Intelligent On-Line Energy Management System for Plug-in Hybrid Electric Vehicles based on Evolutionary Algorithm

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ABSTRACT

Energy management system (EMS) is crucial to a plug-in hybrid electric vehicle (PHEV) in reducing its fuel consumption and pollutant emissions. The EMS determines how energy flows in a hybrid powertrain should be managed in response to a variety of driving conditions. In the development of an EMS, the battery state-of-charge (SOC) control strategy plays a critical role. This paper proposes a novel evolutionary algorithm (EA)-based EMS with a self-adaptive SOC control strategy for PHEVs, which can significantly improve the fuel efficiency without knowing the trip length (in time). Numerical studies show that this proposed system can save up to 13% fuel, compared to other on-line EMS with different SOC control strategies. Further analysis indicates that the proposed system is less sensitive to the errors in predicting propulsion power demand in real-time, which is favorable for on-line implementation. Original publication: X. Qi, G. Wu, K. Boriboonsomsin and M. J. Barth, Evolutionary algorithm based on-line PHEV energy management system with self-adaptive SOC control, Intelligent Vehicles Symposium (IV), 2015 IEEE, Seoul, 2015, pp. 425-430.

Keywords

Evolutionary algorithms; Estimation Distribution Algorithms; PHEV; Energy Management System

1. INTRODUCTION

Air pollution and climate change impacts associated with the use of fossil fuels have motivated the electrification of transportation systems. In recent years, there has been significant interest in plug-in hybrid electric vehicles (PHEVs) as an effective means to decrease the dependence on fossil fuel and to reduce emissions of greenhouse gases (GHGs) and other criteria pollutants from transportation activities [1]. By having the battery charging capability via external sources (i.e., plugging into outlets), PHEVs can achieve much better fuel economy than conventional hybrid electric vehicles (HEVs). In 2012, PHEVs captured 3.5% of U.S. market and 20% of Japanese market, respectively [1], and their market shares are expected to grow in the next decades.

The fuel efficiency of a PHEV powertrain significantly depends on its energy management system (EMS), characterized by the state-of-charge (SOC) profile of the battery pack.

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However, most of the existing EMS employ either rule-based models which rely on a set of simple rules without a priori knowledge of driving conditions, or off-line optimization based models which are aimed at optimizing some predefined cost function according to the driving conditions of the entire trip [1]. To date, there have been very few studies on real-time EMS models.
The major challenges in implementing a real-time EMS for PHEVs lie in obtaining a priori knowledge of the system states (e.g., second-by-second speed) as well as the time delay of consecutive intensive computation tasks.

In this paper, we propose an evolutionary algorithm based on-line energy management for PHEVs with a self-adaptive SOC control strategy in a receding horizon control framework. The proposed method can adaptively control the use of battery power to achieve much better fuel efficiency for the internal combustion engine (ICE) in real-time. More importantly, it does not require trip length information which is usually assumed to be known in the other existing EMS. The proposed SOC control strategy is validated and compared with other strategies on a driving cycle synthesized from real traffic data.

2. PHEV EMS FORMULATION

Mathematically, the optimal (in terms of fuel economy) energy management for PHEVs can be formulated as a nonlinear constrained optimization problem (see Appendix A or [1]), where the objective is to minimize the total fuel consumption along the entire trip. In order to facilitate on-line optimization powered by an evolutionary algorithm, we herein discretize the engine power and reformulate the optimization problem as follows:

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

subject to:

$$\sum_{k=1}^{j} f\left(P_k - \sum_{i=1}^{N} x(k,i) P_i^{eng}\right) \le C \quad \forall j = 1, \dots, T \tag{2}$$

$$\sum_{i=1}^{N} x(k,i) = 1 \qquad \forall k \tag{3}$$

$$x(k,i) = \{0,1\} \qquad \forall k, i \tag{4}$$

where N is the number of discretized power level for ICE; 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 η_i^{eng} is the associated engine efficiency; and P_k is the driving power demand at time step k. Therefore, the problem is reformulated to a combinatory optimization problem whose objective is to select the optimal ICE power level at each time step given the predicted information in order to achieve the highest fuel efficiency for the entire trip. Fig.1 gives three example ICE power output solutions. The solution represented by the blue line has a lower total ICE power consumption (i.e., 70 units) than the red line (i.e., 90 units), while the green line represents an infeasible solution due to the violation of SOC constraints.

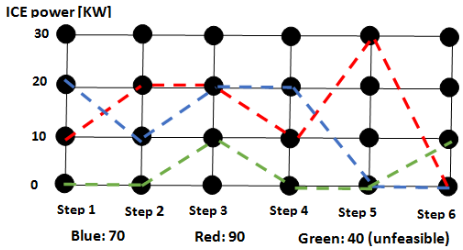

Fig. 1. Example solutions of power-split control

3. EA BASED EMS WITH SOC CONTROL

As previously mentioned, most of the existing strategies for PHEV energy management are off-line. In this work, we apply the receding horizon control framework where the entire trip is divided into small segments or time horizons (see Appendix B or [1]). As shown in Fig. 2 the prediction horizon (N sampling time steps) needs to be longer than the control horizon (M sampling time steps) to guarantee the real-time performance. Both horizons keep moving forward while the system is operating. For each step, the EA based EMS relies on the information obtained from each prediction horizon and determines optimal control actions within each control horizon.

