Real-time energy management based on ECMS with stochastic optimized adaptive equivalence factor for HEVs

Xiaohong Jiao\textsuperscript{1*}, Yang Li\textsuperscript{2}, Fuguo Xu\textsuperscript{2} and Yuan Jing\textsuperscript{2}

Abstract: For both globally suboptimal solution and implementable strategy, a real-time energy management strategy, based on equivalent consumption minimization strategy (ECMS), is proposed for commuter hybrid electric vehicles (HEVs) running on fixed routes. The determination of the adaptive equivalence factor is a focus. By the statistical characteristics deriving from historical driving data, the infinite-horizon stochastic dynamic programming (SDP) optimization with a discount factor is first formulated for finding proper equivalence factor according to uncertain driving cycles on a fixed route. And then, a mapping of equivalent factor on the system state is established off-line by stochastic optimal solution deriving from SDP policy iteration algorithm. In the power splits online, the equivalence factor of the implemented adaptive ECMS is obtained from the mapping according to the real time driving condition to achieve the near global optimal control objective that fuel consumption is minimized and the battery state of charge (SOC) is maintained within the boundaries over the whole driving route. Based on the HEV test platform...
established by specialized GT-Suite, simulation results and comparisons in some real driving cycles are presented to verify the effectiveness of the proposed strategy and to evaluate the advantages over other strategies.

Subjects: Automotive Design; Energy & Fuels; Automation Control; Control Engineering; Dynamical Control Systems

Keywords: Hybrid Electric Vehicles (HEVs); equivalent consumption minimization strategy (ECMS); equivalence factor; stochastic dynamic programming (SDP); policy iteration

1. Introduction

As is well known, hybrid electric vehicles (HEVs) usually utilize the rational distribution of the power demand between internal combustion engine (ICE) and electric motor to improve fuel economy without compromising consumer expectation with respect to performance, comfort, safety, quality, and cost of ownership with the help of proper energy management strategies, especially the optimization technique-based strategies (Liu, He, Sun, & Wang, 2018; Malikopoulos, 2014; Salmasi, 2007). And meanwhile, if the vehicle driving cycle is entirely known, deterministic dynamic programming (DDP) can ideally achieve the global optimal solution to fuel economy. However, the given sequence of DDP optimal power splits is not implementable in the real driving cycle for the global optimal management due to the inherent randomness of the real driving conditions. Consequently, to find both globally suboptimal and implementable energy management strategies has recently drawn increased attention in the energy management problem of HEVs.

In the earlier days, one of the control ideas is to extract rules from the off-line dynamic programming (DP) optimization control actions to give the on-line preliminary rule-based control strategy “sub-optimal” function so as to improve the performance of the rule-based control significantly (Bianchi et al., 2010; Lin, Peng, Grizzle, & Kang, 2003). Unfortunately, the implementable rule-based controller with the post-processing step approaches the DP optimal results only for the driving cycle that is used for rule extraction. To remedy this problem, stochastic dynamic programming (SDP) with multiple driving cycles is naturally suggested as possible solution (Jiao & Shen, 2014; Liu & Peng, 2008; Moura, Fathy, Callaway, & Stein, 2011; Opila et al., 2012). In fact, the essential of SDP is to predict the most likely future driving cycle by utilizing the statistical characteristics extracted from a mass of traffic information data, and then to achieve the near-optimal energy management results. Alternative solution is to predict the short-term driving cycle in the near future and then to execute the optimization over this short predicted horizon, that is the control concept of model predictive control (MPC) with the finite receding horizon optimization (Borhan et al., 2012; Cairano, Bernardini, Bemporad, & Kolmanovsky, 2014; Zhang & Shen, 2016). In this case, the benefits of the energy management strategy are directly related to the accuracy of the prediction information, that is to say, the quality of the prediction information, as well as the length of the prediction horizon determine the success of the control strategy. It should be also noted that these techniques are implementable online but tend to require high computational capabilities for the future driving conditions.

