



Energy management of a power-split plug-in hybrid electric vehicle based on genetic algorithm and quadratic programming



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HIGHLIGHTS

- Develop an intelligent controller to realize energy management of plug-in hybrid vehicles.
- Use quadratic equations to simulate the relationship between battery current and fuel rate.
- Employ genetic algorithms to optimize power threshold for engine to turn on.
- Use quadratic programming to calculate optimal battery current for engine-on operations.
- Consider the battery state of health to extend the applicability of the proposed algorithm.

ARTICLE INFO

Article history:

Received 18 June 2013

Received in revised form

13 September 2013

Accepted 20 September 2013

Available online 30 September 2013

Keywords:

Fuel-rate

Genetic algorithm (GA)

Plug-in hybrid electric vehicle (PHEV)

Quadratic programming (QP)

State of charge (SOC)

State of health (SOH)

ABSTRACT

This paper introduces an online and intelligent energy management controller to improve the fuel economy of a power-split plug-in hybrid electric vehicle (PHEV). Based on analytic analysis between fuel-rate and battery current at different driveline power and vehicle speed, quadratic equations are applied to simulate the relationship between battery current and vehicle fuel-rate. The power threshold at which engine is turned on is optimized by genetic algorithm (GA) based on vehicle fuel-rate, battery state of charge (SOC) and driveline power demand. The optimal battery current when the engine is on is calculated using quadratic programming (QP) method. The proposed algorithm can control the battery current effectively, which makes the engine work more efficiently and thus reduce the fuel-consumption. Moreover, the controller is still applicable when the battery is unhealthy. Numerical simulations validated the feasibility of the proposed controller.

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1. Introduction

Plug-in hybrid electric vehicles (PHEVs) represent the direction of vehicle development due to excellent fuel economy, environmental advantages and all electric drive capability. They are driven by two main power sources: one or two electric motors and an internal combustion engine (ICE) or fuel cells [1–3]. Compared with conventional hybrid electric vehicles (HEVs), PHEVs are equipped with a larger energy storage system, which can power the vehicle by only using the stored energy charged from the power grid [4]. Due to this issue, it becomes more complicated to manage the energy distribution between the two drive trains for a PHEV.

Generally, the simplest way to manage the energy distribution between the battery and ICE for a PHEV is to first use the electric energy to drive the vehicle until the battery state of charge (SOC) drops to a preset low-threshold, referred to as charge depletion (CD) mode. Usually, this low-threshold of SOC is 30%. During this mode, the engine is not turned on. After that, the vehicle is powered by motors and engine together like a conventional HEV, and the battery SOC maintains at the vicinity of the preset threshold. This mode is the so-called charge sustaining (CS) mode [4]. During this mode, the maximum output power of the battery may be limited due to safety issues and high internal resistance of the battery. Therefore, the CD and CS modes may not save fuel-consumption, as the ICE may not work in the high efficiency region and are only to satisfy the driveline power demand.

Besides the simplified working modes classification for the PHEVs, substantial research efforts have been implemented on the energy management of PHEV and HEV to reduce emissions [5,6],

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improve fuel economy [6–25], and prolong battery life [2,11,12], considering the road patterns [6,17,18,26,27] and battery state of health (SOH) [28]. The algorithms can be classified into three categories: (1). Optimal theory methods including minimum principle [13,14], quadratic programming (QP) [29,30] and dynamic programming (DP) method [8,17,29,31,32]; (2). Intelligent control algorithms such as neural networks (NNs) [8,29,33], and model predictive control methods (MPC) [34,35], fuzzy logic [9,15,16], genetic algorithm method [36], and swarm optimization method [33]; and (3). Analytic methods and rule based methods [3,17]. In Refs. [12], a global optimal CD energy management method was proposed for PHEV using DP method and onboard intelligent transportation system (ITS). The proposed method needs considerable calculation time and computation labor. In Refs. [18], a stochastic DP method to optimize PHEV energy management was proposed considering the fuel and electricity price. The method had the function of predicting road conditions. However, the calculation is too large. A minimum principle based method to optimize the energy management is applied in Refs. [19,20], and it needs a precise model of vehicle powertrain, which is not realistic in a highly nonlinear system. A neural network based framework that combines DP and QP to predict the road pattern and manage the energy between engine and battery was proposed in Refs. [8,29,33]. The algorithm needs to train the NN controller using abundant offline data. It can only be applied to HEV which keeps the SOC to vary with a small range. A fuzzy logic energy-management system of a PHEV [15] is introduced to make a decision on the power split between the battery and the engine. The controller can work effectively and can prevent the battery from over-charging. A novel fuzzy logic based algorithm is applied for a fuel cell HEV [37]. It employed GA to train the membership function adaptively based on the different patterns. It is with a small capacity of battery and the beginning and ending SOC of the battery remains unchanged. In Refs. [34], a nonlinear MPC strategy was utilized to obtain the power split between the engine and the motors for a HEV. An adaptive energy management strategy for a series HEV based on GA optimized maps and the simulation of urban mobility predictor is presented in Ref. [38]. It adopts vehicle communications to identify the road condition online to assist the energy management. Particle swarm optimization based strategy was proposed in Ref. [5] to achieve the optimal design and minimum fuel consumption for a fuel cell HEV. In Refs. [31], a rule-based control strategy for a series hybrid solar vehicle is built via comparison with a GA-based optimization. The GA is regarded as a benchmark to formulate a rule-based on-board strategy. In Refs. [39], an optimal charge patterns is introduced for a PHEV considering the timing and price with which the PHEV is charged from the power grid. An intelligent power strategy for a blended-mode PHEV was proposed in Ref. [17]. It cannot give an optimal solution for the energy management only with simple loss model and powertrain analysis. In Refs. [3], the power management strategy for a blended-mode PHEV was represented by a pair of power parameters, i. e., the power threshold for turning on the engine and the optimum battery power in engine-on operations. The method is not universal for all PHEVs which also include extended-range PHEVs.

Based on the above references, it is necessary to build an intelligent controller which can manage the energy distribution for a PHEV effectively with fast calculation. Now the PHEVs are mostly equipped with GPS, which can supply trip information in detail. Moreover, the battery status, such as SOC, and SOH, can be obtained by the battery management system [28,40]. With consideration of the trip information and battery degradation influence, an optimal energy management controller can be built to realize the energy management effectively. In this paper, the research target is to reduce the fuel consumption of a power-split PHEV. The power-

split PHEV [2,8,9,33] utilizes a planetary gear set to connect two motors/generators and an engine. The engine can power the vehicle directly and can drive one motor to charge the battery. The two motors can also drive the vehicle directly. The powertrain of the power-split PHEV has two degrees of freedom which is the same with the powertrain of a series PHEV. But for a series PHEV, the engine cannot drive the vehicle directly. Confidently, the algorithm developed for the energy management of the power split PHEV can also be applied for that of a series or parallel PHEV. Based on the detailed analysis of the powertrain structure of the PHEV, a simplified model which can describe the powertrain characteristics is employed to simulate the engine fuel-rate with regard to different battery current. It is important to determine the power threshold at which the engine is turned on and determine the battery current when the engine is on for a certain trip. In this paper, genetic algorithm (GA) is applied to find the optimal engine-on power, and the QP method is employed to calculate the battery current when the engine is on. The proposed method is effective to improve fuel economy through variety of simulations. Besides, battery SOH is also considered to increase the applicability of the proposed algorithm.

