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# Development and Evaluation of an Evolutionary Algorithm-Based Online Energy Management System for Plug-In Hybrid Electric Vehicles

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***Abstract*— Plug-in hybrid electric vehicles (PHEVs) have been regarded as one of several promising countermeasures to transportation-related energy use and air quality issues. Compared with conventional hybrid electric vehicles, developing an energy management system (EMS) for PHEVs is more challenging due to their more complex powertrain. In this paper, we propose a generic framework of online EMS for PHEVs that is based on an evolutionary algorithm. It includes several control strategies for managing battery state-of-charge (SOC). Extensive simulation testing and evaluation using real-world traffic data indicates that the different SOC control strategies of the proposed online EMS all outperform the conventional control strategy. Out of all the SOC control strategies, the self-adaptive one is the most adaptive to real-time traffic conditions and the most robust to the uncertainties in recharging opportunity. A comparison to the existing models also employing short-term prediction shows that the proposed model can achieve the best fuel economy improvement but requiring less trip information.**

***Index Terms*— Plug-in hybrid electric vehicle, intelligent transportation system, energy management, evolutionary algorithm.**

## I. Introduction

AIR pollution and climate change impacts associated with the use of fossil fuels have motivated the electrification of transportation systems. In the realm of powertrain electrification, groundbreaking changes have been witnessed in the past decade in terms of research and development of hybrid electric vehicles (HEVs) and electric vehicles (EVs) [1]. As a combination of HEVs and EVs, plug-in hybrid electric vehicles (PHEVs) can be plugged into the electrical grid to charge their batteries, thus increasing the use of electricity and achieving even higher overall fuel efficiency, while retaining the internal combustion engine that can be called upon when needed [2].

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In comparison to conventional HEVs, the energy management systems (EMS) in PHEVs are significantly more complex due to their extended electric-only propulsion (or extended all-electric range capability) and battery chargeability via external electric power sources. Numerous efforts have been made in developing a variety of EMS for PHEVs [3], [4]. From the control perspective, existing EMS can be roughly classified as rule-based [5] and optimization-based [6]. This is discussed in more detail in Section II.

In spite of all these efforts, most of the existing PHEVs' EMS have one or more of the following limitations:

1) *Lack of adaptability to real-time information, such as traffic and road grade.* This applies to rule-based EMS (either deterministic or using fuzzy logic) whose parameters or criteria have been pre-tuned to favor certain conditions (e.g., specific driving cycles and route elevation profiles) [3]. In addition, most EMS that are based on global optimization off-line assume that the future driving condition is known [2]. Thus far, only a few studies have focused on the development of on-line EMS for PHEVs [7].
2) *Dependence on accurate (or predicted) trip information that is usually unknown a priori.* Many of the existing EMS require at a minimum the trip duration as known or predicted information prior to the trip [20]. Furthermore, it is reported that the performance of EMS is largely dependent on the time span of the trip [20]. There are very few studies analyzing the impacts of trip duration on the performance of EMS for PHEVs.
3) *Emphasis on a single trip level optimization without considering opportunistic charging between trips.* The most critical feature that differentiates PHEVs from conventional HEVs is that PHEVs' batteries can be charged by plugging into an electrical outlet. Most of the existing EMS are designed to work on a trip-by-trip basis. However, taking into account inter-trip charging information can significantly improve the fuel economy of PHEVs [2].

To address these limitations, we herein propose a generic framework of on-line EMS for PHEVs that uses an evolutionary algorithm (EA) to optimize vehicle fuel economy in real time. For the purpose of on-line implementation, the optimization is conducted on a sliding time window basis rather than on an entire trip basis. Meanwhile, two types of state-of-charge (SOC) control strategies (i.e., SOC reference control and self-adaptive control), which govern the utilization of vehicle battery power to achieve optimal fuel efficiency for the vehicle without the knowledge of trip duration, are proposed within the framework and compared with conventional binary control strategies.

The major contributions of this paper include: 1) development of a generic framework of on-line EMS for PHEVs; 2) exclusion of trip duration as required information for PHEVs' energy management; 3) quantification of the performance of the proposed EMS with respect to different trip durations; and 4) consideration of the impacts due to inter-trip charging opportunities.

The remainder of this paper is organized as follows: Section II presents background information on PHEVs, in particular some of the existing EMS strategies. We then formulate the PHEV's EMS problem and develop an EA-based on-line EMS framework in Section III. Next, we propose a variety of SOC control strategies, including a self-adaptive implementation which does not require the knowledge of trip duration in Section IV and extensively evaluate the proposed on-line EMS in Section V using data collected in the real world. Lastly, Section VI concludes this paper along with further discussion on future work.

## II. Background & Related Works

### A. PHEV Modeling

Typically, there are three major types of PHEV powertrain architectures: a) series, b) parallel, and c) power-split (series-parallel). This study is focused on the power-split architecture where the internal combustion engine (ICE) and electric motors can, either alone or together, power the vehicle while the battery pack may be charged simultaneously through the ICE. Different approaches with various levels of complexity have been proposed for modeling PHEV powertrains [21]. However, a complex PHEV model with a large number of states may not be suitable for the optimization of PHEV energy control. A simplified but sufficiently detailed power-split powertrain model has been developed in MATLAB and used in this study. For more details, please refer to [2].

### B. Operation Mode and SOC Profile

During the operation of a PHEV, the SOC may vary with time, depending on how the energy sources work together to provide the propulsion power at each instant. The SOC profile can serve as an indicator of the PHEV' operating modes, i.e., charge sustaining (CS), pure electric vehicle (EV), and charge depleting (CD) modes [3], as shown in Fig. 1.

The CS mode occurs when the SOC is maintained at a certain level (usually the lower bound of SOC) by jointly using power from both the battery pack and the ICE. The pure EV mode is when the vehicle is powered by electricity only. The CD mode represents the state when the vehicle is operated using power primarily from the battery pack with supplemental power from the ICE as necessary. In the CD mode, the ICE is turned on if the electric motor is not able to provide enough propulsion power or the battery pack is being charged (even when the SOC is much higher than the lower bound) in order to achieve better fuel economy.

