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# Integrated-Connected Eco-Driving System for PHEVs With Co-Optimization of Vehicle Dynamics and Powertrain Operations

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**Abstract**—In the past several decades, various types of technologies have been developed to improve vehicle fuel efficiency and reduce tailpipe emissions across different dimensions. For example, powertrain-related technologies improve fuel efficiency by optimizing the powertrain operations in response to different driving conditions (e.g., energy management system for plugin hybrid electric vehicles); another technology dimension lies in intelligent transportation systems (ITS), which improve vehicle fuel efficiency by optimizing the vehicle dynamics or speed under different traffic conditions (e.g., eco-speed harmonization and eco-approach and departure). However, very little effort has been made to investigate the combined benefit of integrating both powertrain and ITS technology dimensions together. In this paper, an integrated and connected eco-driving assistance system with co-optimization of vehicle dynamics and powertrain operations for PHEVs is proposed. To fully evaluate the performance of the proposed system at different vehicle automation levels, real-world driving data for different eco-driving technological stages were collected: uninformed manual driving, eco-driving with an in-vehicle advisory display, and an eco-driving system with automatic longitudinal control. The numerical analysis shows that the co-optimization is able to achieve on average 24% fuel savings for typical urban driving conditions.

**Index Terms**—Co-optimization, energy management system, eco-approach and departure, hybrid powertrain.

## I. INTRODUCTION

**R**EDUCING transportation-related energy consumption and greenhouse gas (GHG) emissions have been a common goal of many public agencies and research institutes for years. In 2013, the total energy consumed by the transportation

sector in the United States was as high as 24.90 Quadrillion BTU [1]. The U.S. Environmental Protection Agency (EPA) reported that nearly 27% GHG emissions resulted from fossil fuel combustion for transportation activities in 2013 [2]. Therefore, the resulted air pollution and climate change impacts have motivated many researchers to search different ways to reduce transportation activity related fuel consumption and GHG emissions. From technical perspective, there are generally four major ways:

- 1) Develop and use cleaner alternative energy sources to replace fossil fuels, such as electricity from renewable resources (e.g., solar, wind) and hydrogen. With these alternative fuels, many new powertrain types can be developed, such as, electric and fuel cell vehicles. In recent years, transportation electrification has been a very active research area. Groundbreaking changes have been witnessed in powertrain electrification during the past several decades, such as the development of hybrid electric vehicles (HEVs) and battery electric vehicles (BEVs). HEVs are able to achieve higher fuel efficiency than internal combustion engine (ICE) by taking advantage of additional electric energy efficiencies. BEVs removed the use of fossil fuels by using only electricity. However, the massive adoption of EVs is impeded by the limited charging infrastructure and limited cruise range per charge. This also usually causes the driver's anxiety which is called "range anxiety" [3]. Toward this end, plug-in hybrid electric vehicles (PHEVs) have emerged as a transitional vehicle type between ICE vehicles and BEVs. Compared with HEVs, PHEVs have larger capacity batteries and can be re-charged by plugging into the electrical grid, thus increasing the use of electricity and achieving even higher overall fuel efficiency [4], [5]. At the same time, the complementary fossil fuel power source can reduce the driver's anxiety of the limited all-electric-range (AER).
- 2) Build more efficient vehicles, including the design of more efficient powertrain systems and energy management systems (EMS) to achieve higher fuel economy. This is especially important for PHEVs. In comparison to conventional HEVs, the EMS for PHEVs are significantly more complex due to their extended electric-only propulsion and battery chargeability via external electric power sources. Numerous efforts have been made in

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developing a variety of EMS for PHEVs [6], [7]. From the optimization and control perspective, all these efforts are about improving vehicle fuel economy through powertrain operation optimization.

- 3) Improve efficiency of transportation systems and encourage fuel-efficient driving, such as reducing traffic congestion or unnecessary stop-and-go maneuvers at signalized intersections by using connected vehicle (CV) technologies. It is reported that nearly 7 billion hours of delay and more than 3 billion gallons of fuel were wasted in 2014 due to traffic congestion in the U.S. [8], a significant portion of which is due to getting stuck at traffic signals. Technologies such as eco-approach and departure (EAD) systems [9] have been developed to help vehicles travel through the signalized intersection smoothly and avoid unnecessary idling and acceleration/deceleration based on using signal phase and timing (SPaT) information. In terms of optimization and control, these efforts are trying to improve vehicle fuel efficiency by modifying the vehicle (longitudinal) dynamics.

Good progress is being made in these individual technological dimensions. However, to the best of our knowledge, very few efforts have been made to tightly integrate all these above mentioned technologies together for achieving maximum vehicle fuel economy. Therefore, to fill this gap, in this paper, we propose an integrated and connected eco-driving system with co-optimization of vehicle dynamics and hybrid powertrain operations for PHEVs. The proposed system combines the advantages of all the abovementioned technologies together to greatly boost the fuel economy in urban driving.

The remainder of the paper is organized as follows: In Section II, the state-of-the-art of the relevant work is presented, the drawbacks of the existing work and the major contributions are also provided. In Section III, the mathematical formulation for the proposed co-optimization as well as the designing of each component are given. The system architecture and flowchart are also provided. In Section IV, the details about the real-world test-driving and data collection are also elaborated. The results and discussion are given in Section V and conclusions can be found in Section VI.

## II. RELATED WORKS & STATE-OF-THE-ART

### A. EMS for PHEVs

Typically, there are three major types of PHEV powertrain architectures [17]: a) series, b) parallel, and c) power-split (series-parallel). This study is focused on the power-split architecture (see Fig. 1(a)) where the ICE and electric motors can, either alone or together, power the vehicle while the battery pack may be charged simultaneously through the ICE. Fig. 1(b) depicts the configuration of a power-split PHEV, in which three major sub-systems: a) ICE, b) planetary gear set (PGS), and c) motor/battery are modeled as described below.