2. Vehicle driveline power and powertrain analysis

The objective of this paper is to optimize the fuel-consumption of a power-split PHEV over a certain trip,

$$\min F = \min \sum_{t=0}^{t_{on}} m_f(t) \quad (1)$$

$$m_f = f(T_e, w_e) \quad (2)$$

where F is total fuel-consumption, t_{on} is the engine-on time and is less than the total trip duration, m_f is the fuel-rate determined by engine speed w_e and engine torque T_e , and f is a high nonlinear function calculating the fuel-rate. In order to minimize F , it is necessary to analyze the vehicle powertrain structure and the vehicle power demand in detail to find what influences the fuel-consumption.

2.1. Vehicle power demand and analysis

The distribution of vehicle driveline power [3] in a general trip with zero beginning and zero ending speed is shown in Fig. 1, in which the whole driveline power can be modeled as a Cauchy distribution limited by the minimum and maximum powers, as shown in Fig. 2.

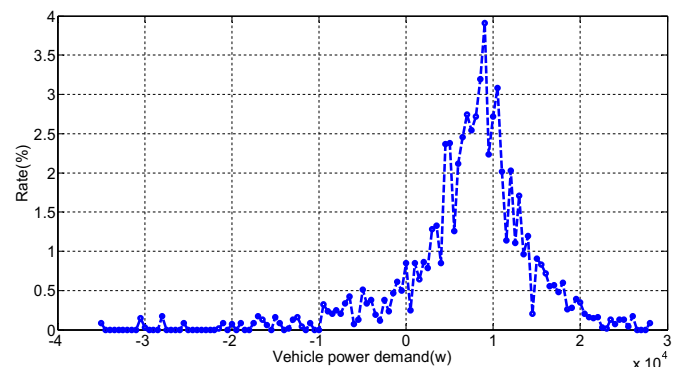


Fig. 1. The vehicle driveline power.

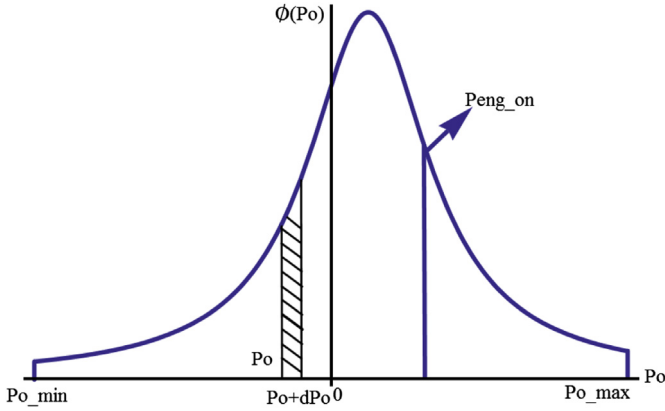


Fig. 2. Idealized vehicle driveline power distribution.

Suppose the total trip duration is t_{total} , and the power threshold at which the engine is turned on is P_{eng_on} , as shown in Fig. 2. It means that when the driveline power is less than P_{eng_on} , the vehicle is powered by the battery only, and when the driveline power is more than P_{eng_on} , the engine will be turned on and the vehicle is powered by the engine and battery together. Now, we can easily get,

$$\begin{cases} \int_{P_{o_min}}^{P_{eng_on}} \Phi(P_o) dP_o = t_{off} & \text{Engine off} \\ \int_{P_{eng_on}}^{P_{o_max}} \Phi(P_o) dP_o = t_{on} & \text{Engine on} \\ t_{off} + t_{on} = t_{total} \end{cases} \quad (3)$$

where P_o is the driveline power, $\Phi(P_o)$ represents the ratio of a whole trip duration when the driveline power is within the interval P_o and $P_o + dP_o$, P_{o_min} and P_{o_max} are the minimum and maximum driveline power, t_{off} and t_{on} are the engine off and on duration respectively. From this point, how to determine the optimal P_{eng_on} becomes very critical, which can influence the engine-on time and thus influence the fuel-consumption. Based on Eq. (3), we can get,

$$\begin{cases} \Delta_1 = \int_{P_{min}}^{P_{eng_on}} I(P_o) \Phi(P_o) dP_o \\ \Delta_2 = \int_{P_{eng_on}}^{P_{max}} I(P_o) \Phi(P_o) dP_o \\ \Delta_1 + \Delta_2 = C \cdot \Delta SOC \end{cases} \quad (4)$$

where Δ_1 and Δ_2 are the SOC variation when engine is off and on, I is the battery current, C is the battery capacity, ΔSOC is the SOC difference between the ending value and the initial value. In the paper, the ending SOC is set to 30%, so we can get

$$\Delta SOC \in [0 \quad 70\%] \quad (5)$$

According to Eq. (4), P_{eng_on} can determine Δ_1 and Δ_2 , however, it cannot determine the battery current when the engine is on. As shown in Fig. 3, we need to determine the battery current (battery power) when the engine is on.

Based on the above discussion, the fuel-consumption can be influenced by the engine-on power threshold and the battery current when the engine is on. Therefore, the engine-on power threshold should be determined and the relationship between the

engine fuel-rate and battery current should be built. Hence, the vehicle powertrain needs to be analyzed in detail first.

2.2. Vehicle powertrain analysis

The powertrain structure of the power-split PHEV analyzed in the paper is shown in Fig. 4. It consists of a gasoline ICE, a lithium-ion battery pack, two electric motors, and a planetary gear set which connects the motor, engine, and the final driveline together with a predetermined gear ratio [1,2,9]. Table 1 lists the vehicle parameters, and Fig. 4 details the powertrain structure.

From Fig. 4, P_o equals the sum of P_r and P_{mot1} , i.e.,

$$P_o = T_o w_o = P_r + P_{mot1} = T_r w_r + T_{mot1} w_{mot1} \quad (6)$$

where T_r , T_o , and T_{mot1} denote the torque of ring gear of the planetary gear set, driveline, and motor 1, w_r , w_o , and w_{mot1} denote their speeds respectively. We can get

$$\begin{cases} T_o = (T_r + T_{mot1} r_{mot1}) \cdot r_{final} \\ w_{mot1} = w_o / (r_{final} r_{mot1}) \\ w_r = w_o / r_{final} \end{cases} \quad (7)$$

where r_{final} , and r_{mot1} are the gear ratios between driveline and vehicle wheels, motor 1 and driveline, respectively. The planetary gear set consists of a ring gear, a sun gear, and carrier [2,9], which connects driveline, motor 2, and the engine respectively. Neglecting inertia losses and friction, there are two basic equations for torque and speed of the planetary gear set

$$\begin{cases} T_e = (1 + 1/\rho) \cdot T_{mot2} = (1 + \rho) \cdot T_r \\ (1 + \rho) \cdot w_e = \rho \cdot w_{mot2} + w_r \end{cases} \quad (8)$$

where ρ is the ratio between sun gear and ring gear, w_{mot2} , w_e denote the speed of motor 2, engine, and T_{mot2} and T_e are their torques. Based on Eqs. (6)–(8), we can calculate T_e further

$$\begin{aligned} T_e &= \frac{T_o - T_{mot1}}{1 + \rho} \\ &= \frac{T_o - P_{mot1} / (r_{final} w_o)}{1 + \rho} \\ &= \frac{T_o - (P_b - P_a - P_{mot2}) \cdot \eta_{mot1} / (r_{final} w_o)}{1 + \rho} \\ &= \frac{T_o - (P_b - P_a - T_{mot2} w_{mot2} / \eta_{mot2}) \cdot \eta_{mot1} / (r_{final} w_o)}{1 + \rho} \\ &= \frac{1}{1 + \rho} \cdot \left[T_o - \left(P_b - P_a - \frac{T_e \cdot ((1 + \rho) \cdot w_e - r_{final} w_o)}{\eta_{mot2} (\rho + 1)} \right) \cdot \eta_{mot1} / (r_{final} w_o) \right] \\ &= \frac{1}{1 + \rho} \cdot \frac{T_o - (P_b - P_a) \cdot \eta_{mot1}}{r_{final} w_o} + \frac{1}{(1 + \rho)^2} \cdot \frac{((1 + \rho) \cdot w_e - r_{final} w_o) \cdot \eta_{mot1}}{r_{final} w_o} \cdot T_e \end{aligned} \quad (9)$$

where η_{mot1} and η_{mot2} represent efficiencies of motor 1 and motor 2. Solving Eq. (9), we can get

$$T_e = \frac{\frac{1}{1 + \rho} \cdot \frac{T_o - (P_b - P_a) \cdot \eta_{mot1}}{r_{final} w_o}}{1 - \frac{1}{(1 + \rho)^2} \cdot \frac{((1 + \rho) \cdot w_e - r_{final} w_o) \cdot \eta_{mot1}}{r_{final} w_o}} = g(T_o, P_b, w_o, w_e) \quad (10)$$

From Eq. (10), T_e can be determined by P_b , T_o , w_o , and w_e . P_b can be approximately calculated using battery open circuit voltage V_{ocv} , battery current I , and battery internal resistance R [8],

$$P_b = V_{ocv} I + I^2 R \quad (11)$$

Hence, according to Eqs. (10) and (11), Eq. (2) can be changed to

$$m_f = f(T_e, w_e) = f_{new}(T_o, w_o, I, w_e) \quad (12)$$

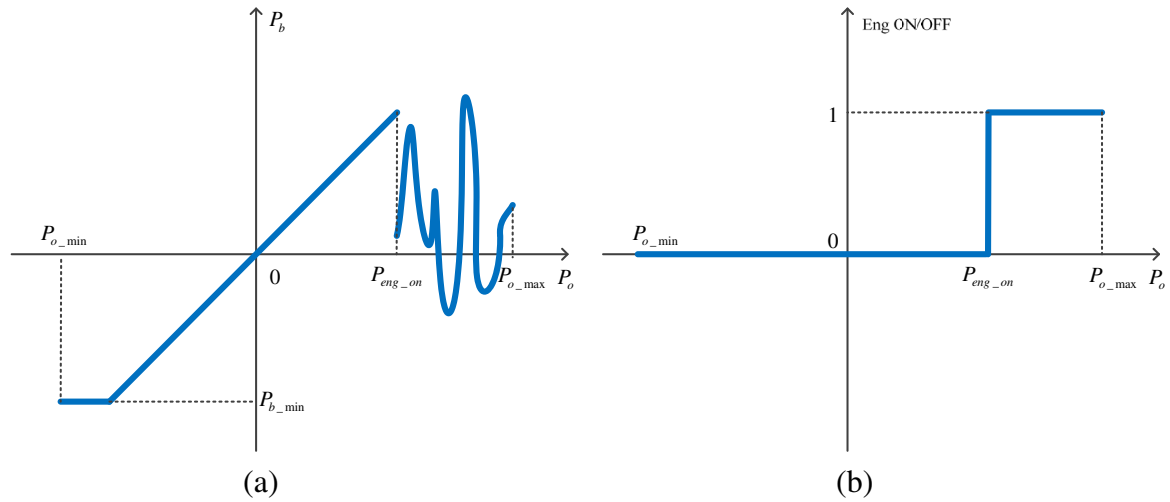


Fig. 3. Battery power and engine on/off command, (a) battery power; (b) engine on/off command, where P_b is the battery power, P_{b_min} is the minimum battery power.

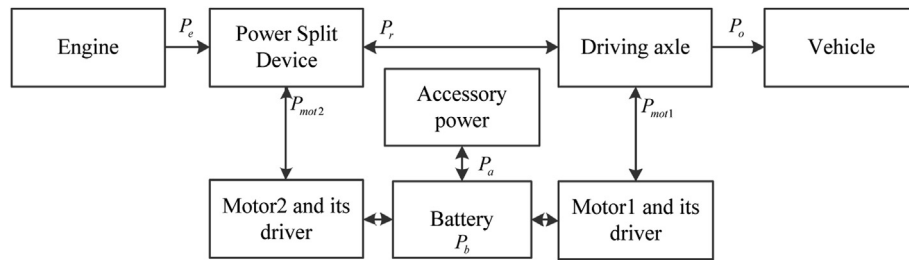


Fig. 4. Power-split PHEV powertrain, where P_e is the engine power, P_r is the ring power in the planter gear set, P_a is the accessory power, P_{mot2} is the motor 2 power, P_{mot1} is the motor 1 power.

Now we can see that engine speed w_e , battery current I , driveline power P_o and vehicle speed w_o can influence the fuel-rate. No doubt, it is a highly nonlinear system and not realistic to get a numerical solution based on Eqs. (6)–(12). We introduce quadratic equations to simulate them at different driveline power and vehicle speed.

3. Quadratic programming application

From Eq. (12), P_o and w_o are the driving demand and cannot be changed, only w_e and I can be optimized to minimize the fuel-consumption for a given trip. Obviously, the powertrain is with two degrees of freedom, which brings a lot of calculation and difficulty to optimize the fuel fate. Here, a method is proposed to convert the problem into a one degree of freedom problem. By analyzing the engine efficiency map, we can find the optimal operating efficiency point at different engine power. That is to say, the optimal engine speed w_e at which the engine works most efficiently can be determined. It indicates that the engine can only work most efficiently at different power levels, and the fuel-rate can only be determined by engine torque T_e . Fig. 5 shows the optimal engine speed w_e with regard to different engine power P_e . Therefore, we can easily find the relationship between w_e and T_e ,

$$w_e = g_1(T_e) \quad (13)$$

Now based on Eqs. (6)–(13), we can solve the fuel-rate based on I , P_o and w_o . The calculation process includes some nonlinear efficiency coefficients, such as η_{mot1} , η_{mot2} , and fuel-rate function f . In order to simplify the problem without influencing the control

performance for the PHEV, the quadratic equations are employed to fit the relationship between battery current and fuel-rate at different P_o and w_o , as shown in Eq. (14). It is worth mentioning that we adopt the average values of the battery open circuit voltage, internal resistance and the motors' efficiencies when identifying the quadratic equations' parameters.

$$m_f = f(T_e, w_e) = \varphi_2(w_o, P_o) \cdot I^2 + \varphi_1(w_o, P_o) \cdot I + \varphi_0(w_o, P_o) \quad (14)$$

where $\varphi_0(w_o, P_o)$, $\varphi_1(w_o, P_o)$, and $\varphi_2(w_o, P_o)$ are coefficients at different w_o and P_o , and are shown in Fig. 6. We can see from Fig. 6 that $\varphi_2(w_o, P_o)$ is larger than zero at any power and vehicle speed. Fig. 7 shows some curves at different driveline power and vehicle speed which confirms that the quadratic equations can describe the relationship between fuel-rate and battery current effectively.

