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Gain-Scheduled Control of Modular Battery for Thermal and State-of-Charge Balancing ⋆

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Abstract: This paper proposes a simple constrained proportional controller with gain scheduling for simultaneous thermal and state-of-charge (SOC) balancing of a multilevel converter based modular battery. The proposed balancing controller is devised by investigating structural properties of constrained linear quadratic (LQ) model predictive controller (MPC) introduced in our earlier study. This investigation reveals a particular factorization of time-varying control gain matrices, which leads to approximation of matrix gains as scalar gains under the assumption of small parametric variations among battery cells. The gains are scheduled in load current for nominal cells. This special structure enables the identification of two dominant operational modes of the balancing controller: SOC balancing mode in low to medium load current range and thermal balancing mode in high current range. This study also proposes a simple algorithm for control projection on constraint polytope. The proposed balancing controller is tested in simulations for a modular battery with four significantly mismatched cells. The performance is comparable to MPC, which uses true battery parameters. The performance and the simplicity of the controller make it attractive for real-time implementation in large battery packs.

Keywords: Batteries, cell balancing, SOC balancing, thermal balancing, modular battery, multilevel converters, gain scheduling, LQ Control, model predictive control.

1. INTRODUCTION

The transportation is going through a critical transition phase to improve energy efficiency and reduce CO_2 emissions. The battery-powered electrified vehicles (xEVs) are one of the competitive solutions. The main drawback of xEVs is the high initial cost and relatively short lifetime of battery pack. The lithium-ion battery system is currently emerging as a dominant technology for future xEVs. However, like all other battery types, the ageing rate of each Li-ion cell is greatly affected by various factors like state-of-charge (SOC) level, depth-of-discharge (DOD), temperature, and c-rate etc as shown by Vetter et al. (2005); Wang et al. (2011); Bandhauer et al. (2011), and Groot (2014). In short, the cells in the string being stored or cycled at higher SOC-level, DOD and temperature may age faster than those at lower SOC, DOD, and temperature, resulting in nonuniform ageing of cells. The cell imbalance and nonuniform ageing are also tightly coupled, which may lead to a vicious cycle resulting in the premature end of battery life. In addition to nonuniform ageing, the SOC imbalance also has a detrimental impact on the total usable capacity of the battery, see review papers by Lu et al. (2013) and Altaf et al. (2014) for details. Thermal, SOC, and DOD imbalance is inevitable in battery packs of xEVs due to variations in cell parameters and operating conditions, see Dubarry et al. (2010); Mahamud and Park (2011). Thus, thermal and SOC balancer is very critical for optimal performance of automotive batteries. The SOC balancing can be achieved using various types of passive or active SOC balancers, see Gallardo-Lozano et al. (2014); Cao et al. (2008), whereas thermal balancing can potentially be achieved using reciprocating air-flow as proposed by Mahamud and Park (2011).

The notion of *simultaneous thermal and SOC balancing* using a single active balancing device was introduced in our previous work, see Altaf et al. (2012, 2013); Altaf (2014). A similar kind of conceptual study has also been carried out by Barreras et al. (2014). Thermal and SOC balancing are two tightly coupled and somewhat conflicting objectives, but it is possible to achieve both simultaneously in average sense subject to load variations and *surplus battery voltage* (Altaf et al. (2014)). In addition, it requires a special balancing device, like multilevel converter (MLC) (Malinowski et al. (2010)), which enables *bidirectional power flow* from each battery module to achieve non-uniform load scheduling. The MLC-based *modular battery* consists of n cascaded power units/modules (PUs), each containing a smaller battery unit and a full-bridge dc-dc converter. The modular battery is reconfigurable and provides a large redundancy in the voltage synthesis, which gives extra degree-of-freedom in control.

The modular battery has multiple electro-thermal control objectives including thermal balancing, SOC balancing, and terminal voltage control. In Altaf et al. (2016, 2015), a linear quadratic model predictive control (LQ MPC) scheme is proposed, which achieves the balancing objectives by using only one-step prediction. The control scheme is based on the decomposition of controller into two orthogonal components, one for voltage control and the other for balancing control. The *voltage control problem* is a simple minimum norm problem, whereas the *balancing*

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problem is formulated as a *control-constrained LQ MPC* problem, which is solved in two stages, see Altaf et al. (2015). The *first stage* issues an optimal balancing control policy (control gains) by solving a standard time-varying unconstrained LQ problem. The *second stage* generates feasible control actions via Euclidean projection of unconstrained LQ controls on a control constraint polytope.

This paper is an extension of Altaf et al. (2016, 2015). The main purpose is to further simplify the balancing controller. The idea is to approximate the LQ control gains by studying their structural properties and solve control projection problem by a simple algorithm. This leads to a simple proportional controller with load current dependent scalar gains. The controller can be easily implemented online as it is based on evaluating simple gain functions and doing straightforward iterations for Euclidean projection instead of strictly solving an optimization problem. In addition, this study completely unfolds the internal working and reveals two dominant operational modes of the balancing controller, which leads to very simple balancing rules based on load current sign and magnitude.

Two proposed controllers (one based on the gain functions and other based on the balancing rules) are evaluated and compared to MPC through simulations. We assume Toyota Prius PHEV, running in EV mode for *US06* drive cycle, as load for an air-cooled modular battery consisting of four cells. To analyze the effectiveness of the controllers, we assume significant variations among resistances, capacities, and initial SOCs of cells.

The paper is organized as follows. The modeling of MLC-based modular battery and the previous LQ MPC scheme are briefly summarized in sections 2 and 3 respectively. The proposed proportional controller is presented in Section 4. The simulation results are discussed in Section 6 and conclusions are drawn in Section 7.

