**SCIENCE CHINA**
Information Sciences

• LETTER •

August 2019, Vol. 62 089203:1–089203:3
https://doi.org/10.1007/s11432-018-9529-7

# Energy management of HEVs based on velocity profile optimization

Lulu GUO[1,2], Hong CHEN[1,2], Bingzhao GAO[1] & Qifang LIU[2*]

[1] *State Key Laboratory of Automotive Simulation and Control, Jilin University, Changchun* 130025*, China;*
[2] *Department of Control Science and Engineering, Jilin University (Campus NanLing), Changchun* 130025*, China*

Received 19 March 2018/Revised 23 May 2018/Accepted 29 June 2018/Published online 27 February 2019

**Citation** Guo L L, Chen H, Gao B Z, et al. Energy management of HEVs based on velocity profile optimization. Sci China Inf Sci, 2019, 62(8): 089203, https://doi.org/10.1007/s11432-018-9529-7

Dear editor,
Ecological awareness and economical reasons call for a substantial reduction of the fuel consumption of all future automobiles. One of the most realistic short-term solutions to energy saving is represented by hybrid electric vehicles (HEVs). Those strategies that determine power distribution within the hybrid powertrain, as well as the gearshift schedule to enhance fuel economy are often referred as energy management systems (EMSs), such as rule-based methods [1,2] and optimization-based methods [3–5]. In optimization-based methods, although numerous constraints exist, a truly optimal fuel consumption can be achieved when the entire driving cycle is known a priori.

Another feasible approach to reduce energy consumption is "eco-driving", which has gained wide attention from researchers because of its potential for using external information, such as those derived from navigation and intelligent transportation systems [4,6,7]. With the popularity of cruising system, the issue is to optimize vehicle speed and realize economic cruise, which plays a significant role in fuel economy. Therefore, for HEVs, the key of energy optimization is concentrated in cruise speed optimization and EMS [8]. In this study, we present a decomposition of the overall problem into two layers. The higher controller focuses on optimizing the velocity profile under the constraint of the preceding vehicle to minimize the overconsumption of energy with regard to the overall power output. The lower controller handles the optimization of torque split ratio and gearshift schedule, as shown in Figure 1(a). Different from other traditional EMS, the proposed method considers the influence of gearshift control and combines the velocity optimization and the powertrain control to improve fuel economy.

*System modeling and methodology.* The dynamics of the vehicle longitudinal motion is

$$m_{\mathrm{v}}\dot{v}(t) = [F_{\mathrm{t}}(t) - F_{\mathrm{b}}(t) - F_{\mathrm{a}}(t) - F_{\alpha}], \qquad (1)$$

as well as $\dot{s}(t) = v(t)$, where $m_{\mathrm{v}}$ is the vehicle mass, $v$ is the vehicle speed, $s(t)$ is the traveling distance, the differential of $s(t)$ represents the longitudinal speed $v$, $F_{\mathrm{a}}$ is the aerodynamic friction, $F_{\alpha}$ is the force caused by gravity and rolling friction, $F_{\mathrm{t}}$ and $F_{\mathrm{b}}$ are the traction and brake forces, respectively. The force $F_{\mathrm{t}}(t) - F_{\mathrm{b}}(t)$ in (1) is provided by the total torque $T_{\mathrm{d}}$ obtained from the power sources (i.e., engine and motor), formulated as

$$F_{\mathrm{t}}(t) - F_{\mathrm{b}}(t) = T_{\mathrm{d}}(t) i_{\mathrm{g}}(t) i_0 \eta_{\mathrm{t}} / r_{\mathrm{w}}, \qquad (2)$$

where $i_{\mathrm{g}}$, $i_0$, $\eta_{\mathrm{t}}$, $r_{\mathrm{w}}$ are the transmission ratio, final drive ratio, total efficiency of the drive train and tire radius, respectively.