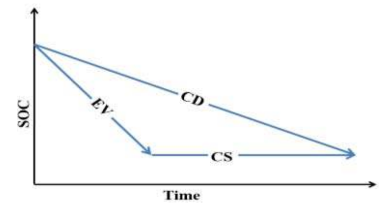


Fig. 1. Basic operation modes for PHEV.

### C. EMS for PHEVs

The goal of the EMS in a PHEV is to satisfy the propulsion power requirements while maintaining the vehicle's performance in an optimal way. A variety of strategies have been proposed and evaluated in many previous studies [4]. A detailed literature review on EMS for PHEVs is provided in this section. Broadly speaking, the existing EMS for PHEVs can be divided into two major categories:

- *Rule-based EMS* are fundamental control schemes operating on a set of predefined rules without prior knowledge of the trip. The control decisions are made according to the current vehicle states and power demand only. Such strategies are easily implemented but the resultant operations may be far from being optimal due to not considering future traffic conditions.
- *Optimization-based EMS* aim at optimizing a predefined cost function according to the driving conditions and behaviors. The cost function may include a variety of vehicle performance metrics, such as fuel consumption and tailpipe emissions.

For *Rule-based EMS*, deterministic and fuzzy control strategies (e.g., binary control) have been well investigated. For *Optimization-based EMS*, the strategies can be further divided into three subgroups based on how the optimizations are implemented: 1) *off-line* strategy which requires a full knowledge of the entire trip beforehand to achieve the global optimal solution; 2) *prediction-based* strategy or so called real-time control strategy which takes into account predicted future driving conditions (in a rolling horizon manner) and achieves local optimal solutions segment-by-segment. This group of strategies are quite promising due to the rapid advancement and massive deployment of sensing and communication technologies (e.g., GPS) in transportation systems that facilitate the traffic state prediction; and 3) *learning-based* strategy which is recently emerging owing to the research progress in machine learning techniques. In such a data-driven strategy, a dynamic model is no longer required. Based on massive historical and real-time information, trip characteristics can be learned and the corresponding optimal control decisions can be made through advanced data mining schemes. This strategy fits very well for commute trips. Figure 2 presents a classification tree of EMS for PHEVs and the typical strategies in each category, based on most existing studies.

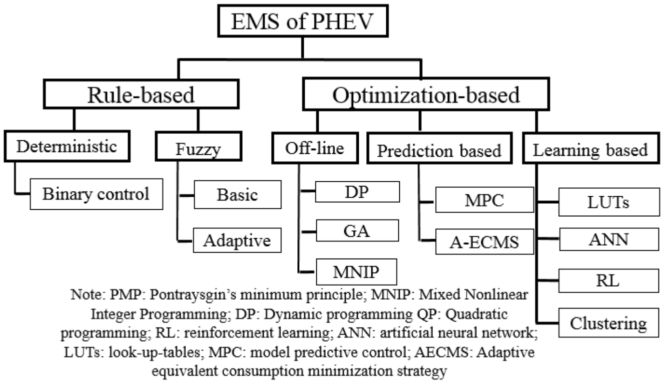



Fig. 2. Basic classification of EMS for PHEV.

TABLE I
CLASSIFICATION OF CURRENT LITERATURE

| | Rule-based | Off-line optimization | Prediction based | Learning based |
|---|---|---|---|---|
| Optimality | local | global | local | local |
| Real time | Yes | No | Yes | Yes |
| SOC control | No | Yes | Yes | No |
| Need trip duration | No | Yes | Yes | Yes |
| Example references | [7],[8], [9],[10] | [2],[11], [12],[6] [17],[18][6] | [13],[14] [16],[20] [29][30][31] | [13], [14], [15][19], [21][32] |

In addition to the classification above, Table I highlights several important features which help differentiate the aforementioned strategies. Example references are also included in Table I.

### *D. PHEVs' SOC Control*

For a power-split PHEV, the optimal energy control is, in principle, equivalent to the optimal SOC control. Most of the existing EMS for PHEVs implicitly integrate SOC into the dynamic model and regard it as a key control variable [18], while only a few studies have explicitly described their SOC control strategies. A SOC reference control strategy is proposed in [15] where a supervisory SOC planning method is designed to pre-calculate an optimal SOC reference curve. The proposed EMS then tries to follow this curve during the trip to achieve the best fuel economy. Another SOC control strategy is proposed in [19] where a probabilistic distribution of trip duration is considered. More recently, machine learning-based SOC control strategies (e.g., [6]) have emerged, where the optimal SOC curves are pre-calculated using historical data and stored in the form of look-up tables for real-time implementation. A common drawback for all these strategies is that accurate trip duration information is required in an either deterministic or probabilistic way. In reality, however, such information is hard to be known ahead of time or may vary significantly due to the uncertainties in traffic conditions. To ensure the practicality of our proposed EMS for PHEVs, we employ a self-adaptive SOC control strategy in this study which does not require any information about the trip duration (or length).

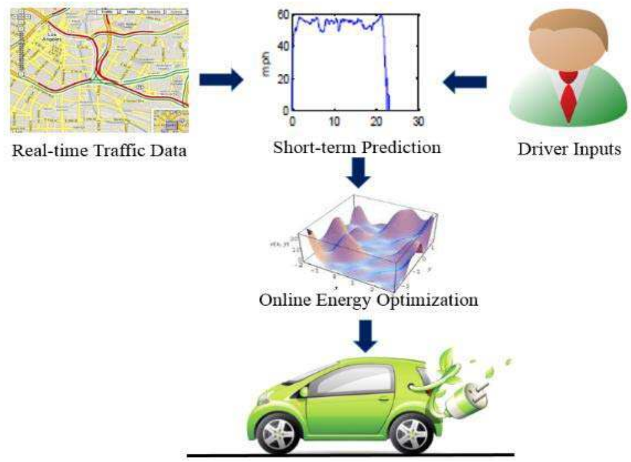



Fig. 3. Flow chart of the proposed on-line EMS.

