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# An on-line predictive energy management strategy for plug-in hybrid electric vehicles to counter the uncertain prediction of the driving cycle

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## HIGHLIGHTS

- An online predictive energy management approach was proposed using a DPSO algorithm.
- Energy optimal problem with a dynamic cost function was formulated.
- Fuzzy logic-based correction method was proposed to counter the imprecise prediction.
- The effect of the presented strategy and correction algorithm was verified.

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## ABSTRACT

Predictive energy management could be implemented in real-time with a short period of future driving cycle prediction. However, the completely precise prediction of the future driving cycle remains quite difficult. Two areas of effort have been explored in this study. The first is the implementation of a dynamic-neighborhood particle swarm optimization algorithm in the local optimal energy management strategy of plug-in hybrid electric vehicles based on data from the prediction of the future driving cycle. Second, the influence of an imprecise driving cycle prediction is considered, and then an online correction algorithm is proposed based on the backup control strategy and a fuzzy logic controller. In addition to these efforts, a predictive energy management strategy with an online correction algorithm is finally proposed. Compared with the optimal heuristic method, the presented energy management strategy could reduce the energy by up to 9.7% if the prediction of the future driving cycle is precise. For the situation of imprecise prediction, the online correction algorithm could reduce the deviation from the actual optimal policy by up to 32.39%.



## 1. Introduction

The development of plug-in hybrid electric vehicles (PHEVs) has recently struck a chord with automobile engineers, researchers, and automakers throughout the world [1–4]. PHEVs can achieve better fuel economy and lower exhaust emissions than traditional internal combustion engine vehicles and normal hybrid electric vehicles (HEVs), forming a viable solution to the environmental pollution problem and the energy crisis caused by urban transportation [5]. The benefits of PHEVs mainly lies to the onboard high-capacity battery pack that can be directly recharged by the power grid [6]. PHEVs can operate in a charge-depleting manner with clean characteristics similar to those of pure electric vehicles (EVs). When the battery state of charge (SoC) reaches a low level, the vehicle can operate in a charge-sustaining manner, and in this situation, the battery could be used as a buffer to enhance the engine efficiency and recapture kinetic energy during the regenerative braking operation. However, because the PHEV contains two types of energy sources-gasoline and electricity, the complicated power flow and extra degree of freedom result in a complex energy control problem. Therefore, the performance of a PHEV depends significantly on the efficiency of the employed energy management strategy (EMS) [7–9].

### 1.1. Literature review

The main task of the EMS can be described as minimizing the cost function by splitting the power request between the battery

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**Nomenclature**

| | |
|---|---|
| $P_{batt}$ | operation power of the battery (positive value represents discharge and negative value represents charge process) |
| $P_E$ | power of the engine |
| $P_{Batt,max}$, $P_{Batt,min}$ | upper bound and lower bound of the battery power, respectively |
| $P_{E,max}$ | the maximum power of the engine |
| $\gamma_{\varphi}$ | the cost of energy consumption at each time step |
| $\upsilon_{fuel}$ | the price of fuel |
| $\upsilon_{grid}$ | price of electricity from grid |
| $\eta_{ch}$ | battery charging efficiency |
| $b_{ch}$ | engine fuel consumption rate in the high efficiency range |
| $\Psi_A$ | the unit conversion coefficient and the efficiencies of the generator and inverters |
| $\sigma$ | a constant coefficient, $0 < \sigma < 1$ |
| $\chi_g$ | a dynamic proportionality factor that denotes the proportion of electricity from the grid in the current electricity consumption |
| $\varepsilon_1$, $\varepsilon_2$ | two thresholds of battery SoC |
| $K$ | the number of the current interval |
| $w$ | the inertia weight |
| $c_1$, $c_2$ | two weight coefficients |
| $r_{1j}$, $r_{2j}$ | Random quantities, $0 < r_{1j}, r_{2j} < 1$ |
| $p_{ij}$ | the personal optimal position |
| $g_{ij}$ | the local optimal position |
| $\aleph_i$ | the neighborhood of particle |
| $P_L$, $P_H$ | two thresholds to describe the range of high efficiency in the map of engine operation |
| $P_{\sigma}$ | a control value for the engine power. |

