Applied Energy 145 (2015) 172–179

Contents lists available at ScienceDirect

Applied Energy

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

A novel energy management method for series plug-in hybrid electric vehicles

Zheng Chen [a,b], Bing Xia [b], Chenwen You [b], Chunting Chris Mi [b,*]

[a] Faculty of Transportation Engineering, Kunming University of Science and Technology, Kunming, Yunan, 650500, PR China
[b] Department of Electrical and Computer Engineering, University of Michigan-Dearborn, Dearborn, Michigan, 48128, United States

HIGHLIGHTS

- Quadratic equations are employed to determine the fuel-rate.
- QP and SA methods are used to determine battery and engine-on power.
- Simulation shows that the proposed algorithm can reduce fuel consumption.
- The battery state of health is taken into account to extend the application.

ARTICLE INFO

Article history:
Received 8 October 2014
Received in revised form 19 January 2015
Accepted 2 February 2015

Keywords:
Plug-in hybrid electric vehicles
Fuel consumption
Quadratic programming
Simulated annealing
State of health

ABSTRACT

In this paper, an energy management strategy is proposed for a series plug-in hybrid electric vehicle. A number of quadratic equations are employed to determine the engine fuel-rate with respect to battery power. The problem is solved by using quadratic programming and simulated annealing method together to find the optimal battery power commands and the engine-on power. The influences induced by the inertias of the engine and generators are analyzed to improve the calculation precision. In addition, the state of health of the battery is taken into account to extend the application of the proposed method. Simulations were performed to verify that the proposed algorithm can decrease fuel consumption of plug-in hybrid electric vehicles.

© 2015 Elsevier Ltd. All rights reserved.

1. Introduction

Nowadays, plug-in Hybrid Electric Vehicles (HEVs) have attracted considerable attention due to the advancement of both Electric Vehicles (EVs) and HEVs. Plug-in HEVs can be powered by an internal combustion engine (ICE) or an electric motor together an energy storage system, such as a battery pack [1,2]. In addition, the battery can be charged from the power grid, thereby providing an all-electric driving range (AER). For a plug-in HEV, its user always prefers to use the stored electricity to power the vehicle first, since the price and the economy of the electricity are more competitive than gasoline. A low cut-off threshold can explain the maximum discharge energy of the battery. This threshold can be measured by the state of charge (SOC), which presents the percentage of the available battery capacity over the nominal capacity [3]. Before the SOC reaches the predetermined threshold, the vehicle is only powered by the battery – a process called charge depletion (CD) mode. After the SOC reaches the cut-off threshold, the vehicle is powered by the engine and the battery together – referred to as charge sustaining (CS) mode [4]. The CD/CS mode is the easiest and most direct way to realize energy management in a plug-in HEV; however, this method can only partially optimize the fuel economy by properly determining its control parameters, since it does not globally consider the energy distribution optimization in a certain driving trip. This method can be further improved with the help of modern intelligent transportation system (ITS) and the intelligent energy management strategies [5].

The energy management for plug-in HEVs can be regarded as a stochastic optimization problem. Provided that all the driving information is known before the trip starts, the optimal energy management can be obtained with the targets of improving fuel economy [6], reducing emissions [7], and decreasing the overall cost in view of the prices of electricity and fuel gasoline [8], etc. This has prompted many researchers to attempt to optimize the energy management by applying various control algorithms, such

* Corresponding author. Tel.: +1 (313) 583 6434.
E-mail address: chrismi@umich.edu (C.C. Mi).

http://dx.doi.org/10.1016/j.apenergy.2015.02.004
0306-2619/© 2015 Elsevier Ltd. All rights reserved.

as rule-based methods [9,10], optimal theory [11–16], artificial intelligence methods [14,15,17–24], and analytical methods. A comparative study for energy management of HEVs is proposed in [25,26] which classifies all the methods into two main classes: (1) rule-based control, and (2) optimization approach control. Rule-based methods [9,10] are simpler, easier to apply, and more reliable than optimization approach control methods, and they have been widely adopted by vehicle manufacturers. However, it is difficult to find an optimal solution only based on the rules, and sometimes it can be very complex. Methods based on dynamic programming (DP) [17,20,22,23,27,28] and Pontryagin's Minimal Principle (PMP) [5,29,30] occupy considerable percentages among all the control methods due to their claims of finding the global optimal solution. However, DP suffers from the computation complication, which is referred to as the "curse of dimensionality," while PMP involves solving a complex Hamilton function that is constrained by the boundary conditions and derivation of the variables [29]. Some adaptive optimal control strategies are also proposed without knowing the detailed trip information [31]. Quadratic programming (QP) [32] and convex optimization based methods [33] bring much attention by researchers, provided that the driving conditions can be known in advance. Equivalent consumption minimization strategy (ECMS) [11,21,34] is also a popular control strategy which translates the global optimization into local minimization. For a plug-in PHEV, it becomes difficult to apply optimally for different driving conditions. Artificial intelligent methods, such as neural networks (NN) [13], fuzzy logic [17], genetic algorithm (GA) [32], particle swarm optimization [26,35], and the simulated annealing (SA) method [5], have all been successfully applied to improve the energy management. NN [12,13] methods require sufficient data to train all the possible combinations of the road conditions. Fuzzy logic [17] can only obtain an approximately optimal result; in addition, considerable effort is needed to build the fuzzy logic table. GA [32] is time-consuming because the algorithm must complete a series of actions that include crossover, mutation, and elite selection. Analytical methods [36–38], and the model predictive control method [39] are also candidates for improving energy management of plug-in HEVs. In [36], the energy management strategy is stated by a pair of parameters which define the battery's optimal power and the engine-on power threshold. The research objects can be classified into series plug-in HEVs, parallel plug-in HEVs, power-split plug-in HEVs [2], as well as some particular structures, such as the Chevy-Volt [25,40] and the Honda Accord [41].

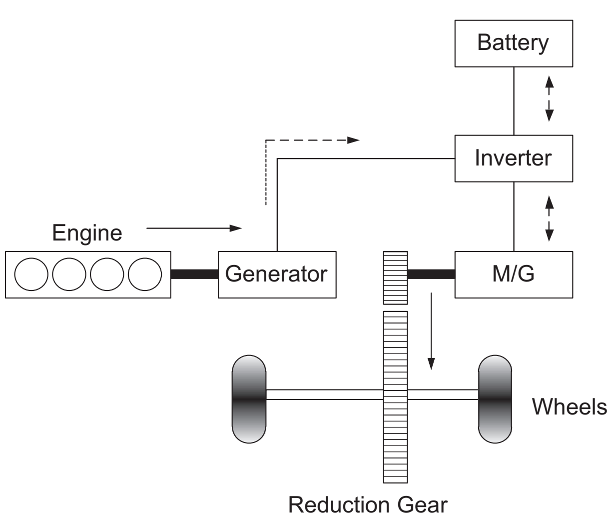

Fig. 1. Powertrain structure of a series plug-in HEV.