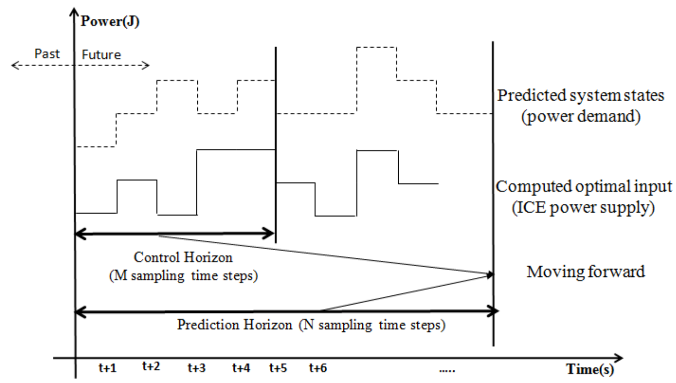



Fig. 4. Time horizons of prediction and control.

## III. PROBLEM FORMULATION

### *A. Proposed On-Line EMS Framework for PHEVs*

In this paper, we propose an on-line EMS framework for PHEVs, using the receding horizon control structure (see Fig. 3). The proposed EMS framework consists of information acquisition (from external sources), prediction, optimization, and power split control. With the receding horizon control, the entire trip is divided into segments or time horizons. As shown in Fig. 4, 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 (i.e., 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 inputted into the powertrain control system (e.g., electronic control unit (ECU)) at the required sampling frequency. In this study, we focus on the on-line energy optimization, assuming that the short-term prediction model is available (which is one of our future research topics).

### B. Optimal Power-Split Control Formulation

Mathematically, 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.

$$\begin{cases} min \left\{ \int_0^T h(\omega_e, q_e, t)\, dt \right\} \\ subject\ to: \\ S\dot{O}C = f(SOC, \omega_{MG1}, q_{MG1}, \omega_{MG2}, q_{MG2}) \\ (\omega_e, q_e) = g(\omega_{MG1}, q_{MG1}, \omega_{MG2}, q_{MG2}) \\ SOC_{min} \le SOC \le SOC_{max} \\ \omega_{min} \le \omega_e \le \omega_{max} \\ q_{min} \le q_e \le q_{max} \end{cases} \tag{1}$$

where $T$ is the trip duration; $\omega_e, q_e$ are the engine's angular velocity and engine's torque, respectively; $h(\omega_e, Tq_e)$ is ICE fuel consumption model; $\omega_{MG1}, q_{MG1}$ are the first motor/generator's angular velocity and torque, respectively; $\omega_{MG2}, q_{MG2}$ are the second motor/generator's angular velocity and torque, respectively; $f(SOC, \omega_{MG1}, q_{MG1}, \omega_{MG2}, q_{MG2})$ is the battery power consumption model; For more details about the model derivations and equations, please refer to [2].

Such formulation is quite suitable for traditional mathematical optimization methods [11] with high computational complexity. In order to facilitate on-line optimization, we herein discretize the engine power and reformulate the optimization problem represented by (1) as follows:

$$\min \sum_{k=1}^{T} \sum_{i=1}^{N} x(k,i)\, P_i^{eng} / \eta_i^{eng} \tag{2}$$

subject to:

$$\sum_{k=1}^{j} f\left(P_k - \sum_{i=1}^{N} x(k,i)\, P_i^{eng}\right) \le C \forall j = 1, \ldots, T \tag{3}$$

$$\sum_{i=1}^{N} x(k,i) = 1 \forall k \tag{4}$$

$$x(k,i) = \{0, 1\} \forall k, i \tag{5}$$

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; $P_i^{eng}$ is the $i$-th discretized level for the engine power and $\eta_i^{eng}$ is the associated engine efficiency; and $P_k$ is the driving power demand at time step $k$.

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 (3) can be replaced by

$$\begin{aligned} SOC^{ini} - SOC^{max} &\le \sum_{k=1}^{j} x(k,i)\, \Delta SOC(k,i) \\ &\le SOC^{ini} - SOC^{min} \\ \forall j &= 1, \ldots, T \end{aligned} \tag{6}$$

where $SOC^{ini}$ is the initial SOC; and $SOC^{min}$ and $SOC^{max}$ are the minimum and maximum SOC, respectively.

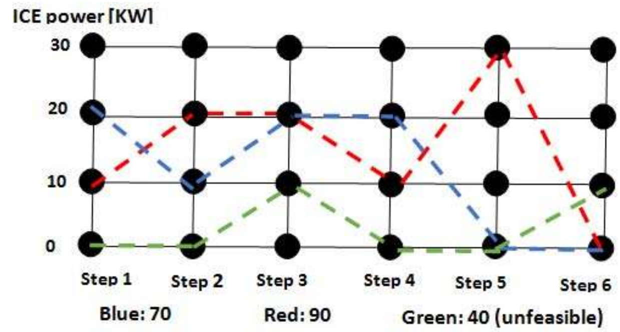



Fig. 5. Example solutions of power-split control.

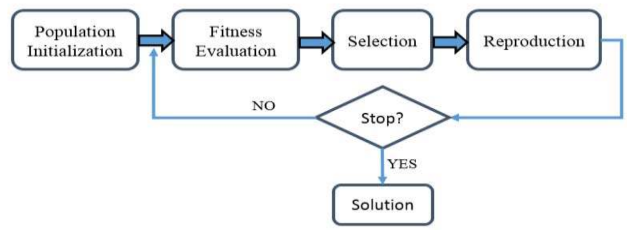



Fig. 6. Estimation and sampling process of EA.

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. Fig.5 gives three example ICE power output solutions. The solution represented by the blue line has a lower total ICE power consumption (i.e., 40 units) than the red line (i.e., 90 units), while the green line represents an infeasible solution due to the SOC constraint.

### C. Evolutionary Algorithm (EA) Based On-Line Optimization

The motivations for applying EA are: 1) compared to the traditional derivative or gradient-based optimization methods, EAs are easier to implement and require less complex mathematical models; 2) EAs are very good at solving non-convex optimization problems where there are multiple local optima; and 3) it is very flexible to address multi-objective optimization problems using EAs.

Theoretically, in the proposed framework, any EAs can be used to solve the optimization problem for each prediction horizon described in Fig. 4. A typical EA is a population-based and iterative algorithm which starts searching for the optimal solution with a random initial population. Then, the initial population undergoes an iterative process that includes multiple operations, such as fitness evaluation, selection, and reproduction until certain stopping criteria are satisfied. The flow chart of an EA is provided in Fig. 6.

