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An energy management strategy based on stochastic model predictive control for plug-in hybrid electric buses

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HIGHLIGHTS

- Velocity is predicted by multi scale single step method with post-processing.
- A state reconstitution method is proposed to tackle reference state deficiencies.
- SMPC-based strategies with variable horizons are built to improve energy management for practical cycle.
- HIL experiments with practical driving cycles are conducted to verify the strategy.

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ABSTRACT

Model predictive control (MPC) can effectively solve online optimization issues, even with various constraints, when maintained at high robustness. Considering the energy management issue of plug-in hybrid electric bus (PHEB) as a constrained nonlinear optimization problem, a strategy based on stochastic model predictive control (SMPC) is put forward and verified in this paper. Firstly, Markov Chain Monte Carlo Method (MCMC) is adopted to forecast velocity sequences at every current state, in the form of multi scale single step (MSSS), with post-processing algorithms to moderate fluctuations of the prediction results like average filtering, quadratic fitting, and the like. The offline simulation results show that the optimization can effectively improve the predictive accuracy, make the following energy management feasible and reduce the fuel consumption by 1.9%. Then the SMPC-based energy management strategy is proposed. In order to prevent the driving cycle state deficiencies from interrupting the prediction for practical application, a state reconstitution method is constructed accordingly. Besides, the predictive steps are made time-varying by an online accuracy estimation method and a corresponding threshold to maintain the accuracy of forecast. Finally, the hardware-in-the-loop (HIL) experiments are conducted and the results show that the SMPC-based strategy is reasonable and the fuel consumption decreases by 3.9% further with variable predictive steps than that of fixed ones. In summary, this paper illustrates an effective SMPC-based methodology for energy management for PHEB, and techniques like MSSS prediction with post-processing, state reconstitution method, online accuracy estimation can be adopted to solve similar problems.

1. Introduction

There are different energy resources for plug-in hybrid electric bus (PHEB) but commonly by petrol and electricity. The electricity can come from coal or nuclear energy. The configurations of PHEB power train include series, parallel and power-spilt (or series-parallel) and the various working state combinations of engine, motor and other components make many kinds of working modes with dissimilar efficiencies. To outweigh the power, emission, lifespan of power battery or any other performances, energy management strategy plays the key roles [1]. This issue can be abstracted to be an optimal problem with a bunch of constraints and abundant approaches have been put forward in the work of Serrao et al. [1] and Sciarretta et al. [2].

Basically, for the problem mentioned above, the primary method is to design rules [3] or fuzzy logics [4] to limit engine working in relative higher-efficiency areas by adjusting the outputs of motors and batteries. It has excellent real-time performance and is adopted in related industries. But it is difficult to

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get the best results as global optimization for unknown driving conditions and disturbs. Besides, it depends on specific driving cycles, which means when the running cycle changes, the original parameters will not be suitable and the management results could be bad. Equivalent consumption minimization strategy (ECMS) [5] and strategies based on Pontryagin's minimum principle (PMP) [6,7] are real-time optimization approaches. However, to ensure the energy management effect, an equivalent factor in ECMS and co-state in PMP need to be adjusted to accommodate complicated, random driving conditions at any time. Only an exact initial figure cannot do it well. Thus Adaptive-ECMS (A-ECMS) [8], whose equivalent factors are updated with the driving conditions, is proposed to make this kind of approaches more feasible for practical applications. The improved part in A-ECMS, compared with original ECMS, is a challenging task.

Generally, driving information is required to conduct the optimization of energy management to search for optimal or suboptimal control traces. According to a known driving cycle, methods based on dynamic programming (DP) [9,10], genetic algorithm [11] and so on were used to find the global optimal solutions. And the results of DP-based strategies are always used as the benchmark for other strategies. However, in practical application, the future driving cycle cannot be pre-obtained. And strategies of this kind generally have considerable calculation burden and thus bad real-time performance. For the former problem, predictive algorithms can be adopted to forecast the velocity or acceleration sequences in a certain horizon. Related solutions includes approaches based on stochastic model predictive control (SMPC) [12], stochastic dynamic programming (SDP) [13] and so on. The real time prediction of velocities based on current moment can provide the controlling model with feedbacks and revise it in time.

