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Model predictive control for power management in a plug-in hybrid electric vehicle with a hybrid energy storage system ☆

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HIGHLIGHTS

- An integrated power management for a PHEV with multi-energy sources was proposed.
- A model predictive controller was used to regulate the power allocation of the HESS.
- The robustness of the proposed approach was verified by three typical driving cycles.
- The results show that the proposed control strategy can promote fuel economy greatly.

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ABSTRACT

The fuel economy performance of plug-in hybrid electric vehicles (PHEVs) strongly depends on the power management strategy. This study proposes an integrated power management for a PHEV with multiple energy sources, including a semi-active hybrid energy storage system (HESS) and an assistance power unit (APU). The HESS consists of battery packs and ultracapacitor packs. In the integrated control strategy, the output power between the battery packs and ultracapacitor packs is regulated by the model predictive control strategy, while the output power between the APU and HESS is allocated by the rule-based strategy. In the model predictive control process, a period of the future velocity will be predicted, and the dynamic programming algorithm will be applied to optimize the control strategy accordingly. The robustness of the proposed approach is verified by three typical driving cycles, including the Manhattan cycle, CBDC cycle and UDDSHDV cycle. The results show that the proposed control strategy can promote fuel economy compared with the original control strategy, especially in the charge sustain mode under the MANHATTAN driving cycle (21.88% improvement).

1. Introduction

Fossil fuel depletion and serious air pollution have greatly encouraged the development of plug-in hybrid electric vehicles (PHEVs) [1,2]. Compared with the pure electric vehicles, PHEVs have a longer driving range because, when the battery's state of charge (SoC) is low, the engine can keep the vehicle working for an additional driving range similar to that of a conventional vehicle. Conversely, when the vehicle speed or the power requirement of the vehicle is low, the engine can be turned off and the vehicle can be driven by the electric power system, which is helpful for improving the efficiency performance. Moreover, the application of a hybrid energy storage system (HESS), a combination of a battery and an ultracapacitor, can effectively reduce the charging/discharging rate of the battery and prolong the battery life. For a series PHEV system with HESS, the fuel economy performance highly depends on how the output power from the assistant power unit (APU), battery packs and ultracapacitor packs is allocated.

1.1. Literature review

Much valuable work involving the power management of electric vehicles has been widely conducted by many researchers [3,4]. The most basic and widely applied power management strategy is the rule-based control strategy [5], including fuzzy logic-based control strategy [6,7] that can be recognized as a combination of

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different control rules. Ref. [6] proposed a fuzzy logic-based control strategy for parallel hybrid vehicles to determine the output power of the engine and motor/generator, and the results showed potential improvements. The merit of the rule-based control strategy is its easy implementation, but the performance of this type of control strategy usually depends on the engineering experience of the designer, and its robustness cannot be guaranteed. To further improve the performance of the power management for electric vehicles, various intelligent algorithms have been introduced [8,9]. In Ref. [8], particle swarm optimization algorithm was employed for the power management of a hybrid electric vehicle and great improvement was obtained. In Ref. [9], the simulated annealing algorithm was applied to determine the engine power and maximum current coefficient for power-split plug-in hybrid electric vehicles. Though the promotion of the efficiency performance can be achieved, the optimal performance in real-time via an intelligent algorithm-based control strategy can hardly be guaranteed.

Some researchers have attempted to optimize the power management by various optimization algorithms such as convex optimization algorithm and PSO algorithm [10,11], dynamic programming optimization (DP) [12–14] and Pontryagin's minimum principle (PMP) [15,16], among which the most powerful method is DP. The DP algorithm can locate the global optimal control strategy, but because DP-based power management requires future road and vehicle speed information, this algorithm cannot be applied directly. Moreover, when the model is complex, the calculation time for the DP algorithm will be unacceptable. Another popular optimization algorithm is PMP where an optimal control strategy can be obtained by minimizing a Hamiltonian function [15]. Though the PMP-based method cannot ensure the global optimization, the control performance from PMP is sometimes similar to the performance from DP [16]. However, as the co-states in the Hamiltonian function are determined by a trial-and-error method, the PMP-based method cannot be applied directly [17,18].