Among many EAs, the estimation distribution algorithm (EDA) is very powerful in solving high-dimensional optimization problems and has been successfully applied to many different engineering domains [20]. In this study, we choose EDA as the major EA kernel in the proposed framework due to the high-dimensionality nature of the

TABLE II
REPRESENTATION OF ONE EXAMPLE INDIVIDUAL

| Time | 1s | 2s | 3s | 4s | ……………… | n-3 | n-2 | n-1 | n |
|---|---|---|---|---|---|---|---|---|---|
| Individual | 3 | 0 | 1 | 4 | ……………… | 1 | 2 | 0 | 5 |

PHEV energy management problem. This selection is justified by experimental results in the following sections.

In the problem representation of EDA, each individual (encoded as a row vector) of the population defined in the algorithm is a candidate solution. For the PHEV energy management problem, the size of the individual (vector) is the number of time steps within the trip segment. The value of the *i*-th element of the vector is the ICE power level chosen for that time step. In the example individual in Table II, the ICE power level is 3 (or 3 kW) for the $1^{st}$ time step, 0 kW (i.e., only battery pack supplies power) for the $2^{nd}$ time step, 1 for the $3^{rd}$ time step, and so forth.

It is very flexible to define a fitness function for EAs. Since the objective is to minimize fuel consumption, the fitness function herein can be defined as the summation of total ICE fuel consumption for the trip segment defined by Eq. (5) and a penalty term

$$f(s) = C_{fuel} + P \tag{7}$$

where $s$ is a candidate solution; $C_{fuel}$ is fuel consumption; and $P$ is imposed penalty that is the largest possible amount of energy that can be consumed in this trip segment. The penalty is introduced to guarantee the feasibility of solution, satisfying Constraint (3) which means that the SOC should always fall within the required range at each time step. Then, all the individuals in the population are evaluated by the fitness function and ranked by their fitness values in an ascending order since this is a minimization problem. A good evaluation and ranking process is crucial in guiding the evolution towards good solutions until the global optima (or near optima) is located.

Furthermore, EDA assumes that the value of each element in a good individual of the population follows a univariate Gaussian distribution. This assumption has been proven to be effective in many engineering applications [21], although there could be other options [22]. For each generation, the top individuals (candidate solutions) with least fuel consumption values are selected as the parents for producing the next generation by an estimation and sampling process [26].

The flow chart of the proposed EDA-based on-line EMS is presented in Fig. 7. $t_0$ is the current time; N is the length of the prediction time horizon and M is length of the control time horizon. The block highlighted by the red dashed box is the core component of the system and more details about this block is given in section IV.

### D. Optimality and Complexity

Evolutionary algorithms are stochastic search algorithms which do not guarantee to find the global optima. Hence, in the proposed on-line EMS, the optimal power control for each trip

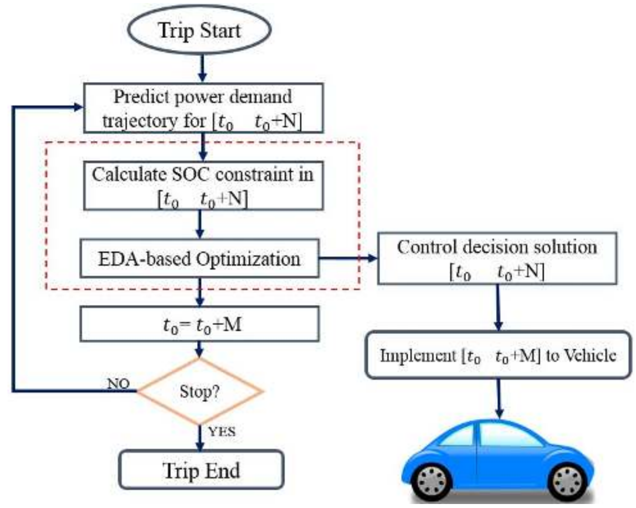



Fig. 7. EDA-based on-line energy management system.

segment is not guaranteed to be found. Moreover, EAs are also population-based iterative algorithms which are usually criticized due to their heavy computational loads [23], especially for real-time applications. Theoretically, time complexity of EAs is worse than $\theta(m^2 * \log(m))$ where $m$ is the size of the problem [24]. However, we apply the receding horizon control technique in this study, where the entire trip is divided into small segments. Therefore, the computational load can be significantly reduced since the EA-based optimization is applied only for each small segment rather than the entire trip. In this sense, the proposed framework can be implemented in “real-time”, as long as the optimization for the next prediction horizon can be completed in the current control horizon (see Fig. 4). As previously discussed, the *rule-based EMS* can run in real-time but the results may be far from being optimal while most of the *optimization-based EMS* have to operate off-line. Therefore, the proposed on-line EMS would be a well-balanced solution between the real-time performance and optimality.

## IV. SOC CONTROL STRATEGIES

An appropriate SOC control strategy is critical in achieving the optimal fuel economy for PHEVs [25]. In the previously presented problem formulation, the major constraint for SOC is defined by Eq.(6), which means that at any time step the SOC should be within the predefined range (e.g., between 0.2 and 0.8) to avoid damage to the battery pack. However, this constraint only may not be enough to accelerate the search for the optimal solution. Hence, additional constraint(s) on battery use (e.g., reference bound of SOC) should be introduced to improve the on-line EMS. To investigate the effectiveness of different SOC control strategies within the proposed framework, two types of SOC control strategies, i.e., reference control and self-adaptive control, are designed and evaluated in this study.

