

[16] Autonomie, Argonne National Laboratory, https://www.autonomie.net/. Accessed in July, 2018

[17] E. W. Dijkstra, "A note on two problems in connexion with graphs", *Numerische Mathematik*. 1: 269–271, 1959.