On the other hand, instead of the future driving conditions, only the system variables on current operation, real-time control strategies based on an instantaneous optimization were developed for the power split, among which the most common is known as the equivalent consumption minimization strategy (ECMS) (Dincmen & Guvenc, 2012; Sciarretta, Back, & Guzzella, 2004; Serrao, Onori, & Rizzoni, 2011). ECMS was really developed from a heuristic concept that the usage of the electric energy can be exchanged to equivalent fuel consumption. The instantaneous cost function to be minimized at each instant of ECMS is constructed as a sum of the fuel consumption and an equivalent fuel consumption related to the battery state of charge (SOC) variation. The definition of such a cost function requires an equivalence factor for comparing the electrical energy with the
fuel energy. And a proper value of the equivalence factor used is crucial to the optimality of power splits, since for a well-tuned equivalence factor, the performance of ECMS can be close to that of DP (Pisu & Rizzoni, 2007). It is further shown that ECMS can be regarded as a realization of Pontryagin’s minimum principle (PMP)-based optimal control problem (Kim, Cha, & Peng, 2011, 2012; Kim et al., 2014; Serrao, Onori, & Rizzoni, 2009) because the equivalent fuel consumption cost function can be considered as a Hamiltonian-like function when the equivalence factor optimized in ECMS can be linked to the optimal costate of PMP. Finding the proper value of the equivalence factor is not a straightforward process because it is necessary to consider the overall power conversion efficiencies and battery charge sustaining strategy for the target driving cycle in advance. The equivalence factor in the conventional ECMS is a constant, which is hard to keep robust performance of the power split optimality for uncertain driving cycles. In order to overcome this drawback, various modified ECMS approaches have been proposed, such as adaptive-ECMS with the estimation for the equivalence factor (Chen, Kessels, & Weiland, 2015; Musardo, Rizzoni, Guzennec, & Staccia, 2005; Sciarretta & Guzzella, 2007; Sivertsson, Sundstrom, & Eriksson, 2012), ECMS with equivalence factor optimized by genetic algorithm (Park & Park, 2012), and ECMS with stochastic optimization equivalence factor utilizing past and present driving information (Zeng & Wang, 2015, 2016).

For both globally suboptimal and implementable power splits, this paper provides a novel real-time energy management strategy based on ECMS with stochastic optimization equivalence factor for commuter HEVs. The contributions of this paper are three aspects. One is the segments building the stochastic model on a fixed route are divided in terms of the similar statistical characteristics in each segment based on the historical real driving data like as (Jiao & Shen, 2014), rather than the point where the vehicle stops (Zeng & Wang, 2015). The second is the infinite horizon stochastic optimization with discount factor is formulated in each segment to find the optimal equivalence factor rather than the finite horizon optimization on the whole route with the segment as a sampling point (Zeng & Wang, 2015). The third is the optimization equivalence factor is varying in each segment whose map is obtained off-line by utilizing SDP policy iteration algorithm, which is a simple causal closed-loop optimal solution in mean sense. Thereby, the optimal equivalence factor in the implemented ECMS-based energy management strategy can be adjusted in real time to accommodate changes in actual driving circumstances.

The rest of this paper is built up as follows: In Section 2, the problem description is presented with the analysis of split-type HEV model and benchmark problem on optimizing fuel consumption. In Section 3, based on ECMS with an adjustable equivalence factor, a globally suboptimal and implementable energy management strategy is proposed. In particular, stochastic optimization equivalence factor map is obtained by formulating infinite-horizon stochastic optimization based on the statistic characteristics of historical driving data, and solving the SDP with discount factor by the policy iteration algorithm. Effectiveness of the developed strategy and comparisons with other strategies are shown on the HEV test platform established by specialized GT-Suite in Section 4, and concluding remarks are made in Section 5.

2. Problem description
This paper focuses on the energy management problem considering both the global near-optimization and the implementation in real-time for a non-plug-in commuter HEV that is described in JSAE-SICE Benchmark Problem 2 of (Yasui, 2012), shown as Figure 1.

The basic physical parameters applied in the optimization design and simulation research are presented in Table 1, which are from the GT-SUITE HEV model provided by Yasui (2012).

