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Design and analysis of power management strategy for range extended electric vehicle using dynamic programming

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HIGHLIGHTS

- Two-point boundary DP problem formulated for RE–EV under charge depleting operation.
- Analysis of power management strategy with different design criteria for RE–EV.
- A rule-based multi-mode switch strategy with rule-extraction phase of DP.
- A driving pattern recognition technique with seven representative driving patterns.
- A power management strategy for RE–EV improving fuel economy and battery protection.

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ABSTRACT

This paper describes a systematic procedure, which includes analysis of strategy design criteria and development of real-time implementable strategy, to investigate the power management strategy for a range extended electric vehicle (RE–EV) using dynamic programming (DP). Since battery life is an important factor in replacement costs, battery energy losses are treated as one design criterion for battery protection. Fuel energy losses are another design criterion to address fuel economy. These two design criteria are expressed as two different cost functions for DP to evaluate both fuel-energy-loss-oriented and battery-energy-loss-oriented power management strategies. Considering driver comfort and battery life, limitations of noise, vibration, harshness, and battery charging/discharging currents are expressed as constraints in the DP process. Analysis results show that the fuel-energy-loss-oriented strategy can have better fuel economy, but its higher battery energy losses and average charging/discharging currents are unfavorable for battery life. On the contrary, battery-energy-loss-oriented strategy sacrifices some fuel economy in exchange for benefits to battery life. A rule-based, multi-mode switch strategy is then proposed as a power management strategy for RE–EV, which can require lower computation efforts. The proposed strategy employs a driving pattern recognition technique of switching among the control rule sets extracted from DP results of each representative driving pattern. Simulation results using three untrained driving patterns show that the proposed strategy improves the control performance of fuel economy and battery protection compared to that of conventional thermostat control strategy.

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1. Introduction

Due to the trend in increasingly stringent emission regulations, many automobile manufacturers have begun to develop electric vehicles (EVs) and hybrid electric vehicles (HEVs). However, EV's disadvantages on traveling distance and battery life cycle are still an obstacle to its development. In order to overcome this drawback, the range extended electric vehicle (RE–EV) seems to be the most promising short-term solution.

The range extender consists of an engine and a generator, i.e. genset, which could provide extra electric power for charging the battery, thus extending the traveling distance of RE–EV [1,2]. The genset can also provide additional electric power to assist the battery to satisfy large transient power demand from the electric motor [3]. In other words, the genset has a potential to increase battery life by reducing the average discharging current [4,5].

Because RE–EV could obtain the electric power from genset and electric power grid, it is classified as a plug-in series hybrid electric vehicle (P-SHEV) [6]. Many power management strategies for HEV have been proposed which mainly focused on optimizing fuel economy, i.e. fuel energy. These power management strategies can be classified into two categories, rule-based and optimization-based strategies. For the simplification of real-time

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implementation, some studies utilized rule-based approaches to design power management strategies [7–13]. Conventionally, the RE–EV can be operated in purely electric mode at the beginning of a route. When the battery state of charge (SOC) is below a threshold value, the RE–EV will be operated in the charge sustaining mode. Thermostat control strategy (TCS) can be employed to turn on/off the genset for keeping the battery SOC at a certain level [7,8]. Several power follower control strategy [9–11] for series hybrid electric vehicle were proposed to view the genset as the main electric power source to satisfy the power demand from the motor. Some studies [12–13] utilized the fuzzy logic to establish a rule-based power management strategy for the nonlinear time-varying P-SHEV. Although the rule-based algorithms are simple to implement for real-time control, engineering intuition or trial-and-error often takes time to achieve satisfactory performance of RE–EV.

Some studies used optimization-based approaches to design the power management strategy for HEV, such as equivalent consumption minimization strategy (ECMS) [14,15], equivalent fuel consumption control strategy (EFCOCS) [16] and dynamic programming (DP). The DP is a horizon optimization method which guarantees to obtain a global optimal power management strategy for HEV over a defined time horizon if the associated driving cycle is known in advance. Therefore, the DP results can be viewed as the performance upper bound for developing power management strategies [11,17]. In contrast, instantaneous optimization methods such as ECMS and EFCOCS cannot guarantee the global optimality over the horizon, but it may result in near-optimal performance. Using DP, Karbowski et al. [18] pointed out that battery energy losses can be reduced while the plug-in HEV is operated under charge depleting (CD) mode in which the lower SOC value is reached only at the end of a route. In addition, the time duration at low battery SOC can be reduced for CD mode operation, which can benefit battery life [4]. Since battery life depends on the total energy throughput that the active chemicals can tolerate, it deteriorates rapidly if the battery always works at low SOC. Although DP results are noncausal and not implementable in real-time, Lin et al. [19] and Wu et al. [20] extracted control rules by observing DP behaviors. With rule design reference, these control rules are evidently found to have good control performance and can be implemented for real-time control.