In this paper, the research target is a series plug-in HEV [42], whose powertrain structure is shown in Fig. 1. It can be observed that the engine is totally separate from the driving train, and thus cannot power the vehicle directly. Obviously, the vehicle is a system with two degrees-of-freedom, which brings certain complexities to splitting the energy distribution, compared with splitting the energy distribution in a vehicle with only one degree-of-freedom, such as a parallel HEV with a fixed gear ratio. Consequently, the developed algorithm in this paper can be also applied to a parallel plug-in HEV or a power-split plug-in HEV. To simplify the problem, a novel method is proposed herein to transform the degrees-of-freedom from two to one, as detailed in Section 2. Quadratic equations are then introduced to build the nonlinear relationship between the engine fuel-rate and the input, i.e., the battery power. Then, given the vehicle trip speed and power demand, the quadratic programming (QP) method [32] and the SA method are introduced to find the global optimal solutions, including battery power and engine-on power. The interior-point method is applied to solve the QP problems. Compared with the DP based methods [13,17], the QP methods needs less time to finish the energy distribution without influencing the optimization results. The SA method is also faster to find an quasi-optimal engine-on power than neural network method [12,13,43] and genetic algorithm [32]. During the process of calculating the power demand, the influences induced by the inertias of the engine and generator are considered in order to improve the calculation precision. In addition, a battery management system (BMS), which monitors and oversees the battery pack, can provide detailed battery information, such as SOC [3], state-of-health (SOH) [44], and other related information to the vehicle controller [45]. The SOH can reflect the maximum available energy stored in the battery pack, which varies with temperature and battery degradation. Here, the SOH is also added into the controller to provide more considerations to extend the application of the proposed method. Finally, simulations are performed to verify the improvements of the proposed method.

2. Vehicle driveline analysis and simplification

As shown in Fig. 1, the vehicle consists of an engine, a generator, a battery pack, and a motor. These parameters are briefly summarized in Table 1. The maximum engine power is 60 kW, and the nominal voltage and rated capacity of the battery are 260 V and 41 Ampere-hour (Ah), respectively. The maximum motor power is 62 kW. Based on Fig. 1, the fuel consumption can be calculated,

$$F = \int_0^{t_{total}} m_f dt \tag{1}$$

$$m_f = f(T_e, w_e) \tag{2}$$

where m_f is the fuel-rate calculated by engine speed w_e and engine torque T_e, and F is the total fuel-consumption. In order to calculate m_f, the vehicle powertrain should be analyzed in detail to find which variable can regulate w_e and T_e. From Fig. 1, based on the

Table 1
Vehicle specifications.

Type	Power-split plug-in HEV
Vehicle mass	1925 kg
Drive type	Forward wheel drive
Lithium-ion battery	Rated capacity 41 Ah
Engine	Maximum power 88.3 kW
Motor	Rated power 62 kW
Generator	Rated power 45 kW Maximum power 75 kW

vehicle speed v_o and the driveline power demand P_o, the motor power P_{mot_in} and the motor speed w_{mot} can be formulated,

$$\begin{cases} w_{mot} = \frac{v_o}{wheel\_r} \times f_{d\_ratio} \\ P_{mot\_in} = P_o/\eta(w_{mot}, T_{mot}) \end{cases} \tag{3}$$

where $wheel\_r$ and $\eta(w_{mot}, T_{mot})$ denote the radius and efficiency of the motor, and f_{d_ratio} is the final driveline ratio, which represents the speed ratio between the motor and the wheels. In this paper, the vehicle parameters are from a template of the simulation software Autonomie [46]. In this model, f_{d_ratio} equals 4.231. The generator power P_{gen_out} can be determined according to P_{mot_in},

$$P_{gen\_out} = P_{mot\_in} + P_{bat} + P_L \tag{4}$$

where P_{bat} is the battery power, and P_L is the accessory power, which is supposed to be a constant, i.e., 200 W.

The temporary engine power P^*_{eng} can then be formulated accordingly,

$$P^*_{eng} = P_{gen\_out}/\eta_{gen} \tag{5}$$

where η_{gen} represents the efficiency of the generator. Since the powertrain of a series HEV (SHEV) has two degrees-of-freedom, the optimized engine speed with which the engine can output power P^*_{eng} most efficiently can be determined,

$$w^*_{eng} = g(P^*_{eng}). \tag{6}$$

Fig. 2 shows the optimal engine speed profile with engine power as the input. It can be observed that the speed profile is almost linear with the engine power. Based on the calculated w^*_{eng} and P^*_{eng}, the temporary generator power $P^*_{gen\_out}$ can be easily calculated,

$$P^*_{gen\_out} = g(w^*_{eng}, T^*_{eng}) \tag{7}$$

where T^*_{eng} denotes the engine torque. Here, a power difference P_d between P_{gen_out} and $P^*_{gen\_out}$ can be obtained,

$$P_d = (P_{gen\_out} - P^*_{gen\_out})/\eta_{gen}. \tag{8}$$

Now, the engine power P_{eng}, and engine speed w_{eng} can be consequently updated,

$$P_{eng} = P^*_{eng} + P_d \tag{9}$$

$$w_{eng} = g(P_{eng}) \tag{10}$$

$$T_{eng} = P_{eng}/w_{eng}. \tag{11}$$

From (3) to (4), it is clear that m_f can be determined by P_o, v_o, and P_{bat},

$$m_f = f(T_{eng}, w_{eng}) = f(P_o, P_{bat}, v_o). \tag{12}$$

Since the energy distribution controller cannot compromise the performance of the vehicle, the driveline power P_o and vehicle speed v_o are pre-determined at each step. Therefore, only P_{bat} can be the input determining m_f. Since P_o and v_o vary with the driving conditions, it becomes difficult to build a relationship between m_f and P_{bat}. In order to simplify the problem without influencing the precision, a number of quadratic equations, whose coefficients are determined by P_o and w_o, are introduced to formulate the fuel-rate m_f with battery power P_{bat},

$$m_f = \varphi_2(w_o, P_o) \cdot P^2_{bat} + \varphi_1(w_o, P_o) \cdot P_{bat} + \varphi_0(w_o, P_o) \tag{13}$$

where $\varphi_2(w_o, P_o)$, $\varphi_1(w_o, P_o)$, and $\varphi_0(w_o, P_o)$ are coefficients of the quadratic equations [13]. It should be mentioned that when the engine is off, the fuel-rate equals zero, thus

$$m_f = \begin{cases} \varphi_2(w_o, P_o) \cdot P^2_{bat} + \varphi_1(w_o, P_o) \cdot P_{bat} + \varphi_0(w_o, P_o) & engine\_on = 1 \\ 0 \quad engine\_on = 0 \end{cases} \tag{14}$$