2.1. Split-type HEVs powertrain model
As shown in Figure 1, the split-type HEV is comprised of a planetary gear set, three power sources including an ICE, two electric motors and a battery pack. For the planetary gear system, supposed
that there are no friction losses and rigid connection, the relationship of the angular speeds of the planet carrier $\omega_c$, sun gear $\omega_s$ and ring gear $\omega_r$ and inertial dynamics of the powertrain can be described as follows, respectively,

$$\omega_s R_s + \omega_r R_r = \omega_c (R_s + R_r)$$  

(1)
\[J_g \dot{\omega}_g = T_g + FR_s \quad (2)\]
\[J_e \dot{\omega}_e = T_e - F(R_s + R_r) \quad (3)\]
\[J_m \dot{\omega}_m = T_m + FR_r - \frac{T_f}{g_f} \quad (4)\]

where \(T[N \, m]\), \(\omega[\text{rad/s}]\) denote torque and speed, respectively, and the subscript \(g\), \(m\) and \(e\) mean M/G1, M/G2 and ICE, respectively. \(F[N]\) is the internal force on pinion gears, \(T_f[N \, m]\) represents the required torque on the differential axle. Note that \(\omega_s = \omega_g\), \(\omega_r = \omega_m\), \(\omega_c = \omega_e\) and \(\omega_m = \frac{g_f}{R_{tire}} v\), where \(v[m/s]\) denotes the vehicle speed.

In consideration of the typical aerodynamic drag, tire rolling resistance, climbing resistance and brake torque, the vehicle dynamics is represented by
\[M \ddot{v} = \frac{\eta_f T_f - T_{br}}{R_{tire}} - Mg \cos \theta - Mg \sin \theta - \frac{1}{2} \rho AC_d v^2 \quad (5)\]

where \(\eta_f\) is transmission efficiency of differential gear, \(T_{br}\) is brake torque, and \(\theta\) is road grading.

The battery can supply power and store energy from two electrical machines, whose power \(P_{\text{batt}}[W]\) can be calculated by
\[P_{\text{batt}} = \eta_g T_g \omega_g + \eta_m T_m \omega_m \quad (6)\]

where \(\eta_i\) and \(P_i\) \((i = g, m)\) are efficiencies and powers of M/G1 and M/G2, respectively. \(P_i < 0\) represent generating states and \(P_i > 0\) represent motoring states. Symbol \(\text{sgn}(\cdot)\) is the sign function. \(P_{\text{batt}} > 0\) and \(P_{\text{batt}} < 0\) mean battery discharge and charge.

Battery SOC dynamics can be described by
\[\dot{\text{SOC}} = -\frac{V_{oc} - \sqrt{V_{oc}^2 - 4P_{\text{batt}}R_{\text{batt}}}}{2Q_{\text{max}}R_{\text{batt}}} \quad (7)\]

where \(V_{oc}[V]\) and \(R_{\text{batt}}[\Omega]\) are battery open-circuit voltage and battery internal resistance, respectively, which both are functions on battery SOC.

### 2.2. Benchmark problem

As given in Yasui (2012), the benchmark problem of “Fuel Consumption Optimization of Commuter Vehicle Using Hybrid Powertrain”, provided by JSAE, SICE and Japanese automobile industry, is to design an energy management strategy by applying an advanced control algorithm to reduce as much as possible the fuel consumption of the HEV while satisfying the battery charge-sustaining constraints and the overall vehicle power demands in real driving operation running on the fixed route between user’s house and office.

For the split-type hybrid powertrain as shown in Figure 1, the energy management can realize the following several control modes: M/G2 or engine alone as the power source propels the vehicle; M/G2 and engine jointly as the power sources propel the vehicle; during vehicle stopping and driving, engine start-up using M/G1 generates electrical power and charges the battery; and M/ G2 generates electrical power when the vehicle is decelerated. In real driving operation, the driver power demand \(P_{\text{dem}}[W]\) is formulated as
\[P_{\text{dem}} = T_g \omega_g + T_m \omega_m + T_e \omega_e \quad (8)\]

Usually, the fuel consumption is measured by the fuel mass flow rate \(m_{\text{eng}}[g/s]\) defined as follows:
\[ m_{\text{eng}}(t) = \frac{BSFC \cdot T_e \cdot \omega_e}{(36 \times 10^5)} \]  
with brake specific fuel consumption BSFC[g/kWh].