Different from a traditional vehicle, the total torque is provided by both the engine and the motor, that is, $T_{\mathrm{d}}(t) = T_{\mathrm{f}}(t) + T_{\mathrm{m}}(t)$, where $T_{\mathrm{f}}$, $T_{\mathrm{m}}$ are torques from the engine and motor. It is worth noting that if a negative value of the traction force required, it can be provided by the motor, which would work as a generator. Other

* Corresponding author (email: liuqf@jlu.edu.cn)

 

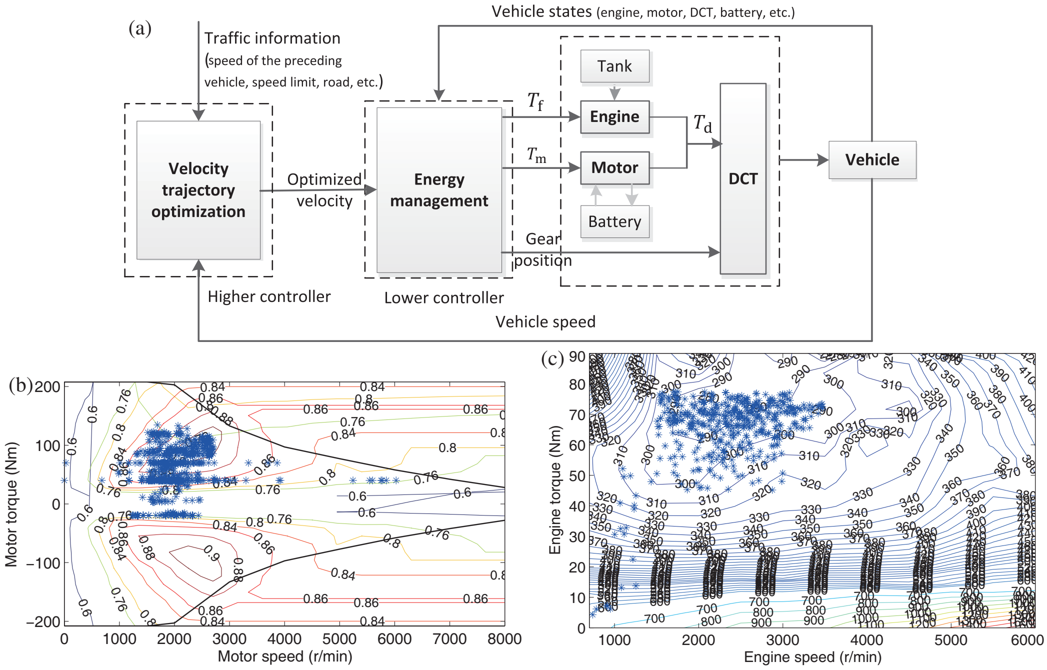


**Figure 1** (Color online) (a) Diagram of the hierarchical control strategy; (b) motor operation points; (c) engine operation points.

forces are given by $F_a(t) = AC_d\rho v^2(t)/2$ and $F_\alpha = m_v g f \cos(\theta) + m_v g \sin(\theta)$. Here, $A$ is the frontal area of the vehicle, $C_d$ is the coefficient of air resistance, $\rho$ is the air density, $g$ is the acceleration of gravity, $f$ is the coefficient of rolling resistance, $\theta$ is the road grade.

The fuel rate of the engine is given by a steady-state map, which is a function of engine torque and speed. For simplification, a parameter-varying formulation is used in this study to express the fuel cost, formulated as $\zeta \approx \alpha_1 T_f + \alpha_2$, where $\zeta$ is the fuel rate $(g/s)$, and $\alpha_1$, $\alpha_2$ are the coefficients determined by the engine speed $\omega_f$ with $\alpha_1 = p_1\omega_f^2 + p_2\omega_f + p_3$ and $\alpha_2 = p_4\omega_f + p_5$. As for the electric machine model, the electric motor can work either as a motor or a generator, and the power can be expressed as

$$P_m(t) = T_m(t)\omega_m(t)\eta_m^\kappa(T_m(t), \omega_m(t)), \quad (3)$$

where $\eta_m$ is the motor efficiency, which varies with different operation points. When the torque is positive, the electric machine works as a motor to drive the vehicle, and then $\kappa = -1$. When the electric machine works as a generator and the corresponding efficiency is $\kappa = 1$. To simplify the calculation model in (3), the motor power can be also fitted by an approximate expression, formulated as

$$P_m(t) \approx \beta_1 T_m^2(t) + \beta_2\omega_m^2(t) + \beta_3 T_m(t)\omega_m(t), \quad (4)$$

where $\beta_{1,2,3}$ are the coefficients.