Here, a simplified battery model is selected to calculate P_{bat}, as shown in Fig. 3. It can be observed that the battery model is comprised of an open circuit voltage (OCV) source and an internal resistor, which are connected in series. Based on this simplified model, P_{bat} can be determined,

$$P_{bat} = E_o \cdot i - i^2 R_0. \tag{15}$$

where E_o is the OCV, and R_0 is the internal resistance. Accordingly, the battery current and the SOC can be calculated,

$$\begin{cases} i = \frac{E_o - \sqrt{E_o^2 - 4R_0 P_{bat}}}{2R_0} \\ SOC = SOC_0 - \frac{1}{C_{bat}} \int_0^T i dt \end{cases} \tag{16}$$

where SOC_0 is the initial SOC when the trip begins, and C_{bat} is the battery current capacity.

It is worth to mention that the average values of the OCV, the internal resistor of the battery, and generator efficiencies are used to obtain these coefficients. The maximum driveline power and the maximum speed of the vehicle should be 62 kW and 38 m/s, respectively. The increments of maximum driveline power and maximum speed necessary to obtain $\varphi_2(w_o, P_o)$, $\varphi_1(w_o, P_o)$, and $\varphi_0(w_o, P_o)$ by the curve-fitting method are 1 kW and 0.5 m/s, respectively; therefore, the dimensions of these coefficients are 62 by 76. As can be seen from Fig. 4, $\varphi_2(w_o, P_o)$ is always more than zero, while $\varphi_1(w_o, P_o)$ is always less than zero. Thus, this case is a typical convex optimization problem. Fig. 5 compares the fuel-rates obtained by simulation and by calculation based on the quadratic equations, hence proving that the quadratic equations can approximate the fuel-rate effectively.

Now, based on (14), the engine start/stop commands, together with the battery power commands, can be potentially optimized to reduce the fuel consumption. In the next step, the QP and SA methods will be applied to control the commands, thereby reducing the fuel consumption for series plug-in HEVs.

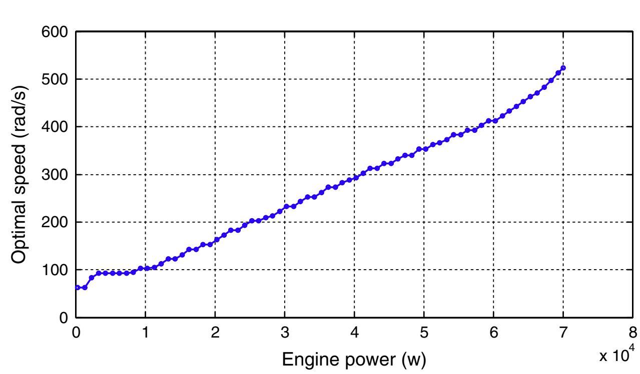

Fig. 2. Optimal engine speed profile.

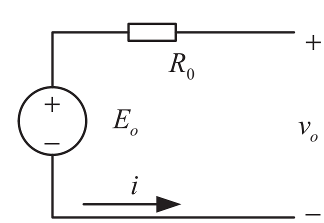

Fig. 3. Battery model.

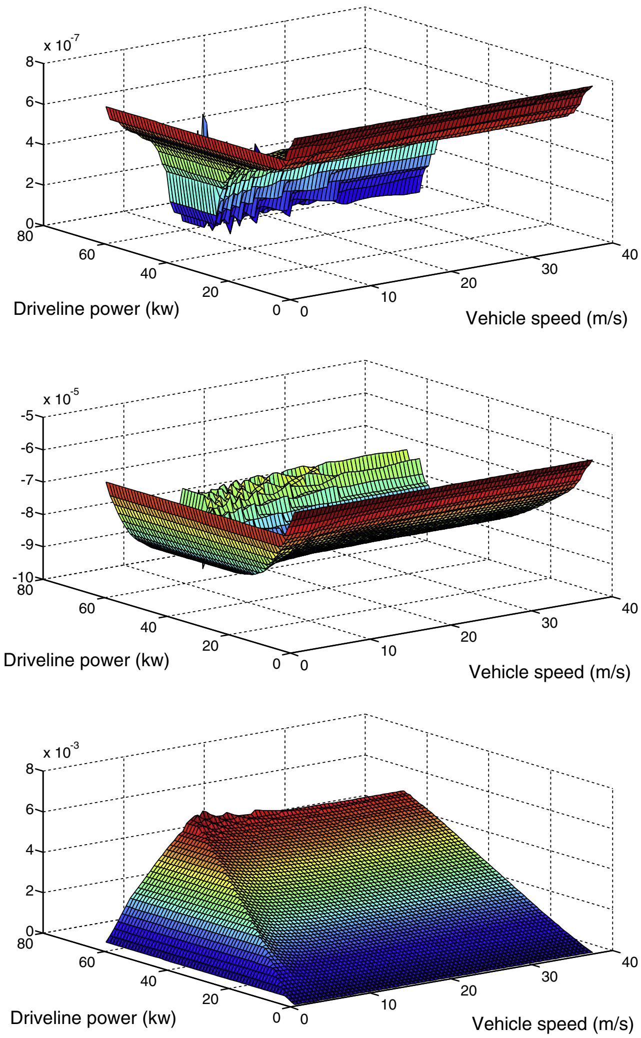

Fig. 4. Coefficients of $\varphi_2(w_o, P_o)$, $\varphi_1(w_o, P_o)$, and $\varphi_0(w_o, P_o)$.

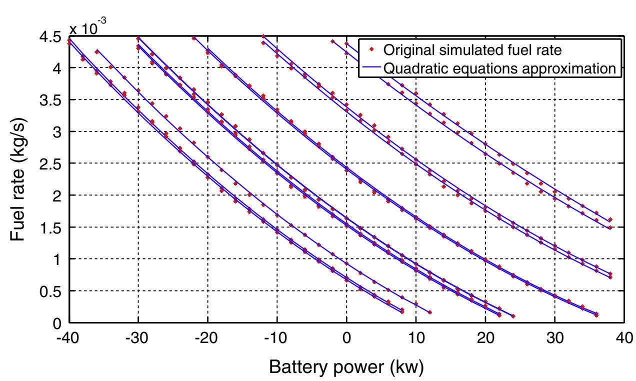

Fig. 5. Fuel rate validation with quadratic equations.