### A. SOC Reference Control (Known Trip Duration)

When the trip duration is known, a SOC curve can be pre-calculated and used as a reference to control the use of battery

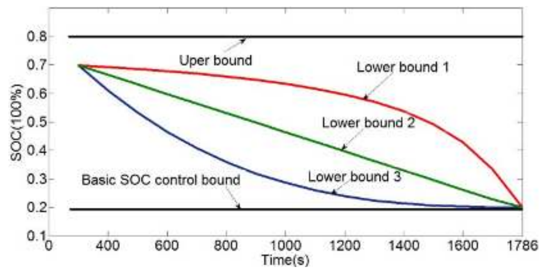



Fig. 8. SOC reference control bound examples.

power along the trip to achieve optimal fuel consumption. We propose three heuristic SOC references (i.e., lower bounds) in this study (see Fig. 8 for example): 1) concave downward; 2) straight line; and 3) concave upward. These SOC minimum bounds are generated based on the given trip duration information by the following equations, respectively:

- Concave downward control: (lower bound 1)

$$SOC_i^{min} = \frac{(SOC_{init} - SOC^{min})}{T - (i * M)} * N + SOC^{init} \quad (8)$$

- Straight line control :( lower bound 2)

$$SOC_i^{min} = \frac{-(SOC_i^{min} - SOC^{min})}{T} \cdot ((i-1) \cdot M + N) + SOC^{init} \quad (9)$$

- Concave upward control :( lower bound 3)

$$SOC_i^{min} = \frac{-(SOC_{i-1}^{end} - SOC^{min})}{T - (i * M)} * N + SOC_{i-1}^{end} \quad (10)$$

where $i$ is the segment index; $SOC_i^{min}$ is the minimum SOC at the end of $i$-th segment; and $SOC_{i-1}^{end}$ is the SOC at the end of last control horizon. It is self-evident that the concave downward bound (i.e., lower bound 1) is much more restrictive than a concave upward bound (i.e., lower bound 3) in terms of battery energy use at the beginning of the trip.

A major drawback for these reference control strategies is that they assume that the trip duration (i.e., $T$) is given, or at least can be well estimated beforehand. As mentioned earlier, this assumption may not hold true for many real-world applications. Therefore, a new SOC control strategy without relying on the knowledge of trip duration would be more attractive.

### B. SOC Self-Adaptive Control (Unknown Trip Duration)

In this study, we also propose a novel self-adaptive SOC control strategy for real-time optimal charge-depleting control, where trip duration information is not required. Unlike those SOC reference control strategies which control the use of battery by explicit reference curves, the self-adaptive control strategy controls the battery power utilization implicitly by adopting a new fitness function in place of the one in Eq. (7):

$$f(s) = R_{fuel} + R_{soc} + P' \quad (11)$$

where $R_{fuel}$ and $R_{soc}$ are the ranks (in an ascending order) of ICE fuel consumption and SOC decrease, respectively, of an individual candidate solution $s$ in the current population;

TABLE III

EXAMPEL FITNESS EVALUATION BY DIFFERENT FITNESS FUNCTIONS

| Indiv. Index | Fuel Con. | SOC decrease | $R_{fuel}$ | $R_{soc}$ | Rank by Eq.(7) | Rank by Eq.(11) |
|---|---|---|---|---|---|---|
| **1** | 0.001 | 0.005(***P***) | 5 | 35 | 98 | 140 |
| **2** | 0.010 | 0.002 | 25 | 14 | 33 | **39** |
| **3** | 0.007 | 0.003 | 19 | 23 | **24** | 42 |
| **4** | 0.002 | 0.004(***P***) | 7 | 32 | 99 | 139 |
| **….** | …… | …….. | ……. | …… | …….. | ……. |

TABLE IV

ABBREVIATIONS OF DIFFERENT SOC CONTROL STRATEGIES COMPARED IN THIS STUDY

| SOC control strategies | Abbreviations |
|---|---|
| Binary control | B-I |
| Basic SOC control | B-A |
| Concave downward | C-D |
| Straight line | S-L |
| Concave upward | C-U |
| Self-adaptive SOC control | S-A |

and $P'$ is the added penalty when the individual $s$ violates the constraints given in Eq.(6). The penalty value is selected to be greater than the population size in order to guarantee that an infeasible solution always has a lower rank (i.e., larger fitness value) than a feasible solution in the ascending order by fitness value. Compared to the fitness function adopted for SOC reference control (see Eq. (7)), this new fitness function tries to achieve a good balance between two conflicting objectives: least fuel consumption and least SOC decrease. For a better understanding of the differences between these two fitness functions, Table III provides an example of fitness evaluation of the same population. In this case, the population size is 100. As we can see in the table, Individual 2 which has a better balance between fuel consumption and SOC decrease is more favorable than Individual 3 in the ranking by Eq. (11) than that by Eq.(7).

### C. EDA-Based On-Line EMS Algorithm With SOC Control

Details of the proposed EDA-based on-line EMS algorithm with SOC control are summarized in the Algorithm 1 below. This algorithm is implemented on each prediction horizon (N time steps) within the framework presented in Fig. 8 (see the box with red dashed line).

In the following section, we compare the performance of the proposed self-adaptive SOC control with other SOC control strategies. For convenience, we list the abbreviations of all the involved strategies in Table IV.

## V. CASE STUDY

### A. Synthesized Trip Information

To validate the proposed EMS for PHEVs, we use real-world data collected on January 17th, 2012, along I-210 between I-605 and Day Creek Blvd in San Bernardino, California, as a case study (see Fig. 9). Please refer to [2] for more detailed description of data collection and specifications of the power-split PHEV model if interested.

**Algorithm 1** Algorithm 1 EDA-Based on-Line EMS With SOC Control

1: Initialize a random output solution $I_{best}$(N time steps)
2: $P_{current}$ <= Generate initial population randomly
3: While iteration_number $\leq$ Max_iterations, do
4: For each individual $s$ in $P_{current}$
5: Calculate fuel consume $C_{fuel}$ using eq. (1).
6: Calculate SOC decrease using eq. (5)
7: Obtain the rank index of $s$: $R_{fuel}$
8: Obtain the rank index of $s$:$R_{soc}$
9: If SOC reference control is adopted
10: Calculate the lower bound using eqs.(8)(9)(10)
11: If individual $s$ violates eq.(6)
12: $P = P_0$;*//largest fuel consumption in N steps*
13: Else
14: $P$=0;
15: End If
16: Calculate the fitness value for $s$using eq.(7)
17: Else If SOC self-adaptive control is adopted
18: If individual $s$ violates eq.(6)
19: $P^{'} = S$
20: Else
21: $P^{'}$=0;
22: End If
23: Calculate the fitness value for $s$using eq.(11)
24: End If
25: End For
26: Rank $P_{current}$ in ascending order based on fitness
27: $P_{top}$<= Select top$\alpha$ individuals from $P_{current}$
28: E <= Estimate a new distribution from $P_{top}$
29: $P_{new}$ <= Sample N individuals from built model E
30: Evaluate each individual in $P_{new}$ using line 5 to 14
31: Mix $P_{current}$ and $P_{new}$ to form 2N individuals
32: Rank 2N individuals in ascending order by fitness
33: $P_{current}$ <= Select top N individuals
34: Update $I_{best}$ if a better one is identified.
35: Iteration_number ++
36: End While
37: Output $I_{best}$

