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Reinforcement learning-based real-time power management for hybrid energy storage system in the plug-in hybrid electric vehicle

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HIGHLIGHTS

- A reinforcement learning-based real-time energy management is proposed in this paper.
- The algorithm can learn current driving power information and then update the strategy.
- The electricity consumption has been taken into consideration in the optimization.
- The battery health has also been taken into consideration in the optimization.
- The proposed strategy was verified in different temperatures, SoHs, initials of SoCs.

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ABSTRACT

Power allocation is a crucial issue for hybrid energy storage system (HESS) in a plug-in hybrid electric vehicle (PHEV). To obtain the best power distribution between the battery and the ultracapacitor, the reinforcement learning (RL)-based real-time power-management strategy is raised. Firstly, a long driving cycle, which includes various speed variations, is chosen, and the power transition probability matrices based on stationary Markov chain are calculated. Then, the RL algorithm is employed to obtain a control strategy aiming at minimizing the energy loss of HESS. To reduce the energy loss further, the power transition probability matrices should be updated according to the new application driving cycle and Kullback-Leibler (KL) divergence rate is used to judge when the updating of power management strategy is triggered. The conditions of different forgetting factors and KL divergence rates are discussed to seek the optimal value. A comparison between the RL-based online power management and the rule-based power management shows that the RL-based online power management strategy can lessen the energy loss effectively and the relative decrease of the total energy loss can reach 16.8%. Finally, the strategy is verified in different conditions, such as temperatures, states of health, initials of SoC and driving cycles. The results indicate that not only can the RL-based real-time power-management strategy limit the maximum discharge current and reduce the charging frequency of the battery pack, but also can decrease the energy loss and optimize the system efficiency.

1. Introduction

The fact that current transportation highly depends on nonrenewable fuels raises more and more concern over sustainability development of the global environment [1]. The air pollution caused by traditional vehicles and the depletion of oil resources has greatly accelerated the development of electric vehicles [2]. Plug-in hybrid electric vehicles (PHEV), driven in multiple modes and reducing the fuel consumption, have attracted much attention. For the energy storage system (ESS) in the PHEV, it requires not only enough energy to drive the long distances but also enough power to accelerate, brake, climb and so on. Some kinds of the battery can satisfy both the high power density and high energy density, however the battery pack may overheat and the lifetime of the battery pack is short [3]. Consequently, some other power sources need to be involved. Ultracapacitors, owing to long life cycles and instant high power properties, are crucial supplement for the ESS. The power densities of most ultracapacitors are twice or three times as much as the power densities of batteries [4]. The working temperature range of ultracapacitors is from −40 °C to 70 °C and much wider than that of batteries. However, low energy density

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Nomenclature

M	total mass of the vehicle
η_0	efficiency of the transmission system
f	rolling resistance coefficient
A_{air}	windward area
C_{ar}	air resistance coefficient
R_i	internal resistance of the battery
C_D	polarization capacitance of the battery
R_D	polarization resistance of the battery
U_D	polarization voltage of the battery
i_L	total current of the battery
U_t	terminal voltage of the battery
U_{oc}	open circuit voltage of the battery
R_C	internal resistance of the ultracapacitor
i_C	load current of the ultracapacitor
U_{co}	voltage of the ideal capacitor
U_{ct}	terminal voltage of the ultracapacitor
i_R	output current of DC/DC converter
P_R	output power of DC/DC converter
P_{req}	required power of the vehicle
β	inclination angle of the road
v_a	speed of the target vehicle
η	efficiency of the transmission system
δ	conversion ratio of vehicle rolling mass
Δt	sampling interval
τ_{bat}	time constant of the battery
η_b	coulomb efficiency of the battery
Q_b	capacity of the battery pack
C_u	capacity of the ultracapacitor pack
$s(k)$	state vector
$a(k)$	action variable
J	optimization target
η_{dcdc}	efficiency of the DC/DC converter
P_{bat}	output power of the battery pack
z	logical value
SoC_H	upper bound of SoC
SoC_L	lower bound of SoC
SoV_H	upper bound of SoV
SoV_L	lower bound of SoV
i_{Lmin}	lower bound of the battery current
i_{Lmax}	upper bound of the battery current
$V(s)$	value of state s
γ	discounting factor
α	recession factor
P	transition probability matrix
P^*	steady-state probability distribution of P
μ	tiny constant
I	unit matrix with the same dimension as the matrix P
$M_{i,j}$	transition times from P_{req}^i to P_{req}^j
M_i	total number of transition times from P_{req}^i
r_t	reward function
$f_{i,j}(t)$	transition events from P_{req}^i to P_{req}^j
$f_i(t)$	transition events started from P_{req}^i
$F_{i,j}(L)$	frequency of transition events $f_{i,j}(t)$
$F_i(L)$	total frequency of transition events $f_i(t)$
ϕ	decaying factor

