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A control-oriented cycle-life model for hybrid electric vehicle lithium-ion batteries

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ABSTRACT

In this paper, a semi-empirical Lithium-iron phosphate-graphite battery aging model is identified over data mimicking actual cycling conditions that a hybrid electric vehicle battery encounters under real driving scenarios. The aging model is then used to construct the *severity factor map*, used to characterize relative aging of the battery under different operating conditions. This is used as a battery degradation criterion within a multi-objective optimization problem where battery aging minimization is to be achieved along with fuel consumption minimization. The method proposed is general and can be applied to other battery chemistry as well as different vehicular applications. Finally, simulations conducted using a hybrid electric vehicle simulator show how the two modeling tools developed in this paper, i.e., the severity factor map and the aging model, can be effectively used in a multi-objective optimization problem to predict and control battery degradation.

1. Introduction

Global concerns over pollution and greenhouse gas emissions, increasingly stringent vehicle emission regulations and fluctuating prices of depleting non renewable petroleum resources have encouraged research in sustainable and clean alternatives for modern transportation systems [1]. Hybrid electric vehicles (HEVs) typically have two sources of power, an electric motor and internal combustion engine, and battery and fuel/fuel tank their respective energy storage devices.

The extra degree of freedom offered by the hybrid architecture is exploited to achieve better fuel economy and lower exhaust emissions. Most of the research on energy management strategies design in HEVs has been mainly focused on minimizing fuel consumption under a global constraint of charge sustainability [2]. It is well understood, though, that battery performance significantly affects the long term operation of a hybrid vehicle in terms of expected monetary savings and desired energy efficiency of the powertrain system. The strategies developed and implemented on HEVs thus far have not posed any consideration on extending battery life. Only recently, researchers have started being concerned about battery wear within a vehicle energy management framework [3], and the issue of modeling battery aging for inclusion in a model-based supervisory control has gained more attention [4].

The design, integration, and control of the energy storage system to match the life of a vehicle becomes a new engineering challenge. A possible approach to tackle this challenge can be found in the design of a supervisory control strategy that includes a battery aging model in the minimization function [5].

Mathematically, this can be described as a multi-objective optimization problem aimed at minimizing fuel while ensuring that the battery matches the life of the vehicle. The first formal attempt of investigating the inclusion of battery aging (in terms of capacity degradation) in the energy management problem for HEVs was presented in Ref. [4]. However, the limitation of the approach proposed was in the use of a postulated battery aging model from the manufacturer's datasheet and not from application-driven aging data. A second attempt was presented in Ref. [5], where the authors designed a HEV energy management strategy using the aging model from Ref. [6]. However, this strategy does not predict capacity loss under realistic driving scenarios, and does not include the dependence on one of the main aging factors, *i.e.* state-of-charge (SOC). In Ref. [7], an anode Solid Electrolyte Interface (SEI) layer growth model from Ref. [8] was used to obtain a resistive film growth rate map that was integrated in the optimal control design of power management for a PHEV while including battery aging. Contributions in this area of research are very limited due to the