Based on the collected traffic data along with road grade information, second-by-second vehicle velocity trajectory and power demand have been synthesized as described in [2]. As pointed out earlier, it is impractical to have *a priori* knowledge of the exact vehicle velocity trajectory. In this study, we focus on the development of the optimal power-split control, assuming perfect prediction of vehicle velocity trajectory. Research on improving the prediction of vehicle velocity trajectory in real time is part of our future work.

### *B. Off-Line Optimization for Validation*

To justify the selection of EDA as the kernel of the proposed framework, we first test EDA on the full-trip off-line optimization. The results are compared with those obtained from two other popular evolutionary algorithms: genetic algorithm (GA) and particle swarm optimization (PSO). The fitness (i.e., total ICE energy consumption) of EDA-based off-line optimization obtains better fuel economy (0.346 gallons) than the other two (0.364 gallons for GA and 0.377 for PSO, respectively), at the same computational expense (i.e., same population size and same number of iterations) [26]. In addition, the result from EDA is much closer to the global optimum (0.345 gallons in this case) with the difference being less than 1%.

Fig. 9. Example trip along I-210 in Southern California used for evaluation.

### *C. Real-Time Performance Analysis and Parameter Tuning*

As aforementioned, a necessary condition for on-line implementation of the proposed EMS is that the optimization for the next prediction horizon has to be finished within the current control horizon (see Fig.4). In our study, for example, the optimization for a prediction horizon of 50 seconds can be completed within 1.1 seconds (with Intel Core i7 3.4GHz, RAM 4G, and 64bit-Matlab 2012). In addition, one of our previous work [26] has shown that the lengths of prediction horizon and control horizon may significantly affect the algorithm performance. The best combination of these two parameters is found to be $N = 250$ and $M = 10$ in this case.

Unlike the conventional MPC whose optimization has to be implemented along each prediction horizon, our proposed EA based online EMS (see Fig.7) can take advantage of the optimal results from previous prediction horizons, which avoids a new optimization starting from scratch and therefore saves a lot of computational overhead. As can be seen in Fig. 10, part of the optimal decisions from previous prediction optimization horizon is adopted as the seed for initial population of current prediction horizon optimization. For example, when the control horizon is 3s and prediction/optimization horizon is N, only 3 control decisions need to be randomly initialized and optimized in the second prediction/optimization horizon. This allows the optimization or search to be much more efficient, compared to the same process over entire prediction horizon. To further validate this computational performance, we designed an EA based MPC (EAMPC) which activates a complete new optimization for each prediction/optimization horizon and compared it with our proposed model. The computation time track in Fig.11 shows that for a 50-seconds prediction horizon, the conventional MPC takes around 1.1 seconds for each optimization horizon but our proposed model can take only less than 0.1s to finish the optimization from the second prediction horizon.

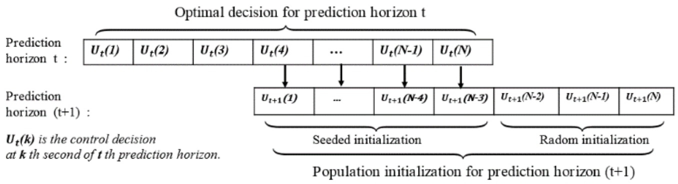



Fig. 10. Population initialization from the second prediction horizon (i.e., t≥ 2).

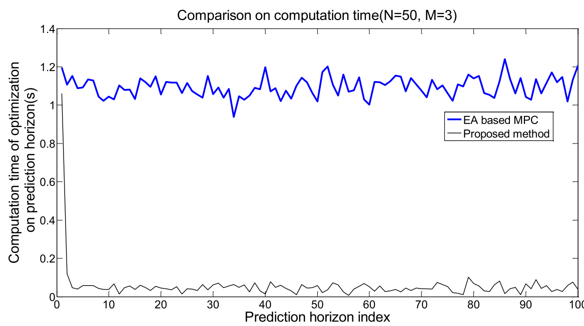



Fig. 11. Comparison on computation time.

## D. On-Line Optimization Performance Comparison

To fully evaluate the performance of the proposed on-line EMS strategies, we compare them to the conventional binary control (implementable in real-time) strategy as well as the off-line global optimal control strategy (with the use of dynamic programming [9]). The comparisons are carried out on both the single trip scenario and multiple trips scenario.

When tested on a single (westbound) trip, the fuel consumption and SOC profiles by different strategies are illustrated in Fig. 12. It is shown that the proposed S-A algorithm achieves the lowest fuel consumption (0.3515 gallons) which is only 1.56% worse than that of global optima obtained by the off-line optimization (0.3460 gallons). These results can be explained by the shape of the resultant SOC profiles. For instance, SOC decreases very quickly in the B-I strategy, and reaches the lower bound (i.e., 0.2) at around 1,200 seconds because the use of battery power is always prioritized whenever available. Therefore, ICE has to supply most of the demanded power after 1,200 seconds. This is very similar to the cases of the B-A and C-U strategies where the battery power is also consumed aggressively at the beginning of the trip with very loose constraints. On the other hand, the S-L and C-D strategies perform better since their battery power is used more cautiously along the trip. These findings are consistent with the conclusions of many other studies [19], [25] in that a smoother distribution of battery power usage along the trip would result in higher fuel efficiency.