Table 1
Vehicle parameters.

Vehicle type	Plug-in split HEV
Vehicle mass	1641.3 kg
Engine power	57 kW
Motor power	25 kW, peak power 50 kW
Generator power	15 kW, peak power 30 kW
Planetary gear set	Sun gear 30 Ring gear 78
Battery	Lithium-ion battery Rated capacity 20 Ah Rated voltage 356 V

Based on Eqs. (1), (2), and (14), we can get,

$$F = \sum_{t=0}^{t_{on}} m_f(t, v) = \sum_{t=0}^{t_{on}} \varphi_2(t) \cdot I(t)^2 + \varphi_1(t) \cdot I(t) + \varphi_0(t). \quad (15)$$

According to Eq. (4), there also exists a constraint,

$$\sum_{t=0}^{t_{on}} I(t) = \Delta_2 \cdot C \quad (16)$$

Now the minimization of fuel-consumption becomes a typical QP problem. Adjoining Eq. (16) and applying the Lagrange method,

$$H(I(t), \lambda) = \sum_{t=0}^{t_{on}} \varphi_2(t) \cdot I(t)^2 + \varphi_1(t) \cdot I(t) + \varphi_0(t) - \lambda \cdot \left(\sum_{t=0}^{t_{on}} I(t) - \Delta_2 \cdot C \right) \quad (17)$$

Take the partial derivative of H with respect to $I(t)$ and λ ,

$$\frac{\partial H}{\partial I(t)} = 0, \quad \frac{\partial H}{\partial \lambda} = 0 \quad (18)$$

Solving Eq. (18), we can get

$$\begin{cases} \frac{\partial H}{\partial I(t)} = 2 \sum_{t=0}^{t_{on}} \varphi_2(t) I(t) + \sum_{t=0}^{t_{on}} (\varphi_1(t) - \lambda) = 0 \\ \frac{\partial H}{\partial \lambda} = \sum_{t=0}^{t_{on}} I(t) - \Delta_2 \cdot C = 0 \end{cases} \quad (19)$$

Then $I(t)$ and λ can be calculated,

$$\begin{cases} \lambda = \frac{\Delta_2 \cdot C + \sum_{t=0}^{t_{on}} \frac{\varphi_1(t)}{2\varphi_2(t)}}{\sum_{t=0}^{t_{on}} \frac{1}{2\varphi_2(t)}} \\ I(t) = \frac{\lambda - \varphi_1(t)}{2\varphi_2(t)} = \frac{\Delta_2 \cdot C + \sum_{t=0}^{t_{on}} \frac{\varphi_1(t)}{2\varphi_2(t)} - \varphi_1(t) \sum_{t=0}^{t_{on}} \frac{1}{2\varphi_2(t)}}{2\varphi_2(t) \sum_{t=0}^{t_{on}} \frac{1}{2\varphi_2(t)}} \end{cases} \quad (20)$$

As $\varphi_2(t)$ is always larger than zero, the fuel-consumption calculated using $I(t)$ in Eq. (20) is the minimum value. Now the optimal current $I(t)$ when the engine is on is obtained. By applying the calculated current command when the engine is on, the fuel-consumption can be minimized. Next step, we need to find the optimal power threshold at which the engine is turned on.

4. Engine on/off power calculation

From Eqs. (3), (4), and (20), P_{eng_on} affects t_{on} , t_{off} , Δ_1 , and Δ_2 and determines the battery current command when the engine is on. So it influences the fuel-rate. Thus, in order to save fuel-consumption, it is necessary to find an optimal P_{eng_on} value which can minimize the fuel-consumption for a certain trip. From Fig. 1, the power demand is highly stochastic, and it is difficult to obtain optimal P_{eng_on} by analytic methods. In this paper, GA is introduced to find the optimal P_{eng_on} through a series of actions including encoding, selection, mutation and crossover [21–23,32,36,41].

GA has been successfully applied in the multi objective optimization of HEV fuel economy and emissions [5,41], and has been introduced to identify the battery SOH in real time for electric vehicles [36]. Typically, GA consists of selection, encoding, mutation and crossover. During each generation, some of the current

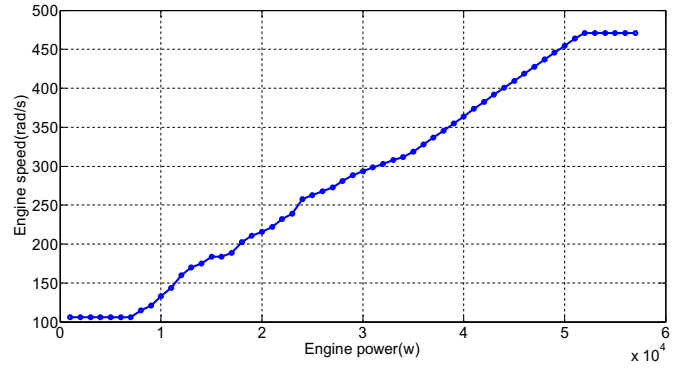


Fig. 5. The optimal speed profile at different engine power output.

population is selected to generate the next offspring, and some of the existing population is regarded as the elitists and selected as the next offspring directly without any change. During the crossover process, the chromosome of the parent is hybridized to generate the new offspring, and during the mutation process, some bits in the chromosome are mutated randomly or uniformly. The main function of mutation process is to avoid falling all solutions into a regional optimum of the solved problem. Finally, the next generation population of chromosomes which is different from the previous one is generated by the above processes. This generational process is iterated until a termination condition is reached. Common terminating conditions are:

- The GA finds the solution which can satisfy the minimum criteria
- The GA outputs satisfy the setting fitness value
- The GA evolution time exceeds the budget time or the number of evolution generations reach the maximum allowable amount

Fig. 8 presents the whole process to calculate the engine-on power and to calculate the battery current to minimize the fuel consumption. The whole process will first choose the initial engine-on power threshold randomly within the constraints of the engine maximum and minimum power, then based on the power threshold, the current commands can be generated when the engine is on using the Lagrange method, the fitness function will calculate the fuel-consumption and the battery energy consumption. In the next step, based on the fitness value, the GA is applied to generate the new engine-on power threshold through a series of elitist selection, crossover, and mutation. Based on the new engine-on power, the battery current command can be calculated and the fuel consumption can be obtained then. If the ending condition is not met, another GA calculation will be applied again until the ending condition is satisfied. Finally, the controller will output engine-on power threshold and the battery current command when the engine is on. The convergence of GA has been proved in Refs. [23,42], in which we can see that GA can reach any state through a series of mutation, crossover and selection. If the elitist individual can be selected, the convergence to the optimum value can be assured, and thus the algorithm can finally converge to the optimal value. In this paper, we only have one variable, i.e., engine-on power to optimize. By varieties of simulations, the population, the elitist amount and the mutation rate are set to 6, 1, and 0.05 respectively, which ensure that the algorithm can obtain the optimal or quasi-optimal engine-on power theoretically. The following simulations also proved that the algorithm is effective to find an appropriate engine-on power to manage the energy distribution.

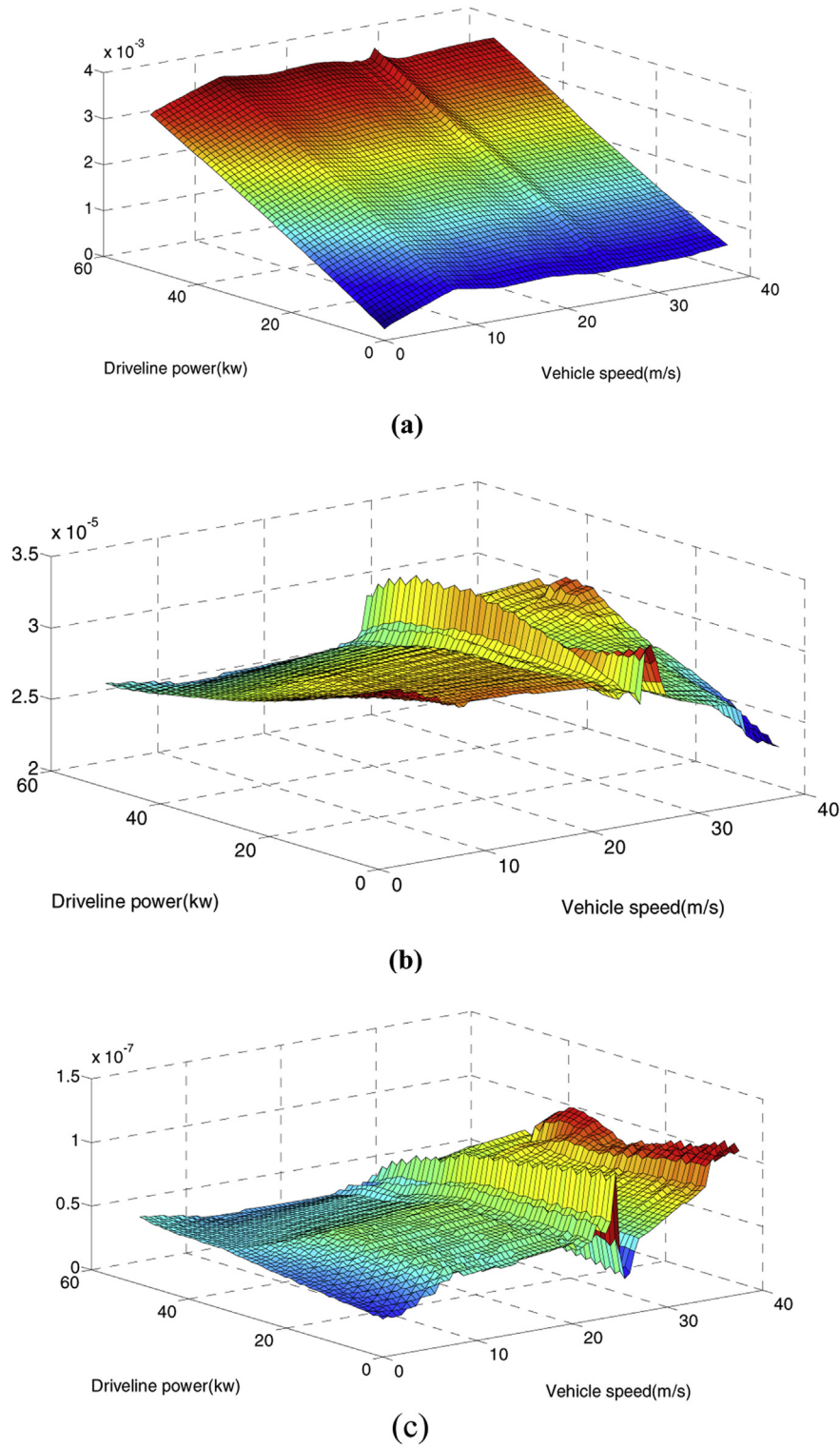


Fig. 6. Coefficients. (a) $\phi_0(w, P_o)$. (b) $\phi_1(w, P_o)$. (c) $\phi_2(w, P_o)$.

In this paper, the target is to minimize the fuel-consumption with the ending SOC of 30%. When the ending SOC is not 30%, the SOC correction method [3,17,29] will be applied to calculate the equivalent fuel-consumption to compensate the SOC difference. We introduce the linear regression method to ensure that the initial and final SOC are the same. Linear fitting method was applied to obtain fuel-consumption and corrected with SOC.

The process is realized in Matlab and Autonomie. Matlab [24] is a high-level and powerful language for numerical computation, simulation and programming. It can be used to analyze numerical data, develop intelligent algorithms, and build mathematical models. Autonomie [25] is a Matlab-based software environment and framework for automotive control system design, simulation and analysis. During the calculation

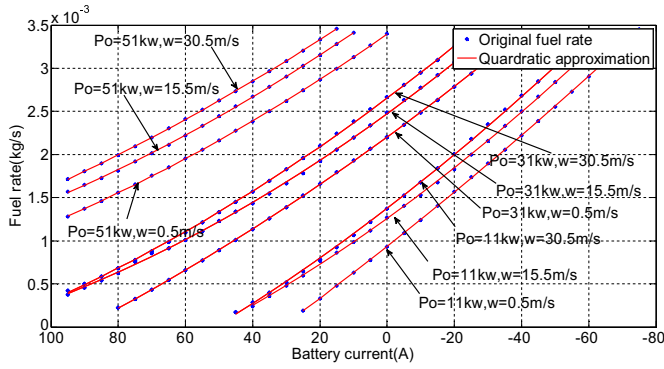


Fig. 7. Fuel-rate approximation.

process, some constraints should be satisfied, as shown in Eq. (21).

$$\begin{cases} 0 < P_{eng_on} < \min(P_{eng_max}, P_{o_max}) \\ I_{bmin}(t) < I_b(t) < I_{bmax}(t) \\ 0 < \Delta SOC < SOC_0 - 0.3 \end{cases} \quad (21)$$

where P_{eng_max} and P_{o_max} are the maximum engine power and maximum driveline power, $I_{bmin}(t)$ and $I_{bmax}(t)$ are the minimum allowed battery current and maximum battery current when the engine is on. Generally, $I_{bmin}(t)$ is calculated when the vehicle is driven by battery only, and $I_{bmax}(t)$ is the maximum battery current which can be calculated by the difference of driveline power and maximum engine power. SOC_0 is the initial battery SOC.