The off-board recharging capability of RE–EV allows the battery energy can be depleted for less fuel consumption. When the battery SOC is depleted gradually, different battery SOC values result in different battery energy conversion efficiencies. Along with higher battery charging/discharging currents, poor battery energy conversion efficiency, i.e. higher battery energy losses, will result in higher battery temperature which is a crucial factor of battery life [21]. Since battery life is an important factor in replacement costs, we try to analyze a power management strategy of RE–EV that favors battery life.

This paper describes a systematic procedure to investigate the power management strategy for RE–EV, which starts with analyzing the trade-off between design criteria of fuel economy and battery protection, and then a rule-based power management strategy is established for real-time implementation. The battery energy losses are treated as one design criterion for battery protection. The fuel energy losses are expressed as another design criterion to address fuel economy. Since DP can guarantee to obtain a global optimal power management strategy, these two design criteria are expressed as two different cost functions for DP to evaluate the performance upper bound of both fuel-energy-loss-oriented and battery-energy-loss-oriented power management strategies. First, a vehicle model is established to simulate the RE–EV. The vehicle model is further simplified as a backward-in-time model for DP process. Since the optimization result [18] shows that better power management strategy for RE–EV is to deplete battery SOC at the end of a route, two-point boundary DP problems are formulated. Noise, vibration and harshness (NVH) effect and battery charging/discharging limitations are considered as constraints in DP process. These cost functions are then minimized for four driving patterns at a driving distance around 105 km. Since the driver is sensitive to the engine operation at low vehicle speeds, the engine is not turned on for low vehicle speeds. The DP results are analyzed on fuel consumption, battery energy losses, average battery charging/discharging current, which affects the battery life directly, and time duration at low SOC. The control results of conventional TCS are also provided as the performance lower bound.

A rule-based, multi-mode switch strategy is then proposed as the power management strategy for RE–EV. It starts with selecting seven representative driving patterns (RDPs). The implementable control rule sets can be extracted by learning the behaviors of DP results of each RDP. The driving pattern recognition (DPR) technique classifies actual driving scenario into one of RDPs, and then the multi-mode switch strategy can switch among these control rule sets according to the recognized driving pattern. The multi-mode switch strategy is finally verified using three untrained Taiwan driving patterns.

The remainder of this paper is organized as follows. The nonlinear vehicle model and simplified backward-in-time model are introduced in Section 2, followed by the dynamic programming in Section 3. The design procedures of multi-mode switch strategy are expressed in Section 4. Simulation results are shown in Section 5. Finally, conclusions are made in Section 6.

2. Modeling

In order to evaluate the power management strategies of RE–EV, a backward-in-power nonlinear vehicle model is established in Matlab/Simulink which neglects the effects of driver and regenerative braking. The vehicle model consists of longitudinal vehicle dynamics, wheel, gear, motor, battery, generator, and engine dynamics [22], which are revisedfrom a series HEV model in ADVISOR [23], as shown in Fig. 1.

The engine is a 1.2 L four-stroke, water-cooled spark ignition engine. The brake specific fuel consumption (BSFC) map is used for the engine model and is represented by a 2-D look-up table indexed by engine speed and torque. The BSFC map is further corrected by engine thermal behavior. The output engine torque, which is compensated by the engine rotational inertia, is employed for driving the generator. The generator dynamics are similar to that of motor dynamics, but at reverse calculation from generator speed and torque to electric power. In order to express battery dynamics with high accuracy and low computation effort, the RC model [23] from ADVISOR is selected as the battery model. In addition, a thermal model is used to compensate the temperature effect on battery parameters.

Since the DP process works backward-in-time, this complex vehicle model is not suitable due to its large number of states and heavy computation load. A simplified dynamic model [22] was developed to reduce the computational load for emulating the system dynamics of RE–EV. All necessary dynamics of the simplified model are discretized as backward-in-time difference equations.

The simplification processes can be started from the longitudinal vehicle dynamics. The wheel torque T_w as shown in Eq. (1) needs to overcome road loads, which consist of rolling resistance, aerodynamic drag, and road grade to follow the given driving cycle.

$$\begin{aligned} T_w(k) = {} & \left[\frac{V_v(k+1) - V_v(k)}{t_s} m_v r_w\right] + \left[\frac{b_w V_v(k)}{r_w}\right] \\ & + \left[\frac{\omega_w(k+1) - \omega_w(k)}{t_s} I_w\right] + F_r r_w + F_a r_w \end{aligned} \tag{1}$$

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