3. Quadratic programming and simulated annealing application

The subject of this paper can be clearly regarded as a quadratic programming problem with varied coefficients. However, the engine on/off commands should be tackled properly in advance, since the problem is highly nonlinear due to the stochastic driving conditions. Here, the SA method is introduced to estimate the engine-on power based on driving conditions and fuel-rate equations [5]. The SA method is effective in solving unconstrained and bound-constrained optimization problems, since it can find a quasi-optimal solution for these problems with higher computational efficiency than an exhaustive method. Compared with the method proposed in [5], the SA method is applied with a shorter calculation time and without influencing the performance of the controller. During the iteration process, the interior point method is introduced to solve the proposed QP problem to determine the optimal battery powers. The interior point method is a programming method that realizes optimization by penetrating the middle of the solid defined by the problem, instead of around its surface. This method is widely adopted by researches in order to find the optimal solutions for convex optimization problems with high computational efficiency [47,48]. In this paper, the interior point method is realized by Matlab [49].

The whole algorithm application is shown in Fig. 6. First, the current AER is estimated by the battery current SOC and SOH. Currently, some artificial intelligent methods have been applied to estimate the AER precisely [50], however, these methods are not realistic in plug-in HEVs due to large calculation labor. Here, a relatively simple method is introduced to calculate the AER based on the specifications of the vehicle. Suppose the maximum AER when the battery is with rated capacity is L_{AER0}, the current AER can be estimated based on the current battery SOC SOC_0, and battery SOH h,

$$L_{AER} = L_{AER0} \cdot \frac{SOC_0 - SOC_s}{1 - SOC_s} \cdot h \tag{17}$$

where L_{AER} is the calculated AER, SOC_s is the cut-off threshold at which the vehicle controller is transferred from the CD mode into the CS mode. In this paper, SOC_s equals 0.3. If the AER is greater than the trip length, the vehicle will only be powered by the battery. If the AER is less than the trip length, the SA and the interior point methods will be applied together to find the controlling commands, i.e., engine-on power and battery powers.

The realization of the SA method and the interior point method in solving the QP problem is depicted in Fig. 7. The engine-on power and the fuel-consumption are chosen as the control input and the target, respectively. First, the SA method selects a random value for the engine-on power as the initial input. Usually a high value is set in advance; when the algorithm runs, the engine-on power decreases gradually. A new value is randomly generated based

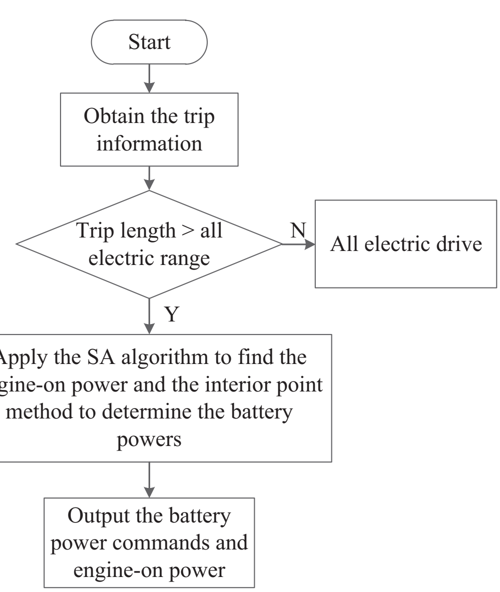

Fig. 6. The application process of the whole control algorithm.

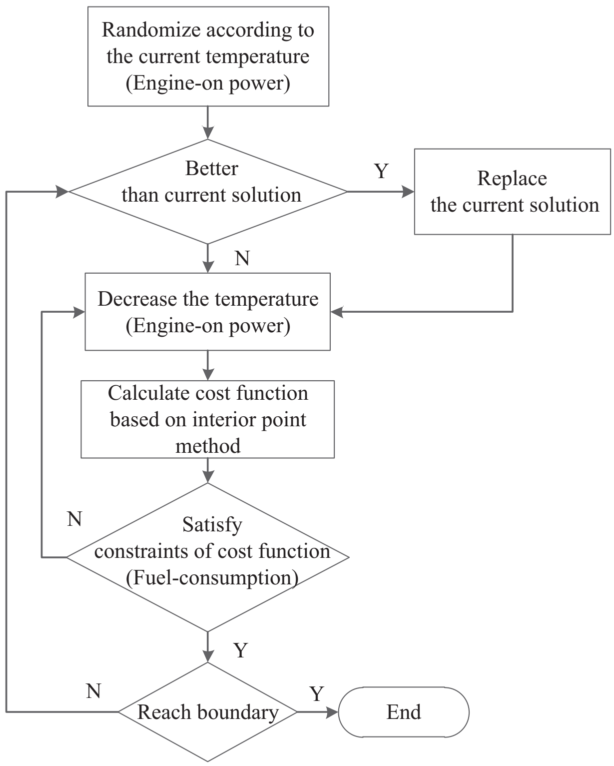

Fig. 7. The whole calculation process.

on the present value when the next iteration begins. The interval between the updated and the current values of the engine-on power is subject to a probability distribution. In this way, the SA method is prevented from sinking into a local minimum region, and has the ability to find a better solution globally. When the termination conditions are reached, the iteration processes will stop and eventually output the optimal battery powers along with the engine-on power.

During the calculation, some constraints should be properly considered,

$$\begin{cases} 0 < P_{eng\_on} \leqslant P_{eng\_on\ \max} \\ P_{bat\ \min}(t) \leqslant P_{bat}(t) \leqslant P_{bat\ \max}(t) \\ 0.2 \leqslant SOC \leqslant 0.9 \end{cases} \tag{18}$$

where $P_{eng\_on\ \max}$ represents the minor values of engine maximum power $P_{eng\_\ \max}$ and driveline maximum $P_{o\max}$, $P_{bat\ \min}(t)$ and $P_{bat\ \max}(t)$ are the minimum and maximum battery powers, and the SOC is within [0.2,0.9], while its final value when the trip ends is set to be 0.3. In order to improve precision, the inertia influences of the generator and the engine are also taken into consideration. When the driveline power changes, the engine and the generator must accelerate or decelerate to meet the power demand, therefore, the driveline power can be updated,

$$P_{onew}(t) = P_o(t) + (J_{eng} + J_{gen}) \cdot (w(t) - w(t-1))/\Delta t \cdot w(t) \tag{19}$$

where J_{eng} and J_{gen} denote the inertias of the engine and the generator, and Δt is the data acquiring interval. In this paper, Δt equals 1 s. $w(t)$ represents the rotating speeds of the engine and the generator, and $P_{onew}(t)$ is the updated driveline power to calculate the fuel-rate based on (13).