Moreover, the energy management strategy optimizing fuel consumption not only satisfies the driver power demand but also meets the following physical restrictive constraints:

\[
\begin{align*}
\omega_{e, \text{min}} & \leq \omega_e \leq \omega_{e, \text{max}}, & T_{e, \text{min}} & \leq T_e \leq T_{e, \text{max}} \\
\omega_{m, \text{min}} & \leq \omega_m \leq \omega_{m, \text{max}}, & T_{m, \text{min}} & \leq T_m \leq T_{m, \text{max}} \\
\omega_{g, \text{min}} & \leq \omega_g \leq \omega_{g, \text{max}}, & T_{g, \text{min}} & \leq T_g \leq T_{g, \text{max}}
\end{align*}
\]  

2.3. ECMS-based optimization problem formulation

In this paper, the ECMS is chosen as the basic framework to design the energy management strategy achieving the optimal operating points of the ICE and the electrical motors. The design idea of ECMS is to minimize total equivalent fuel consumption \( m_{\text{eq}}(t) [g/s] \) consisting of the engine fuel consumption \( m_{\text{eng}}(t) [g/s] \) and the converted equivalent consumption from the electrical power \( m_{\text{ele}}(t) [g/s] \), described as,

\[ m_{\text{eq}}(t) = m_{\text{ele}}(t) + m_{\text{eng}}(t) \]  

\[ m_{\text{ele}}(t) = \lambda \cdot P_{\text{batt}}(t)/H_l \]  
where \( H_l [J/g] \) is lower heating value of fuel. \( \lambda \) is the equivalence factor.

Note that the value of the equivalence factor can influence the control input and the optimal solution, and Pisu & Rizzoni, (2007) has pointed out that ECMS has an outstanding performance for HEVs when proper equivalence factor is given. While, the suitable equivalence factor in ECMS is not known in advance, accordingly, finding proper equivalence factor is critical to achieving optimization power-split. This can be formulated as the following optimization problem:

\[ \min J = \int_{t_0}^{t_0+T} (m_{\text{eng}}(t) + \lambda \cdot P_{\text{batt}}(t)/H_l) dt \]  
subject to the dynamic equation (7) with \( \text{SOC}_{\text{min}} \leq \text{SOC} \leq \text{SOC}_{\text{max}} \) and the physical constraints (10).

\[ [T_e, \omega_e, \lambda] = \arg \min J \]  

Compared to the conventional ECMS, the optimization solution (14) to (13) involves not only the required engine torque and engine speed according to the power demand, but also the equivalence factor.

3. ECMS-based optimal and implementable real-time energy management

In view of the near global optimal solution resulting from the proper equivalence factor for the ECMS energy management, the main attention in this paper revolves around how to obtain the real-time proper equivalence factor of the ECMS. Meanwhile, keep in mind that the equivalence factor would be like accommodating the changes in real driving condition for the implementable energy management strategy in practice. To this end, traffic information is first used to establish the stochastic model as did in the previous work (Jiao & Shen, 2014). And then, the stochastic optimization framework will be adopted to find the desirable equivalence factor, i.e. converting the determination of real-time proper \( \lambda \) into the stochastic optimization problem and using an optimization algorithm to obtain the closed-loop optimal solution on the system states. Furthermore, in actual driving route, the equivalence factor of the implemented ECMS can tuned real-time according to the current system states corresponding to the real driving condition. Therefore, the main results of the proposed stochastic optimization-based ECMS energy management with adaptive equivalence factor include the following three aspects:
(i) Building stochastic model utilizing the history traffic information to formulate stochastic optimization problem for the proper equivalence factor;
(ii) Solving offline the stochastic optimization problem by an appropriate algorithm to obtain the proper equivalence factor map on the system state;
(iii) Implementing online the ECMS with the real-time tuned equivalence factor according to the actual driving circumstances.

Specifically, the design and implementation of the proposed energy management strategy are as follows.

3.1. Stochastic optimization for equivalence factor

3.1.1. Statistical characteristics in segments

For a private commuter car, although the route is not necessarily fixed like a public bus, but is mostly regular after a long run. And on this regular route, information about the position for every crossing, intersection, speed bump, and traffic light, together with the road slope is completely known, meanwhile, uncertainty and randomness existing in the traffic flow information still cause the different instantaneous speeds at the same position of the same route during the same departure time. In the JSAE-SICE benchmark problem of (Yasui, 2012), 15 working days sample driving speed profile are provided, in which driving speed profiles of three days away from home to office in a fixed route as example shown in Figure 2.

The intuitional information obtained from Figure 2 is nothing but there exists traffic jam in certain segments of this route, which means that the stochastic characteristics is not extracted from the instantaneous speeds profile directly. However, from the average speed based on the trip distance shown in Figure 3, it can be seen that the distribution of the average speed vs. distance in a certain segment has similar statistical characteristics, such as the segment-1 from 0 to 2 km, the segment-j from 6.0 to 7.2 km, which means that the statistical characteristics of the traffic speed may be easily captured in a certain segment of the route by using mathematical statistics method.

