



Adaptive real-time optimal energy management strategy based on equivalent factors optimization for plug-in hybrid electric vehicle



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HIGHLIGHTS

- A method for dividing driving cycles into segments is proposed.
- The near-optimal reference SOC trajectory is designed.
- The linear weight PSO is adopted to optimize the EFs in each segments.
- A novel adaptive real-time optimal energy management strategy is realized.

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ABSTRACT

Plug-in hybrid electric vehicle (PHEV) is one of the most promising products to solve the problem about air pollution and energy crisis. Considering the characteristics of urban bus route, maybe a fixed-control-parameter control strategy for PHEV cannot perfectly match the complicated variation of driving conditions, and as a result the ideal vehicle fuel economy would not be obtained. Therefore, it is of great significance to develop an adaptive real-time optimal energy management strategy for PHEV by taking the segment characteristics of driving cycles into consideration. In this study, a novel energy management strategy for Plug-in hybrid electric bus (PHEB) is proposed, which optimizes the equivalent factor (EF) of each segment in the driving cycle. The proposed strategy includes an offline part and an online part. In the offline part, the driving cycles are divided into segments according to the actual positions of bus stops, the EF of each segment is optimized by linear weight particle swarm optimization algorithm with different initial states of charge (SOC). The optimization results of EF are then converted into a 2-dimensional look up table, which can be used to make real-time adjustments to online control strategy. In the online part, the optimal instantaneous energy distribution is obtained in this hybrid powertrain. Finally, the proposed strategy is verified with simulation and hardware in the loop tests, and three kinds of commonly used control strategies are adopted for comparison. Results show when the initial SOC is 90%, the fuel economy with the proposed strategy can be improved by 15.93% compared with that of baseline strategy, and when the initial SOC is 60%, this value is 16.02%. The proposed strategy may provide theoretical support for control optimization of PHEV.

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1. Introduction

In recent years, the development of new energy vehicle has made a great contribution to reducing energy consumption and pollutant emission of automobiles [1–3]. Plug-in hybrid electric vehicle (PHEV) is one of the most promising products in this field. In PHEV, fuel economy can be improved by controlling the energy

flow between internal combustion engine and electric machine connected with a set of high-voltage batteries [4]. The maximum energy conversion efficiency in hybrid powertrain can be achieved if the battery is depleted to its minimum allowable charge at the end of its trip [5]. However, the complicated and transient driving cycles of city bus affect the reasonable torque distribution in PHEV, resulting in lower fuel economy of the vehicle. Accordingly, designing an efficient energy management strategy for PHEV running in complex driving cycles has important theoretical and practical significance [6].