To propose a robust and implementable control strategy, driving pattern recognition (DPR)-based power management strategies have been developed [19]. For DPR-based methods, researchers have attempted to design different control strategies according to different driving conditions, and once the driving condition is identified by the DPR module, the corresponding control strategy will be applied [19,20]. Thus, the performance of DPR-based power management strongly depends on the identification precision. However, as the DPR module usually identifies the current driving condition according to historical driving information and assumes that the driving condition will not change, misidentification cannot be avoided [21]. Some researchers have attempted to design the power management via model predictive control (MPC), which will predict a period of vehicle velocity and then apply various optimization methods to design the control strategy based on the predicted velocity. The vehicle velocity could be predicted by an artificial neural network algorithm [22], torque requirement exponentially decreasing model [23] or Markov Chain-based velocity predictor [24], and the control strategy optimization methods could be the PMP algorithm [25], DP algorithm [26], nonlinear programming algorithm [27] or quadratic programming algorithm [28].

Most of the above work focuses on the power management strategy for the vehicles only with two power sources, and few of them for the PHEVs with three or more power sources, including battery packs, ultracapacitor packs and an APU. Though an adaptive control strategy for a PHEV containing three energy sources has been studied in Ref. [19], the HESS is regarded as a single source during its operation process. Because the output power of the battery and ultracapacitor was determined by rule-based control once the required power is deterministic.

1.2. Motivation and innovation

This study proposes an integrated power management system for PHEVs that includes three power sources: battery packs, ultracapacitor packs and an APU. In the new control strategy, an MPC-based controller was integrated with the original control strategy. The output power of the engine and HESS is determined according to the original control rules, and the control of the battery packs and ultracapacitor packs will be realized by the MPC controller. The integrated control strategy will be verified by three different types of driving cycles: Manhattan drive cycle, CBDC drive cycle and UDDSHDV drive cycle.

1.3. Organization of the paper

The organization of this study is as follows: Section 2 illustrates the modeling of the system and the original control strategy. Then, the integrated control strategy and MPC formulation will be presented in Section 3. After that, the verification and discussion will be illustrated in Section 4. Finally, conclusions are provided in Section 5.

2. System modeling and original control strategy

2.1. PHEV configuration and modeling

Many different types of topologies for the HESS have been developed, including active HESS topologies, semi-active HESS topologies and passive HESS topologies [29–32]. In this study, a semi-active HESS topology is applied in our target system, as displayed in Fig. 1 [19]. The battery packs and ultracapacitor packs compose the HESS, and the engine and generator compose the APU system. The output power of the battery packs can be controlled by a DC/DC converter, while the output power of the ultracapacitor packs is controlled passively. To describe the dynamic performance of the PHEV, a simplified but sufficiently complex backward simulation model was constructed, including battery packs, ultracapacitor packs, DC/DC converter, APU, vehicle and transmission system.

(1) *Battery pack*. To analyze the dynamic performance of a battery pack, the *Thevenin* battery lumped parameters model has been selected, and its operation process can be given by the following equation [33]:

$$\begin{cases} \dot{U}_D = -\frac{1}{C_D R_D} U_D + \frac{1}{C_D} i_L \\ U_t = U_{oc} - U_D - i_L R_i \end{cases} \tag{1}$$

where U_D and U_t denote the diffusion voltage and terminal voltage for the battery pack, respectively, C_D and R_D denote the diffusion capacitance and the diffusion resistance for an RC network, which is used to represent the dynamic voltage performances and the mass transport effects, i_L denotes the battery output current, U_{oc} denotes the open circuit voltage, and R_i denotes the electrical resistance of various battery components. The battery packs include 138 $LiMn_2O_4$ lithium-ion battery cells, and they are connected in series. The nominal capacity of the battery cells is 77 Ah, and the nominal voltage is 3.7 V. The upper and lower cutoff voltages are 4.2 V and 3.0 V, respectively. The identification results for these parameters including U_{oc}, C_D, R_D and R_i under different SoC levels are presented in Fig. 2 (the identification method comes from Ref. [34]).

(2) *Ultracapacitor pack*. The ultracapacitor pack is modeled as a series combination of an idle capacitor and resistance R_c [32]. The operation process of the capacity can be expressed by the following equation: