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An Optimal Energy Management System for Battery Electric Vehicles

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Abstract: Environmental pollution and high fuel costs have increased demands for an alternative energy source for transportation. Battery Electric Vehicles (BEVs) are attracting the attention of researchers of automotive engineering field to address these concerns because of their reputation for being fully green as well as more efficient than Internal Combustion Engine Vehicles (ICEVs). However, two major problems with BEVs are their short driving range and the limited service life of their costly batteries. Enhancing BEVs' driving range and their batteries' lifetime are possible through developing more effective energy management systems (EMSs) for them. This study proposes an optimal EMS for a BEV, the Toyota RAV4 EV, by considering the power flow between the energy consumers inside the vehicle. Dynamic programming (DP) is used to find an optimal power distribution between the vehicle drivetrain and the heating system for a standard driving cycle. A high-fidelity model of the vehicle in Autonomie is also employed to demonstrate the effectiveness of the devised EMS. The results show that the proposed strategy can improve the battery health of the considered BEV.

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Keywords: Battery Electric Vehicles, Energy Management System, Battery Health, Dynamic Programming.

INTRODUCTION

Global warming, limited fossil fuel resources, and the increasing price of oil have encouraged people to find a clean, safe and efficient solution for their mobility, and it seems that the electrified transportation is the right way to go. Hybrid Electric Vehicles (HEVs) were introduced in the last decade, and gained a lot of attention from research communities and car manufactures. They take advantage of an IC engine along with an electric motor/generator, and also a battery as their storage unit. This hybridization of the vehicle powertrain makes the engine smaller and more efficient. The HEVs' potentials in the efficiency enhancement, energy saving and emission reductions have resulted in many successful commercial products. Later, Plug-in Hybrid Electric Vehicles (PHEVs) were introduced to the car market as a bridge from HEVs to the full-electric transportation. They use larger batteries than conventional HEVs that can be fully charged before starting off, which results in a better fuel economy (Taghavipour, Vajedi et al. 2012). Although HEVs and PHEVs have been successful, they are only an interim solution to reduce our ecological footprints. Due to the use of ICEs in HEV/PHEVs, they are not entirely green and zero-emission level. On the other hand, full electric vehicles use on-board electrical energy storages and electric motors for the energy generation. BEVs are fully green because the battery is used as the only energy source of the vehicle, and also, they are very efficient due to the use of electric motors instead of ICEs. However, in comparison with ICEVs and HEVs, BEVs have a short operating range, and also, their expensive battery has a limited service life, which restricts BEVs' wide market presence at the end. The development of an effective Energy Management System (EMS) for BEVs is critical to address the above-mentioned issues.

Many EMSs have been developed for HEVs, and they have caused a significant effect on reducing the vehicle's energy consumption and emissions (Sciarretta and Guzzella 2007, Wirasingha and Emadi 2011). EMSs for HEVs can be categorized into rule-based and model-based control strategies. The rule-based strategies try to operate each vehicle powertrain's subsystem (ICE or electric motor) at its highest efficiency points. In (Banvait, Anwar et al. 2009, Liu, Du et al. 2012), a deterministic rule-based EMS was developed for PHEVs. This strategy does not require future knowledge of the vehicle's path, and it works based on a set of the rules that have been set up before the actual operation. Fuzzy logic controllers are another kind of rule-based EMSs with less computational burden, but they are only optimum for special predefined driving cycles. In (Xia and Langlois 2011, Denis, Dubois et al. 2015), an adaptive fuzzy logic controller was introduced, which adapts to different driving cycles but increases the computational load. The rule-based controllers find the near optimum working condition for each component of the vehicle's powertrain, but not the global optimal point in the general case. However, the model-based control strategies can find a global optimal solution to the power distribution problem for every driving condition. (Piccolo, Ippolito et al.

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2001, Delprat, Lauber et al. 2004) used offline optimization methods to solve the energy distribution problem in a given vehicle. Their proposed EMS can be useful for offline tunings of the energy flow in the design process, but cannot be employed in real-time applications. Stochastic dynamic programming (SDP) can be used to determine the optimal energy flow for a more general case in real-world driving scenarios. (Moura, Stein et al. 2013) used SDP to investigate trade-offs between the battery health and energy consumption of a given vehicle. Model predictive controllers (MPC) are also very popular for the real-time energy management of HEVs (Borhan, Vahidi et al. 2012). (Taghavipour, Vajedi et al. 2012) utilized the MPC theory for the optimal EMS design of a PHEV with four different cases of the knowledge of future trip information.