In this paper, the maximum limit of iteration for the SA calculation is 40, the initially iterated value of the engine-on power is the minor value of 30 kW and $P_{eng\_on\ \max}$, and the termination tolerance on the function value is 0.005. The next step is to conduct the simulations to show the calculation process and to compare the control performance.

4. Simulation validation

Simulations are necessary to test and verify the performance of the built algorithm. In this paper, a powerful vehicle simulation software, Autonomie, is introduced to simulate vehicles with different control algorithms. Autonomie, developed by Argonne National Laboratory, can effectively model a vehicle, apply a controller for the vehicle, validate the performance of the vehicle, and program the controller with high precision [46]. From (16), C_{bat} is the battery capacity, which varies with the battery temperature and battery usage. Thus, if the battery capacity can be determined in advance, the proposed algorithm can still be applied to improve the fuel economy regardless of the battery's health status. Therefore, the simulations were separately conducted with healthy and unhealthy batteries.

4.1. Simulation with a healthy battery

The Highway Fuel Economy Test (HWFET) cycle [5] and the Urban Dynamometer Driving Schedule (UDDS) were adopted to simulate the vehicle based on the different energy management algorithms. Their speed curves are shown in Fig. 8. It can be observed that the HWFET cycle is used to simulate highway fuel economy, while the UDDS cycle simulates an urban route.

First, the simulation based on the CD/CS mode was benchmarked for comparing the improvement of fuel consumption. The beginning SOC is set to 90%. During the CD mode, the engine is always off and only the battery powers the vehicle. When the battery is discharged until the SOC reaches near 30%, the control strategy is transferred into the CS mode. Then, the engine is turned on and the vehicle is powered by the engine and battery together, thus maintaining the battery SOC in the vicinity of 30%. During the CS mode, the battery power can be calculated,

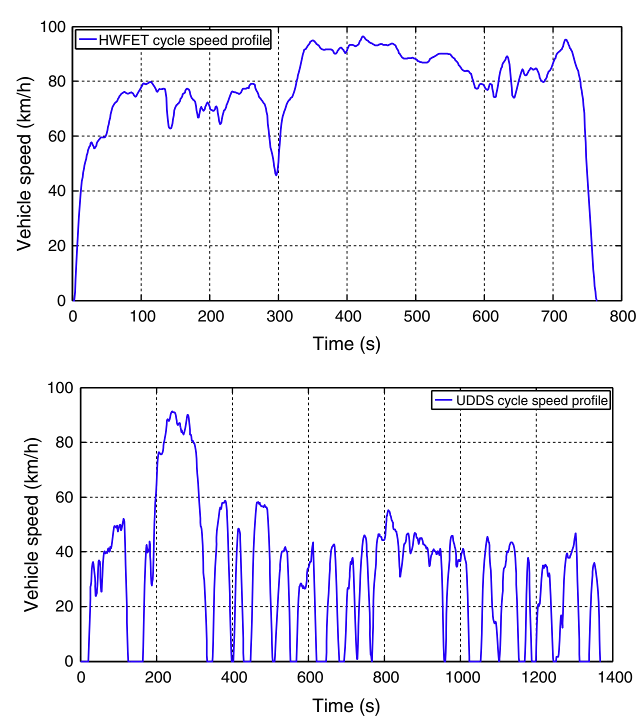

Fig. 8. The speed profiles of the HWFET and UDDS drive cycles.

$$P_{bat} = \begin{cases} P_o & SOC > 36\% \\ \min(7395.3 \cdot (SOC - 0.33)/0.03 + 30381.3, P_o) & 33\% \leqslant SOC < 36\% \\ \min(30381.3 \cdot (SOC - 0.3)/0.03, P_o) & 30\% \leqslant SOC < 33\% \\ \max(36860.7 \cdot (SOC - 0.3)/0.03, P_o) & P_o < 0, 27\% \leqslant SOC < 30\% \\ \max(36860.7 \cdot (SOC - 0.3)/0.03, P_o - P_{eng\_max}) & P_o > 0, 27\% \leqslant SOC < 30\% \\ \max(-36860.7, P_o) & P_o < 0, SOC < 27\% \\ \max(-36860.7, P_o - P_{eng\_max}) & P_o > 0, SOC < 27\% \end{cases} \quad (20)$$

where max( ) and min( ) denotes the maximum and minimum values of the two values included in the parenthesis, and P_{eng_max} is the maximum engine power. Once the engine power is determined, the vehicle controller will seek the optimized combination of engine torque and speed based on Fig. 2, making the engine working most efficiently. It is necessary to mention that the minimum engine on and off time is 2 s, and 1.5 s, respectively. In addition, the engine-on and engine-off power thresholds are 25 kW, and 6 kW, respectively. All the coefficients in (20) and engine operation parameters have been optimized by the developers of Autonomie according to the characteristics of the motors and the engine. Thus, the CD/CS strategy can also be treated as an optimized method to some extent. Fig. 9 shows the iteration process of the SA method for eight consecutive UDDS drive cycles. The iterations threshold for the SA is set to 40, compared with 100 in [5], as this value is enough to obtain a good result with much less calculation labor. Based on the calculation of the proposed algorithm, the engine-on power and the battery power commands when the engine is on can be obtained. The engine-on power after calculation is 16.25 kW. It means that when the driveline power demand is less than this threshold, the engine will be off, and the vehicle will be powered by the battery only;

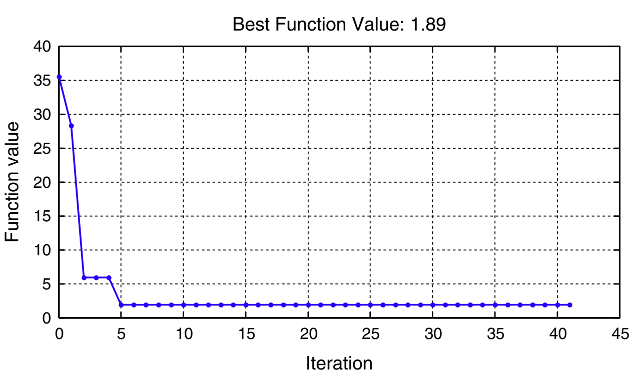

Fig. 9. The SA method calculation process.

