Optimal Vehicle Dynamics and Powertrain Control for Connected and Automated Vehicles

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Abstract—The implementation of connected and automated vehicle technologies enables for a novel computational framework for real-time control actions aimed at optimizing energy consumption and associated benefits. In this paper, we present a two-level control architecture for a connected and automated plug-in hybrid electric vehicle to (1) optimize vehicle speed profile in terms of energy consumption using two different control approaches and (2) optimize the powertrain efficiency of the vehicle given the optimal speed profile. We evaluate the effectiveness of the efficiency of the proposed architecture through simulation in a network of vehicles. The results show that the proposed approach yields significant fuel consumption and travel time savings.

I. INTRODUCTION

Recognition of the necessity for connecting vehicles to their surroundings has gained momentum. The main focus to date has been on passenger safety and how accidents could be prevented by developing multi-scale systems based on vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) communication to alert drivers for a potential collision. The question is whether we could use connectivity and automation to optimize the efficiency of a vehicle in addition to safety. We are, in particular, interested in investigating the opportunities to improve the efficiency of hybrid electric vehicles (HEVs) and plug-in HEVs (PHEVs) [1] when these vehicles are connected and automated, i.e., they can exchange information with their surrounding environment.

In an earlier work, we discussed the potential benefits of optimally coordinated connected and automated vehicles (CAVs) in a corridor using a traffic microsimulation environment without considering powertrain optimization [2]. In this paper, we apply a two-level supervisory control architecture for connected and automated PHEVs (CA-PHEVs) that consists of a vehicle dynamics (VD) controller and a powertrain (PT) controller. The supervisory controller oversees the VD and PT controllers and communicates the endogenous and exogenous information appropriately. The VD controller optimizes online the vehicle acceleration/deceleration profile to avoid stop-and-go driving in situations where there is a potential conflict with other vehicles, e.g., ramps, intersections, stop signs, roundabouts, etc. The PT controller computes the optimal nominal operation (set-points) for the engine and motor corresponding to the optimal solution derived from the VD controller. The complexity of the problem dimensionality can be managed by establishing two parallel and appropriately interacting computational levels, namely a cloud-based level, and a vehicle-based level.

The objectives of this paper are to (1) optimize vehicle speed profile in terms of energy consumption and compare two different control approaches, and (2) optimize power management of the vehicle for the optimal speed profile obtained in (1). We evaluate the effectiveness of the efficiency of the proposed architecture through simulation in a network of CA-PHEVs in MCity, a 32-acre vehicle testing facility located at the north campus of University of Michigan. The contribution of this paper is the analysis of online optimization of the vehicle- and powertrain-level operation of a CA-PHEV and classification of the improvements.

The remainder of the paper is organized as follows. In Section II, we summarize the relevant research efforts on vehicle dynamics control for CAVs and powertrain optimization for HEVs and PHEVs. In Section III, we introduce the control architecture that consists of the VD controller and the PT controller. In Section III, we evaluate the effectiveness of the efficiency of the proposed approach in a simulation environment. Finally, we draw conclusions and discuss next steps in Section IV.

II. LITERATURE REVIEW

Several research efforts have been reported in the literature proposing either centralized or decentralized approaches on coordinating CAVs. One of the very early efforts in this direction was proposed in 1969 by Athans [3] for safe and efficient coordination of merging maneuvers with the intention to avoid congestion. Varaiya [4] discussed extensively the key features of an automated intelligent vehicle-highway system and proposed a related control system architecture. Dresner and Stone [5] proposed the use of the reservation scheme to control a signal-free intersection. Other research efforts have focused on coordinating vehicles at intersections to improve the traffic flow [6–8]. More recently, online optimal control frameworks were established for coordinating CAVs in different transportation segments [9–11]. Later, closed-form,
analytical solutions were presented and tested in different transportation scenarios for coordinating online CAVs \[1\], \[12\]–\[17\]. A survey paper \[18\] includes detailed discussions of the research reported in the literature to date on coordination of CAVs to improve vehicle-level operation.