5. Results validation

Abundant simulations are applied to validate the proposed algorithm, which includes some typical drive cycles simulations. Based on Eqs. (16) and (20), the proposed method can be applicable only if the battery available capacity is known. It means that the proposed method can still be feasible when the battery is unhealthy, i.e., the battery capacity drops. Therefore, the whole validation can be divided into two parts: (1). Drive cycle simulation with healthy battery. (2). Drive cycle simulation with unhealthy battery.

5.1. Drive cycle simulation with healthy battery

We applied two typical drive cycles, Urban Dynamometer Driving Schedule (UDDS) drive cycle, and Highway Fuel Economy Driving Schedule (HWFET) drive cycle, to simulate and evaluate the

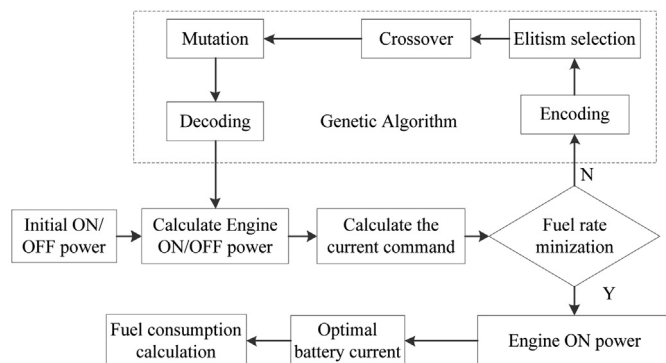


Fig. 8. The fuel-rate optimization process.

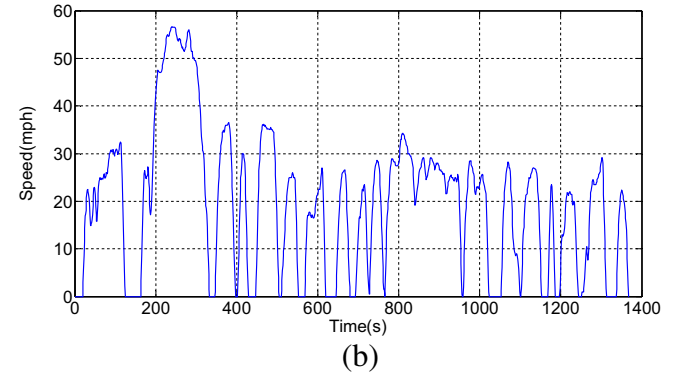
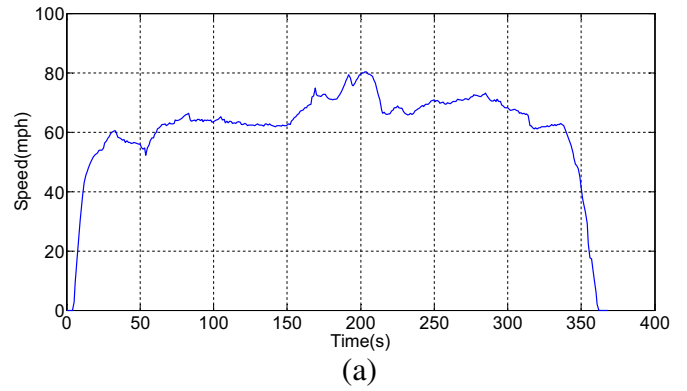


Fig. 9. Highway and urban drive cycles. (a) HWFET drive cycle. (b) UDDS drive cycle.

performance of the proposed algorithm. UDDS, also called “LA4” or “the city test”, represents city driving conditions. HWFET drive cycle represents the highway driving conditions. Their speed profiles are shown in Fig. 9.

In order to compare the performance of the proposed algorithm, the default algorithm, namely, the CD/CS method were applied to

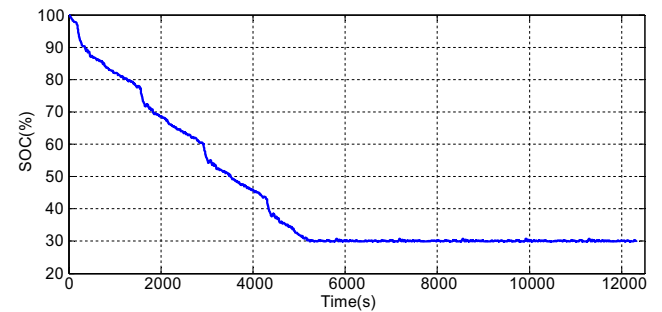


Fig. 10. Battery SOC variation and Engine fuel-rate.

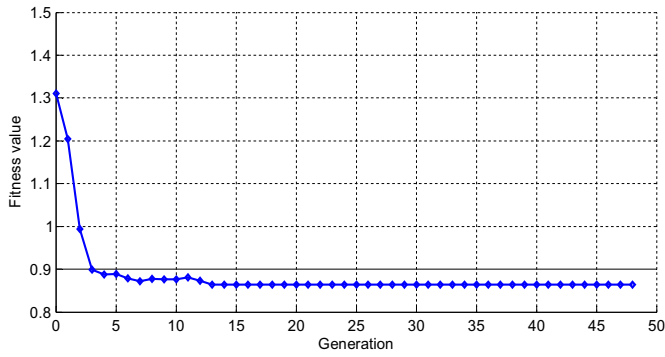


Fig. 11. The evolution of GA.

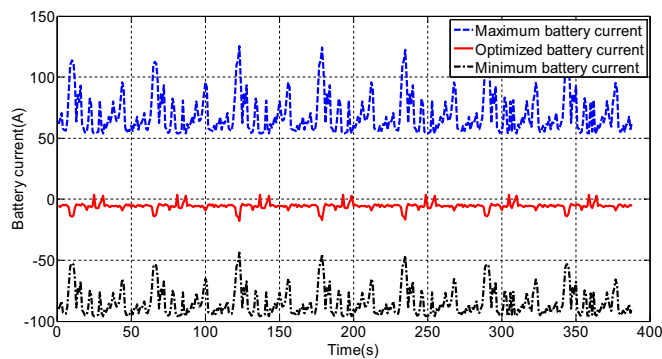


Fig. 12. Battery optimal current when engine is on.

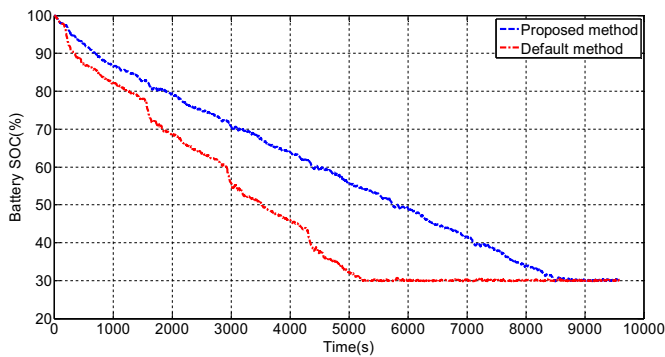


Fig. 13. SOC comparison.