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Nomenclature

Symbols and descriptions

Q_{nom}	Nominal Capacity
V_{oc}	Open Circuit Voltage
R	Internal Resistance
SOC	State of charge
I	current
I_c	Current rate normalized to battery charge capacity
θ	internal temperature
$\overline{SOC}$	Average state of charge
$\overline{I_c}$	Average current rate
$\overline{\theta}$	Average battery internal temperature
Q_{loss}	Normalized capacity loss
Q_{batt}	Remaining battery capacity
p	Vector of severity factors
Ah	Accumulated charge throughput
z	Power law exponent
z^*	Optimum power law exponent
σ_{funct}	Severity factor function
σ^*_{funct}	Optimum severity factor function
σ_{map}	Severity factor map
E_a	Activation energy
R_g	Universal gas constant
α, β, η	Model parameters
ε	Total error
$Q^{data}_{loss,\%,i}$	Capacity loss at the *ith* Ah throughput
$Q^{model}_{loss,\%,i}$	Capacity loss from proposed aging model at the $i-thAh$ throughput
$\bar{z}$	Average power law exponent
R^2	Goodness of fit coefficient
SS_{res}	Residual sum of squares
SS_{tot}	Total sum of squares
EOL	end-of-life
$I_{c,nom}$	Nominal current rate
SOC_{nom}	Nominal state of charge
θ_{nom}	Nominal battery temperature
Γ	Total charge throughput of the battery operated under nominal load cycle
γ	Total charge throughput of the battery operated under a given load cycle
SEI	Solid electrolyte interface
$\frac{\partial \sigma_{map}}{\partial I_c}$	Sensitivity of severity factor map with respect to current rate
$\frac{\partial \sigma_{map}}{\partial \theta}$	Sensitivity of severity factor map with respect to battery internal temperature
$\frac{\partial \sigma_{map}}{\partial SOC}$	Sensitivity of severity factor map with respect to battery state of charge
CVT	Continuous variable transmission
T_{req}	Torque request
T_{em}	Electric machine torque
T_{ice}	Engine torque
T_{br}	Brake torque
T_{CVT}	CVT torque
ω_{em}	Electric machine speed
ω_{ice}	Engine speed
v_{veh}	Vehicle speed
$\dot{m}_f$	Instantaneous fuel consumption rate
P_{batt}	power
u	Control variable
c_a	Transformation coefficient
θ_{amb}	Ambient temperature
Ah_{eff}	Effective charge throughput

lack of formal modeling tools to deal with battery degradation. In order to properly cast a multi-objective optimization problem that accounts for battery life and fuel consumption, a control-oriented battery aging model is needed that is predictive enough for the application under study. In this paper, the life cycle model from Ref. [9] is improved to predict degradation for HEV battery. In particular, the model is validated, for the first time, against Lithium-iron phosphate ($LiFePO_4$)-graphite battery used in the field. In addition, a methodology to design aging degradation maps suited for multi-objective optimization is proposed. HEV batteries undergo frequent charge/discharge cycling which tend to decrease the charge capacity and output power that the battery can deliver [10]. The capacity drop, in general, is due to parasitic side reactions, structural degradations, positive-electrode material dissolution, SEI layer formation and loss of contact between the electrode and the current collector [11]. These batteries usually undergo two different types of aging: cycle life aging and calendar aging. In this paper, only the cycle life aging is considered for which two main families of modeling approaches have been proposed in literature:

- *Electrochemical aging models*: These are physics based models describing the actual phenomena of diffusion [8] and charge transport of ions of lithium inside a battery [12]. The main advantages of these models are their accuracy and their ability to simulate aging under different operating conditions. Their limitations, on the other hand, are in their need for a detailed knowledge of the aging mechanisms and the high CPU time [13]. The integration of these models inside a Battery Management System (BMS) for real time control is currently under research [14].
- *Semi-empirical aging models*: Typically these are phenomenological models developed from data obtained in a laboratory through large scale testing under different aging conditions. Although these models have lower predictability than their electrochemical counterpart as they only describe how the aging mechanisms manifests and do not capture their physics, they are suitable for estimation-control applications as they require low computation time to predict degradation and can be easily integrated within a BMS. In Ref. [6], a semi-empirical aging model was proposed and calibrated over wide temperature and current range (Depth of discharge dependence is neglected in the model); in Ref. [15], a similar model is experimentally validated to predict aging at low SOC of operation at constant temperature; in Ref. [16], an aging model was developed to predict capacity degradation both during discharging and fast charging; a cell degradation study was performed in Ref. [17] that combines driving and vehicle-to-grid (V2G) usage for PHEV batteries; and finally, in Ref. [18], a lifetime prediction model for lithium-ion batteries is validated on profiles defined by the VDA (German association of the automotive industry).

The focus of this paper is on life cycle semi-empirical battery aging models.

This paper is organized in the following way. In Section 2, the identification steps conducted to design the newly calibrated aging model are presented. In Section 3, the derivation of the severity