SCIENCE CHINA
Information Sciences

• LETTER •

January 2021, Vol. 64 119204:1–119204:3
https://doi.org/10.1007/s11432-018-9595-3

Multi-objective energy management for PHEV using Pontryagin's minimum principle and particle swarm optimization online

Yuying WANG & Xiaohong JIAO*

Institute of Electric Engineering, Yanshan University, Qinhuangdao 066004, China

Received 6 June 2018/Revised 4 August 2018/Accepted 5 September 2018/Published online 11 March 2020

Citation Wang Y Y, Jiao X H. Multi-objective energy management for PHEV using Pontryagin's minimum principle and particle swarm optimization online. Sci China Inf Sci, 2021, 64(1): 119204, https://doi.org/10.1007/s11432-018-9595-3

Dear editor,

Plug-in hybrid electric vehicles (PHEVs), which can be charged through an external power grid, have been regarded as one of the research areas for the developing methods to reduce petroleum demand and exhaust emissions. Energy management strategies (EMSs) are crucial for reducing the energy consumption for PHEVs because the power demands during the driving cycle are usually provided by multiple energy sources. In addition, PHEVs are often equipped with high-cost batteries, which need to be charged and discharged repeatedly. This indicates that, to achieve the economic feasibility of PHEVs, battery health cannot be ignored with respect to energy management [1].

Multi-objective energy management involving battery lifetime has recently become a popular research topic for PHEVs. In [2], this multi-objective optimal control problem was solved by utilizing an offline particle swarm optimization (PSO) algorithm and stochastic dynamic programming according to the probabilistic characteristics of the driving cycles, thereby forming an optimal management strategy as a mapping of the system's operating states. In addition, as the best compromise between the two objectives, the weight coefficient is obtained using PSO offline to improve the economy. In this study, we mainly concentrate on the design of an energy management strategy (EMS) that can be used to solve the problem of multi-objective energy management in real-time with the objectives of minimum energy consumption and battery life loss. Pontryagin's minimum principle (PMP) is now widely applied to solve online energy management problems, such as in [3]. However, when considering the battery health, the Pareto set will be obtained by sweeping different weights between the energy consumption and battery health because selecting different weight coefficients under different conditions is beneficial to the economy [4]. As a result, we adopt PSO in this study to optimize these weight coefficients online using a rolling style. In addition, combined with the PMP, the global optimization strategy is used to achieve a better real-time energy allocation for multi-objective optimization online in real driving cycles.

Model description and optimal problem. The utilized PHEV is identical to that in [5], which has a power-split powertrain configuration. The purpose of this study is to design an EMS that can be used in real-time to improve the energy economy and battery health of a PHEV. Accordingly, it is essential to construct a proper battery model to quantify the battery health. Under the assumption that the total ampere-hour (Ah)-throughput is a determined value before reaching the end of life [6], and the well-known fact that the different conditions result in different aging effects, the effective Ah-throughput $\mathrm{Ah}_{\mathrm{eff}}$ is used to evaluate the battery health:

$$\mathrm{Ah}_{\mathrm{eff}} = \int_0^t \sigma(\cdot) \cdot |I_{\mathrm{batt}}| \, \mathrm{d}t, \tag{1}$$

where I_{batt} is the actual current of the battery. $\sigma(\cdot)$ is the severity of different conditions that can express the different damage multipliers of battery health. In addition, $\sigma(\cdot)$ is estimated based on the curve fitting for the experimental data given in [7]. The fitting result is shown in Figure 1(a).

According to the model features and control objectives, the battery state of the charge SOC is chosen as the system state, and the motor torque T_{m} and generator speed ω_{g} are chosen as the control inputs. Considering the energy consumption and battery life loss simultaneously, an appropriate cost function is defined as

$$\begin{aligned} J = \int_0^{t_f} \bigg\{ & (1-\theta)\frac{[\dot{m}_{\mathrm{fuel}}(t) + \beta \cdot P_{\mathrm{elec}}(t)]}{\Omega} \\ & + \theta \frac{\sigma(t) \cdot |I_{\mathrm{batt}}(t)|}{\Lambda} \bigg\} \mathrm{d}t, \end{aligned} \tag{2}$$

subject to system state

$$\begin{aligned} \dot{\mathrm{SOC}} &= -\frac{I_{\mathrm{batt}}(\mathrm{SOC}, T_{\mathrm{m}}, \omega_{\mathrm{g}})}{Q_{\mathrm{batt}}} \\ &= -\frac{V_{\mathrm{OC}} - \sqrt{V_{\mathrm{OC}}^2 - 4P_{\mathrm{batt}}R_{\mathrm{batt}}}}{2Q_{\mathrm{batt}}R_{\mathrm{batt}}}. \end{aligned} \tag{3}$$