The battery performance (e.g., voltage $V_{oc}$, internal resistance $R_{int}$, current $I$, and efficiency) is the outcome of thermally dependent electrochemical processes that are relatively complicated. Under the assumption that battery states are temperature independent, the current can be expressed as

$$I(t) = \left(V_{oc} - \sqrt{V_{oc}^2 - 4R_{int}P_m(t)}\right)/(2R_{int}). \quad (5)$$

Then, the battery state of charge (SOC), which reflects the energy status, can be expressed as

$$\dot{SOC} = -I(t)/C_{batt}, \quad (6)$$

where $C_{batt}$ is the nominal battery capacity.

Recently, significant advances in vehicle's onboard navigation system have been developed, and these technologies can provide a variety of useful exogenous information in a trip. In real-life traffics, because future velocity is exclusively determined by the driver, predicting a definite velocity profile ("velocity profile" means vehicle speed profile) is rather difficult. However, we can obtain the average upper and lower bounds in a given road segment using monitoring systems. For example, one can use the known speed trajectories of the preceding vehicle to predict the speed boundaries. Under this assumption, a hierarchical control strategy can be used to optimize the energy efficiency.

Firstly, we consider the velocity profile optimization of the higher controller. The main objective is to reduce the fuel consumption of the vehicle. Therefore, the discrete-time optimal problem is formulated as

$$\min J = \sum_{k=1}^{N_{\mathrm{p}}} \big[\varepsilon_1(F_{\mathrm{t}}(k)v(k))^2 + \varepsilon_2(F_{\mathrm{b}}(k))^2, + \varepsilon_3(F_{\mathrm{t}}(k) - F_{\mathrm{t}}(k-1))^2\big]\Delta T \quad (7)$$

subject to the system dynamic equation (1). The physical constraints are given as $F_{\mathrm{t}} \in [F_{\mathrm{t,min}}, F_{\mathrm{t,max}}]$, $F_{\mathrm{b}} \in [F_{\mathrm{b,min}}, F_{\mathrm{b,max}}]$. The speed and traveling distance limits are set as $v_{\mathrm{low}} \leqslant v(k) \leqslant v_{\mathrm{up}}$, $s_{\mathrm{low}} \leqslant s(k) \leqslant s_{\mathrm{up}}$ $(k = 1, 2, \ldots, N_{\mathrm{p}})$ to ensure dynamic performance, where $(\cdot)_{\{\mathrm{low,up}\}}$ and $(\cdot)_{\{\mathrm{min,max}\}}$ represent the lower and upper boundaries, respectively. In the above equation, $\Delta T$ is the time interval for discretization, and $N_{\mathrm{p}}$ denotes the prediction time horizon. The overall fuel consumption in the cost function is mainly reflected by the total output power, that is $F_{\mathrm{t}}v$; the second term is added to reduce unnecessary braking, and the third one is used to avoid frequent acceleration changing. Here, $\varepsilon_{1,2,3}$ are the weighting factors.

Then, in the lower controller, the EMS is used to optimize the torque split ratio and the gearshift timing, which can be viewed as a constrained nonlinear optimal problem. In this study, we define the torque split ratio $\nu$ as the ratio of the torque contribution of the electric system to the total torque demand. The total torque $T_{\mathrm{d}}$ and gear ratio $i_{\mathrm{g}}$ provided by the engine and motor should satisfy the force demand $(F_{\mathrm{t}}^* - F_{\mathrm{b}}^*)$ obtained in the higher controller, formulated as

$$T_{\mathrm{d}}(k)i_{\mathrm{g}}(k) = [F_{\mathrm{t}}^*(k) - F_{\mathrm{b}}^*(k)]r_{\mathrm{w}}/(i_0\eta_{\mathrm{t}}) \quad (8)$$