In terms of model predictive control (MPC), it can solve constrained optimal problems real-timely. This method was first adopted by Vahidi et al. [14] to avoid oxygen starvation for a fuel cell power system and then they proposed and verified the application of linear time-variant and nonlinear MPC in HEV [15]. Along with the development of theoretical researches on SMPC [16–18], Bichi et al. [20] are enlightened by using Markov Chain to predict the disturbances during driving processes [13,19], and designed energy management strategies. Approaches of this kind have developed to certain stage now. Although the specific predictive, optimal algorithms and constrains may be a little distinct, the ideas are similar. In addition, in the stochastic models, to predict disturbances, approaches based on exponent variation [21], Markov chain [22,12], neural network [21,23], Kalman filter [24], and so on are explored. C Sun et al. [21] compared several methods under certain assumptions and Cairano et al. [25] doubted the reliability of the statistical characteristics of original data.

Reviewing the energy management problem for PHEB, with meeting the instantaneous power requirement and characteristics of every component, the strategy should figure out proper amounts for control variables which include torque, speed of engine, motor and so on, in order to reach optimal fuel economy, namely, least fuel consumption. A-ECMS and SMPC are the most representative ones with bright applying prospects. To achieve practical applications, one important task is to obtain the characteristics of driving cycles to correct controlling systems. This paper is also motivated by the advantage of MPC on issues of this kind as MPC can conduct online optimization, deal with diverse constraints effectively and correct state errors in time by implementing results of strategy in a rolling way. Meanwhile, MPC is of high robustness and can be constructed flexibly. Thus MPC-related methodology, engineering assumptions and details for energy management are illustrated and explored. As the prediction model in MPC is to forecast driving cycles, which is a random process, the whole methodology can be named as SMPC.

In this paper, an energy management strategy based on SMPC with MCMC and DP as subcomponents is proposed. The contributions of this paper are as follows, firstly, when predicting velocity, multi-scale single step prediction with post-processing like average filtering, quadratic fitting and component constraints are adopted to make the forecast velocity sequences more accurate as well as reasonable. Then, in the velocity prediction based on MCMC, a state reconstitution method is proposed to tackle reference state deficiencies which are caused by the limitation of original database. During the process of predicting velocities for practical cycles, the forecast results of real cycles are screened by the online accuracy, causing the available velocity sequences in the optimization part with time-variable horizons. Finally, hardware-in-the-loop experiments with real driving cycles are conducted to verify the entire strategy.

The remainder of this paper is organized as follows. Section 2 shows velocity prediction and Section 3 illustrates the methodology of energy management strategy based on SMPC. In Section 4, the application of this strategy in practical driving cycles and corresponding processing are depicted. Comparison of results is listed in Section 5. The last section is a conclusion of this paper.

2. Velocity prediction based on Markov Chain Monte Carlo Method

In order to serve the energy management, a velocity sequence for short = time future should be forecast, here, by Markov Chain Monte Carlo Method (MCMC). And this task can be completed independently before the energy management strategy is designed. It is the preparation for the whole control framework.

Markov chain is used to depict discretely random processes. According to the first-order Markov assumption [26], the state value of the next moment can be predicted according to that of the current moment. And the primary statistical characteristics would not change with time, which means Markov chain is a stationary distribution. Thus, from the angle of Bayesian statistics, the possible state in the next moment of this random process can be gotten by Monte Carlo approach in the sample space which supports the posterior distribution. In other words, the figure of Markov chain can be predicted by sampling in the stationary distribution. So in this section, after analyzing Markov characteristics of cycles, MCMC is used to forecast velocities.

2.1. Analysis of Markov characteristics of driving cycles

Take a typical driving cycle as an example, calculate the correlation coefficients of neighboring velocities whose intervals are n ($n = 1, 2, 3\ldots$) seconds in a row and fit all the results (Fig. 1). For most driving cycles, when the interval time is 35-s, the correlation coefficients tend to be less than 0.3, which means the numbers have weak relevance. Thus only in small time scales, velocities that meet certain accuracy requirements can be predicted according to neighboring points due to the high correlation coefficients. Eventually, 35-s is chosen as the basic prediction horizon.

What should be mentioned is the Chinese Typical Urban Driving Cycle (CTUDC) (Fig. 2), which is selected to evaluate the control strategy hereafter. The maximum, average velocity and maximum acceleration of this cycle are 60 km/h, 16.16 km/h and 0.914 m/s^2 respectively.

2.2. Velocity prediction

During velocity prediction process, when the probability distribution is calculated, in the horizon, the reference state of prediction process can affect the outcome. To be specific, take a