* Corresponding author (email: jiaoxh@ysu.edu.cn)

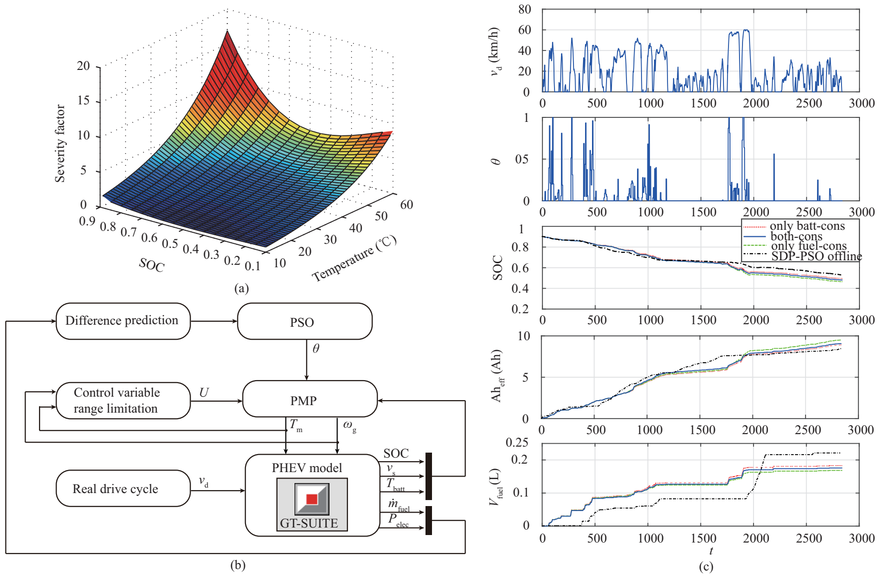

Figure 1 (Color online) (a) Severity factors' map; (b) schematic of PHEV in the simulation; (c) simulation results.

In (2), the first term represents the energy consumption, which is composed of two parts, namely, the fuel and electric costs, and β is the coefficient translating the electric cost into the fuel cost at the same price. The second term can characterize the battery life decay cost. Here, θ is the weight combining two objectives. To balance these two terms numerically, Ω and Λ are used for normalization. In addition, V_{OC}, R_{batt}, and Q_{batt} represent the open circuit voltage, resistance, and capacity of the battery, respectively. The fuel flow rate $\dot{m}_{\mathrm{fuel}}$ and instantaneous electric power P_{elec} can be expressed through the following formula:

$$\dot{m}_{\mathrm{fuel}} = \mathrm{BSFC}(\omega_{\mathrm{e}}, T_{\mathrm{e}}) \cdot T_{\mathrm{e}} \cdot \omega_{\mathrm{e}} \cdot 10^{-5}/36, \tag{4}$$

$$P_{\mathrm{elec}} = V_{\mathrm{OC}} I_{\mathrm{batt}} \dot{\mathrm{SOC}}, \tag{5}$$

where BSFC is the break-specific fuel consumption, which is described through a map of the engine speed ω_{e} and torque T_{e}.

Energy management strategy. The PMP and PSO are used to solve the energy management control problem when considering the energy consumption and battery health. First, the problem of finding the EMS that minimizes the cost function can be converted to minimizing the Hamilton function shown below using the PMP.

$$\begin{aligned} H =& (1-\theta)\frac{[\dot{m}_{\mathrm{fuel}}(t) + \beta \cdot V_{\mathrm{OC}} I_{\mathrm{batt}} \dot{\mathrm{SOC}}]}{\Omega} \\ &+ \theta \frac{\sigma(t) \cdot |I_{\mathrm{batt}}(t)|}{\Lambda} + \lambda(t)\dot{\mathrm{SOC}}(t), \end{aligned} \tag{6}$$

where $\lambda(t)$ is the co-state variable expressed through the following dynamic equation:

$$\begin{aligned} \dot{\lambda}(t) =& -\left[(1-\theta)\beta\frac{\partial P_{\mathrm{elec}}(t)}{\partial \mathrm{SOC}(t)} + \theta\left(\frac{\partial\sigma(t)\,|I_{\mathrm{batt}}(t)|}{\partial \mathrm{SOC}(t)}\right.\right. \\ &\left.\left. + \sigma(t)\frac{\partial\,|I_{\mathrm{batt}}(t)|}{\partial \mathrm{SOC}(t)}\right)\right] + \lambda(t)\frac{\partial \dot{\mathrm{SOC}}(t)}{\partial \mathrm{SOC}(t)}. \end{aligned} \tag{7}$$