EMS is the core component of a PHEV powertrain system, whose functionality is to control the power streams from both the internal combustion engine (ICE) and the battery pack, based

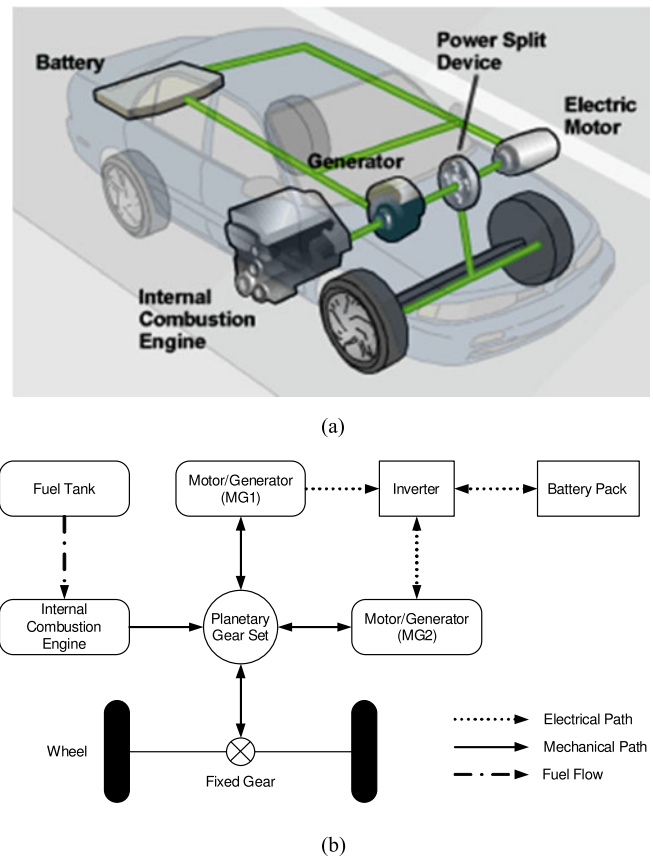


Fig. 1. Power-split plug-in hybrid electric vehicle [42]. (a) Hardware structure of power-split architecture. (b) Power-split plug-in hybrid electric vehicle configuration.

on vehicle operating conditions (e.g., current vehicle battery state-of-charge).

In the past decade, a large variety of EMS implementations have been developed for PHEVs, whose control strategies may be well categorized into three major classes. First, rule-based strategies rely on a set of simple rules without a priori knowledge of driving conditions [10]–[13]. Such strategies make control decisions based on instant conditions only and are easily implemented, but their solutions are often far from being optimal due to the lack of consideration of variations in trip characteristics and prevailing traffic conditions. Second, prediction-based optimization strategies are aimed at optimizing some predefined cost function according to the predicted driving conditions and vehicle’s dynamics [14]–[19]. The selected cost function is usually related to the fuel consumption or tailpipe emissions. Based on what information is predicted, such strategies are further divided into full trip prediction and short-term prediction-based methods. And third, learning based strategies which are based on data-driven models and are capable of learning the optimal strategies from historical driving data [4], [5].

### B. Eco-Approach and Departure at Signalized Intersection

With the rapid advance in vehicle and communication technology, eco-friendly transportation operations have shown promising performance in energy savings and emission

reduction. Many pioneer programs, such as Applications for the Environment: Real-Time Information Synthesis (AERIS) [20] in the United States, and Compass4D [21] and eCoMove [22] in Europe, have been conducted to develop energy efficient transportation systems based on vehicle-to-vehicle (V2V) and vehicle-and-infrastructure (V2I/I2V) communications. The EAD at signalized intersection is one of the key applications in those programs, as unnecessary acceleration and hard braking in response to traffic signals is a major reason for wasted energy and elevated emissions in urban areas [23]–[27]. In an EAD system, traffic signals broadcast SPaT and Geometric Intersection Description (GID) information to all vehicles that equipped with Dedicated Short Range Communications (DSRC) devices. The drivers are then guided to follow well-planned trajectories (e.g., with piecewise trigonometric functions) to approach and depart from signalized intersections. Connected vehicles that follow the advisory speed can improve their fuel economy by 12% [9]. Microscopic traffic simulation models were used to evaluate the performance of the algorithms for intersection with fixed-time signal control, which shows 10-15% reductions in fuel consumption and carbon dioxide emission [28]. The benefits of EAD in real world were evaluated in a field test at the Turner Fairbanks Highway Research Center (TFHRC) in McLean, Virginia in 2012 [29]. The EAD application for intersection with actuated signal control which considers the dynamic uncertainty of traffic conditions and signal states was recently developed [30]. Simulations and field tests were conducted to validate the proposed framework and algorithms of EAD for actuated signals [31]. The EAD application is also applicable to congested traffic conditions where preceding vehicles and queues exist for most of the times. With the knowledge of queue information via real-time vehicle detection, optimal trajectories can be designed to avoid red time and queues [32]. In [33], the mobility and energy efficiency of the EAD system is further enhanced using vehicle platoons [33]. To the best of the authors' knowledge, most existing research on EAD applies to gasoline or diesel vehicles. The application and importance of EAD for PHEVs has not been well investigated.

### C. Initial Relevant Effort on Co-Optimization Technology

The existing research reviewed in previous sections show that vehicle fuel efficiency can be improved at least from two different perspectives: vehicle dynamics and powertrain control. The majority of existing studies are mainly focused on only one of them. Very few research on the combined optimization of vehicle dynamics and powertrain operations have been conducted. In one of our previous work [34], a power-based longitudinal control algorithm with co-optimization of vehicle dynamics and powertrain operations for ICE vehicles was proposed and tested. The algorithm took into account the vehicle's brake specific fuel consumption (BSFC) map, roadway grade, downstream traffic conditions, and traffic signal status of the upcoming intersection in the calculation of an optimal speed profile in terms of fuel savings and emissions reduction. Hu *et al.* [35] recently developed an eco-driving assistance system for hybrid electric vehicles (HEV) on rolling terrains. The system was capable of optimizing the powertrain operations of HEVs by taking

advantage of the information obtained via connected vehicle technology. Zulkefli *et al.* [36], proposed a combined approach of a time-efficient powertrain optimization strategy for HEVs, utilizing trajectory prediction based on connected vehicle technology. Gipps' car following model and cell-transmission-model are adopted for predicting future driving trajectory. Luo *et al.* [37] designed an optimal speed advisory strategy for HEV by combining the existing green light optimal speed advisory system (GLOSA) and a simulated HEV model. Zhang *et al.* [38] proposed a real-time energy management system for HEVs based on a chaining neural network (CNN) used for multi-step speed prediction. Although these initial effort, more deep investigation is still needed for the topic. The major drawbacks for the existing methods are summarized as followings:

- a) No general mathematical formulation of co-optimization of vehicle dynamics and powertrain operations are formed which can be used to provide a theoretical foundation for advanced optimization strategy design.
- b) For most of the existing work, the traffic information is directly fed to the powertrain optimization model. Hence, there is actually no vehicle dynamics optimization process. These models can be regarded as only EMS models.
- c) Most of the existing work are not evaluated with real-world test driving data, especially driving data resulted from different connected eco-driving technologies.
- d) Most of the existing work are for HEV not for PHEV. Since the battery for PHEV is re-chargeable, the objective for PHEV EMS is to maximize the use of the battery during the defined entire trip (charging-depletion and charging-sustaining) so that fuel consumption can be minimized. However, the battery for HEV is not re-chargeable hence the objective for HEV EMS is to minimize the fuel consumption and maintaining the SOC level at the same level during the entire trip(only charging-sustaining). Therefore, the optimization problem formulation for these two type of vehicles are different. In addition, for PHEV EMS, the opportunistic charging between trips can also be optimized to further reduce fuel consumption.