In order to know the statistical significance of the different EMS strategies, we test them on 30 randomly selected trip profile data extracted from the same road segment on 12 different days. The results are also compared to the binary control and dynamic programming (D-P) strategies. For the purpose of comparison, we set the fuel consumption obtained by the binary control strategy as the baseline and calculate

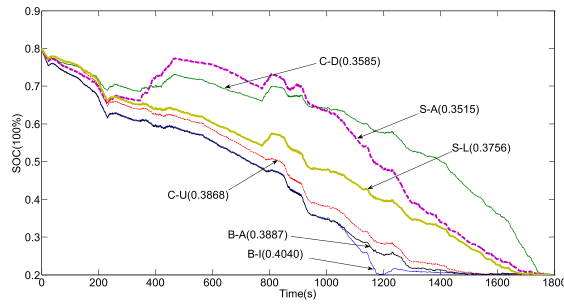



Fig. 12. SOC trajectories resulted from different control strategies.

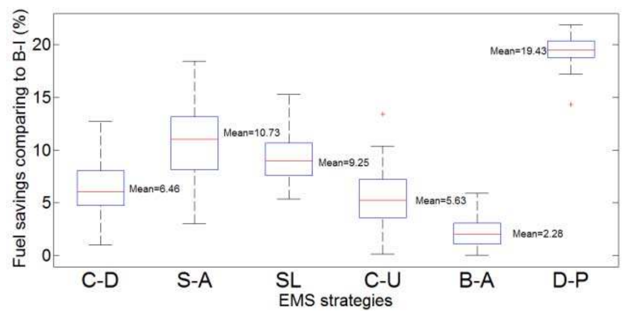



Fig. 13. Box-plot of fuel savings on 30 trips.

the percentage of fuel savings achieved by the other EMS strategies. As we can see in Fig. 13, the D-P strategy achieves the best fuel savings with an average of 19.4% and the least variance simply because it is an off-line optimization strategy. The proposed S-A strategy achieves an average of 10.7% fuel savings which is higher than all other on-line strategies and consistent with the result of the single trip test. An interesting observation is that the S-L strategy has better average fuel savings (i.e., 9.3%) than the C-D and C-U strategies which is not consistent with the test result of the single trip test. A possible reason is that the C-D strategy performs better on some trips in which the power demand is higher in later stages of the trip but the C-U strategy performs better on the trips in which the power demand is higher in earlier stages. On the other hand, the S-L strategy balances the SOC control between these two types of trip pattern, and therefore has better average performance.

For further validation, the proposed S-A strategy with the best performance is compared with other existing PHEV EMS strategies that employ short-term prediction. Although these strategies were proposed to handle powertrain models with different fidelity as well as different data set for validation, they all used the binary control strategy as a benchmark (the same as in this work). This provides us a chance to compare all models in a relatively fair manner. The comparison results are listed in table V, which proves that our model achieves the largest improvement of fuel efficiency (with regard to the binary control strategy) but requires less trip information.

## E. Analysis of Trip Duration

In this section, we analyze and compare the effectiveness of the proposed on-line EMS for longer trips. These longer trips are constructed by concatenating multiple trip profiles and the

TABLE V
COMPARISONS WITH EXISTING MODELS

| EMS model | Year | STP[1] | Trip distance | FE I[2] | Consider Charging? |
|---|---|---|---|---|---|
| **This work** | **2016** | **Yes** | **Unknown** | **10.7%** | **Yes** |
| **EAMPC** | **2016** | **Yes** | **Unknown** | **7.9%** | **Yes** |
| MPC[29] | 2014 | Yes | Known | 8.5% | No |
| MPC[16] | 2015 | Yes | Known | 6.7% | No |
| A-ECMS[29] | 2014 | Yes | Known | 10.2% | No |
| A-ECMS[13] | 2015 | Yes | Known | 7.6% | No |
| DP[30] | 2015 | Yes | Known | 5.8% | No |
| SDP[3] [31] | 2011 | Yes | Known | 7.7% | No |

[1]Short-term prediction; [2]Fuel economy improvement comparing to binary

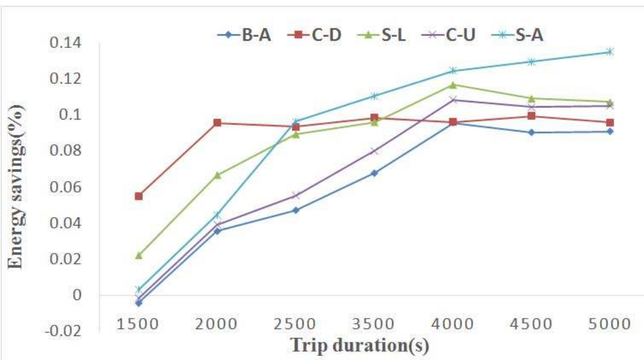



Fig. 14. Fuel savings for trips with different duration, compared to B-I.

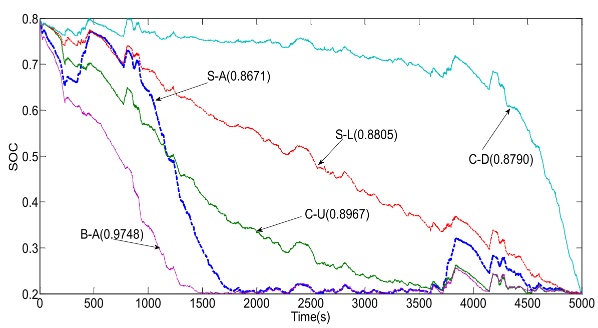
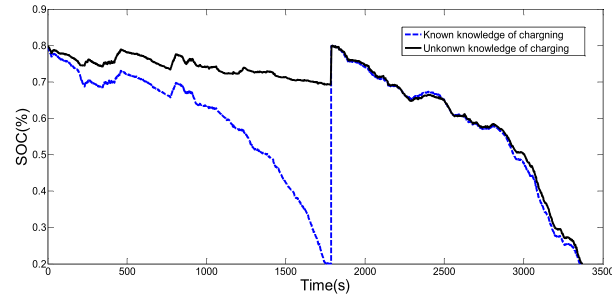
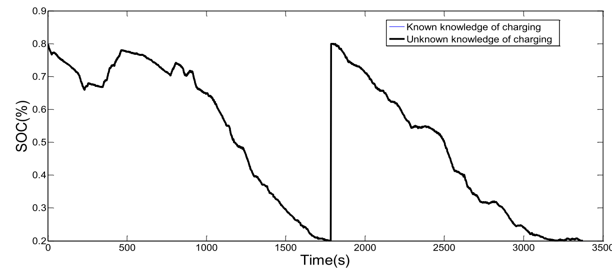