Accordingly, as did in Jiao & Shen, (2014), utilizing the identical statistic of the average vehicle speed vs. distance in a certain segment of the route, the route is divided into several segments (in research the 14 km commute route into eight segments: \( L = 0 – 2, 2 – 2.8, 2.8 – 4.4, 4.4 – 6, 6 – 7.2, 7.2 – 8, 8 – 11.2, 11.2 – 14\)[/sub]km). And the probability of the average speed vs. distance in each segment can be obtained by utilizing the mathematical statistic theory:

**Figure 2. Example of real driving cycles in a fixed route.**
with estimates of the mean $\hat{\mu}$ and the deviation $\hat{\sigma}$

$$\hat{\mu} = \frac{\sum_{j=1}^{n} x_j}{n} = \bar{x}, \quad \hat{\sigma}^2 = \frac{\sum_{j=1}^{n} (x_j - \bar{x})^2}{n}$$

Figure 4. Probability of the average speed in each segment.

3.1.2. Stochastic optimization problem formulation
Based on the obtained statistical characteristics in each segment above, stochastic model with identical statistics can be built to formulate stochastic optimization problem for the proper equivalence factor in each segment. And in the formulation of the stochastic optimization problem, it is fully taken into account to obtain easily an optimal solution by an appropriate algorithm. Thereby, motivated by the framework of the stochastic optimization problem...
formulation and the solution method of policy iteration in Jiao and Shen (2014), the stochastic optimization problem with infinite horizon is formulated in each segment, further, the time-varying optimization equivalence factor in each segment can be obtained offline by utilizing SDP policy iteration method, which is a simple closed-loop optimal solution depending on the system state.

Specifically, the battery SOC is selected as the system state, engine torque $T_e$, the engine speed $\omega_e$ and the equivalent factor $\lambda$ are regarded as control inputs, and the average vehicle speed in a certain distance (in research chosen as 200 m) as the stochastic disturbance considering that the distribution of the average speed vs. distance can reflect uncertain traffic flow in real driving cycle and has similar statistical characteristics in a certain segment stated as the previous section, i.e.

$$x_k = \text{SOC}_k, \quad u_k = [\bar{T}_{e.k}, \bar{\omega}_e.k, \lambda_k]^T,$$

and the equivalent factor $\lambda$ can be determined by the BSFC map on the engine.

$$\bar{T}_{e,k}, \bar{\omega}_e,k$$

note the corresponding average torque and the average speed. The state $x_k$ is regarded as control inputs, and the average vehicle speed in each segment is transformed into the stochastic $\bar{v}_k$. $\bar{v}_k$ notates the average vehicle speed vs. distance, $\bar{T}_{e,k}, \bar{\omega}_e,k$ note the corresponding average torque and the average speed. The state $x_k \in S = \{\text{SOC}_1, \text{SOC}_2, \ldots, \text{SOC}_N\}$, the control $u_k \in C$, the random disturbance $w_k \in D, S, C, D$ are finite sets. $u_k$ is constrained to take values in a given nonempty subset $U(x_k)$ of $C$, i.e. $u_k \in U(x_k), \forall x_k, x_k \in S$. The random disturbances $w_k, k = 0, 1, \ldots$ have identical statistics and are characterized by probabilities $P(\mid x_k, u_k) \equiv \text{characteristic function of } w_k$ when the current state and control are $x_k$ and $u_k$, respectively. Thereby, the dynamics of battery SOC in the stochastic optimization problem can be represented by the following discrete form:

$$\text{SOC}_{k+1} = f(\text{SOC}_k, \bar{T}_{e,k}, \bar{\omega}_e,k, \bar{v}_k) = \text{SOC}_k + \Delta \text{SOC}_k$$

with

$$\Delta \text{SOC}_k = -V_{oc,k} + \frac{\sqrt{V_{oc,k}^2 - 4R_{bott,k}P_{bott,k}}}{{2Q}_{max}R_{bott,k}} \cdot \frac{\Delta L}{\bar{v}_k}$$