Abbreviations

HESS	hybrid energy storage system
PHEV	plug-in hybrid electric vehicle
RL	reinforcement learning
KL	Kullback-Leibler
ESS	energy storage system
DP	dynamic programming
GA	genetic algorithm
HPPC	hybrid pulse power characterization
SoH	state of health (for the battery)
OCV	open circuit voltage
NEDC	New European Driving Cycle
SoC	state of charge (for the battery)
SoV	state of voltage (for the ultracapacitor)
CBDC	Chinese Bus Driving Cycle
TPM	transition probability matrixes

limits its widespread application. In addition, the ultracapacitors can fully absorb regenerative energy when the vehicle is breaking. To meet the high energy and power requirements of the ESS simultaneously, the hybrid energy storage system (HESS) integrating the batteries and ultracapacitors systematically is investigated in recent years [5–9]. In this system, batteries are mostly used to provide the entire electricity energy and the ultracapacitors buffer the power when the power is relatively high or negative [5–6]. It can be seen that ultracapacitors serve as assistive energy source and help to improve the efficiency and dynamic response of the energy storage system.

Recently, there have been many power management strategies aimed at optimizing the performance of the HESS and they can be divided into two categories: the rule-based ones and optimization-based methods. On one hand, the performance of rule-based strategies is usually decided by current state of the HESS [6–13]. In Ref. [6], a power management strategy based on a fuzzy logic algorithm is presented and the results show that the energy efficiency is better than that of original rule-based strategies. However, this strategy is focused on the specified driving cycle and it can't adapt to different driving cycles automatically. In Ref. [11,14], because dynamic programming algorithm cannot be applied in real time, a new rule-based power management strategy was attained by using dynamic programming (DP) algorithm and extracting relevant rules from the optimization results. Ali et al. [8] presented a rule-based strategy and this strategy showed a better performance compared with the optimization-based strategy when the ultracapacitor voltage range is low. It is proved that the optimized rule-based strategy improves the system efficiency under some typical driving cycles. In Ref. [11], the inaccurate terrain information was taken into account for the strategy and the total cost of the HESS was effectively reduced. On the other hand, compared with the rule-based approaches, the optimization-based strategies are superior to those since the optimization-based strategies make full use of the prior and the prediction driving cycles to distribute the power between different power sources [14–22]. In Ref. [14], a real-time optimization using a genetic algorithm was proposed and by employing this method the RMS current was reduced by 40% comparing with the battery-powered EV. However, the aging model of the battery was not considered in that strategy. Odeim [23] presented a new formulation of the real-time strategy optimization problem. The real-time controllers were developed by specific simulation and experiment validation for fuel cell hybrid vehicles. In Ref. [23,24], predictive algorithms were used to optimize the system, however the performance of these approaches highly depends on the forecast precision of future driving cycles.

From the above analysis, it can be concluded that power management performance should mainly consider three aspects. Firstly, the optimization goal should consider minimizing the electricity consumption, more reasonable power distribution between different power sources and prolonging battery calendar life. Secondly, the power management should be applied in real time condition. Lastly, the power management strategy should be applied in different conditions such as

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