Applied Energy 203 (2017) 883–896

Contents lists available at ScienceDirect

Applied Energy

journal homepage: www.elsevier.com/locate/apenergy

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

Chao Yang [a], Siyu Du [b], Liang Li [a,c,*], Sixong You [a], Yiyong Yang [b], Yue Zhao [a]

[a] State Key Laboratory of Automotive Safety and Energy, Tsinghua University, Beijing 100084, China
[b] School of Engineering and Technology, China University of Geosciences (Beijing), Beijing 100083, China
[c] Collaborative Innovation Center of Electric Vehicles in Beijing, Beijing 100084, China

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.

ARTICLE INFO

Article history:
Received 11 March 2017
Received in revised form 20 June 2017
Accepted 28 June 2017

Keywords:
Plug-in hybrid electric vehicle
Energy management strategy
Real-time optimization
Linear weight particle swarm optimization
Driving cycle segmentation

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.

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].

* Corresponding author at: State Key Laboratory of Automotive Safety and Energy, Tsinghua University, Beijing 100084, China.
E-mail address: liangl@tsinghua.edu.cn (L. Li).

http://dx.doi.org/10.1016/j.apenergy.2017.06.106
0306-2619/

Nomenclature

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