and $V_{oc,k}$, $R_{bott,k}$ and $P_{bott,k}$ are shorthand for $V_{oc}(\text{SOC}_k)$, $R_{bott}(\text{SOC}_k)$ and $P_{bott}(\bar{T}_{e,k}, \bar{\omega}_e,k, \bar{v}_k)$, respectively. Moreover, considering $\dot{\omega}_e = 0$, $\dot{\omega}_g = 0$, no friction losses and rigid connection, $P_{bott,k}$ is expressed as:

$$P_{bott,k} = -\eta_f \text{sgn}(\dot{\omega}_s) \bar{T}_{e,k} (\bar{\omega}_e,k) + \left(\frac{e + 1}{R_{tire}}\right) \frac{g_f}{\bar{v}_k} + \eta_f \text{sgn}(\dot{\omega}_s) \left(\frac{1}{\bar{f}_e} - \frac{1}{\bar{f}_e} \bar{T}_{e,k} \frac{g_f}{R_{tire} \bar{v}_k}\right)$$

In terms of the stochastic model built in each segment, the issue obtaining real time equivalence factor $\lambda_k$ dependent on the system state SOC in each segment is transformed into the stochastic optimization problem defined as for a given initial state $x_0 = \text{SOC}_0$ to find a policy $\pi = \{\mu_0, \mu_1, \ldots\}$, minimizing the expected sum of a running cost function

$$J_e(x_0) = \lim_{N \to \infty} \mathbb{E} \left\{ \sum_{k=1}^{N-1} \alpha^k g(x_k, \mu_k(x_k), w_k) \right\}$$

subject to the discrete time system described as (17) and the physical constraints (10), where $\mu_k : S \rightarrow C, \mu_k(x_k) \in U(x_k)$.

Moreover, considering the optimal engine operating line, the limitation $T_{e,\text{min}}(\omega_e) \leq 0.6T_{e,\text{opt}}(\omega_e) \leq T_e \leq 1.1T_{e,\text{max}}(\omega_e)$ is adopted for the engine torque. $T_{e,\text{opt}}$ is the torque value of the optimal engine operating point. $\alpha$ is a discount factor with $0 < \alpha < 1$. The cost function $g(x_k, \mu_k(x_k), w_k)$ is defined as

$$g(x_k, \mu_k(x_k), w_k) = g_f(\bar{T}_{e,k}, \bar{\omega}_e,k) + \lambda_k P_{bott,k} / H_f$$

with $g_f(\bar{T}_{e,k}, \bar{\omega}_e,k) = \text{BSFC}_k \cdot \bar{T}_{e,k} \cdot \bar{\omega}_e,k / 36 \times 10^5$. BSFC can be determined by the BSFC map on the torque and the speed for the used engine.
3.2. Optimal solution to equivalence factor offline

To obtain a simple closed-loop optimal solution depending on the system state to the infinite-horizon optimization problem (19), a modified policy iteration algorithm of SDP is adopted in each segment of the route for time-varying equivalence factor.

The modified policy iteration contains policy evaluation and policy improvement steps:

In the policy evaluation step, calculate the corresponding cost function $J(\mu_k)$ based on the given initial stationary policy $\mu^0_0 = \{\mu^0(1), \ldots, \mu^0(N)\}$, $\mu^0$ does not affect the optimization result, and the corresponding cost function is calculated by

$$J(\mu_k^k) = [I - \alpha P(\mu^k)]^{-1} g(\mu^k)$$  \hspace{1cm} (21)

where $P(\mu^k) = [p_{ij}(\mu^k(i))]_{N \times N}$, $g(\mu^k) = [g(i, \mu^k(i))]_{N \times 1}$ denote matrixes of transition probabilities and cost per stage with effect of $\mu^k$, respectively. $I$ is the $N \times N$ identity matrix, $p_{ij}$ and $g(i, \cdot)$ are defined as:

$$p_{ij}(\mu^k(i)) = P(x_{k+1} = j|x_k = i, u_k = \mu^k(i))$$
$$g(i, \mu^k(i)) = \sum_{j=1}^{N} p_{ij}(\mu^k(i))g(i, \mu^k(i), j)$$

