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Battery Life Extending Charging Strategy for Plug-in Hybrid Electric Vehicles and Battery Electric Vehicles ⋆

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Abstract: This paper presents an optimal control based charging strategy for plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs). This work proposes a method to minimize battery capacity degradation incurred during charging by optimizing current profile. A semi-empirical battery aging model is adopted to quantify the capacity loss; a generic control-oriented vehicle cabin thermal model is developed to describe the battery surroundings taking into account solar radiation. Optimal control solution offered by Pontryagin's Minimum Principle (PMP) is presented. Simulation-based results show that the benefit of this strategy in terms of decreasing battery aging is significant, when compared with the existing strategies, such as the widely accepted constant current constant voltage (CC-CV) protocol.

Keywords: Battery aging, battery charging, optimal control, lithium-ion battery

1. INTRODUCTION

As PHEVs and BEVs are commercialized, interest has grown in reducing the overall cost of ownership. A battery pack, which represents a major component of vehicle cost, draws a lot of attention from both automotive industry and academia. Finding the minimum battery size that meets vehicle energy and power output requirements is an essential way to reduce vehicle cost significantly. Unfortunately, a lithium-ion battery pack, which is usually the second energy storage system in a PHEV or the primary energy storage system in a BEV, will experience degradation in both energy capacity and internal resistance due to some irreversible electrochemical processes. The temperature and current rate at which a battery is charged and the state of charge (SOC) profile as a function of time have critical effects on battery life. Therefore, an intelligent or aging-aware charging strategy capable of estimating and minimizing related aging effects can potentially extend battery life, maintain vehicle performance, and reduce cost.

The literature has examined xEV charging patterns from a number of different perspectives. Among all charging algorithms, the constant current constant voltage strategy is well developed and widely adopted because of its simplicity and easy implementation (Shen et al., 2012). The charging time with CC-CV is dependent on the charging current in the CC mode. In general, the lower the charging rate, the higher the charging efficiency and longer charging time and the battery life. The pulse charger has been claimed to be a fast and efficient charging algorithm for lithium-ion batteries, because pulse charging strategy is designed to establish the link between charging current profile and the chemical reaction process so that electrochemical reactions neither produce heat nor cause the accumulation of pressure inside the battery (Li et al., 2001). Significant research has been conducted on optimal PHEV charging and power management. In Bashash et al. (2011), the authors present a charging strategy for PHEVs that takes into account the combined effects of total energy cost, battery health, electricity pricing, and PHEV driving patterns. In Patil et al. (2013), the authors study the tradeoffs and synergies between optimal charging and power management in minimizing the overall CO_2 emissions.

Instead of trading off multiple objectives, the focus of this work is to develop a control strategy to minimize battery capacity degradation during charging for any given time window taking into account the environmental conditions. Combining the battery aging model and the battery thermal model, an optimal charging current profile is determined by solving an optimal control problem. This paper is organized in the following way: in section 2, all the models are described including battery electric model, battery heat generation model, battery aging model as well as the vehicle cabin and battery thermal model. In section 3, optimal control problem formulation is presented. In section 4, the optimal solutions from PMP are studied; simulation results for various charging scenarios are analyzed; and comparisons between optimal charging and CC-

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CV protocol are conducted. Conclusions are made in the last section.

2. MODELS

2.1 Battery electric model

The battery is represented by an equivalent circuit comprising a voltage source, E_0, and its internal resistance, R_0, in series. Thus the battery cell current is given by Serrao et al. (2011):

$$I_{cell} = \frac{E_0 - \sqrt{E_0^2 - 4 \cdot R_0 \cdot P_{cell}}}{2 \cdot R_0} \tag{1}$$

in which P_{cell} is the cell power. Assuming that all the cells are equivalent, battery SOC is computed from the battery cell current as

$$\dot{SOC}(t) = -\frac{I_{cell}(t)}{C_{cell}}. \tag{2}$$

in which C_{cell} is the cell capacity.