Compared with the extensive literature on the EMS design for HEV/PHEVs, there are only a few studies on the energy management of pure EVs, which could be because of their simpler powertrain architectures and limited degrees of freedom for the energy distribution. Many studies have investigated an optimum power distribution between ultracapacitors and batteries for EVs hybridized with ultracapacitors, which will increase the vehicle's driving range and the lifecycle of its energy storage system (Romaus, Gathmann et al. 2010, Trovao, Santos et al. 2013). There are more limitations in terms of the EMS enhancement in BEVs because they have only batteries as their energy sources. In (Kachroudi, Grossard et al. 2012), the authors used the particle swarm optimization (PSO) method to optimally control the energy flow between the powertrain and the other vehicle's auxiliaries for a given BEV. They tried to decrease the vehicle's energy consumption, and at the same time maintain the comfort of the passengers, by providing some suggestions to the driver. (Masjosthusmann, Kohler et al. 2012) took advantage of the heating system's power control, and (Roscher, Leidholdt et al. 2012) used the cooling system's power control to reduce the overall energy consumption and increase the battery health of BEVs. They developed a rule-based method that turned off the vehicle's HVAC system in high drivetrain power demands, and turned it on again in the low driving power demands so the resulting battery current peaks diminished. These methods cannot guarantee finding optimum power distributions in different conditions to maintain the comfort and increase the fuel economy. Also, they cannot be adjusted by the driver to choose different operating modes, such as the comfort or fuel economy.

In this study, the authors develop an optimal EMS for a BEV, the Toyota RAV EV, to increase the battery's service life. The drivetrain and heating system as the two major energy consumers are considered, and then, DP is applied to find an optimal power distribution between them. The optimal power distribution means smoother current demands from the battery with reduced current peaks. This will result in less sudden heat generations and temperature gradients inside the battery which cause shortening the battery life (Savoye, Venet et al. 2012). The proposed strategy is simulated using an Autonomie-based model of the vehicle in the FTP driving cycle.

In what follows, first, the modeling of the vehicle's longitudinal dynamics and the cabin's thermal model are

introduced. Then, the proposed EMS and the applied DP method will be mentioned. After implementing the proposed strategy on the vehicle's model, the results of the simulations will be presented, along with some discussions and concluding remarks.

BEV SYSTEM MODEL

The Autonomie software was used to create a high-fidelity model of the considered BEV. Autonomie is an automotive modeling and simulation package developed by the Argonne National Lab. In this study, we employed a modified version of the Autonomie's default BEV model by incorporating known parameters of the baseline RAV4 EV. Figure 1 shows the considered high-fidelity model in the Simulink environment. The mechanical part of the model includes the longitudinal dynamics of the vehicle and the drivetrain system. The electrical portion of the model consists of high-voltage and low-voltage batteries, a DC/DC converter, and also, an electrical heater unit.



Figure 1. Autonomie-based BEV model

The longitudinal dynamics model is based on the external forces applied to the vehicle, as shown in Figure 2:

$$a_{x} = \frac{1}{m_{v}} * \left(F_{p} - F_{a} - F_{rr} - F_{g}\right)$$
(1)

where a_x is the vehicle's acceleration, m_v is the vehicle's equivalent mass, F_p is the propulsion force form both vehicle's driving wheels, F_a is the aerodynamic resistance force, F_{rr} is the friction force due to the rolling resistance of the wheels, and F_a is the gravity force due to the road slope:

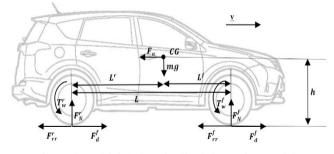


Figure 2. Vehicle's longitudinal dynamics model

$$F_p = \frac{\tau_{Rw} + \tau_{Lw} - \tau_{br}}{r_w} \tag{2}$$

$$F_{a} = \frac{1}{2} \rho. A_{v}. c_{a}. v^{2}. sgn(v)$$
(3)

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