and engine without compromising the vehicle's performance [10]. To achieve this goal, many advanced global optimization algorithms have been proposed with the designing process of the vehicular EMS, in which dynamic programming (DP) is the most representative approach. For example, Kum [11] deployed the DP algorithm to design a parallel HEV supervisory control strategy and proposed a rule-based strategy based on the DP results. In this study, both the energy consumption and pipe emissions were considered in the cost function. Perez [12] proposed a nonlinear finite horizon optimal energy management strategy for HEVs based on a DP algorithm, which is intended to be applied offline and could be used as a benchmark for EMS design and the sizing of components. Other examples of DP algorithms employed in EMS applications can be found in Refs. [13–15]. In addition to DP algorithms, some other optimization algorithms, such as the genetic algorithm (GA) [16] and particle swarm optimization (PSO) [17,18], have been investigated for the EMS application. These optimization algorithms are quite useful for determining the global optimal control policy for any given driving cycle; however, a shortcoming of these global optimization-based strategies is that they all rely on *a priori* driving cycle, which is rarely known in practice, so they cannot be directly applied to real-time control situations.

Local optimization-based energy management, also known as predictive energy management (PEM), involves the implementation of optimization algorithms to a short period of the future driving cycle [19]. Theoretically, PEM is suitable for using in real-time control if the future traffic information is available to the controller. The accuracy and computational efficiency of prediction of future driving conditions are quite crucial to the PEM [20]. Two types of approaches are often used to obtain the future driving information: (1) a stochastic prediction method based on the Markov chain and (2) a telematics technology-based approach, which relies on telematics techniques such as the global positioning system (GPS) and intelligent transportation system (ITS).

The Markov chain is a stochastic process prediction approach in which future conditions are assumed to be independent of the past, and the driver's behavior is modeled as a time-invariant stochastic process that generates an acceleration request. The Markov chain-based method has attracted considerable attention in recent years, and a detailed description and specific process for establishing a Markov chain can be found in Refs. [21,22]. Stochastic dynamic programming (SDP) [23–25] has been investigated for optimizing the control policy in the EMS based on the driving cycle prediction from a Markov chain, and the investigations indicated that stochastic energy management could achieve a near-optimal control performance. However, a problem with Markov chain-based stochastic control is that the control policy is optimal only for that specific Markov chain. In other words, the transition probabilities in the Markov chain are based on collected driving cycles [26], and if the real driving conditions obviously differ from the collected data, the prediction will be imprecise and the algorithm cannot guarantee the optimality.

Telematics techniques have also begun to play an important role in PEM. Some examples of predictive control for HEVs incorporating GPS information are shown in Refs. [27–29]. With the help of a GPS, the information such as the driving distance, future traffic or terrain conditions is attainable. In Ref. [29], the expected speed profile is established based on GPS predictive information and a DP-based optimal control is deployed accordingly. Although the GPS input could be useful for predicting information regarding future driving conditions, it can not handle stochastic traffic events, such as the abrupt actions of other neighboring vehicles. To obtain precise future driving cycle information, another communication technology such as the internet of vehicles (IOV) is also required; however, there is not yet a satisfactory method for blending the information from those outboard devices.

### 1.2. Motivation and innovation

As mentioned above, the PEM has the advantage of online implementation for the PHEVs, but the precise prediction of the future driving cycle is a prerequisite for achieving optimal control performance. Contrary to earlier publications, this study is not concerned with how to precisely predict the future driving cycle; instead, the presented investigation is focused on effective techniques for cases in which the prediction is imprecise. Two specific directions have been explored in this study. First, a novel local optimal energy management approach is proposed for the PHEVs using a dynamic-neighborhood particle swarm optimization (DPSO) algorithm assuming that a precise prediction of the future driving cycle is available. Second, the influence of imprecise prediction has been investigated, and an online correction algorithm is proposed for improving the control performance of predictive energy management.

There are two main differences between this manuscript and existing works. One is that the adopted algorithm and optimization objective are totally different. The other is that most existing approaches for PEM ignore the energy management under the imprecise prediction of driving cycle.

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