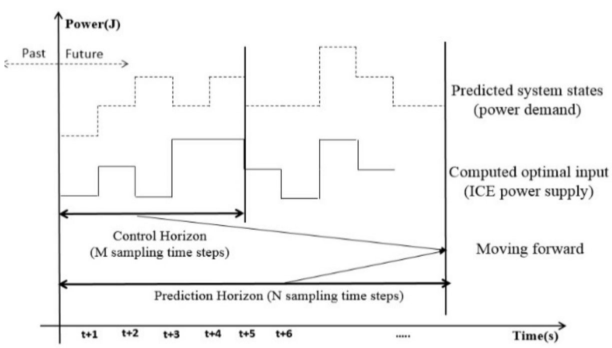

Fig. 2. Time horizons of prediction and control.

In this study, the estimation distribution algorithm (EDA) is adopted for the control strategy since it is very powerful in solving high-dimensional optimization problems. In the problem representation of EDA, each individual (encoded as a row vector) of the population is a candidate control 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 1, the ICE power level is 3 (or 3 kW) for the 1st time step, 0 kW (i.e., only battery pack supplies power) for the 2nd time step, 1 for the 3rd time step, and so forth.

Table 1. Representation of one example individual

Time	1s	2s	3s	4s	....	n-2	n-1	n
Individual	3	0	1	4	....	1	2	5

Since the objective is to minimize fuel consumption while maintaining the SOC constrains, the fitness function herein can be defined as the summation of total ICE fuel consumption rank and SOC decrease rank for the trip segment as well as a term to penalize the cases when the SOC constraints are violated:

$$f(s) = R_{fuel} + R_{soc} + \mathrm{P} \quad (5)$$

where s is the individual for evaluation; R_{fuel} and R_{soc} are the rank of ICE fuel consumption and SOC decrease of individual s in the current population (in an ascending order), respectively; P is the added penalty when individual s violates the constraints given in Eq.(2). The value of the penalty equals the population size (or more), which guarantees a non-feasible solution always has a much higher fitness values (minimization problem). It is noteworthy that an optimal SOC profile along the entire trip can be generated self-adaptively in such way without pre-calculation. The pseudocode of the proposed SA-ROCD algorithm is given in Appendix C and [1].

4. SIMULATION AND ANALYSIS

We use real-world traffic data collected on January 17th, 2012, along I-210 between I-605 and Day Creek Blvd. in San Bernardino, California, to synthesize a commute trip (see Appendix D or [1] for more details) for evaluating the proposed EMS. Compared to other EMS with different SOC reference control strategies, including linear (S-L), concave downward (C-D), concave upward (C-U), binary control (B-C), and no control (N-C), the proposed EA based on-line EMS (S-A) is able to achieve the best fuel economy(13% improvement with respect to B-C), and the resultant SOC profile is closest to the global optimal profile that is obtained off-line with Dynamic Programming (see Fig. 3).

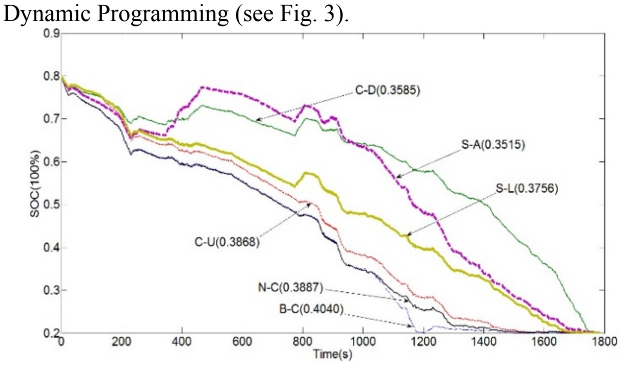

Fig.3.SOC profiles resulted by different control strategies.

5. CONCLUSIONS

This paper proposes a novel evolutionary algorithm based EMS with a self-adaptive SOC control strategy for PHEVs. The experimental results show that it outperforms other EMS with different SOC control strategies in terms of consuming the least amount of fuel for the example commute trip. There are two major contributions of this work. Firstly, the proposed EA based EMS strategy can self-adaptively control the use of battery power (characterized by SOC profile) to significantly improve ICE fuel efficiency, and avoid the SOC profile planning procedure that is required by most of the existing EMS. And secondly, the proposed EMS can be implemented without a priori knowledge about the trip length, which is a major advantage over other SOC control strategies.

6. REFERENCES

[1] X. Qi, G. Wu, K. Boriboonsomsin and M. J. Barth, Evolutionary algorithm based on-line PHEV energy management system with self-adaptive SOC control, *Intelligent Vehicles Symposium (IV), 2015 IEEE*, Seoul, 2015, pp. 425-430. doi: 10.1109/IVS.2015.722572