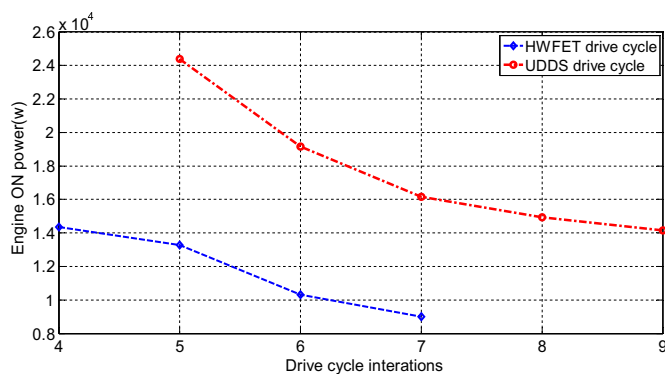


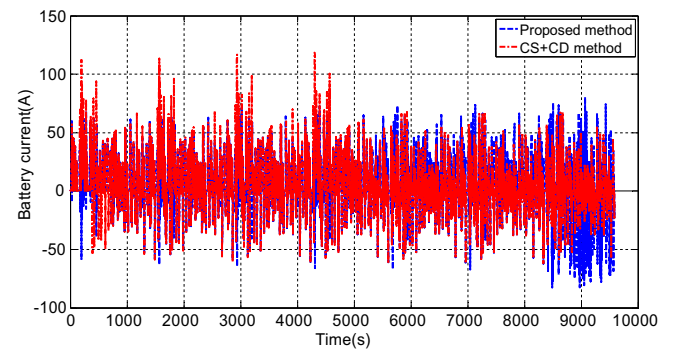
Fig. 14. Engine-on power threshold for different drive cycles.

Table 2
Fuel-consumption comparison.

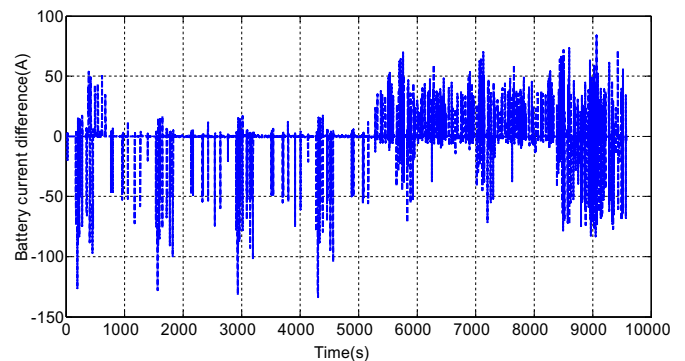
Drive cycle	Default algorithm		Proposed algorithm		Savings(%) (SOC corrected)
	Fuel-consumption (kg)	Ending SOC (%)	Fuel-consumption (kg)	Ending SOC (%)	
5 UDDS	0.315	30.17	0.307	30.23	2.90
6 UDDS	0.668	29.79	0.599	30.23	11.57
7 UDDS	0.927	29.90	0.870	30.23	6.82
8 UDDS	1.183	29.81	1.122	30.19	5.76
9 UDDS	1.450	30.17	1.400	30.19	3.47
4 HWFET	0.756	29.93	0.703	30.99	9.66
5 HWFET	1.200	29.94	1.152	31.04	5.73
6 HWFET	1.645	29.95	1.586	30.95	4.74
7 HWFET	2.090	29.94	2.024	30.97	4.09

get the fuel-consumption under different drive cycles. The initial battery SOC is set to 100%. Fig. 10 shows the battery SOC variation and the engine fuel rates under UDDS driving cycle test. Before 5300s, the engine is off and the vehicle is powered by the battery and motors. When the battery SOC decreases to 30%, the engine starts and the vehicle works in CS mode, and the battery SOC maintains at the vicinity of 30%.

Fig. 11 shows the evolutions of GA, where we can see that after 48 generations, the evolution terminates and the fitness value, i.e., the fuel-consumption is 0.864. The optimal engine-on power threshold calculated by GA is 16.336 kW, and the optimal battery current when the engine is on is shown in Fig. 12, which also shows the maximum and minimum current constraints when the engine is on. We can see that the optimized current is within their constraints. Fig. 13 compares the SOC variation based on CD/CS method and the proposed method. The SOC drops slower when the



(a)



(b)

Fig. 15. Battery current comparison. (a) Based on CD/CS algorithm. (b) Based on the proposed controller.

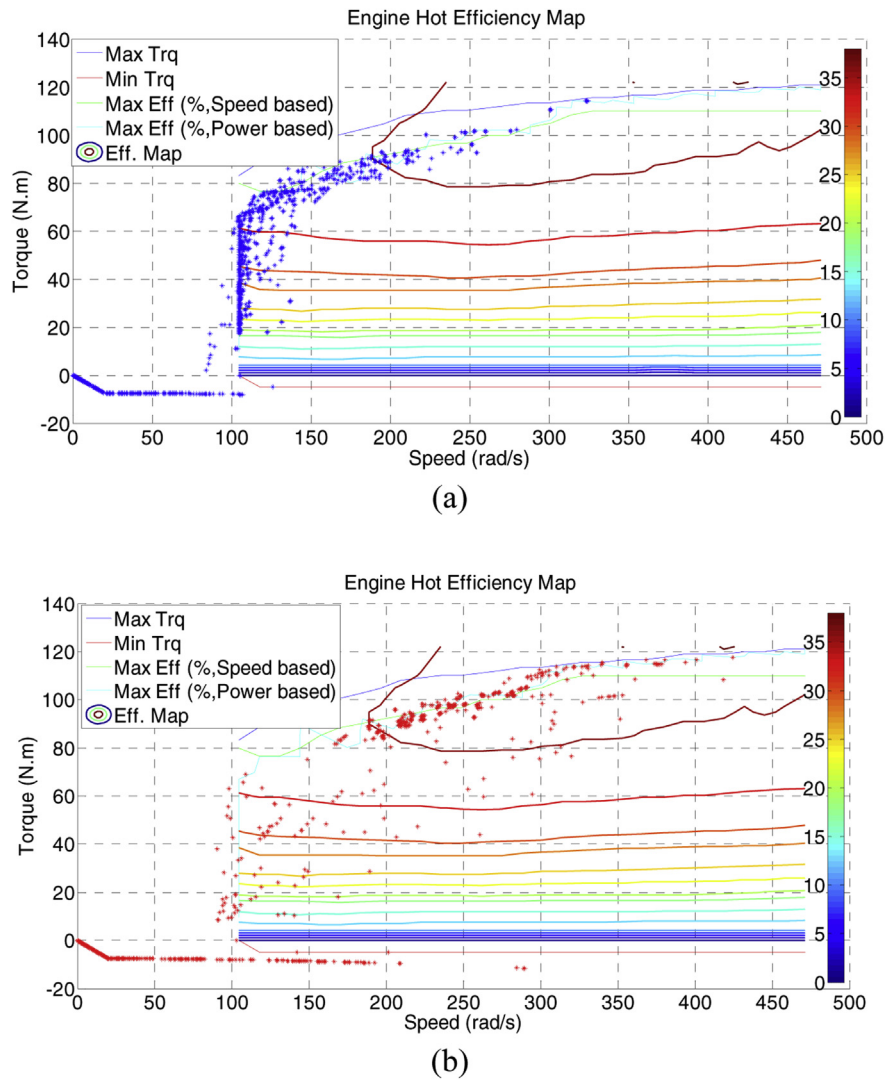


Fig. 16. Engine operating efficiency map. (a) Based on CD/CS algorithm. (b) Based on the proposed controller.