To add additional valuable findings for the topic, in this paper, An integrated and connected eco-driving system with co-optimization of vehicle dynamics and hybrid powertrain operations for parallel PHEVs is proposed. The designed vehicle dynamics optimization can be implemented in two different technological stages: 1) an in-vehicle advisory stage and 2) an automatic longitudinal control stage. And the designed the EMS is implemented in conventional binary control (baseline) and real-time EMS. The fuel performance for different technologies combinations are evaluated with real-world driving data. The major contributions of this study are:

- a) A mathematical formulation for the theoretical study of co-optimization of vehicle dynamics and hybrid powertrain operations for PHEVs is proposed;
- b) A bi-level optimization framework is designed to solve and obtain the near optimal solution of the formulated co-optimization problem which increases the applicability and ensures the real-time performance of the designed system;



Fig. 2. Flowchart of co-optimization system.

- c) The performance of the designed system is extensively validated and tested with real-world driving data with different technology combinations (i.e., different levels of automation and powertrain operation strategy)

### III. METHODOLOGIES

#### A. Co-Optimization Formulation of Vehicle Dynamics and Powertrain Operations

In this work, an integrated and connected eco-driving system is proposed to improve fuel efficiency of PHEVs in an urban driving environment (e.g., along signalized corridors) through the co-optimization of vehicle dynamics and powertrain operations. The objective of the co-optimization is to minimize the total fuel consumption of PHEV along a trip considering all the factors that influence the vehicle fuel consumption. As shown in Fig. 2, the inputs for the co-optimization model are real-time traffic information and downstream traffic signal information that can be obtained through cellular network or vehicle-and-infrastructure (V2I/I2V) wireless communications. The outputs are the optimal powertrain operation strategy and vehicle speed trajectory.

Mathematically, the co-optimization of vehicle dynamics and powertrain operations for PHEVs is formulated as a nonlinear constrained optimization problem. The ICE power supply at each time step  $t$  is optimized to minimize the total fuel consumption by ICE of a PHEV along the entire trip by taking advantage of the real-time information that is obtained or predicted within the connected vehicle environment. If only consider longitudinal velocity ( $v_t$ ) and assume no road grade, then the formulation of this co-optimization can be written as:

$$\min_{\omega, \tau} \int_t \frac{P_e(\omega_e(t), \tau_e(t))}{\eta_e(\omega_e(t), \tau_e(t))} \quad (1)$$

subject to

(Power Related):

$$P_e(\omega_e(t), \tau_e(t)) = P_{tr}(v(t); \mathbf{A}) - P_{batt}(\omega_{MG1}(t), \tau_{MG1}(t), \omega_{MG2}(t), \tau_{MG2}(t), SOC(t); \mathbf{B}, SOC_0) \quad \forall t$$

(Travel Distance Related):

$$\int_t v(t) = \int_t \gamma(\omega_e(t), \omega_{MG1}(t), \omega_{MG2}(t); \mathbf{C}, v_0) = L_0$$

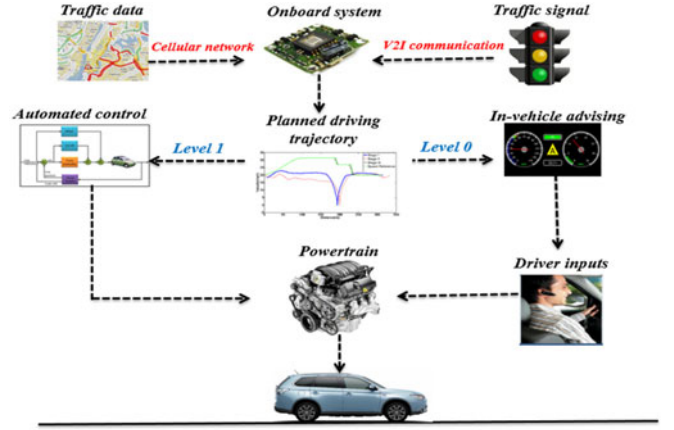


Fig. 3. Framework of the proposed integrated and connected eco-driving assistance system.

(Boundary Related):

$$\begin{cases} \omega_{(\cdot)}^{\min} \leq \omega_{(\cdot)}(t) \leq \omega_{(\cdot)}^{\max} \\ \tau_{(\cdot)}^{\min} \leq \tau_{(\cdot)}(t) \leq \tau_{(\cdot)}^{\max} \\ P_e^{\min} \leq P_e(t) \leq P_e^{\max} \\ P_{batt}^{\min} \leq P_{batt}(t) \leq P_{batt}^{\max} \\ 0 \leq v(t) \leq v^{\max} \\ SOC^{\min} \leq SOC(t) \leq SOC^{\max} \end{cases} \quad \forall t$$

(Initial Conditions Related)

$v_0, L_0,$  and  $SOC_0$  are given.

where  $\omega_e, \tau_e$  are the engine's angular velocity and engine's torque, respectively;  $\omega_{MG1}, \tau_{MG1}$  are the first motor/generator's angular velocity and torque, respectively;  $\omega_{MG2}, \tau_{MG2}$  are the second motor/generator's angular velocity and torque, respectively (see Fig. 1(b));  $P_e$  is the output power from engine, which is a function of  $\omega_e$  and  $\tau_e$ ; and  $\eta_e$  is the engine efficiency.  $P_{tr}$  models the tractive power as a function of vehicle speed,  $v$ , with a vector of related parameters,  $\mathbf{A}$ , including vehicle mass, frontal area, air density, road-tire friction coefficient, and gravitational acceleration.  $P_{batt}$  models the output power from/to battery pack as a function of  $\omega_{MG1}, \tau_{MG1}, \omega_{MG2}, \tau_{MG2}$ , and State-of-Charge (SOC), given initial State-of-Charge,  $SOC_0$ , and another vector of parameters,  $\mathbf{B}$ , including battery induction, resistance, and open-circuit voltage.  $\gamma(\cdot)$  models the velocity as a function of  $\omega_e, \omega_{MG1}$ , and  $\omega_{MG2}$ , given initial velocity,  $v_0$ , and a vector of parameters,  $\mathbf{C}$ , including gear ratio and final drive ratio.  $L_0$  is the initial distance-to-go. The terms with superscript of *min* and *max* are the boundary values for the associated variables.

