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

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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.

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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.

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

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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].

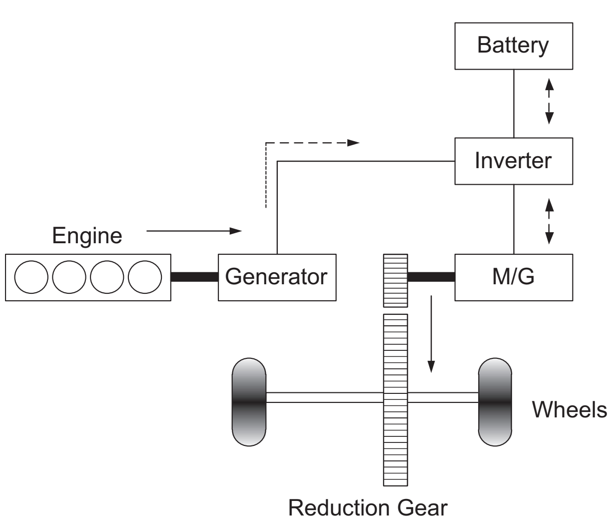

Fig. 1. Powertrain structure of a series plug-in HEV.

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