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Battery SOC constraint comparison for predictive energy management of plug-in hybrid electric bus

Gaopeng Li [a,b], Jieli Zhang [a], Hongwen He [a,*]

[a] National Engineering Laboratory for Electric Vehicles, Beijing Institute of Technology, Beijing 100081, China
[b] Zhengzhou Yutong Bus Co., Ltd., Zhengzhou 450061, China

HIGHLIGHTS

- A multi-step Markov prediction method is proposed to predict the future driving conditions.
- Three constraint methods are proposed and compared to restrain the battery SOC near the reference value.
- The fuel consumption under MPC-based energy management strategy is reduced by 8.7% over a ruled-based strategy.

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ABSTRACT

In this paper, model predictive control (MPC) is employed to resolve the energy management problem of a plug-in hybrid electric bus (PHEB). Dynamic programming (DP), as a global optimization method, is inserted at each time step of the MPC, to solve the optimization problem regarding the prediction horizon. A multi-step Markov prediction model is constructed to forecast the near future driving velocities for the MPC. The battery SOC is restrained to fluctuate near a reference trajectory to ensure the global performance of MPC. Three novel restraining methods are proposed and compared in this paper. The resultant fuel economy performance with different SOC constraint methods are evaluated. Simulation results indicate that by restraining the battery SOC adaptively to the control variables gains the best fuel economy performance, and the fuel consumption of MPC is 8.7% less than a ruled based strategy.

1. Introduction

The powertrain energy management method solves the power distribution problem between the two (or more) power sources in PHEVs. Usually, it can be classified into two categories: rule-based strategies and optimization-based strategies [1,2]. ECMS evaluates the instantaneous cost function as a sum of the fuel consumption and the equivalent fuel cost of electric energy [3–6], by solving the power-split problem at each time instant rather than over the whole time horizon. DP has been selected to realize a global optimization of energy management for HEVs [7–10]. Nevertheless, the performance of DP algorithm highly depends on the detailed information of driving cycle, which is difficult to know precisely.

Model predictive control (MPC) is a novel control method with the idea of using history or telemetry data to predict the future traffic information [11]. Borhan et al. developed two MPC-based methodologies based on two different cost functions to solve the fuel minimization problem of power-split hybrid electric vehicles [12]. In order to improve the fuel economy, the second method introduced a second cost function by dividing the fuel consumption cost into a stage cost and an approximation of cost-to-go as a function of battery's state of charge. Chao et al. provided a comprehensive and comparative analysis of three velocity prediction strategies applied within a MPC framework, and has proved that 1-step Markov chain velocity predictor is inadequate for HEV energy management [13]. Hadi Amini et al. proposed an ARIMA-based time series forecasting method of the electric vehicle charging demand, and the results show that ARIMA is able to maintain an acceptable prediction accuracy [14,15]. Gong et al. presented a novel algorithm, which uses information from GPS and digital maps to schedule the use of the energy buffer along the planned route, for predictive control of parallel hybrid vehicle powertrains [16]. Johannesson and Ripaccioli both proposed stochastic model predictive control (SMPC) for power management in a series

* Corresponding author.
E-mail address: hwhebit@bit.edu.cn (H. He).

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Nomenclature

MPC	model predictive control
PHEB	plug-in hybrid electric bus
DP	dynamic programming
ECMS	equivalent consumption minimization strategy
PED	pure electric driving
HDCD	hybrid driving charge depleting
HDCS	hybrid driving charge sustaining
PMSM	permanent magnet synchronous motor
ARIMA	Autoregressive Integrated Moving Average Model

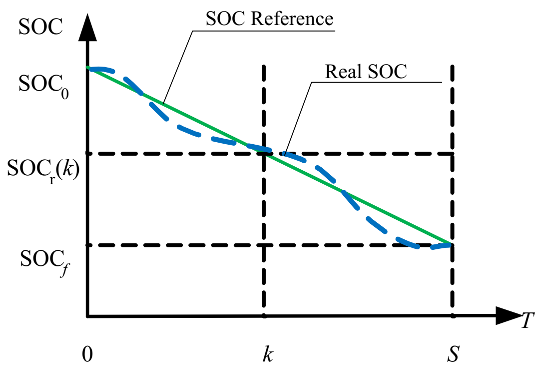

Fig. 1. Comparison between the battery SOC constraint and real SOC.

hybrid electric vehicle [17,18]. In the proposed strategy, the power demand from the driver is modeled as a Markov chain estimated on several driving cycles and used to generate scenarios in the SMPC law. MPC has been proved to be very powerful and effective in the optimization of control strategies in HEVs [19,20].