In the specific implementation of the optimization algorithm based on the PMP, the Hamilton function is solved according to the power demand of the vehicle at the current sampling point based on the coverage control variables T_{m} and ω_{g}. T_{m} and ω_{g} at current sampling point, which reduce the Hamilton function to the minimum value, are determined, and the corresponding co-state variable $\lambda(t)$ is found at the same time. In addition, to reduce the number of calculations and improve the real-time simulation performance, the range of control variables U at the next sampling point is limited according to the control variables at the current sampling point. The optimal control strategy can be given as follows:

$$u^* = \arg\min_{u\in U} H[x(t), u(t), \lambda(t)]. \tag{8}$$

Meanwhile, the PSO is used to optimize the weight coefficient between the energy consumption and battery health in a step-by-step rolling manner. Each step contains several sampling points. First, the evaluation values of the energy consumption and battery life attenuation that may be generated in the next step are predicted through a differential prediction method based on the simulation data of the previous samples. Such values represent the multi-objective costs of the next step, which are balanced using the PSO in this study. After normalization, they constitute the fitness value of the PSO. Therefore, the fitness function of the PSO can be defined as follows:

$$\begin{aligned} F(x_i) = \sum_{k=1}^{n}&\left[(1-x_i)\frac{\dot{m}_{\mathrm{fuel}}(k) + \beta P_{\mathrm{elec}}(k)}{\Omega}\right. \\ &\left. + x_i\frac{\sigma(k)\,|I_{\mathrm{batt}}(k)|}{\Lambda}\right], \end{aligned} \tag{9}$$

where x_i represents the position of the ith particle and k represents the number of sampling points in a step receding horizon.

Based on the driving performance of the previous steps, particle swarms are updated and iteratively optimized according to the update rule and fitness functions of the PSO. The optimal result is used as the weight coefficient θ in (2) to solve the optimal solution of the PMP in the next step receding horizon. In addition, this optimal result is also used as the initial value of the next PSO to improve the convergence speed. It should be pointed out that the weight coefficient is not determined by the PSO during the first two steps. A weight coefficient of zero is directly selected for θ to further ensure the consideration of the energy consumption because the energy consumption is usually large initially.

In summary, a real-time EMS for the next sampling point is calculated using the PMP, and the weight coefficient during the next step is updated in a rolling style by the PSO so as to balance the energy consumption and battery health. A schematic of a PHEV with a supervisory controller during the simulation is shown in Figure 1(b).

Simulation and conclusion. The benchmark PHEV simulator on the GT-SUITE platform is used to verify the effectiveness and real-time application of the proposed EMS. The actual driving speed profile of a single day from [5] is used, and the simulation results and a comparison with the SDP-PSO offline strategy from [2] are given in Figure 1(c). As can be seen, improving the battery life and reducing the fuel consumption are two conflicting objectives. To achieve an optimal overall economic performance, the EMS when considering both the energy consumption and the battery, as proposed in this study, can reduce the battery degradation with a much smaller increase in energy consumption.

Acknowledgements This work was supported by National Natural Science Foundation of China (Grant No. 61573304) and Natural Science Foundation of Hebei Province (Grant No. F2017203210). Vehicle speed and battery degradation data were provided by Dr. Yuji Yasui and Mr. Masakazu Sasaki.

References

1 Bashash S, Moura S J, Forman J C, et al. Plug-in hybrid electric vehicle charge pattern optimization for energy cost and battery longevity. J Power Sources, 2011, 196: 541–549
2 Wang Y, Jiao X, Sun Z, et al. Energy management strategy in consideration of battery health for PHEV via stochastic control and particle swarm optimization algorithm. Energies, 2017, 10: 1894
3 Hou C, Ouyang M, Xu L, et al. Approximate Pontryagin's minimum principle applied to the energy management of plug-in hybrid electric vehicles. Appl Energy, 2014, 115: 174–189
4 Guan X M, Zhang X J, Lv R L, et al. A large-scale multi-objective flights conflict avoidance approach supporting 4D trajectory operation. Sci China Inf Sci, 2017, 60: 112202
5 Yasui Y. JSAE-SICE benchmark problem 2: fuel consumption optimization of commuter vehicle using hybrid powertrain. In: Proceedings of the 10th World Congress on Intelligent Control and Automation, Beijing, 2012. 606–611
6 Onori S, Spagnol P, Marano V, et al. A new life estimation method for lithium-ion batteries in plug-in hybrid electric vehicles applications. Int J Power Electron, 2012, 4: 302–319
7 Sasaki M, Shen T. EV bus system control strategy design with consideration of battery lifetime model. In: Proceedings of the 10th International Power and Energy Conference, Ho Chi Minh City, 2012. 213–217