The development and implementation of a power management control algorithm online constitutes a challenging control problem and has been the subject of intense study for the last two decades \[19\]–\[22\]. Significant research efforts have focused on different heuristic approaches to optimize the power management control in PHEVs \[23\], \[24\]. The latter, however, cannot completely encompass all the potential fuel economy and emission benefits of the various HEV architectures. Dynamic programming (DP), on the other hand, can yield global optimal solution for both stochastic and deterministic formulation, and provide a rigorous approach for sequential decision-making problems under uncertainty. The majority of the research efforts on optimizing the power management control in HEVs therefore applied DP \[25\], \[26\], which has been used to benchmark the fuel economy of HEVs. To address the computational constraints associated with DP, research efforts have been concentrated on developing online algorithms consisting of an instantaneous optimization problem. Over the years, different online control approaches based on Pontryagin’s Maximum Principle \[27\], Equivalent Consumption Minimization Strategy (ECMS) \[28\], \[29\], and Adaptive-ECMS \[30\] have been proposed. Recently, there have been efforts to address the vehicle-level and powertrain level operation simultaneously \[31\], \[32\]. However, these efforts have exhibited some limitation for online implementation. A detailed discussion of the research reported in the literature today on the power management control for HEVs/PHEVs can be found in \[1\].

III. CONTROL ARCHITECTURE

We consider a network of CA-PHEVs driving through a corridor in Mcity that consists of several conflict zones, e.g., a highway on-ramp, a speed reduction zone (SRZ), and a roundabout as shown in Fig. 1. The CA-PHEVs are retrofitted with necessary communication devices to interact with other CA-PHEVs and structures within their communication range through V2V and V2I communication. In this paper, we focus on the effectiveness of VD and PT controllers, without detailed analysis on the architecture of supervisory controller. The supervisory controller coordinates the VD and PT controllers to ensure the optimal solution yielded by the VD controller is feasible for the PT controller. However, the details of this coordination along with the implications of the computational efforts of the VD and PT controllers are outside the scope of this paper.

![Fig. 1: The corridor in Mcity with the conflict zones.](image-url)

A. VD Controller

1) Vehicle Dynamics Model: Let \(N(t) = 1, \ldots, N(t)\), where \(t \in \mathbb{R}^+\) is the time, be a queue of vehicles to be analyzed. The dynamics of each vehicle \(i, i \in N(t)\), are represented with a state equation

\[
\dot{x}(t) = f(t, x_i, u_i), \quad x_i(t_0) = x_i^0,
\]

where \(x_i(t), u_i(t)\) are the state of the vehicle and control input, \(t_0\) is the initial time of vehicle \(i\), and \(x_i^0\) is the value of the initial state. For simplicity, we model each vehicle as a double integrator, i.e., \(\dot{p}_i = v_i(t)\) and \(\dot{v}_i = u_i(t)\), where \(p_i(t) \in \mathcal{P}_i, v_i(t) \in \mathcal{V}_i,\) and \(u_i(t) \in \mathcal{U}_i\) denote the position, speed, and acceleration/deceleration (control input) of each vehicle. Let \(x_i(t) = [p_i(t), v_i(t)]^T\) denotes the state of each vehicle \(i\), with initial value \(x_i^0(t) = [0, v_i^0(t)]^T\), taking values in the state space \(\mathcal{X}_i = \mathcal{P}_i \times \mathcal{V}_i\). The sets \(\mathcal{P}_i, \mathcal{V}_i,\) and \(\mathcal{U}_i\) are complete and totally bounded subsets of \(\mathbb{R}\). The state space \(\mathcal{X}_i\) for each vehicle \(i\) is closed with respect to the induced topology on \(\mathcal{P}_i \times \mathcal{V}_i\) and thus, it is compact.

To ensure that the control input and vehicle speed are within a given admissible range, the following constraints are imposed.

\[
\begin{align*}
\underline{u}_{\text{min}} &\leq u_i(t) \leq \underline{u}_{\text{max}}, \quad \text{and} \\
0 &\leq \underline{v}_{\text{min}} \leq v_i(t) \leq \underline{v}_{\text{max}}, \quad \forall t \in [t_i^0, t_i^f]
\end{align*}
\]
where \( u_{\text{min}}, u_{\text{max}} \) are the minimum deceleration and maximum acceleration respectively, \( v_{\text{min}}, v_{\text{max}} \) are the minimum and maximum speed limits respectively, and \( t_i^0, t_i^f \) are the times that each vehicle \( i \) enters and exits the corridor.

To ensure the absence of rear-end collision of two consecutive vehicles traveling on the same lane, the position of the preceding vehicle should be greater than, or equal to, the position of the following vehicle plus a predefined safe distance \( \delta_i(t) \), where \( \delta_i(t) \) is proportional to the speed of vehicle \( i \), \( v_i(t) \). Thus, we impose the rear-end safety constraint

\[
s_i(t) = p_k(t) - p_i(t) \geq \delta_i(t), \forall t \in [t_i^0, t_i^f]
\]

where vehicle \( k \) is immediately ahead of \( i \) on the same lane.