derived by (2). Then, we select the SoC of the battery as the state variable. In the driving process, the gear ratio $i_{\mathrm{g}}$, which reflects the gear position and gearshift timing, affects the operation speed and thus has a great influence on the energy efficiency; thus, it is also selected as the control input. Therefore, the control variables are defined as $u = [\nu, i_{\mathrm{g}}]^{\mathrm{T}}$. Then, the optimal control problem can be formulated as

$$\min J = \sum_{k=1}^{N_{\mathrm{c}}} [\tau_1\zeta(k) + \tau_2 I(k)]\Delta T \quad (9)$$

subject to the system dynamics and constraints $T_{\mathrm{f}}(k) + T_{\mathrm{m}}(k) = T_{\mathrm{d}}(k)$, $\nu(k) = T_{\mathrm{f}}(k)/T_{\mathrm{d}}(k)$, where $\zeta$ is the fuel rate of the engine, and $\tau_1$ and $\tau_2$ are weighting coefficients. The formulated optimal subproblems can be solved with many algorithms such as widely used direct or indirect methods. Because this article mainly focuses on the hierarchical control architecture of the management system, dynamic programming (DP) is used here. When real-time control is required, some computationally efficient methods can be used, such as algorithms in [9].

To evaluate the proposed EMS, a velocity profile from a human driver in the urban expressway is selected, and we add the upper and lower bounds during vehicle speed optimization based on the selected velocity trajectory. The results of the operation points of power sources are shown in Figure 1(b) and (c), from which we can see that the proposed EMS can make the operation points in high efficient areas and thus improve fuel economy.

*Conclusion.* We propose an EMS based on velocity profile optimization. Different from a traditional EMS, the total power/torque demand is optimized by the higher controller rather than derived from the human driver. To fully exploit the potential of the fuel-optimal powertrain control, gear position (or gearshift timing) is also considered in finding the optimal torque split ratio. The simulation results show that the optimized power demand can obtain better performance of comfortability and high efficient.

**Acknowledgements** This work was supported by National Natural Science Foundation of China (Grant Nos. 61790564, 61520106008), China Automobile Industry Innovation and Development Joint Fund (Grant No. U1664257), and in part by Natural Science Foundation of Jilin Province (Grant No. 20190103047JH).

**References**

1 Schouten N J, Salman M A, Kheir N A. Fuzzy logic control for parallel hybrid vehicles. IEEE Trans Control Syst Technol, 2002, 10: 460–468
2 Won J S, Langari R. Intelligent energy management agent for a parallel hybrid vehicle-part II: torque distribution, charge sustenance strategies, and performance results. IEEE Trans Veh Technol, 2005, 54: 935–953
3 Zhang C, Vahid A. Real-time optimal control of plug-in hybrid vehicles with trip preview. In: Proceedings of American Control Conference (ACC), 2010. 6917–6922
4 Guo L L, Gao B Z, Gao Y, et al. Optimal energy management for HEVs in eco-driving applications using bi-level MPC. IEEE Trans Intel Transp Syst, 2017, 18: 2153–2162
5 Fang H, Shang C S, Chen J. An optimization-based shared control framework with applications in multi-robot systems. Sci China Inf Sci, 2018, 61: 014201
6 Guo H Y, Liu F, Yu R, et al. Regional path moving horizon tracking controller design for autonomous ground vehicles. Sci China Inf Sci, 2017, 60: 013201
7 HomChaudhuri B, Lin R, Pisu P. Hierarchical control strategies for energy management of connected hybrid electric vehicles in urban roads. Transp Res Part C-Emerg Technol, 2016, 62: 70–86
8 van Keulen T, Naus G, de Jager B, et al. Predictive cruise control in hybrid electric vehicles. World Electric Veh J, 2009, 3: 494–504
9 Guo L L, Gao B Z, Li Y, et al. A fast algorithm for nonlinear model predictive control applied to HEV energy management systems. Sci China Inf Sci, 2017, 60: 092201