#### B. Bi-Level Approximation of Co-Optimization

In this work, a bi-level optimization is designed to solve and obtain the optimal or near optimal solution of the above formulated co-optimization problem. As shown in Fig. 3, the optimal speed trajectory is calculated by the on-board system based on the obtained information and then communicated to the driver through the in-vehicle advisory display for PHEVs with level

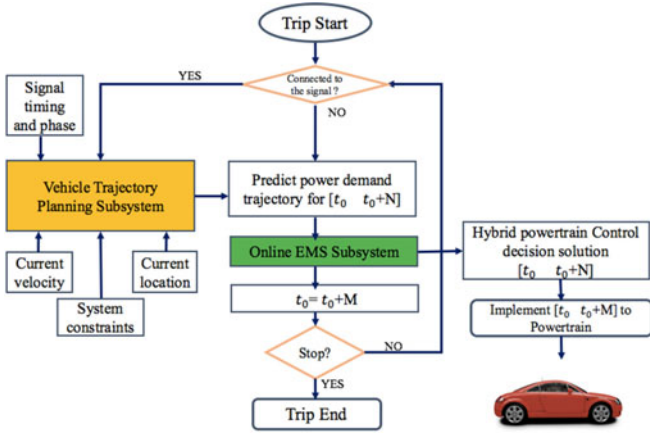


Fig. 4. Flowchart of the proposed system with co-optimization of vehicle dynamics and powertrain operations.

0 automation. If there is level 1 or above vehicle automation, the optimal longitudinal speed trajectory can be fed into the vehicle control system without human intervention. The real-time traffic information and traffic signal information can be obtained through cellular network or V2I/I2V communications. With these information, the future vehicle speed trajectory can be calculated in two different ways: 1) based on the downstream traffic condition when there is no intersection nearby; and 2) based on the SPaT information when approaching a signalized intersection. Besides the vehicle dynamics (i.e., speed) optimization through vehicle trajectory planning, the powertrain optimization is also included in the designed system.

As shown in Fig. 4, the whole system is implemented in a receding horizon framework. For each  $N$  (seconds) step horizon, the future vehicle trajectory is calculated by the vehicle trajectory planning subsystem, and then the optimal powertrain operations is determined based on the given optimal speed trajectory. Finally, only a portion of the optimal powertrain operations ( $M$  seconds) is executed while another calculation for the next  $N$  seconds starts immediately. In such a time horizon receding framework, the EMS can be implemented in real-time. For this study, we use  $N = 200$  and  $M = 50$ .

### C. Vehicle Dynamics Optimization: Connected Eco-Driving

In a connected vehicle environment, vehicle dynamics (e.g., velocity profile) can be optimized to achieve optimal fuel efficiency using the information obtained through connectivity. In this study, an integrated and connected eco-driving system is developed to optimize the vehicle dynamics at an intersection given the SPaT information. A velocity trajectory planning (VTP) algorithm is developed to calculate the target speed of an equipped vehicle based on the current vehicle dynamics, SPaT of the upcoming traffic signal, and the distance to the intersection, as shown in Fig. 4. Depending on the state of the traffic signal and the vehicle, the system identifies a *passing scenario* for the vehicle to pass through the intersection. Fig. 5 shows speed trajectories of four passing scenarios.

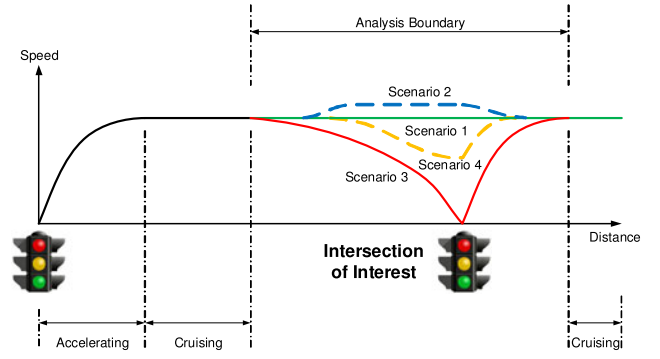


Fig. 5. Illustration of different passing scenarios through an intersection.

*Passing scenario 1* (green): The vehicle arrives at the intersection during the green phase, so it just needs to cruise through the intersection at the current speed.

*Passing scenario 2* (blue): If the remaining green time is not long enough, the vehicle has to speed up (while still obeying the speed limit) to catch the end of the green phase, and then return to the initial speed after passing through the intersection.

*Passing scenario 3* (red): If the vehicle approaches the intersection at the beginning of the red phase and a stop is inevitable, then coasting to stop at the intersection in an eco-friendly manner is recommended.

*Passing scenario 4* (yellow): If the vehicle approaches the intersection towards the end of the red phase, then it can glide through the intersection (i.e., slow down earlier to reach the intersection just when the signal turns green, and then speed up again).

For a given passing scenario, the optimal speed profile for approaching and departing from the intersection is calculated based on the distance to intersection  $d$ , the current speed  $v_c$  and the uniform speed  $v_h$  which is defined as the average speed that the vehicle should keep if it could reach the intersection right at the beginning of the next green phase [28].  $v_h$  is thus equal to the distance  $d$  divided by  $T$ , the time it will take to the next green phase. For scenario 1, the vehicle keeps constant speed  $v_c$  during the passing scenario. For the acceleration scenario (i.e., passing scenario 2), the vehicle speed  $v$  at time  $t$  is determined by the following equation: eq. (2) shown at bottom of the next page, where  $n$  is the maximum value that satisfies

$$\begin{cases} |n \cdot (v_h - v_c)| \leq a_{\max} \\ |n \cdot (v_h - v_c)| \leq d_{\max} \\ |n^2 \cdot (v_h - v_c)| \leq jerk_{\max} \\ n \geq \frac{\frac{\pi}{2} - 1}{T} \end{cases} \quad (3)$$

and,

$$m = \frac{-\frac{\pi}{2}n - \sqrt{\left(\frac{\pi}{2}n\right)^2 - 4n^2 \cdot \left[\left(\frac{\pi}{2} - 1\right) - T \cdot n\right]}}{2 \left[\left(\frac{\pi}{2} - 1\right) - T \cdot n\right]} \quad (4)$$

Here, parameters  $m$  and  $n$  determine the shape of the speed profile. They are also the dominant variables to control the fuel efficiency in the acceleration and deceleration process. Equation (2) is also applicable to the deceleration scenario (i.e., scenario

4). For scenario 3, the speed function is  $\frac{v_c}{2} + \frac{v_c}{2} \cos(nt)$  in the deceleration process and  $\frac{v_c}{2} - \frac{v_c}{2} \cos n(t - T_g)$  in the acceleration process, where  $T_g$  is the start of green time. In our previous work [28], results indicated that if  $m$  and  $n$  satisfy Eqs. (2) and (3), then the tractive power (of a generic vehicle model) would be minimized without compromising the driving comfort and acceleration/deceleration capability. This trigonometric model was tested with ICE vehicles in our previous work [28] and showed 10-15% fuel savings when passing through intersections. In this study, it is expected that this model can also help PHEV improve its fuel efficiency by providing smooth and fuel-efficient speed trajectory for passing through intersections. Noted that in this research, we assume the study vehicle does not follow any other vehicles when approaching. It can be either an isolated vehicle or the leading vehicle of a platoon. The research group also developed models that consider other vehicles in front, but mainly for ICE vehicles, e.g., a trajectory planning system that allows switching between eco-driving mode (HMI assisted driving) and car-following mode (uninformed driving) [40], and a predictive eco-driving system that make effect even when the study vehicle is following others [41]. Those features will be incorporated to the proposed system to increase its robustness and adaptability in the real world traffic.