In the policy improvement step, update the stationary policy of previous iteration. If the stationary policy satisfies convergence condition $TJ(\mu_k) = J(\mu_k)$, the stationary policy is the optimal solution, else to update the stationary policy by $T(\mu_k^k+1)J(\mu_k^k) = TJ(\mu_k^k)$ to next iteration:

$$T(\mu_k^k+1)J(\mu_k^k, i) = g(i, \mu_k^k+1(i)) + \alpha \sum_{j=1}^{N} p_{ij}(\mu_k^k+1(i))J(\mu_k^k, j)$$

$$TJ(\mu_k^k, i) = \min_{u \in U} \left[ g(i, u) + \alpha \sum_{j=1}^{N} p_{ij}(u)J(\mu_k^k, j) \right], i = 1, \ldots, N$$

In the SDP policy iteration algorithm, the two steps are repeated iteratively until the convergence condition is satisfied. For each segment of the route, when the convergence condition of the policy iteration algorithm is satisfied, the optimal solutions of the control inputs $T_e, \omega_e, \lambda$ are obtained, which are function on the state SOC, respectively. Consequently, the equivalence factor, the engine torque and speed maps in the whole route, shown in Figures 5 and 6, can be obtained by solving the optimization problem offline in each segment for the GT-SUITE-based HEV model with the basic physical parameters in Table 0, which are three 2-dimensional maps with the road segment number and the battery SOC as inputs.

Figure 5. Equivalence factor map optimized offline.
It should be noted that the equivalence factor $\lambda$ map is the focus in the optimization solution offline, which will be utilized directly through looking-up by the implemented ECMS of the energy management system mounted on the HEV while actual driving vehicle, whereas the optimized engine torque and speed maps will merely serve as the constraints replacing the physical constraints (10) while optimizing (13) to obtain the instantaneous required engine torque and speed according to the power demand.

It is worth mentioning that although the 2-dimensional map with the road segment number and the battery SOC as inputs and the equivalence factor as output is also established in Zeng & Wang, (2015), the differences are two aspects. One is the different criterion dividing segments, the similar statistic characteristics in each segment based on the historical real driving data to replace the points of the vehicle stopping. The other is the different optimization problem formulation, the stochastic optimization problem with infinite horizon in each segment to replace the finite horizon optimization on the whole route with the segment as a sampling point. Accordingly, the time-varying optimization equivalence factor on each segment can be obtained offline by utilizing SDP policy iteration method, which is a simple closed-loop optimal solution in mean sense. Thereby, the equivalence factor in the implementation of ECMS discussed in the next subsection is varying according to the SOC value at the sampling time in each segment rather than constant in each segment of Zeng & Wang, (2015), it implies that the equivalence factor can be corrected in real time to accommodate changes in actual driving circumstances.

3.3. ECMS with equivalence factor tuned online

Once the optimized equivalence factor mapping Figure 5 is established, ECMS with the designed equivalence factor mapping can calculate the power demand split at each instant as like the conventional ECMS. Namely, the instantaneous required engine torque and speed according to the power demand are obtained by minimizing the equivalent fuel consumption described as the cost function (13) with the physical constrains. Nevertheless, since there exist the optimized engine torque and speed mappings on SOC offline Figure 6, the required engine torque and engine speed $T_{er}, \omega_{er}$ according to the instantaneous power demand are obtained by optimizing (13) with the real time equivalence factor $\lambda$ from mapping Figure 5 and the constraints $T_{e,\min} \leq 0.67 T_e \leq T_e \leq 1.27 T_{e,\max}, \omega_{e,\min} \leq 0.6 \omega_e \leq \omega_e \leq 1.2 \omega_{e,\max}$ instead of the constraints (10), where $T_e$ and $\omega_e$ are obtained from mapping Figure 6. This modification for the coverage of control variables can improve the optimization speed without loss of accuracy.

Specifically, the architecture of the ECMS-based energy management with adaptive equivalence factor is depicted as Figure 7.

When the ECMS-based energy management with adaptive equivalence factor is applied to the commuter HEV running on the actual driving cycle, the equivalent factor controller first accomplishes mapping a right equivalence factor according to the current SOC and road segment. And then, ECMS achieves optimizing instantaneously the required engine torque and speed according
to the power demand and the constraints formulated from mapping Figure 6. Moreover, when a new driving cycle is completed, the data from this cycle can also be used to expend the historical database, consequently, the offline stochastic optimizing solution can be updated with the latest driving cycle information.

4. Simulation results and comparison

The effectiveness of the investigated energy management strategy is verified by the HEV simulation test platform constructed by GT-Suite and Matlab/Simulink. The top layer of the simulating HEV control system is presented as shown in Figure 8, which consists of the driver model, driving environment, and HEV model in GT-Suite and the energy management system in Matlab/Simulink environment.