2. MODULAR BATTERY: MODELING

The electro-thermal model of an air-cooled modular battery is presented in this section, see Altaf et al. (2012, 2013, 2015, 2016) and Altaf (2014) for modeling details.

2.1 Architecture and Terminal Behavior

The (cascaded full-bridge) MLC-based modular battery, supplying voltage $v_L(t) \in [0, v_{L,\max}(t)] \subseteq \mathbb{R}_+$ to a variable load with current demand $i_L(t) \in [i_{L,\min}, i_{L,\max}] \subseteq \mathbb{R}$, is shown in Fig. 1. It consists of n series-connected PUs, each containing an ideal full-bridge (FB) and an isolated Cell$_i$. This modular structure allows four quadrant operation in i_L–v_{Li} plane, which enables control of bidirectional power flow from each Cell$_i$ using control variables u_i (duty cycle). In this study, we assume positively constrained control i.e. $u_i(t) \in [0, 1]$ (so-called *unipolar control mode* (UPC)). This mode does not allow polarity inversion of any cell in the string, which simply implies that at any time instant, either all cells are charging (for $i_L(t) < 0$) or all are discharging (for $i_L(t) > 0$).

The *averaged signals* on two ports of ideal FB$_i$ (see Fig. 1) are linearly related through duty cycle $u_i(t)$ as follows

$$i_{Bi}(t) = i_L(t)u_i(t), \quad v_{Li}(t) = d_{vi}(t)u_i(t), \tag{1}$$

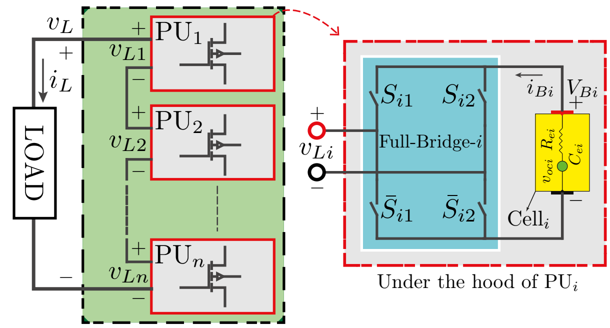

Fig. 1. Block diagram of an MLC-based modular battery.

where i_L and v_{Li} are the terminal current and voltage of PU$_i$ respectively, i_{Bi} is the current through Cell$_i$, and

$$d_{vi}(t) = v_{oci} - i_L(t)R_{ei}, \tag{2}$$

is the ON-time terminal voltage of Cell$_i$, where v_{oci} is OCV and R_{ei} is internal resistance. The terminal voltage and power of the modular battery are given by $v_L(t) = \sum_{i=1}^{n} v_{Li}(t)$ and $P_L(t) = \sum_{i=1}^{n} P_{Li}(t)$ respectively, where $P_{Li}(t) = v_{Li}(t)i_L(t)$ is the terminal power of each PU$_i$.

2.2 Electro-thermal Model

The electrical dynamics of cells is studied using the *simple cell model* (OCV-R), see Hu et al. (2012). The thermal dynamics of air-cooled battery is modeled using lumped capacitance and flow network modeling approach, see Mahamud and Park (2011); Lin et al. (2013a,b). The model considers only cell surface temperature with constant coolant temperature and speed at inlet. All internal parameters of cells are assumed constant. Under these assumptions, the electro-thermal model of any Cell$_i$ of the modular battery for a given load current $i_L(t)$ is given by

$$\dot{\xi}_i(t) = -\frac{1}{3600C_{ei}} i_L(t)u_i(t), \tag{3a}$$

$$\dot{T}_{si}(t) = \textstyle\sum_{j=1}^{i} a_{tij}T_{sj}(t) + \frac{R_{ei}}{C_{si}} i_L^2(t)u_i(t) + w_{ti}T_{f0}, \tag{3b}$$

$$v_{Li}(t) = d_{vi}(t)u_i(t), \tag{3c}$$

where temperature, T_{si}, and SOC, ξ_i, are states, T_{f0} is the constant inlet fluid temperature (measured disturbance), and d_{vi}, given by (2), is a time-varying feed-through gain from control u_i to voltage v_{Li}. The cell parameters R_{ei}, C_{ei}, and C_{si} are internal resistance, coulomb capacity, and heat capacity of Cell$_i$. The coefficient a_{tij} describes unidirectional thermal coupling from upstream Cell$_j$ to downstream Cell$_i$ due to convective heat transfer, whereas the coefficient $w_{ti} = -\sum_{j=1}^{i} a_{tij}$ describes influence of T_{f0} on Cell$_i$, see Altaf et al. (2016, 2015) for details.

The model (3a)–(3c) is discretized using Euler approximation assuming i_L to be constant during each sampling interval $[kh, (k+1)h]$ where h is a sampling step size. Using this discrete cell model as a basic building block and treating T_{f0} as a dummy state, the discrete-time electro-thermal model of a n-cell modular battery is given by the following standard linear time-varying state-space system

$$x(k+1) = A_d x(k) + B_d(i_L(k))u(k), \tag{4a}$$

$$y(k) = Cx(k) + D(i_L(k))u(k). \tag{4b}$$

Here $x(k) = \left[\xi^{\mathrm{T}}(k)\ \vartheta^{\mathrm{T}}(k)\right]^{\mathrm{T}} \in \mathbb{R}^{2n+1}$ is the state vector, $\xi(k) = \left[\xi_1\ \cdots\ \xi_n\right]^{\mathrm{T}} \in \mathbb{R}^n$, $\vartheta(k) = \left[T_s^{\mathrm{T}}\ T_{f0}\right]^{\mathrm{T}} \in \mathbb{R}^{n+1}$ is an