#### D. Powertrain Operation Optimization: Online Energy Management System

Beside the vehicle dynamics optimization in a connected vehicle environment, the operations of powertrain can also be optimized, especially for PHEVs. The optimal (in terms of fuel economy) energy management for PHEVs can be formulated as a nonlinear constrained optimization problem. The objective is to minimize the total fuel consumption by ICE along the entire trip given the required power.

$$\min \int_0^T fuel(\omega_e, \tau_e) dt \quad (5)$$

subject to

$$\begin{cases} \dot{SOC} = f(P_{tr}, SOC, \omega_{MG1}, \tau_{MG1}, \omega_{MG2}, \tau_{MG2}) \\ g(\omega_e, \tau_e, \omega_{MG1}, \tau_{MG1}, \omega_{MG2}, \tau_{MG2}) = 0 \\ SOC^{\min} \leq SOC \leq SOC^{\max} \\ \omega_{(\cdot)}^{\min} \leq \omega_{(\cdot)} \leq \omega_{(\cdot)}^{\max} \\ \tau_{(\cdot)}^{\min} \leq \tau_{(\cdot)} \leq \tau_{(\cdot)}^{\max} \end{cases} \quad (6)$$

where  $T$  is the trip duration;  $fuel(\omega_e, \tau_e)$  is ICE fuel consumption model which is a function of  $\omega_e$  and  $\tau_e$ ;  $f(\cdot)$  models the SOC change as a function of the tractive power  $P_{tr}$ , instantaneous SOC, and other key parameters such as speeds and torques of ICE and motors;  $g(\cdot)$  represents the coupling relationship among ICE and motors. For more details about the model derivations and equations, please refer to our previous work in [17]. This model is shown in Fig. 4 as a subcomponent of the system.

Such formulation is suitable for traditional mathematical optimization methods with high complexity, which are difficult to be implemented in real-time. In order to facilitate on-line optimization, we discretize the engine power and reformulate the optimization problem represented by (5) as follows:

$$\min \sum_{k=1}^T \sum_{i=1}^N x(k, i) P_e(i) / \eta_e(i) \quad (7)$$

subject to:

$$\sum_{k=1}^j f\left(P_{tr}(k) - \sum_{i=1}^N x(k, i) P_e(i)\right) \leq C \quad \forall j = 1, \dots, T \quad (8)$$

$$\sum_{i=1}^N x(k, i) = 1 \quad \forall k \quad (9)$$

$$x(k, i) = \{0, 1\} \quad \forall k, i \quad (10)$$

where  $N$  is the number of discretized power level for the engine;  $k$  is the time step index;  $i$  is the engine power level index;  $C$  is the gap of the battery pack's SOC between the initial and the minimum;  $P_e(i)$  is the  $i$ -th discretized level for the engine power;  $\eta_e(i)$  is the associated engine efficiency; and  $P_{tr}(k)$  is the tractive power demand at a time step;  $x(k, i)$  is a binary function which gives a value of either 1 or 0.

Furthermore, if the change in SOC ( $\Delta SOC$ ) for each possible engine power level at each time step is pre-calculated given the (predicted) power demand, then constraint (8) can be replaced by

$$\begin{aligned} SOC_0 - SOC^{\max} &\leq \sum_{k=1}^j x(k, i) \Delta SOC(k, i) \\ &\leq SOC_0 - SOC^{\min} \\ &\quad \forall j = 1, \dots, T \end{aligned} \quad (11)$$

Therefore, the problem is turned into a combinatory optimization problem whose objective is to select the optimal ICE power level for each time step given the predicted information in order to achieve the highest fuel efficiency for the entire trip.

$$\begin{cases} v_h - (v_h - v_c) \cdot \cos(mt) & t \in \left[0, \frac{\pi}{2m}\right) \\ v_h - (v_h - v_c) \cdot \frac{m}{n} \cos n\left(t - \frac{\pi}{2m} + \frac{\pi}{2n}\right) & t \in \left[\frac{\pi}{2m}, \frac{\pi}{2m} + \frac{\pi}{2n}\right) \\ v_h + (v_h - v_c) \cdot \frac{m}{n} & t \in \left[\frac{\pi}{2m} + \frac{\pi}{2n}, \frac{d}{v_h}\right) \\ v_h + (v_h - v_c) \cdot \cos m\left(t - \frac{d}{v_h} - \frac{\pi}{2m} + \frac{\pi}{2n}\right) & t \in \left[\frac{d}{v_h} + \frac{\pi}{2n}, \frac{\pi}{2m} + \frac{\pi}{2n} + \frac{d}{v_h}\right) \\ v_c & t \in \left[\frac{\pi}{2m} + \frac{\pi}{2n} + \frac{d}{v_h}, +\infty\right) \end{cases} \quad (2)$$

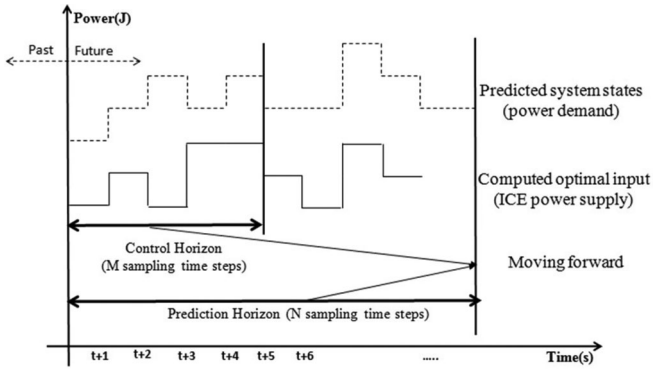


Fig. 6. Time horizons of prediction and control.

Ideally, the optimization can be performed for the entire trip by assuming the entire trip information is known a priori. In practice, however, it is challenging to accurately predict the entire trip information before the trip begins due to a variety of uncertainties. Therefore, an online energy management systems (OEMS) is usually more practical.

In our previous studies [4], [5], [14], [17], different versions of OEMS for PHEVs have been proposed and tested. In this work, we designed a similar estimation distribution algorithm based OEMS for PHEVs, using the receding horizon control structure (see Fig. 6). With the receding horizon control, the entire trip is divided into segments or time horizons. As shown in Fig. 3, the prediction horizon ( $N$  sampling time steps) needs to be longer than the control horizon ( $M$  sampling time steps). Both horizons keep moving forward (in a rolling horizon style) while the system is operating. More specifically, the prediction model is used to predict the power demand at each sampling step (e.g., each second) in the prediction horizon. Then, the optimal ICE power supply for each second during the prediction horizon is calculated with this predicted information.