To illustrate the performance of the proposed energy management, several actual driving cycles, the first Friday, the second Monday and the second Friday speed profiles, are selected for the simulation to test the fuel-saving capability. The simulation results are presented in Figures 9–11, respectively, where figures(a) show the curves of referenced and actual driving cycles, SOC trajectory, and fuel consumption from top down, figures(b) show the curves of ICE, M/G2,M/G1 torques and speeds from top down, and figures(c) show the curve of engine operating points.

From Figures 9(a)–11(a), it can be seen that the drivability is satisfying, SOC can be maintained within the boundaries 0.5–0.7 during actual driving cycles, and the fuel consumption are 427.2 g, 397.1 g, 410.7 g under the three driving cycles, respectively. According to the gasoline density 749kg/m³ provided in the GT-SUITE simulator of Yasui (2012), the kilometers per liter are 25.54 km/L, 26.40 km/L, 25.50 km/L, respectively. From the response of ICE, M/G2 and M/G1 torques and speeds shown in Figures 9(b)–11(b), when driving speeds are low, M/G2 usually alone provides the motive force to propel the vehicle, otherwise, ICE alone propels the vehicle or ICE and M/G2 jointly propel the vehicle. In the condition of deceleration or braking, M/G2 works as a generator for recovering the energy and the energy can be stored in the battery. Figures 9(c)–11(c) show that the operating points of the ICE are distributed highly surrounding the optimal operating line.

To fully verify the effectiveness of the proposed energy management strategy for the fuel economy, the comparisons with the existing real-time energy management strategies will be
given as follows. Two strategies having been implemented in the GT-SUITE simulator provided by Yasui (2012) are selected as comparison, which are Extremum Seeking (EX) algorithm given in Yasui (2012), as benchmark controller, and the switching controller with optimized parameters by simultaneous perturbation stochastic approximation (SPSA) algorithm given in Ahmad, Azuma, Baba, and Sugie (2014). Under the same simulation environment, the comparison results of fuel consumption of the three strategies for driving cycles of 15 workdays are charted in Figure 12 with kilometers per liter [km/L] as evaluation index.

It can be seen easily from Figure 12 that the proposed strategy is most effective on the fuel consumption reduction among the three energy management strategies. Take the third Monday driving cycle for example, the designed controller can achieve 24.32 km/L, the switching controller is 22.44 km/L, and the benchmark controller is 20.10 km/L, which shows the designed controller improves the fuel efficiency approximately 20.9% than the benchmark controller rather than about 11.6% of the switching controller.

5. Conclusion
This paper discussed a novel real-time energy management strategy to minimize fuel-electricity consumptions for commuter HEVs, which is based on ECMS with stochastic optimized adaptive equivalence factor. By utilizing historical driving data, finding real-time equivalence factor is converted into a discrete stochastic optimization problem with infinite-horizon according to the road segment, and establishing equivalence factor mapping on the system state is solved by SDP policy iteration algorithm. Thereby, due to capability of finding suitable real-time equivalence factor for different driving cycles, the proposed energy management strategy can effectively improve the reduction of fuel consumption. Moreover, for non-plug-in HEVs, due to utilizing the proper equivalence factor and the optimal engine operating line, a charge sustaining strategy of energy management can render the battery SOC to remain within a prescribed range during

Figure 8. Simulation test platform in GT-Suite/Matlab.
Figure 9. Result for the first Friday driving cycle.
Figure 10. Result for the second Monday driving cycle.
Figure 11. Result for the second Friday driving cycle.
driving path, which probably benefits from incorporating the offline stochastic optimizing solution to the engine torque and speed according to the optimal operating line of engine into the online instantaneous optimization for the engine torque and speed. The comparison results with two real-time energy management strategies also show that fuel consumption is improved using ECMS with real-time equivalence factor for different driving conditions.

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Author details
Xiaohong Jiao E-mail: jiaoxh@ysu.edu.cn
Yang Li E-mail: 1127264227@qq.com
Fuguo Xu E-mail: xufuguo1990@163.com
Yuan Jing E-mail: yyj0125@163.com
1 Institute of Electrical Engineering, Yanshan University, Qinhuangdao, China.
2 Department of Engineering and Applied Sciences, Sophia University, Tokyo, Japan.

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