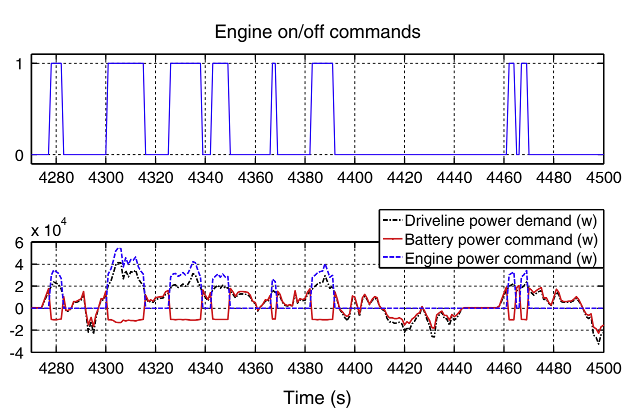

Fig. 10. Engine on/off commands and the correlated powers of the battery and engine.

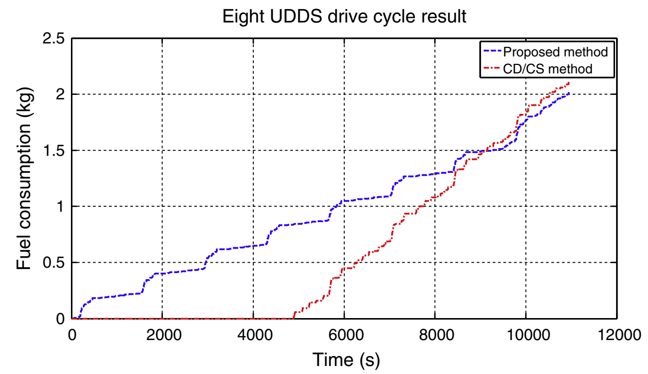

Fig. 11. Fuel-consumption when eight UDDS cycles are simulated with different algorithms.

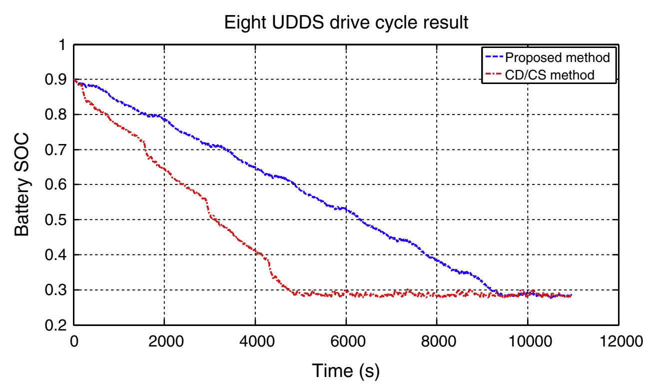

Fig. 12. SOC comparison.

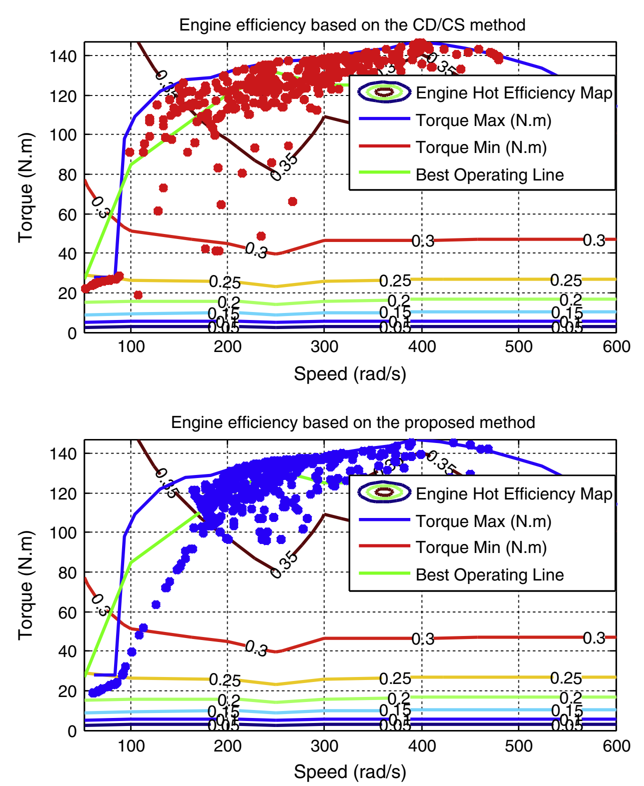

Fig. 13. Engine efficiency comparison.

when the driveline power demand is more than this threshold, the engine will be turned on, and the vehicle can be powered by the engine and the battery together. Fig. 10 presents the engine on/off commands, and the corresponding commands of the battery and engine power. For ease of review the results, we only display portion of the duration during the simulation, from 4270 s to 4500 s. It can be observed that when the engine is off, the battery power commands are always larger than the driveline power demands, since there exists losses when the battery powers the vehicle or is charged from the braking energy regeneration. When the engine is on, the calculated engine power commands are always more than 20 kW, and the corresponding battery power commands are less than zero. This means that the proposed algorithm tries to maximize the engine efficiency to charge the battery and power the vehicle simultaneously with higher power output that represent a higher efficiency of the engine, by searching the optimal combinations of the engine speed and engine torque according to Fig. 2. Moreover, the proposed algorithm prevents the battery from being discharged with large current, thus bringing higher battery efficiency. The simulation based on the calculated battery commands and the engine-on power was conducted with the final fuel consumption of 2.012 kg, as presented in Fig. 11. Compared with the CD/CS mode, the proposed method can reduce fuel. It can also be observed that, based on the CD/CS method, the engine is always off until around 5000 s. Fig. 12 compares the variations in SOC according to the application of different energy management methods. Obviously, the proposed methods can make the battery discharge more slowly compared with the CD/CS method. In order to compare the fuel consumption more equally, a linear approximation method is introduced to locate the ending SOC with the same value [37]. With the SOC corrected, the proposed method can reduce fuel consumption by up to 4.29%. Fig. 13 compares the engine efficiencies when different methods are applied. We can conclude that the average efficiency is higher when the proposed algorithm is applied. Table 2, which compares the results when six to nine UDDS and HWFET cycles are simulated, shows that the proposed controller can reduce the fuel consumption by 3.78–5.10%. The calculation was completed within 1.5 min employing a laptop computer with 8 gigabits of RAM and 2.9 GHz of core i7 processor, thus proving that it is possible to apply the method in the actual vehicle operation.

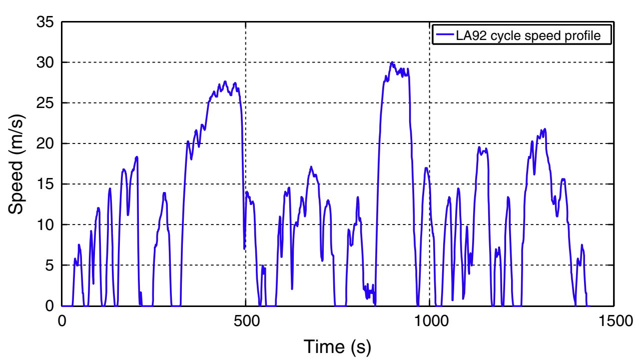

Fig. 14. LA92 drive cycle speed profile.