In the modeling framework described above, we impose the following assumptions:

**Assumption 1:** For each CA-PHEV \( i \), none of the constraints is active at \( t_i^0 \).

**Assumption 2:** Each vehicle is equipped with sensors to measure and share their local information while communication among CA-PHEVs occurs without any delays or errors.

The first assumption ensures that the initial state and control input are feasible. The second assumption might be strong, but it is relatively straightforward to relax as long as the noise in the measurements and/or delays is bounded. For example, we can determine upper bounds on the state uncertainties as a result of sensing or communication errors and delays, and incorporate these into more conservative safety constraints.

In the following section, we introduce two approaches for the VD controller, namely isolated conflict zone control and coordinated corridor control. With the isolated conflict zone control approach, we assume that the conflict zones in the corridor are independent, such that vehicles only coordinate with each other to travel through an immediate downstream conflict zone. On the other hand, with the coordinated corridor control approach, we assume that all the vehicles traveling in the corridor coordinate with each other to pass through all the conflict zones smoothly.

2) **Isolated Conflict Zone Control:** In this control approach, we consider a corridor that contains three conflict zones (Fig. 1), e.g., a merging roadway (conflict zone 1), a SRZ (conflict zone 2), and a roundabout (conflict zone 3). Upstream of each conflict zone, we define a control zone where CA-PHEVs coordinate with each other to avoid any rear-end or lateral collision in the conflict zone. For each conflict zone, there is a coordinator that communicates with the CA-PHEVs traveling within the control range. Note that the coordinator is not involved in any decision of the vehicles. The coordinator just assigns a unique identity to each CA-PHEV when they enter a control zone. The objective of each CA-PHEV is to derive its optimal control input (acceleration/deceleration) to cross the conflict zones without any rear-end or lateral collision with the other vehicles.

Let \( z \in Z \) be the index of a conflict zone in the corridor. When a vehicle enters the control zone, the coordinator receives its information and assigns a unique identity \( i \) to the vehicle. Let \( t_i^z, 0 \) be the time when vehicle \( i \) enters the control zone towards conflict zone \( z \), and \( t_i^z, f \) be the time when vehicle \( i \) exits the corresponding control zone. In each control zone, we denote the sequence of the vehicles to be entering a conflict zone as \( N_z(t) = 1, ..., N(t) \). Thus, we formulate the following optimization problem for each vehicle in the queue \( N_z(t) \)

\[
\min_{u_\delta} \frac{1}{2} \int_{t_i^z, 0}^{t_i^z, f} v_i^2(t) dt, \forall i \in N_z(t), \forall z \in Z
\]

Subject to: (1), (2),

\[
p_i(t_i^z, 0) = p_i^z, 0, v_i(t_i^z, 0) = v_i^z, 0, p_i(t_i^z, f) = p_z,
\]

where \( p_z \) is the location (i.e., entry position) of conflict zone \( z \), \( p_i^z, 0 \), \( v_i^z, 0 \) are the initial position and speed of vehicle \( i \) when it enters the control zone of conflict zone \( z \). To address this problem, we apply the decentralized optimal control framework and analytical solution presented in [11], [12], [16].

3) **Coordinated Corridor Control:** In this control approach, we consider a single coordinator that monitors all vehicles traveling along the corridor. Note that the coordinator serves as an information center which is able to collect vehicular data through V2I and/or V2V communication and is not involved in any decision on the vehicle operation. Road side units could be placed in each conflict zone and used to transmit data between vehicles and the coordinator. Thus, the coverage of the coordinator is flexible and the length of corridor could be extended in the presence of connected infrastructure.

Let \( N(t) \in \mathbb{N} \) be the number of CA-PHEVs in the corridor at time \( t \in \mathbb{R}^+ \). When a vehicle enters the boundary of the corridor, it broadcasts its route information to the coordinator. Then, the coordinator assigns a unique integer \( i \) that serves for identification purpose inside the corridor. Let \( t_i^0 \) be the initial time that vehicle \( i \) enters the corridor, \( t_i^f \) be the time for vehicle \( i \) to enter the conflict zone \( z \), \( z \in Z \), and \( t_i^f \) be the time for vehicle \( i \) to enter the final conflict zone.