In each control horizon, the pre-calculated optimal control decisions are fed into the powertrain control system (e.g., electronic control unit or ECU) at the required sampling frequency. In this study, when the vehicle is connected to the signal controller by V2I/I2V communication, the future driving trajectory can be obtained by the above mentioned VTP algorithm. Otherwise, we assume that the short-term prediction model is available (which is out of the scope this study) and the focus of this subsystem is online power-split optimization.

In this study, for performance comparison, a basic and most common binary control strategy is used as the baseline EMS model. In the binary control strategy, engine power can be used only when the battery power is not able to satisfy the power demand or the SOC lower bound is reached.

#### IV. DATA PREPARATION

##### A. Field Driving Data Collection

To comprehensively evaluate the energy saving performance of the proposed system, the real-world driving data collected by the *GlidePath Prototype Application* [39] under different automation level (or different stages of EAD) of driving assis-

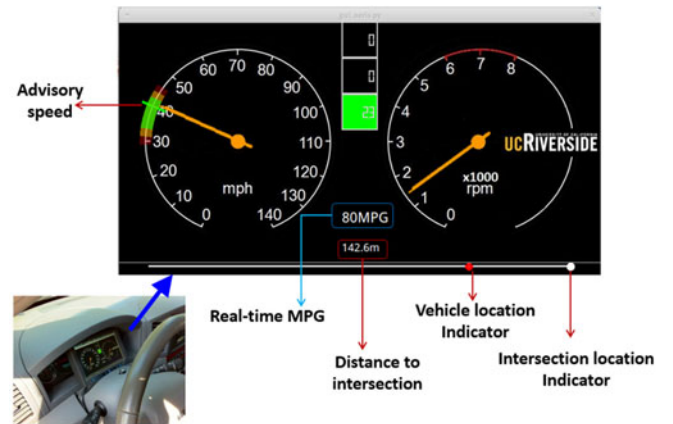


Fig. 7. Graphic interface for “HMI-assisted” or Stage II driving.

tance systems at the Turner-Fairbank Highway Research Center (TFHRC) in McLean, Virginia, were used in this study. The *GlidePath Prototype Application* is a partially automated version of the EAD application, which is the first of its kind, integrating state-of-the-art connected vehicle and automated vehicle control technologies. The driving test was conducted from point “A” to point “B” with a length of 190 meters before the intersection (i.e., stop-bar) and 116 meters after the intersection. The description of different stages of EAD is elaborated below:

- Stage I: “uninformed-manual” driving (MUD) as a baseline. At this stage, the driver approached and traveled through the intersection in a normal fashion without guidance or automation, stopping as needed.
- Stage II: “human-machine-interface-assisted” manual driving (HMI). At this stage, the driver was provided an artificial dashboard which presented a recommended range of driving speed overlaid on a speedometer (see Fig. 7). This information can assist the driver to approach and depart from the intersection in an environmentally friendly manner while obeying the traffic signal. The advisory speed profiles were generated using the VTP model described earlier.
- Stage III: “(partially) automated” driving (AUTO). At this stage, a PID based controller was responsible for longitudinal control of the vehicle, allowing it to speed up or slow down while the driver steered for lateral control. The vehicle automatically controlled the brake and throttle based on the calculated eco-friendly velocity profile according to signal state and distance to the stop-bar.

To investigate the energy performance of different scenarios in terms of a vehicle enters a signalized intersection, the field experiment was designed to have the test vehicle approach the intersection at different time instances (called “entry case” in the rest of this paper) throughout the entire signal cycle (i.e., every 5 seconds in the 60-second cycle). Furthermore, the test vehicle approached the intersection at 25 mph (this low speed range is required by the test facility manager for safety consideration). In the experiment, the green split is 27 s for the study phase. The red time is 30 s and the yellow time is 3 s. For the Stage I and Stage II experiments, a total of 4 drivers were recruited to



Signal Phase	Entering Time(s)	Entry Case	MUD	HMI	AUTO
Green	2	1	1	1	1
	7	2	2	2	2
	12	3	3	3	2
	17	4	3	3	2
	22	5	3	3	4
	27	6	3	3	4
Red	2	7	3	4	4
	7	8	4	4	4
	12	9	1	1	1
	17	10	1	1	1
	22	11	1	1	1
	27	12	1	1	1

Scenario 1

Scenario 2

Scenario 3

Scenario 4

Fig. 8. Changes in passing scenario in different stages (Driver 1).

conduct test runs. Each driver completed a test driving in each of the entry case. Therefore, a total of 12 test cells  $\times$  3 stages  $\times$  4 drivers = 144 test runs were conducted. For each test run, raw data (including signal phase and timing, speed, and distance to the stop bar) were logged at 10 Hz and post-processed to determine energy consumption and other performance measures. Fig. 8 illustrates a testing matrix of Driver 1, indicating different passing scenario under different entry case and stage of EAD system. It is noted that a hybrid vehicle (2012 Ford Escape) was used for the field study where the proposed EMS system was not implemented in the test vehicle. Instead, the speed trajectories from the test vehicle were used for powertrain simulation of PHEVs where the OEMS described in previous section was implemented.

### B. Long-Trip on Urban Route Synthesis

It is noted that the spatial span of each run for the aforementioned EAD testing is only about 306 meters, which is too short to obtain tangible drop in State-of-charge (SOC) of a PHEV (less than 0.01). To address this issue, we propose a methodology to synthesize trips along a signalized corridor with multiple intersections (e.g., 24 intersections in this study), using the field test data from each run (as described in the previous subsection) as well as certain driving cycle which should satisfy at least the following conditions:

- 1) It is a (truncated) standard driving cycle widely accepted by public, e.g., a driving schedule (<https://www.epa.gov/vehicle-and-fuel-emissions-testing/dynamometer-drive-schedules>) accepted in emissions test by U.S. Environmental Protection Agency.
- 2) The speed limit and average speed are consistent with the field test data (e.g., the speed limit is 25 mph for the field test).
- 3) The (truncated) standard driving cycle covers a speed range wide enough to accommodate the variations in the entry speeds (at 190 m before the stop-bar) and exit speeds (at 116 m after the stop-bar) of all trips.