4.2. Simulation with an unhealthy battery

In order to validate the robustness of the proposed controller, simulations were performed with unhealthy batteries. The battery capacity was set to 90% of the rated capacity. The battery internal resistance increases and the battery open circuit voltage decreases by 10%, respectively. LA92 drive cycles were simulated, with speed profiles depicted in Fig. 14. Table 3 lists the results, from which it can be observed that the proposed algorithm can save up to 0.56%, 1.62%, and 1.46% when seven to nine LA92 drive cycles are simulated. These results indicate that even when the battery becomes unhealthy, the proposed algorithm still remains effective in improving the energy management for a series plug-in HEV.

5. Conclusion

In this paper, an intelligent algorithm based on the QP and SA methods is proposed for the energy management of a series plug-in HEV in order to reduce the fuel consumption. A number of quadratic equations are introduced to quantify the fuel-rate with battery power. Based on the analysis of the problem, the SA method is applied to search the optimal engine-on power. The interior point method is introduced to solve the QP method. Through simulations, the proposed algorithm is proven to be effective in improving the fuel economy regardless of the battery's

Table 2
Results comparison when the beginning SOC is 90%.

Drive cycle	CD/CS algorithm		The Proposed algorithm		Savings (%) (SOC corrected)
	Fuel-consumption (kg)	Ending SOC (%)	Fuel-consumption (kg)	Ending SOC (%)	
6 UDDS	1.131	28.51	1.047	27.12	5.10
7 UDDS	1.616	28.49	1.522	27.18	4.28
8 UDDS	2.101	28.47	2.012	28.53	4.29
9 UDDS	2.586	28.46	2.476	27.81	3.78
6 HWFET	2.448	30.53	2.318	29.43	4.46
7 HWFET	3.139	30.53	2.987	29.22	4.05
8 HWFET	3.830	30.53	3.659	28.97	3.69
9 HWFET	4.520	30.53	4.325	29.08	3.71

Table 3
Results comparison when the battery is unhealthy.

Drive cycle	CD/CS algorithm		Proposed algorithm		Savings (%) (SOC corrected)
	Fuel-consumption (kg)	Ending SOC (%)	Fuel-consumption (kg)	Ending SOC (%)	
7 LA92	3.930	29.26	3.905	29.10	0.56
8 LA92	4.705	26.26	4.671	28.54	1.6
9 LA92	5.470	26.26	5.434	28.57	1.46

health status. Simulations revealed that the proposed algorithm can clearly reduce fuel consumption.

Currently, the algorithm proposed in this paper replies on knowing the driving conditions. A driving condition identification technique should be considered in order to extend the applicability of the proposed method. As our next step, experimental validations including the actual vehicle test or hardware-in-the-loop test will be the focus of our future work.

References

[1] Mi C, Masrur A, Gao DW. Hybrid electric vehicles: principles and applications with practical perspectives. Wiley; 2011.

[2] Zhang X, Mi C. Vehicle power management: modeling, control and optimization. Springer; 2011.

[3] Zheng C, Yuhong F, Mi CC. State of charge estimation of lithium-ion batteries in electric drive vehicles using extended Kalman filtering. IEEE Trans Vehic Technol 2013;62:1020–30.

[4] Overington S, Rajakaruna S. High efficiency control of internal combustion engines in blended charge depletion/charge sustenance strategies for plug-in hybrid electric vehicles. IEEE Trans Vehic Technol 2014. vol. PP, pp. 1–1.

[5] Chen Z, Mi CC, Xia B, You C. Energy management of power-split plug-in hybrid electric vehicles based on simulated annealing and Pontryagin's minimum principle. J Power Sources 2014;272:160–8 [12/25/2014].

[6] Ceraolo M, di Donato A, Franceschi G. A general approach to energy optimization of hybrid electric vehicles. IEEE Trans Vehic Technol 2008;57:1433–41.

[7] Yi Z, Heping L, Qiang G. Varying-domain optimal management strategy for parallel hybrid electric vehicles. IEEE Trans Vehic Technol 2014;63:603–16.

[8] Moura SJ, Fathy HK, Callaway DS, Stein JL. A stochastic optimal control approach for power management in plug-in hybrid electric vehicles. IEEE Trans Control Syst Technol 2011;19:545–55.

[9] Chen B-C, Wu Y-Y, Tsai H-C. Design and analysis of power management strategy for range extended electric vehicle using dynamic programming. Appl Energy 2014;113:1764–74 [1/2014].

[10] Kelouwani S, Henao N, Agbossou K, Dube Y, Boulon L. Two-layer energy-management architecture for a fuel cell HEV using road trip information. IEEE Trans Vehic Technol 2012;61:3851–64.

[11] Nüesch T, Cerofolini A, Mancini G, Cavina N, Onder C, Guzzella L. Equivalent consumption minimization strategy for the control of real driving NOx emissions of a diesel hybrid electric vehicle. Energies 2014;7:3148–78.

[12] Murphey YL, Park J, Kiliaris L, Kuang ML, Masrur MA, Phillips AM, et al. Intelligent hybrid vehicle power control—Part II: online intelligent energy management. IEEE Trans Vehic Technol 2013;62:69–79.

[13] Zheng C, Mi CC, Jun X, Xianzhi G, Chenwen Y. Energy management for a power-split plug-in hybrid electric vehicle based on dynamic programming and neural networks. IEEE Trans Vehic Technol 2014;63:1567–80.

[14] Malikopoulos AA. Supervisory power management control algorithms for hybrid electric vehicles: a survey. IEEE Trans Intell Transp Syst 2014;5:1–17.

[15] Elbert P, Flankl M, Onder C, Guzzella L. Convex optimization for the energy management of hybrid electric vehicles considering engine start and gearshift costs. Energies 2014;7:834–56.

[16] Stockar S, Marano V, Canova M, Rizzoni G, Guzzella L. Energy-optimal control of plug-in hybrid electric vehicles for real-world driving cycles. IEEE Trans Vehic Technol 2011;60:2949–62.

[17] Zheng C, Mi CC. An adaptive online energy management controller for power-split HEV based on Dynamic Programming and fuzzy logic. In: Vehicle power and propulsion conference, 2009. VPPC '09. IEEE; 2009. p. 335–9.

[18] Chen Z, Zhang X, Mi CC. Slide mode and fuzzy logic based powertrain controller for the energy management and battery lifetime extension of series hybrid electric vehicles. J Asian Elect Vehic 2010;8:1425–32.