To avoid any possible lateral collision, there is a number of ways to compute \( t_i^z \) for each CAV \( i \). In this paper, we adopt the same upper level scheduling scheme for determining the time \( t_i^z \) that each CAV will enters the conflict zone \( z \in Z \) as in [2]. Thus, for each vehicle, we formulate the following optimal control problem the solution of which yields for each vehicle the optimal control input (acceleration/deceleration) to achieve the assigned time \( t_i^z \) (upon arrival of CAV \( i \) without
corresponding to the HEV state (engine and motor speed, \( T \) demanded by the driver as designated by the pedal position \( T \) is to derive an optimal control policy to split the torque independently or in tandem. The objective of the PT controller to provide the demanded power to the subsystems either of the CA-PHEV enables the engine and the electric motor generator while charging the battery. The parallel configuration are connected to the transmission. The IMG unit acts as an gasoline engine and the integrated motor-generator (IMG) unit.

**B. PT Controller**

In this paper, we consider a CA-PHEV where both the gasoline engine and the integrated motor-generator (IMG) unit are connected to the transmission. The IMG unit acts as an electric motor while providing to the wheel and as a generator while charging the battery. The parallel configuration of the CA-PHEV enables the engine and the electric motor to provide the demanded power to the subsystems either independently or in tandem. The objective of the PT controller is to derive an optimal control policy to split the torque demanded by the driver, \( T_{\text{driver}} \) between the engine and the motor torque, \( T_{\text{eng}} \) and \( T_{\text{mot}} \) respectively, for the optimal speed profile derived by the VD controller.

We model the evolution of the CA-PHEV state at each stage \( t = 0,1,... \) as a controlled Markov chain following the process presented in [19], with a finite state and control space, \( \mathcal{S} \subset \mathbb{R}^n \), and \( \mathcal{U} \subset \mathbb{R}^m \), \( n, m \in \mathbb{N} \) respectively. We introduce the sequence of the random variables \( X_{t(1:2)} = (X_{t(1)}, X_{t(2)}) \) \( T = (T_{\text{eng}}, T_{\text{mot}}) \in \mathcal{S}, U_{t(1:2)} = (U_{t(1)}, U_{t(2)}) \) \( T = (T_{\text{eng}}, T_{\text{mot}}) \in \mathcal{U} \) and \( W_{t(1:2)} \), corresponding to the HEV state (engine and motor speed, \( N_{\text{eng}} \) and \( N_{\text{mot}} \), control action (engine and motor torque, \( T_{\text{eng}} \) and \( T_{\text{mot}} \) and system uncertainty in terms of the torque demanded by the driver as designated by the pedal position respectively. At each stage \( t \), the controller observes the system state \( X_{t(1:2)} = i \in \mathcal{S} \), and executes an action, \( U_{t(1:2)} \in \mathcal{U} \) at that state. At the next stage, \( t + 1 \), the system transits to the state \( X_{t+1(1:2)} = j \in \mathcal{S} \) and a one-stage expected cost, \( k(X_{t(1:2)}, U_{t(1:2)}) \), is incurred corresponding to the engine’s and motor’s efficiency. After the transition to the next state, a new action is selected and the process is repeated.

We select the average cost criterion as we wish to optimize the efficiency of each CA-PHEV on average. Hence, the objective of the PT controller to derive a stationary control policy that minimizes the long-run expected average cost,

\[
J^* = \lim_{T \to \infty} \frac{1}{T + 1} \mathbb{E}^\pi \left[ \sum_{i=0}^{T} k(X_{t(1:2)}, U_{t(1:2)}) \right],
\]

where \( k(X_{t(1:2)}, U_{t(1:2)}) \) is the one-stage cost of CA-PHEV. However, onboad derivation of the control policy by minimizing (6) is not feasible due to the associated computational burden. Therefore, we formulate a multiobjective optimization problem that yields the Pareto control policy. It has been proven that the Pareto policy is equivalent to the optimal control policy derived by solving (6) with DP. The proof of this equivalence can be found in [33]. To this end, we formulated the multiobjective optimization problem by considering the engine’s efficiency, \( \eta_{\text{eng}} \) and the motor’s efficiency, \( \eta_{\text{mot}} \). As the engine’s efficiency is a function of engine torque \( T_{\text{eng}} \) and engine speed \( N_{\text{eng}} \), we construct the engine’s efficiency as \( f_1(N_{\text{eng}}, T_{\text{eng}}) = \eta_{\text{eng}} \). Due to similar dependency, we also write the motor’s efficiency as, \( f_2(N_{\text{mot}}, T_{\text{mot}}) = \eta_{\text{mot}} \).