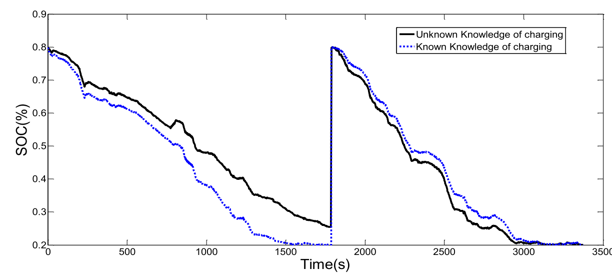

Fig. 15. Resultant SOC curve when trip duration is 5,000 seconds.



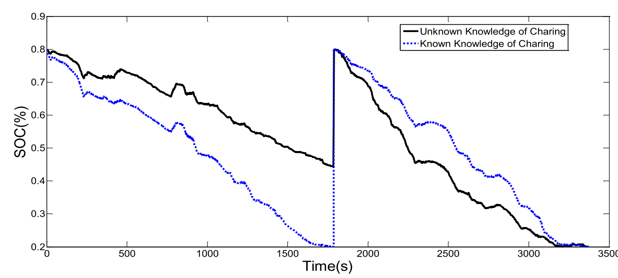

a. C-D




b. S-A




c. C-U




d. S-L

Fig. 16. SOC track with known or unknown charging opportunity.

results are shown in Fig. 14. As can be observed, the B-I strategy has the best fuel economy when the trip duration is shorter than 1,500 seconds. For these short trips, the PHEV can mostly rely on battery energy. However, as the trip duration becomes longer, especially when longer than 2,500 seconds, the S-A strategy outperforms all the others.

To further explain this finding, the resultant fuel consumption and the corresponding SOC profiles for the longest trip (5,000 seconds) are provided in Fig. 15. According to the figure, the S-A strategy has the lowest fuel consumption and its SOC profile is a combination of the CD mode (defined in Fig. 1) before 2,000 seconds and the CS mode after 2,000 seconds. This contradicts with most of the existing studies, which report that an optimal fuel economy for the trip can be achieved by operating solely in the CD mode [20]. Here, we present evidence that it is not always the case, and that the CD+CS operation can result in optimal fuel efficiency for long trips. Furthermore, this finding also implies the potential for the proposed S-A strategy to adapt to different trip durations.

### *F. Performance With Charging Opportunity*

Considering the plug-in capability of PHEVs, we evaluate the performance of the proposed strategies at the tour level. More specifically, we consider the commute trips of the case study as a tour and assume that there is a charging opportunity (to a full charge) between the end of the westbound trip and the beginning of the eastbound trip. We then compare the different SOC control strategies under the following two scenarios:

TABLE VI
INCREASED FUEL CONSUMPTION

| Control strategy | Known (gal) | Unknown (gal) | Increased fuel consumption |
|---|---|---|---|
| B-I | 0.9748 | 0.9748 | 00.0% |
| B-A | 0.7109 | 0.7543 | 06.1% |
| C-D | 0.6729 | 0.8439 | 25.1% |
| S-L | 0.6809 | 0.7853 | 15.0% |
| C-U | 0.7066 | 0.8034 | 13.0% |
| S-A | 0.6681 | 0.6681 | 00.0% |

1) *Scenario I*: The proposed EMS with a priori knowledge of the charging opportunity;
2) *Scenario II*: The proposed EMS without a priori knowledge of the charging opportunity. In this case, a conservative strategy is applied by assuming that there is no charging station available in between the trips.

The results are illustrated in Fig.16. They show that the knowledge of the charging opportunity information has great influence on the resultant SOC profiles for the deterministic SOC reference control strategies but no influence on the SOC self-adaptive control strategy. Table VI presents the increased fuel consumption due to the lack of knowledge of the charging opportunity prior to the tour. As shown in the table, the C-D, S-L, and C-U strategies all have 13% or more increase in fuel consumption if the charging opportunity information is unknown, while the B-I and S-A strategies are not affected because the trip duration is not considered in their decision-making process. But S-A strategy is able to achieve 31.5% fuel savings comparing to B-I strategy when considering charging opportunities. These findings further emphasize the advantage of the proposed SOC self-adaptive control strategy in terms of robustness to the level of knowledge about charging availability.

## VI. CONCLUSIONS

In this study, we develop the framework of an on-line energy management system for plug-in hybrid electric vehicles. The framework applies the self-adaptive strategy to control the vehicle's state-of-charge (SOC) in a rolling horizon manner for the purpose of real-time implementation. The control of the vehicle's SOC is formulated as a combinatory optimization problem that can be efficiently solved by the estimation distribution algorithm (EDA). The proposed energy management system is comprehensively evaluated using a number of trip profiles extracted from real-world traffic data. The results show that the self-adaptive control strategy used in the proposed system statistically outperforms the conventional binary control strategy with an average of 10.7% fuel savings without considering charging opportunity and 31.5% fuel savings when considering charging opportunity.

The real-time performance analysis shows that the proposed mode is very computationally efficient and can be implemented in real-time by taking the advantage of evolutionary optimization.

Another important advantage of the proposed energy management system is that, unlike other existing systems, it does not require a priori knowledge about the trip duration. This allows the proposed system to be robust against real-world uncertainties, such as unexpected traffic congestion that increases the trip duration significantly, and changes in inter-trip charging availability.

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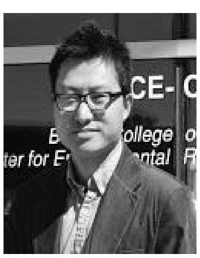

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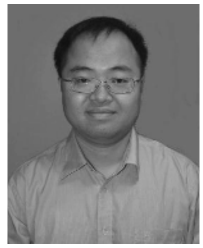

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