[19] Park J, Chen Z, Kiliaris L, Kuang ML, Masrur MA, Phillips AM, et al. Intelligent vehicle power control based on machine learning of optimal control parameters and prediction of road type and traffic congestion. IEEE Trans Vehic Technol 2009;58:4741–56.

[20] Zhiguang Z, Mi C, Zheng C, Masrur A, Murphey YL. Power management of passive multi-source hybrid electric vehicle. In: Vehicle Power and Propulsion Conference (VPPC), 2011 IEEE; 2011, p. 1–4.

[21] Han J, Park Y, Kum D. Optimal adaptation of equivalent factor of equivalent consumption minimization strategy for fuel cell hybrid electric vehicles under active state inequality constraints. J Power Sources 2014.

[22] Ansarey M, Shariat Panahi M, Ziarati H, Mahjoob M. Optimal energy management in a dual-storage fuel-cell hybrid vehicle using multi-dimensional dynamic programming. J Power Sources 2014;250:359–71 [3/15/2014].

[23] Hai Y, Ming K, McGee R. Trip-oriented energy management control strategy for plug-in hybrid electric vehicles. IEEE Trans Control Syst Technol 2014;22:1323–36.

[24] Larsson V, Johannesson mårdh M, Egardt B, Karlsson S. Commuter route optimized energy management of hybrid electric vehicles. IEEE Trans Intell Transp Syst 2014;15:1145–54.

[25] Torres JL, Gonzalez R, Gimenez A, Lopez J. Energy management strategy for plug-in hybrid electric vehicles. A comparative study. Appl Energy 2014;113:816–24 [1/2014].

[26] Tie SF, Tan CW. A review of energy sources and energy management system in electric vehicles. Renew Sustain Energy Rev 2013;20:82–102.

[27] Koot M, Kessels JTBA, de Jager B, Heemels WPMH, Van den Bosch PPJ, Steinbuch M. Energy management strategies for vehicular electric power systems. IEEE Trans Vehic Technol 2005;54:771–82.

[28] Yuan Z, Teng L, Fengchun S, Peng H. Comparative study of dynamic programming and Pontryagin's minimum principle on energy management for a parallel hybrid electric vehicle. Energies 2013;6:2305–18.

[29] Hou C, Ouyang M, Xu L, Wang H. Approximate Pontryagin's minimum principle applied to the energy management of plug-in hybrid electric vehicles. Appl Energy 2014;115:174–89.

[30] Kim N, Cha S, Peng H. Optimal control of hybrid electric vehicles based on Pontryagin's minimum principle. IEEE Trans Control Syst Technol 2011;19:1279–87.

[31] Hou C, Xu L, Wang H, Ouyang M, Peng H. Energy management of plug-in hybrid electric vehicles with unknown trip length. J Franklin Inst 2015;352:500–18.

[32] Chen Z, Mi CC, Xiong R, Xu J, You C. Energy management of a power-split plug-in hybrid electric vehicle based on genetic algorithm and quadratic programming. J Power Sources 2014;248:416–26.

[33] Elbert P, Nuesch T, Ritter A, Murgovski N, Guzzella L. Engine on/off control for the energy management of a serial hybrid electric bus via convex optimization. IEEE Trans Vehic Technol 2014. vol. PP, pp. 1–1.

[34] Han J, Park Y, Kum D. Optimal adaptation of equivalent factor of equivalent consumption minimization strategy for fuel cell hybrid electric vehicles under active state inequality constraints. J Power Sources 2014;267:491–502 [12/1/2014].

[35] Litchy AJ, Nehrir MH. Real-time energy management of an islanded microgrid using multi-objective Particle Swarm Optimization. In: PES general meeting | conference & exposition, 2014 IEEE; 2014. p. 1–5.

[36] Zhang M, Yang Y, Mi CC. Analytical approach for the power management of blended-mode plug-in hybrid electric vehicles. IEEE Trans Vehic Technol 2012;61:1554–66.

[37] Zhang B, Mi CC, Zhang M. Charge-depleting control strategies and fuel optimization of blended-mode plug-in hybrid electric vehicles. IEEE Trans Vehic Technol 2011;60:1516–25.

[38] Huria T, Sanna G, Pede G, Lutzemberger G. Systematic development of series-hybrid bus through modelling. In: Vehicle Power and Propulsion Conference (VPPC), 2010 IEEE; 2010. p. 1–6.

[39] Borhan H, Vahidi A, Phillips AM, Kuang ML, Kolmanovsky IV, Di Cairano S. MPC-based energy management of a power-split hybrid electric vehicle. IEEE Trans Control Syst Technol 2012;20:593–603.

[40] Zhang X, Li C-T, Kum D, Peng H. And: Configuration analysis of power-split hybrid vehicles with a single planetary gear. IEEE Trans Vehic Technol 2012;61:3544–52.

[41] Higuchi N, Sunaga Y, Tanaka M, Shimada H. Development of a new two-motor plug-in hybrid system. SAE Int J Alt Power 2013;2:135–45.

[42] Li SG, Sharkh S, Walsh FC, Zhang C-N. Energy and battery management of a plug-in series hybrid electric vehicle using fuzzy logic. IEEE Trans Vehic Technol 2011;60:3571–85.

[43] Murphey YL, Park J, Chen Z, Kuang ML, Masrur MA, Phillips AM. Intelligent hybrid vehicle power control—Part I: Machine learning of optimal vehicle power. IEEE Trans Vehic Technol 2012;61:3519–30.

[44] Chen Z, Mi CC, Fu Y, Xu J, Gong X. Online battery state of health estimation based on Genetic Algorithm for electric and hybrid vehicle applications. J Power Sources 2013;240:184–92.

[45] Xia B, Chen Z, Mi C, Robert B. External short circuit fault diagnosis for lithium-ion batteries. In: Transportation Electrification Conference and Expo (ITEC), 2014 IEEE; 2014. p. 1–7.

[46] Kim N, Rousseau A, Rask E. Autonomie model validation with test data for 2010 Toyota Prius. Fuel 2012;48:46.

[47] Nemirovski AS, Todd MJ. Interior-point methods for optimization. Acta Numerica 2008;17:191–234.

[48] Mehrotra S. On the implementation of a primal-dual interior point method. SIAM J Optim 1992;2:575–601.

[49] Kim S-J, Koh K, Lustig M, Boyd S, Gorinevsky D. An interior-point method for large-scale l 1-regularized least squares. IEEE J Select Topics Signal Process 2007;1:606–17.

[50] Vaz W, Nandi AKR, Landers RG, Koylu UO. Electric vehicle range prediction for constant speed trip using multi-objective optimization. J Power Sources 2015;275:435–46 [2/1/2015].