The multiobjective optimization problem is formulated as

\[
\min_{U_i} k(X_{t(1:2)}, U_{t(1:2)}) = \max_{U_i} \left( \alpha \cdot f_1(X_{t(1)}, U_{t(1)}) + (1 - \alpha) \cdot f_2(X_{t(2)}, U_{t(2)}) \right)
\]

\[\text{s.t. } \sum_{i=1}^{2} U_{t(i)} = T_{\text{driver}}, \quad (7)\]

where \( \alpha \) is a scalar that takes values in \([0,1]\), \( f_1(N_{\text{eng}}, T_{\text{eng}}) = \eta_{\text{eng}}, f_2(N_{\text{mot}}, T_{\text{mot}}) = \eta_{\text{mot}} \) are the engine’s efficiency and motor’s efficiency constituting the multiobjective function, and \( T_{\text{driver}} \) is the torque demanded by the driver. The multiobjec-

We consider the battery hold mode for all the CA-PHEVs, in which the SOC of the battery is constrained within a \( 1\% \) bandwidth around the target SOC, \( SOC_{\text{target}} \), set by the driver or a supervisory system. Therefore, the current SOC of the battery dictates whether the PT controller uses the Pareto efficiency table to operate the vehicle, or just operate the engine to provide power to the driver and charge the battery.
In the case where $SOC > SOC_{\text{target}}$, the PT controller looks into the stored Pareto efficiency table for the optimal torque split between engine and motor torque based on the torque demanded by the driver, $T_{\text{driver}}$. On the contrary, for $SOC < SOC_{\text{target}}$, the IMG unit is prevented to provide torque to the system and the engine has to take care of all incurred power demand by operating at its most efficient point. In this case, the engine provides all the power demanded by the driver and sends the rest of its power to the IMG unit, which now acts as a generator, to charge the battery.

IV. SIMULATION EVALUATION

A. Simulation Environment

For deriving the optimal control policy of the PT controller, we first calculate the engine’s efficiency map from its brake specific fuel consumption (BSFC) data, contrary to the motor’s efficiency map which is readily available. With the engine’s and motor’s efficiency map, we solve the multiobjective optimization problem in (7) offline. We discretize the torque, speed and the scalar $\alpha$ with the resolution of 10 Nm, 100 RPM and 0.05 respectively, considering a feasible solution time. The optimization process yields a Pareto efficiency set that we store in the CA-PHEV memory for later online use.

We primarily focus on two objectives: 1) to evaluate the network performance with the proposed supervisory control framework, and 2) to evaluate the efficiency of different VD control approaches under three different traffic levels (i.e., light, medium, and heavy traffic conditions). To this end, we develop three scenarios. For each scenario, we apply both baseline and optimal PT controller to estimate fuel efficiency (i.e., adjusted mile-per-gallon, or MPGe) under battery hold mode for all CA-PHEVs traveling in the corridor. The corridor has a length of 1.3 km in MCity (Fig. 1). The desired speeds for the highway, urban and SRZ are set as 17 m/s, 11 m/s and 8 m/s respectively. The length of the speed reduction zone is 125 m.

- Scenario 1: Baseline.
  All vehicles in the network are non-connected and non-automated vehicles. In this scenario, the Wiedemann car following model [34] built in VISSIM is applied. The intersection is controlled by fixed-time signal controller, whose signal timing is optimized for the traffic condition set in the study.

- Scenario 2: Isolated conflict zone control. We consider 100% market penetration of CA-PHEVs in this scenario. The vehicles optimize their trajectory based on the isolated conflict zone control approach presented in Section III.

- Scenario 3: Coordinated corridor control. We consider 100% market penetration of CA-PHEVs in this scenario.

The vehicles optimize their trajectory based on the coordinated corridor control approach presented in Section III.

Under Scenario 2, the length of the control zone for the on-ramp, the SRZ and the roundabout were selected to be 150 m.