MPC is a receding control formulation, and could not ensure the global optimality. Therefore, either the traffic information and other road characteristics is known for global battery SOC planning [21], or a rational battery SOC restraining method is used to ensure that the battery electricity is reasonably consumed. However, to the authors' best knowledge, the literature still lacks a detailed investigation on the battery SOC restraining methods. Fig. 1 demonstrates a comparison between the battery SOC constraint and the real SOC. Because MPC is with a local optimization topology, it usually requires a predefined SOC trajectory for the controller to follow, namely the battery SOC constraint. The quality of the formulated SOC constraint has an important impact on the battery SOC behavior and the resultant fuel efficiency.

In this paper, the main contribution is that three battery SOC restraining patterns are proposed and compared, namely the terminal SOC constraint, full SOC constraint and restrain the SOC adaptively to the control variables. The fuel economy and restraining performance are compared. A multi-step Markov chain prediction method is also presented for velocity prediction. DP algorithm is selected to solve the non-linear finite horizon optimization problem with battery SOC constraints. The remainder of this paper is as, Section 2 gives the PHEV structure, the powertrain model, and the optimal control problem formulation; Section 3 discusses a multi-step Markov chain velocity prediction method; Section 4 proposes the three battery SOC constraint methods; Section 5 presents the simulation results, and Section 6 gives the main conclusion.

2. The MPC energy management strategy

2.1. The parallel PHEB configuration

In this paper, we take a single-axis series-parallel PHEB powertrain as our research object. Fig. 2 shows the powertrain configuration, which mainly includes a conventional internal combustion engine (ICE), an integrated starter generator (ISG) motor, a traction motor, a clutch and a battery pack.

Table 1 presents the main parameters of the series-parallel PHEB. Details of study on this PHEB can be found in [22].

2.2. Optimization problem formulation

PHEV energy management strategies aim to find the optimal power split between the engine and the traction motor whileconsidering the torque request of the driver and the vehicle velocity. For PHEV energy management problem, the MPC framework is employed for the fuel consumption minimization. The principle of MPC is shown as Fig. 3, at each simulation step k, the following steps are taken:

(1) Predict the velocities by multi-step Markov chain within a finite prediction horizon.
(2) Calculate the torque requests, and solve the power distribution problem within the current control horizon based on DP algorithm.
(3) Apply the first element of the optimal control sequence to the real powertrain or the powertrain model. Update the vehicle velocity and states, repeat the control procedure.

The cost function is formulated as Eq. (1).

$$J_k = \sum_{t_k=k}^{k+p} fuel(t_k) \tag{1}$$

where J_k is the cost at time step k, p is the prediction length, t_k is the time step, and *fuel* is the instantaneous fuel consumption at each time step extracted from the engine fuel consumption map. For this partial optimization method, a reference SOC trajectory is required, the SOC is defined to decrease linearly from the initial maximum SOC to the terminal low level of the SOC. The actual SOC is limited to fluctuate near the reference trajectory. At step k, the SOC reference value is calculated by Eq. (2).

$$\mathrm{SOC_r}(k) = \mathrm{SOC_0} - \frac{k}{t_{\mathrm{cyc}}}(\mathrm{SOC_0} - \mathrm{SOC_f}) \tag{2}$$

where $\mathrm{SOC_r}(k)$ is the SOC reference value at step k; $\mathrm{SOC_0}$ is the initial maximum SOC value; SOC_f is the terminal low level of SOC; t_{cyc} is the total travelling time before the battery is charged again, which is assumed to be known. The constraints of system variables are formulated as Eq. (3).

$$\begin{cases} n_{e\text{-min}} \leqslant n_e(k) \leqslant n_{e\text{-max}} \\ T_{e\text{-min}}(n_e(k)) \leqslant T_e(k) \leqslant T_{e-\max}(n_e(k)) \\ T_{ISG\text{-min}}(n_{ISG}(k), \mathrm{SOC}(k)) \leqslant T_{ISG}(k) \leqslant T_{ISG\text{-max}}(n_{ISG}(k), \mathrm{SOC}(k)) \\ T_{m\text{-min}}(n_m(k), \mathrm{SOC}(k)) \leqslant T_m(k) \leqslant T_{m\text{-max}}(n_m(k), \mathrm{SOC}(k)) \\ \mathrm{SOC_{min}}(k) \leqslant \mathrm{SOC}(k) \leqslant \mathrm{SOC_{max}}(k) \\ n_m(k) = n_e(k) = n_{ISG}(k) \quad \text{if} \quad clutch = 1 \\ n_e(k) = n_{ISG}(k) \quad \text{if} \quad clutch = 0 \\ T_e(k) + T_{ISG}(k) = 0 \quad \text{if} \quad clutch = 0 \end{cases} \tag{3}$$

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