proposed method is applied than that when the CD/CS algorithm is applied. The calculation can be finished within 3 min using a laptop with CPU core i7 and 4G RAM when 48 iterations of GA are applied and the population, the elitist amount and the mutation rate are set to 6, 1, and 0.05, respectively. Based on the proposed algorithm, P_{eng_on} under different consecutive UDDS and HWFET cycles is

shown in Fig. 14. P_{eng_on} are 24.39 kW, 19.15 kW, 16.16 kW, 14.93 kW and 14.15 kW when five to nine consecutive UDDS drive cycles are simulated, and are 14.36 kW, 13.27 kW, 10.32 kW and 8.99 kW when four to seven consecutive HWFET drive cycles are simulated. It can be seen that P_{eng_on} decreases as the driving distance becomes longer.

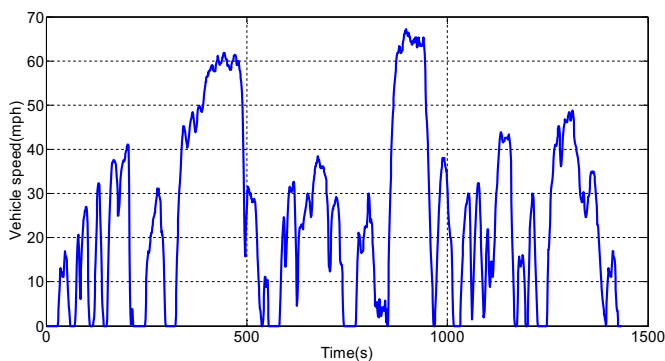


Fig. 17. LA92 drive cycle.

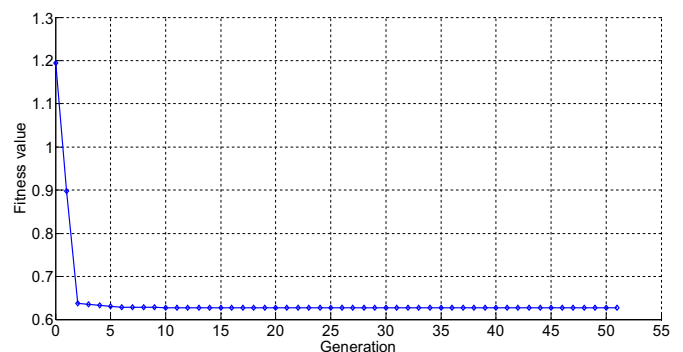


Fig. 18. LA92 battery current command when engine is on.

Table 3
Fuel-consumption comparison.

Drive cycle	Default algorithm		Proposed algorithm		Savings(%) (SOC corrected)
	Fuel-consumption (kg)	Ending SOC (%)	Fuel-consumption (kg)	Ending SOC (%)	
3 LA92	0.685	30.52	0.607	30.33	10.75
4 LA92	1.172	30.74	1.055	30.54	9.64
5 LA92	1.660	30.92	1.551	30.32	5.84

Based on the proposed method, the final fuel-consumption and the ending SOC under different drive cycles are presented in Table 2. It is necessary to use the SOC correction method [3,17,29], which is already explained in Section 4, to update the fuel-consumption in order to compare the fuel saving at the same SOC. From Table 2, it can be seen that when compared with the default CD/CS method with SOC corrected, the fuel savings are 2.90%, 11.57%, 6.82%, 5.76%, and 3.47% when the proposed method is applied under five to nine consecutive UDDS drive cycles, and are 9.66%, 5.73%, 4.74%, and 4.09% when running under four to seven HWFET drive cycles. The fuel-consumption based on the proposed method is 0.870 kg, which is also very near the output of GA algorithm, as shown in Fig. 11. This way, we can prove that the proposed method as well as the quadratic equations can control and simulate the vehicle effectively.

Fig. 15 compares the battery current when the different algorithms are applied under seven consecutive UDDS drive cycles. With the CD/CS algorithm, the battery is discharged more quickly than that with the proposed method. Fig. 16 compares the engine efficiencies based on different algorithms. It can be seen that when the proposed method is applied, the engine average efficiency is higher than that when the default algorithm is applied. To some extent, the comparisons can explain why the proposed method can save fuel-consumption.

5.2. Drive cycle simulation with degraded battery

The original battery capacity is 20 Ah. In order to simulate the performance when the battery is degraded, we set the battery capacity to 16 Ah. To simplify the problem, we assume the battery internal resistance and battery open circuit voltage are unchanged. LA92 drive cycle, whose speed profile is shown in Fig. 17, is applied to simulate and validate the performance of the controller. Fig. 18 shows the evolutions of GA, where we can see that after 51 generations, the evolution terminates. The optimal engine-on power threshold is 31.94 kW. Based on the proposed algorithm, the engine-on power threshold for three and four consecutive LA92 drive cycles is 27.90 kW and 20.05 kW, respectively. As presented in

Table 3, using the proposed algorithm, the fuel consumption can be reduced by 10.78%, 9.64%, and 5.84% with SOC correction included.

Fig. 19 shows the battery SOC when applying different control algorithms, and the SOC drops slower when the proposed algorithm is applied than that when the CD/CS algorithm is applied. Thus it proves that even the battery is degraded, the proposed algorithm is still feasible to manage the energy distribution and save fuel-consumption for the PHEV.

6. Conclusion

An effective online intelligent energy control controller based on GA and QP method has been built to improve the fuel economy of a power-split PHEV. GA is applied to find the optimal engine-on power threshold, and QP method is introduced to obtain the optimal battery current with fast speed based on the calculated engine-on power threshold. The simulation results show the proposed controller can improve the fuel economy. Besides, the proposed algorithm is also applicable when the battery is degraded. Given the battery SOH in advance, it can still effectively improve the fuel economy.

In this paper, without the trip information, the proposed algorithm cannot be applied, and it still needs some time to calculate the engine-on power threshold by GA. Our future work can be carried out to consider the above issues to improve the performance of the proposed controller.

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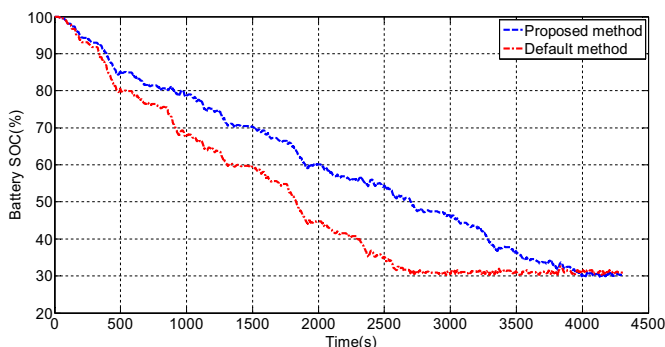


Fig. 19. Battery SOC comparison.

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