2.2 Battery aging model

Aging models for lithium-ion batteries can be classified into two categories, namely, physical-chemical models and empirical models. Physical-chemical models are usually developed to study or describe a single aging mechanism inside the cell (Marcicki et al., 2011, 2012). For instance, a first-principles capacity fade model is developed based on the mechanism for solid electrolyte interface (SEI) growth (Ramadass et al., 2004). This type of models are helpful in understanding of aging under different modes as well as the effect of an aging source on different aspects of the cell performance. Such first-principles models have limitations such as the requirement of a detailed model of the aging processes and often require long computation time. To remedy these shortcomings, various empirical and semi-empirical models have been proposed (Bloom et al., 2001; Cordoba-Arenas et al., 2015). These models are developed by considering simplified physical relations in the model by fitting the parameters of the model with experimental data obtained from aging tests, resulting in a set of equations that describe the main degradation mechanisms. Due to the favorable compromise between simplicity and accuracy, semi-empirical models are employed in the control-oriented models used in this study. We start from a generic model initially proposed in Wang et al. (2011), which has the form

$$Q_{loss} = B \cdot exp(\frac{-E_a}{R \cdot \theta_{batt}}) \cdot (Ah)^z \tag{3}$$

where Q_{loss} is the battery capacity loss in percentage with respect to the nominal capacity, B is a pre-exponential factor, E_a is the activation energy in $J \cdot mol^{-1}$, R is the gas constant, θ_{batt} is the battery temperature expressed in Kelvin, Ah is the Ah-throughput, and z is the power law factor.The generic aging model is calibrated on battery aging data obtained from vehicles in operation, and the data is reported in Table 1 where profile A and B are from Groot (2012) and profile C is from Spagnol et al. (2010). The three profiles are specified in terms of average

Table 1. Battery aging experimental data

DATA	$\overline{SOC}$[%]	$\bar{I}_c[1/h]$	$\bar{\theta}_{batt}$[°C]
Profile A	38.5	2.8	36
Profile B	42.0	3.0	38
Profile C	68.0	6.0	45

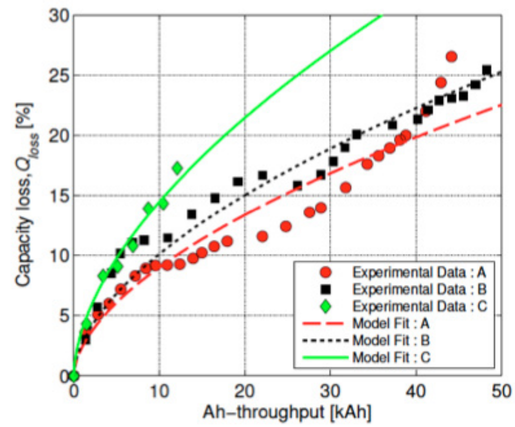

Fig. 1. Curve fitting result of identified aging model with the experimental data Suri G. (2015)

state of charge, $\overline{SOC}$, average C-rate, $\bar{I}_c$ and average battery temperature, $\bar{\theta}_{batt}$. Following a two-step curve fitting procedure, the result is shown in Fig.1. and the identified aging model has the form:

$$Q_{loss,\%} = (\alpha \cdot SOC + \beta) \cdot exp(\frac{-31700 + 163.3 \cdot I_c}{R \cdot \theta_{batt}}) \cdot Ah^{0.57} \tag{4}$$

$$\alpha = \begin{cases} 1287.6, & SOC \leqslant 0.45 \\ 1385.5, & SOC > 0.45 \end{cases}$$

$$\beta = \begin{cases} 6356.3, & SOC \leqslant 0.45 \\ 4193.2, & SOC > 0.45 \end{cases}$$

2.3 Battery heat generation model

Based on the assumption that each cell inside the pack is equivalent, the rate of heat generation in the battery pack is described by the following equation:

$$\dot{Q}_{batt} = R_0 \cdot I_{cell}^2 \cdot N_s \cdot N_p \tag{5}$$

where $\dot{Q}_{batt}$ is the rate of heat generation inside the battery pack, and N_s and N_p are the number of cells in series and the number of cells in parallel respectively.

2.4 Vehicle cabin and battery thermal model

When a vehicle is parked under a clear sky, the thermal load due to solar radiation may be greater than the load due to conduction between the surroundings and the vehicle cabin especially in summer, which makes the battery experience higher temperature than the ambient temperature. Cabin thermal models have been developed using numerical methods and lumped-parameter approaches