B. Evaluation Results

1) The effectiveness of VD Controller: We plot vehicle trajectories in Fig. 2. Under Scenario 1, the vehicles need to slow down or stop for merging into highway or roundabout. Therefore, we can see in the top panel of Fig. 2 that there are many stop-and-go events in vehicle speed profiles under baseline scenario. Under scenario 2 (shown in the middle panel of Fig. 2), with isolated control scheme, we observe smooth speed profiles inside each control zone. At the downstream of each conflict zone, vehicles exit from the VD control zone, thus we see similar speed patterns as under scenario 1 outside the control zones. We also note that while the isolated control approach is able to eliminate stop-and-go driving, the resulting increased traffic flow into the downstream speed reduction zone leads to speed reduction downstream the highway on-ramp segment.

On the contrary, with the coordinated control scheme under scenario 3, traffic information of the entire corridor is shared among all vehicles. Therefore, all the CA-PHEVs travel through the corridor are able to optimize their trajectories at the entry of the corridor and drive smoothly throughout the corridor, even with high traffic demand level (as shown in the bottom panel of Fig. 2).

Under three different traffic conditions, we calculate vehicle travel times through the corridor under different VD control approaches and plot travel time distribution in Fig. 3. We observe that with coordinated corridor control approach, due to longer preparation for downstream roadway segment, the average travel time under light traffic condition is longer than the baseline scenario. However, the results reveal that through the corridor coordination, the traffic flow is further smoothed (much lower variation in vehicle travel times as shown in Fig. 3) compared to the isolated conflict zone control approach.

2) The effectiveness of PT Controller: We take one vehicle as an example to illustrate the impact of the optimal PT controller. Figure 4 shows the vehicle speed profiles corresponding to this vehicle under different VD control approaches. The impact of the PT controller on engine operation is shown in Fig. 5. Under the baseline PT controller, we use a heuristic approach to design the PT controller of the vehicle equivalent to the factory controller of the vehicle. We note that the optimal PT controller operates the engine at the most efficient brake specific fuel consumption (BSFC) regimes (Fig. 5b) and...
(a) light traffic demand level  
(b) medium traffic demand level  
(c) heavy traffic demand level

Fig. 2: Speed profiles for all CA-PHEVs under different VD control approaches and demand levels.

Fig. 3: Travel time distribution under different VD control approaches and traffic demand levels.

TABLE I: Improvements of fuel efficiency over baseline scenarios under different traffic conditions.

|                  | Light Traffic | Medium Traffic | Heavy Traffic |
|------------------|---------------|----------------|--------------|
|                  | Baseline (%)  | Isolated Control | Corridor Coordination |
| Average          | +10.2         | +8.2           | +23.1        | +22.4        | +32.3       |
| Standard Deviation | +55.0         | -24.7          | +71.0        | -57.1        | -48.5       |

Fig. 4: Vehicle speed profiles under different VD control approaches.

In contrast, with the baseline PT controller, there is a spread of operating points in non-efficient regimes (Fig. 5a).

Table I summarizes the results for the baseline and optimal PT controllers for all VD control approaches under different traffic conditions. Under baseline PT controller, the coordinated corridor control approach leads to significantly
MPGe improvement in comparison with the isolated control approach. This improvement can be attributed to the fact that the coordinated corridor control approach eliminates all the uncontrolled patches between the control zones of individual coordinators in isolated control approach and optimizes the whole trajectory inside the corridor, leading to improved fuel efficiency. At the same time, as all the vehicles fall under a single coordinated optimal control policy inside the corridor according to the coordinated corridor control approach, significant decrease in terms of the standard deviation of average MPGe is observed as compared to the isolated control case, as evident in Table I. We observe that for the optimal speed profiles yielded from the corridor coordination control approach, the contribution of optimal PT controller in terms of overall fuel efficiency improvement is lower than those yielded from the isolated control approach. The reason is that under the corridor coordination approach, each vehicle spend a significant amount of time in the regenerative braking event, which reduces opportunity for the Pareto Optimal policy of the PT controller to be active. Note that, the optimal PT controller coupled with different VD control policy shows consistent improvement in terms of MPGe in all traffic conditions for isolated control and for corridor coordination policy). As both the VD control policy eliminate stop-and-go driving and smooths out the velocity profile, the improvement in average MPGe remains consistent irrespective of traffic volumes.

V. CONCLUDING REMARKS

In this paper, we presented a two-level control architecture with the aim to optimize simultaneously vehicle-level and powertrain-level operation of a CA-PHEV. With this approach, we showed that we can optimize both the speed profile and the powertrain efficiency of a CA-PHEV by eliminating stop-and-go driving behavior. We also compared the efficiency of different VD control approaches, and showed that although the coordinated corridor approach improves significantly fuel efficiency, vehicle travel time savings are marginal compared to the isolated conflict zone control approach.