In this study, the truncated Urban Dynamometer Driving Schedule or UDSS (shown in Fig. 9(a)) was selected to catenate

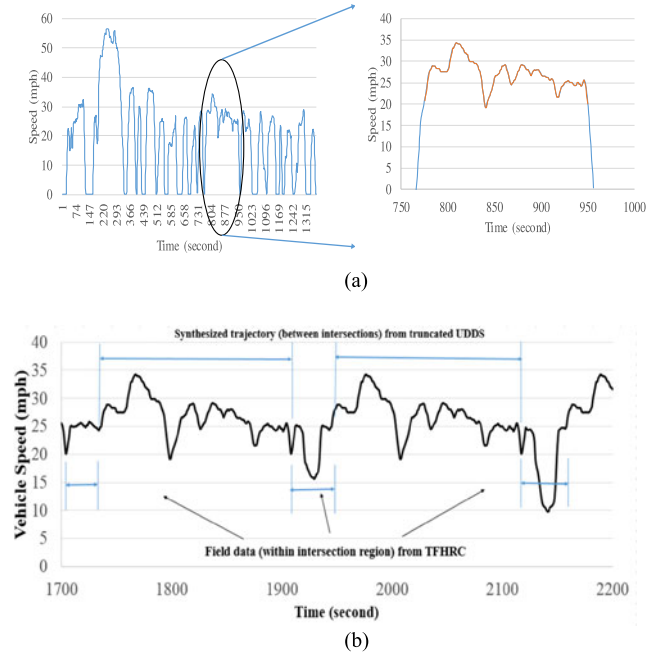


Fig. 9. Urban driving trajectory synthesis. (a) The selected UDSS driving schedule and the truncated portion (zoomed in on the right). (b) An example of synthesized along the hypothetical corridor.

the test data from each run. It should be pointed out the truncated UDSS starts and ends at 0 mph, resulting in additional stop(s) in the synthesized trajectories between intersections. To avoid the occurrence of these stop(s), we only used the portion above the dash-line in Fig. 9(a) for trajectory synthesis. In addition, we shuffled the sequence of each run (at intersections) randomly to generate multiple trajectories for evaluation and comparison in a statistical manner. Fig. 9(b) presents an example of synthesized trajectory along a segment of the hypothetical corridor in this study.

## V. RESULTS AND ANALYSIS

### A. Technology Scenarios Matrix

To fully investigate the energy benefits of the vehicle dynamics and powertrain co-optimization, the proposed integrated and connected eco-driving system in Fig. 4 is implemented with different combinations of EAD stages (i.e., I, II and III) and EMS control modes (i.e., Binary control mode and OEMS mode). We call each of these combinations a technology scenario. A summary of these technology scenarios are provided in Fig. 10.

### B. Evaluation of Short-Trip at Intersections

The proposed system is first evaluated at the intersections only. Vehicle trajectories when passing through the intersections are selected from the real-world driving data to calculate the energy consumption in the different technology scenarios shown in Fig. 10. Due to the short driving distance (190 m upstream and 120 m downstream), the vehicle trajectories within this road segment is only about 30 seconds on average. The energy consumption is not quite demanding if looking at these short

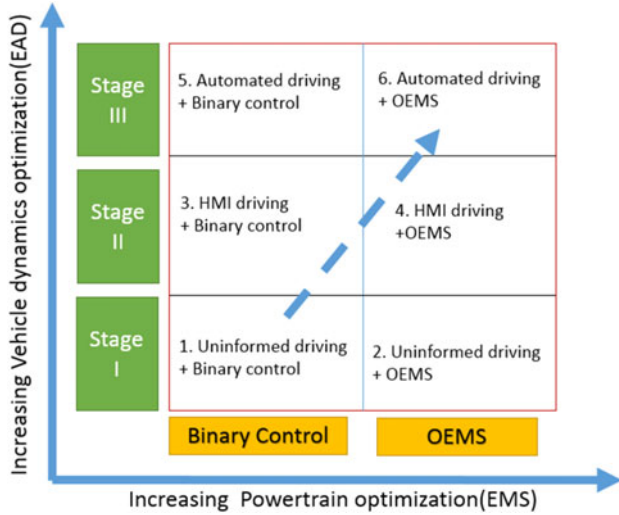


Fig. 10. Technology scenario matrix for comparison.

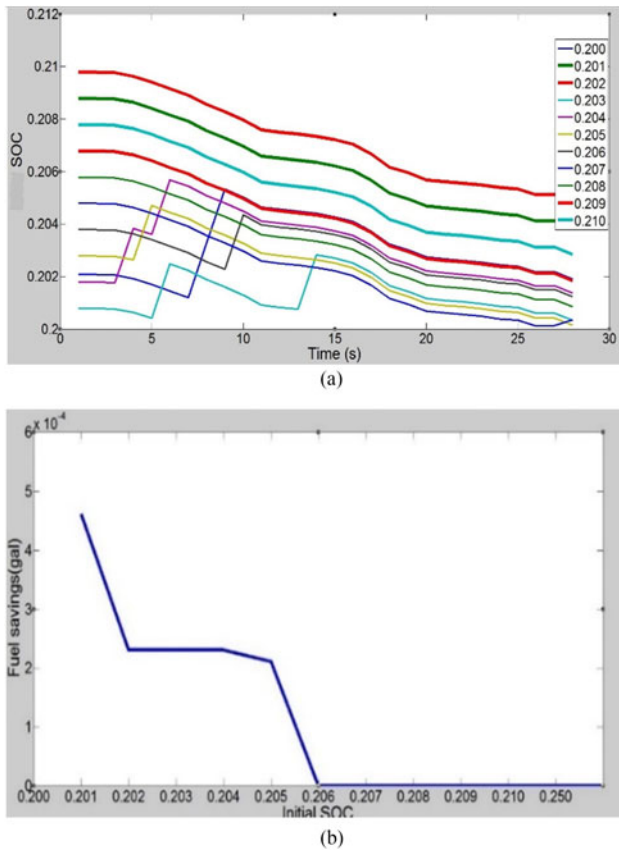


Fig. 11. Initial SOC analysis for stage II and entry case 9. (driver 1). (a) Resulted SOC track for different initial SOC. (b) Fuel savings comparing to Binary control mode.

trips alone. Hence, when the initial SOC is high enough, the PHEV would only use electricity without consuming fuel. As can be seen in Fig. 11(a) and (b), there is no fuel consumption difference between OEMS and binary control mode when the initial SOC is higher than 0.205 (in the case of the minimum SOC being 0.2). This is because the energy from the battery is enough to satisfy all the power demand requirements when

TABLE I  
FUEL CONSUMPTIONS FOR DIFFERENT TECHNOLOGY SCENARIOS  
AND ITS SAVING PERCENTAGE

	Binary control	OEMS
Stage III	0.001053 (-37.51%)	0.000173 (-89.73%)
Stage II	0.001190 (-29.38%)	0.000231 (-86.29%)
Stage I	0.001685 (baseline)	0.000288 (-82.91%)