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Nomenclature

T_w	torque acting on the wheel	P_{EM}	electric motor power
η_t	transmission efficiency	ω_{EM}	rotational speed of electric motor
T_b	braking torque acting on the wheel	η_m	efficiency of traction motor
T_e	engine torque	η_g	efficiency of generator
T_{EM}	electric motor torque	P_b	battery power
i_{AMT}	gear ratio of AMT	\dot{SOC}	change rate of SOC
i_f	gear ratio of final drive	V_{oc}	open circuit of battery
m	vehicle mass	R_b	internal resistance of battery
g	gravity acceleration	Q_b	battery capacity
f_r	rolling resistance coefficient	SOC_r	reference SOC
θ	road angle	SOC_i	initial SOC
C_D	aerodynamic resistance coefficient	n	current segment of road
ρ_d	air density	j	total number of road segments
δ	correction coefficient of rotating mass	f_i	factor of SOC changing rate on road segment i
A	frontal areas of bus	D	distance from current segment to starting segment
v	vehicle speed	l_i	length of road segment i
r	wheel radius	\bar{T}_i^d	average demand torque of road segment i
\dot{m}_f	transient fuel consumption	$x(t)$	state variable
ω_e	rotational speed of engine	$u(t)$	control variable
ρ	density of CNG	T_e^{\min}	lower limit of engine torque
b_e	fuel consumption rate	T_e^{\max}	upper limit of engine torque
T_{EM}^{\min}	lower limit of EM torque	ω_e^{\min}	lower limit of engine speed
T_{EM}^{\max}	upper limit of EM torque	ω_e^{\max}	upper limit of engine speed
ω_{EM}^{\min}	lower limit of EM speed	SOC_l	lower limit of battery SOC
ω_{EM}^{\max}	upper limit of EM speed	SOC_h	upper limit of battery SOC
Y_{CNG}	current price of CNG	J_E	energy consumption during the whole driving cycle
Y_e	current price of electricity	t_0	starting time of the driving cycle
$\lambda(t)$	co-state	t_f	ending time of the driving cycle
C	integration constant	χ_{\max}	initial weight factor
J_P	objective function of <i>LinWPSO</i>	χ_{\min}	final weight factor
t_i	starting time of a segment	T	current iteration number
t_j	ending time of a segment	T_{\max}	maximum iteration number
H_f	low heat value of the fuel	s	equivalent factor
SOC_n	current SOC	s_i	initial equivalent factor
$rand_1$	random number [0,1]	v_i^k	current velocity of particle i at the k generation
$rand_2$	random number [0,1]	v_i^{k+1}	current velocity of particle i at the k + 1 generation
k	correction factor of current SOC	x_i^k	current position of particle i at the k generation
c_1	learning factor	x_i^{k+1}	current position of particle i at the k + 1 generation
c_2	learning factor	χ	weight factor for velocity of particle i
p_{best}	individual optimal value	g_{best}	global optimal value

The energy management strategy (EMS) of PHEV in accordance with its implementation can be divided into two categories: rule-based EMS and optimization-based EMS. The former performs shorter computing time and more feasible application, and the setting of rule base threshold can be obtained through practical engineering experience, engine optimal working point reference and offline optimization strategy extraction [7]. The rule-based strategies are subdivided into deterministic rule-based and fuzzy rule-based methods. For example, authors proposed a classical rule-based energy management strategy for plug-in hybrid electric vehicle, which exhibits good reliability and stability in test driving cycles [8]. Li et al. proposed an optimal fuzzy power control strategy of fuel battery hybrid vehicles, simulation result shows that it performs well in fuel economy and overall system efficiency [9]. Denis et al. proposed a fuzzy-based blended energy management strategy focus on driving conditions of plug-in hybrid electric vehicle, and the efficiency of the proposed strategy is demonstrated through simulations [10]. Although rule-based EMS is easy to design, its thresholds and rule base need be determined by conducting a large number of experiments or experience calibrations. Those with fixed thresholds cannot guarantee a better fuel economy, and sometimes the fuel economy may get worse. Regarding

the optimization-based EMS, which can help PHEV to obtain a better fuel economy by optimizing the energy flows between fuel and electricity in the hybrid powertrain, has been the most attractive one among all current EMSs. Considering the difference of optimization form, EMS can be divided into instantaneous optimization EMS, local optimization EMS, approximate optimization EMS and global optimization EMS. In the global optimization EMS, In order to get the theoretical global optimal fuel economy, deterministic dynamic programming (DDP) algorithm-energy management strategy was designed under a test driving cycle, which achieved the global optimal solution for fuel economy based on Bellman's principle [11]. The global optimal solution can be found by minimizing the equivalent factor (EF) at each step of the DDP solving process. DDP's effectiveness comes at a price, a huge real-time computing burden [12]. Bases on these, there are impediments to DDP algorithm's large-scale application in engineering practice, which are often realized offline and deployed as benchmarks [13]. In the local optimization EMS: model predictive control (MPC) controller enables planning of the power split commands on a future time horizon. MPC is also known as a moving horizon control and receding horizon control because it optimizes over a given time horizon [14]. Due to the vehicle model is nonlinear,

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