Ongoing work considers additional scenarios, including intersections, while incorporating the state and control constraints in the analytical solution of the VD controller. Although potential benefits of full penetration of CA-PHEVs to alleviate traffic congestion and reduce fuel consumption have become apparent, different penetrations of CA-PHEVs can alter significantly the efficiency of the entire system. Future work should focus on the interactions between CA-PHEVs and human-driven vehicles and the influence of different market penetration of CA-PHEVs on the traffic network.

REFERENCES

[1] A. A. Malikopoulos, “Supervisory Power Management Control Algorithms for Hybrid Electric Vehicles: A Survey,” IEEE Transactions on Intelligent Transportation Systems, vol. 15, no. 5, pp. 1869–1885, 2014.
[2] L. Zhao and A. A. Malikopoulos, “Decentralized optimal control of connected and automated vehicles in a corridor,” in 2018 21st International Conference on Intelligent Transportation Systems (ITSC), Nov 2018, pp. 1252–1257.

[3] M. Athans, “A unified approach to the vehicle-merging problem,” Transportation Research, vol. 3, no. 1, pp. 123–133, 1969.

[4] P. Varaiya, “Smart cars on smart roads: problems of control,” IEEE Transactions on Automatic Control, vol. 38, no. 2, pp. 195–207, 1993.

[5] K. Dresner and P. Stone, “Multiagent traffic management: a reservation-based intersection control mechanism,” in Proceedings of the Third International Joint Conference on Autonomous Agents and Multiagents Systems, 2004, pp. 530–537.

[6] I. H. Zohdy, R. K. Kamalanathsharma, and H. Rakha, “Intersection management for autonomous vehicles using iCACC,” 2012 15th International IEEE Conference on Intelligent Transportation Systems, pp. 1109–1114, 2012.

[7] F. Yan, M. Dridi, and A. El Moudni, “Autonomous vehicle sequencing algorithm at isolated intersections,” 2009 12th International IEEE Conference on Intelligent Transportation Systems, pp. 1–6, 2009.

[8] K.-D. Kim and P. Kumar, “An MPC-Based Approach to Provable System-Wide Safety and Liveness of Autonomous Ground Traffic,” IEEE Transactions on Automatic Control, vol. 59, no. 12, pp. 3341–3356, 2014.

[9] J. Rios-Torres, A. A. Malikopoulos, and P. Pisu, “Online Optimal Control of Connected Vehicles for Efficient Traffic Flow at Merging Roads,” in 2015 IEEE 18th International Conference on Intelligent Transportation Systems, 2015, pp. 2432–2437.

[10] I. A. Ntousakis, I. K. Nikolos, and M. Papageorgiou, “Optimal vehicle trajectory planning in the context of cooperative merging on highways,” Transportation Research Part C: Emerging Technologies, vol. 71, pp. 464–488, 2016.

[11] J. Rios-Torres and A. A. Malikopoulos, “Automated and Cooperative Vehicle Merging at Highway On-Ramps,” IEEE Transactions on Intelligent Transportation Systems, vol. 18, no. 4, pp. 780–789, 2017.

[12] Y. Zhang, A. A. Malikopoulos, and C. G. Cassandras, “Optimal control and coordination of connected and automated vehicles at urban traffic intersections,” in Proceedings of the American Control Conference, 2016, pp. 6227–6232.

[13] A. A. Malikopoulos, C. G. Cassandras, and Y. J. Zhang, “A decentralized energy-optimal control framework for connected automated vehicles at signal-free intersections,” Automatica, vol. 93, pp. 244 – 256, 2018.

[14] L. Zhao, A. A. Malikopoulos, and J. Rios-Torres, “Optimal control of connected and automated vehicles at roundabouts: An investigation in a mixed-traffic environment,” in 15th IFAC Symposium on Control in Transportation Systems, 2018, pp. 73–78.

[15] A. Stager, L. Bhan, A. A. Malikopoulos, and L. Zhao, “A scaled smart city for experimental validation of connected and automated vehicles,” in 15th IFAC Symposium on Control in Transportation Systems, 2018, pp. 130–135.

[16] A. A. Malikopoulos, S. Hong, B. Park, J. Lee, and S. Ryu, “Optimal control for speed harmonization of automated vehicles,” IEEE Transactions on Intelligent Transportation Systems, 2018 (in press).