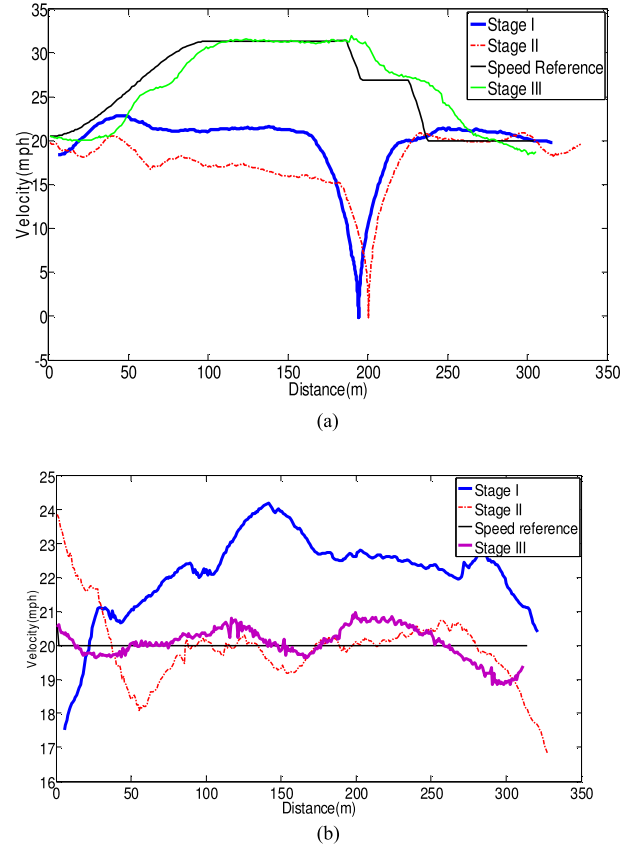


Fig. 12. Speed versus distance for entry case 6 and case 9 (Driver 1). (a) Entry case 6. (b) Entry case 9.

travelling through the intersection. The engine is not kicked in and no engine power supply. Therefore, in this study, in order to investigate the difference in energy consumption resulting from different EMS strategies within the intersection region, the initial SOC has to be selected at a very low level such as 0.205.

The field driving data described in previous section are used for quantifying the fuel savings due to different technology scenarios. Table I indicates that higher fuel savings can be achieved from the optimization of powertrain operation than the optimization of vehicle dynamics. Compared to the baseline technology scenario (i.e., uninformed manual driving with binary EMS control), the technology scenario with OEMS and Stage III EAD (i.e., AUTO) achieves the highest fuel savings (89.73%). In other words, almost 90% of the fuels can be saved due to the co-optimization of vehicle dynamics and powertrain operation when traveling through the intersections.

In order to get a better understanding of how these fuel savings are achieved, more detailed information about driver 1 with

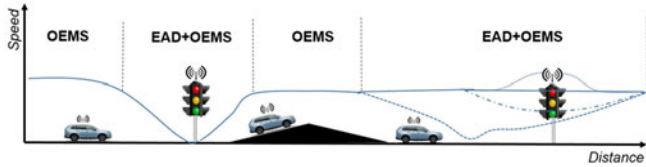


Fig. 13. Effective range of different technologies.

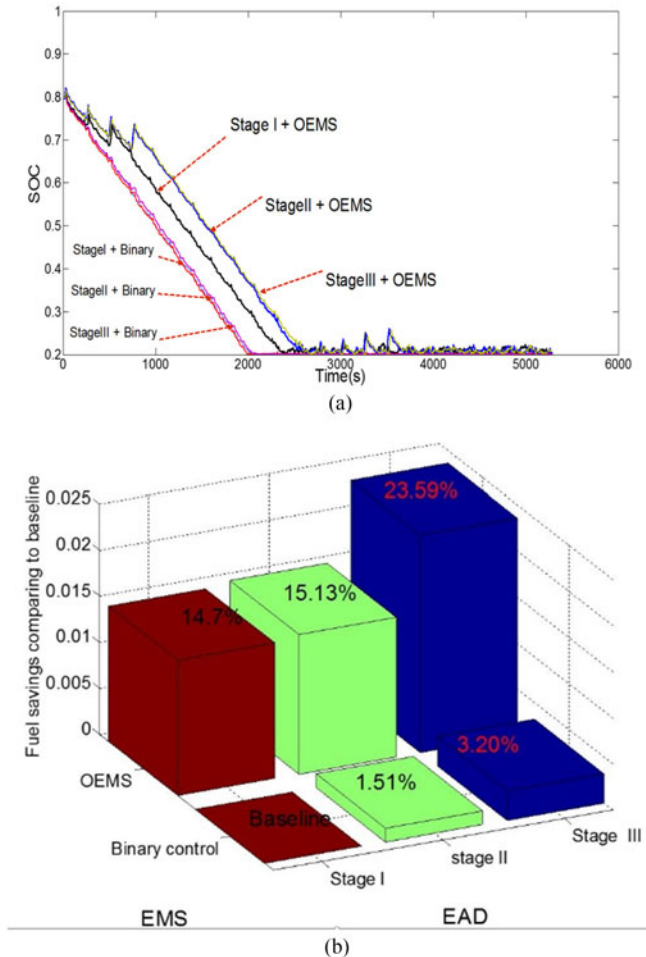


Fig. 14. Fuel savings on hypothetical corridor. (a) SOC tracks of an example synthesized trip by different technology scenarios. (b) Average fuel savings for 6 synthesized trips by different technology scenarios.

OEMS is provided in Fig. 12. As can be seen in the figure, the speed profiles of entry case 6 by the different EAD stages show that the passing scenario changes from 3 to 2 with the assistance of automated longitudinal control (i.e., stage III), which results in the most fuel savings by avoiding the stop-and-go driving in stages I and II. However, for entry case 9, there is no change in the passing scenario across the different EAD stages, and thus no significant fuel savings are achieved.

### C. Evaluation of Synthesized Long-Trips on Urban Route

The synthesized trip data as described in Section IV are used to further investigate the fuel savings for a relatively long urban trip which includes driving data within the intersection regions (as collected in the field) and between intersections (generated

from the truncated UDDS as shown in Fig. 8). The effective range of different technology combinations are given in the Fig. 13. The EAD only works at interaction area but OEMS is always on along the entire trip. The resultant SOC profiles for different technology scenarios of an example synthesized trip are presented in Fig. 14(a). It is observed that all the technology scenarios with OEMS result in more conservative consumption of battery power at the beginning of the trips and are able to achieve more fuel savings. In this study, we synthesized totally 6 synthesized trips for evaluation of fuel savings. As shown in Fig. 14(b), the EAD system (even with automatic longitudinal control) is not able to achieve very significant energy savings because the driving cycles within the intersection regions only account for a small portion of the entire trip (around 10%). The Co-optimization of vehicle dynamics and powertrain operation can save 23.59% of fuel on average for the synthesized urban driving trips.

## VI. CONCLUSION

In this study, an integrated connected eco-driving assistance system with co-optimization of vehicle dynamics and hybrid powertrain operations for PHEVs was designed and evaluated extensively. Real-world driving data with different eco-driving stages were collected and used for comprehensive performance evaluation of the proposed system. The numerical analysis shows that the combination of EAD with automatic longitudinal control and online EMS for PHEVs can achieve around 24% of fuel savings on synthesized typical urban trips as compared to the baseline (i.e., uninformed manual driving with binary mode EMS). Next steps will be focused on further testing and evaluation of the proposed co-optimization system. Furthermore, it is noted that the lateral maneuvers and road grade information have not been considered in this research and will be potential topics for future work.

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