[17] J. Rios-Torres and A. A. Malikopoulos, “Impact of partial penetrations of connected and automated vehicles on fuel consumption and traffic flow,” IEEE Transactions on Intelligent Vehicles, vol. 3, no. 4, pp. 453–462, 2018.

[18] ———, “A Survey on Coordination of Connected and Automated Vehicles at Intersections and Merging at Highway On-Ramps,” IEEE Transactions on Intelligent Transportation Systems, vol. 18, no. 5, pp. 1066–1077, 2017.

[19] A. A. Malikopoulos, “A multiobjective optimization framework for online stochastic optimal control in hybrid electric vehicles,” IEEE Transactions on Control Systems Technology, vol. 24, pp. 440–450, 2016.

[20] M. Shaltout, A. A. Malikopoulos, S. Pannala, and D. Chen, “A consumer-oriented control framework for performance analysis in hybrid electric vehicles,” IEEE Transactions on Control Systems Technology, vol. 23, no. 4, pp. 1451–1464, 2015.

[21] A. A. Malikopoulos, “Stochastic optimal control for series hybrid electric vehicles,” in Proceedings of the 2013 American Control Conference, 2013, pp. 1189–1194.

[22] ———, “Pareto efficient policy for supervisory power management control,” in Proceedings of the 2015 IEEE 18th International Conference on Intelligent Transportation Systems, September 15-18, 2015.

[23] R. Saeks, C. J. Cox, J. Neidhofer, P. R. Mays, and J. J. Murray, “Adaptive control of a hybrid electric vehicle,” IEEE Transactions on Intelligent Transportation Systems, vol. 3, no. 4, pp. 213–234, 2002.

[24] N. J. Schouten, M. A. Salman, and N. A. Kheir, “Fuzzy logic control for parallel hybrid vehicles,” IEEE Transactions on Control Systems Technology, vol. 10, no. 3, pp. 460–468, 2002.

[25] C.-C. Lin, H. Peng, J. W. Grizzle, and J.-m. Kang, “Power Management Strategy for a Parallel Hybrid Electric Truck,” IEEE Transactions on Control Systems Technology, vol. 11, no. 6, pp. 839–849, 2003.

[26] E. D. Tate, J. W. Grizzle, and H. Peng, “SP-SDP for Fuel Consumption and Tailpipe Emissions Minimization in an EVT Hybrid,” IEEE Transactions on Control Systems Technology, vol. 18, no. 3, pp. 1–16, 2010.

[27] L. Serra and G. Rizzoni, “Optimal control of power split for a hybrid electric refuse vehicle,” in Proceedings of the American Control Conference, 2008, pp. 4498–4503.

[28] G. Paganelli, M. Tateno, A. Brahma, G. Rizzoni, and Y. Guezennec, “Control development for a hybrid-electric sport-utility vehicle: strategy, implementation and field test results,” in Proceedings of the 2001 American Control Conference, vol. 6, 2001, pp. 5064–5069.

[29] A. Sciarretta, M. Back, and L. Guzzella, “Optimal Control of Parallel Hybrid Electric Vehicles,” IEEE Transactions on Control Systems Technology, vol. 12, no. 3, pp. 352–363, 2004.

[30] C. Musardo, G. Rizzoni, and B. Staccia, “A-ECMS: An Adaptive Algorithm for Hybrid Electric Vehicle Energy Management,” in Proceedings of the 44th IEEE Conference on Decision and Control, and the European Control Conference, 2005, pp. 1816–1823.

[31] Y. Luo, T. Chen, S. Zhang, and K. Li, “Intelligent hybrid electric vehicle acc with coordinated control of tracking ability, fuel economy, and ride comfort,” IEEE Transactions on Intelligent Transportation Systems, vol. 16, no. 4, pp. 2303–2308, Aug 2015.

[32] L. Li, X. Wang, and J. Song, “Fuel consumption optimization for smart hybrid electric vehicle during a car-following process,” Mechanical Systems and Signal Processing, vol. 87, pp. 17–19, 2017.

[33] A. A. Malikopoulos, “A duality framework for stochastic optimal control of complex systems,” IEEE Transactions on Automatic Control, vol. 18, no. 4, pp. 780–789, 2016.

[34] R. Wiedemann, “Simulation des strassenverkehrsaufkommens.” Ph.D. dissertation, Institut fur Verkehrswesen der Universitat Karlsruhe, 1974.