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Power capability prediction for lithium-ion batteries using economic nonlinear model predictive control

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HIGHLIGHTS

- An economic model predictive control is formulated for battery power prediction.
- A high-fidelity battery model is employed to capture the electrothermal dynamics.
- Constraints of current, voltage, temperature, and SOC are explicitly considered.
- Effects of temperature constraint, prediction horizon, and model accuracy are studied.

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ABSTRACT

Technical challenges facing determination of battery available power arise from its complicated nonlinear dynamics, input and output constraints, and inaccessible internal states. Available solutions often resorted to open-loop prediction with simplified battery models or linear control algorithms. To resolve these challenges simultaneously, this paper formulates an economic nonlinear model predictive control to forecast a battery's state-of-power. This algorithm is built upon a high-fidelity model that captures nonlinear coupled electrical and thermal dynamics of a lithium-ion battery. Constraints imposed on current, voltage, temperature, and state-of-charge are then taken into account in a systematic fashion. Illustrative results from several different tests over a wide range of conditions demonstrate that the proposed approach is capable of accurately predicting the power capability with the error less than 0.2% while protecting the battery from undesirable reactions. Furthermore, the effects of temperature constraints, prediction horizon, and model accuracy are quantitatively examined. The proposed power prediction algorithm is general and then can be equally applicable to different lithium-ion batteries and cell chemistries where proper mathematical models exist.

1. Introduction

A revolutionary paradigm shift from internal combustion engine vehicles towards electrified ones seems indisputable in the near future [1,2], eventually leading to a fossil-fuel-free transportation sector. Achieving such a target relies heavily on continued advance of battery technology, since the battery system is still the most expensive and perhaps the least understood vehicle component [3]. Although researchers from the material and chemistry are showing promising results, e.g., in the development of polymer electrolyte materials [4–6], the mass production of electric vehicles with the technology available in the near future requires tools for safe, efficient, and health-conscious operation. Unlike its conventional counterparts, the battery represents a limiting factor in energy density, "refueling" time, and life cycle. At the same time, the available battery systems are often designed conservatively, resulting in that 20–50% of capacity and power capability remain underutilized [7]. Therefore, it is of great importance to develop advanced battery management systems (BMSs), through which batteries can be used closer to their physical limits but with guaranteed safety and lifetime.

Battery management requires accurate knowledge of state-of-power (SoP), indicative of the peak capability to supply or absorb electric energy in a short time period [8,9]. For hybrid electric vehicles (HEVs) and plug-in HEVs, such state information is used for determination of power split and for regenerative braking, so as to improve vehicle dynamic performance and to optimize energy-efficiency and tailpipe emissions [10,11]. For the battery itself, knowing the maximum available power at some future time period can potentially also slow

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down its degradation process; the charge operation may be made faster under safety promise, for example through the algorithms proposed in Refs. [12,13]. Therefore, predicting the SoP in real-time is one of the most important BMS functionalities and has consequently attracted considerable research efforts.

Currently, characteristic maps are established offline relating the SoP to battery state variables such as state-of-charge (SoC) and temperature, and power pulse parameters [14]. Although these static maps can readily be implemented, they lack the necessary adaptation to the varying performance of cells, caused by aging and past and current operating conditions. In light of this, online SoP prediction/estimation techniques based on mathematical battery models have been explored and exploited. Comparative studies on different models of lithium-ion batteries can be found in Refs. [15,16], for example. However, the technical challenge in this task initially stems from complicated battery models that have multiple state variables being nonlinearly coupled with each other. Furthermore, to protect battery health and safety during cycling, the SoP prediction problem needs to satisfy constraints on current, voltage, and temperature. In addition, battery internal states, such as SoC and core temperature, can significantly influence the available power but are usually unmeasurable in onboard applications [17,18].

Model-based power estimation/prediction for lithium-ion batteries has previously been analyzed. By using a simplified equivalent circuit model, an analytical expression of battery SoP was derived in Refs. [19,20]. Based on a linear-parameter-varying battery model, optimization-based approaches have been conceived to assess the power state on various operating conditions [21,22]. To address inevitable sensor noise, extended Kalman filter [23–25], unscented Kalman filter [26,27], and particle filter [28], synthesized from equivalent circuit models, have been adopted to compute the maximum admissible power. Also, joint/dual estimation algorithms for SoP and other unmeasurable states have been carried out [29,30]. A comprehensive survey of established methods for battery power estimation can be found in the recent review article [31]. Common to the referred works is that current, voltage, and/or SoC constraints were imposed, but not the temperature. In consideration of its importance in battery lifetime and safety, a temperature constraint was included for predicting the power capability in Ref. [32]. One could argue that in these available contributions, the input and state constraints have not been systematically and optimally addressed. Additionally, the coupled nonlinear electrical and thermal dynamics have been partially or fully ignored, linearized, or decoupled. The consequently reduced model fidelity can potentially degrade the prediction capability of the associated algorithms and may lead to premature battery degradation and safety issues. In Refs. [20,33], it was shown that the mentioned analytical solution could be reformulated as a proportional-integral (PI) controlled feedback system with very strong robustness properties. Following this line of thought then feedback control approaches based on more elaborate models can be sought.

Model predictive control (MPC) or receding horizon control (RHC) is a model-based control paradigm in which the control action at each sampling instant is obtained by solving a finite-horizon optimization problem in real-time. The attractive attributes of MPC are its ability to systematically handle input and state constraints, multiple variables, and nonlinearities, making it possible to deal with complex systems and operate them within given boundaries. Considerable success has been achieved with the deployment of MPC in widespread applications, including recent examples in energy management of batteries [34,35] and HEVs [36]. Within the MPC framework, economic MPC (EMPC) provides a direct means to optimize a dynamic economic objective like profitability, return on capital, efficiency of operation, and cost-cutting. As compared to tracking MPC, where deviations of the system inputs and states from some references often are penalized, EMPC can potentially offer superior closed-loop performance and get rid of laborious tuning of weights. A thorough exposition of EMPC theory and techniques can be found in Ref. [37]. In this regard, the EMPC scheme can be a good candidate to solve the power assessment problem.

This paper proposes a new prediction algorithm for the power capability of lithium-ion batteries. Specifically, three original contributions are made to the relevant literature. First, the power prediction problem is formulated in the framework of economic nonlinear model predictive control. The maximum power can then be adopted directly in the objective function, input/state constraints considered explicitly, and model nonlinearities handled in a natural way. Second, the proposed predictor is deployed for battery fast charging and for charge/discharge management in the presence of dynamic loads. Finally, the effects of prediction horizon, temperature constraint, and model fidelity are studied quantitatively.

The remainder of this paper is organized as follows. A general problem formulation for power capability prediction is presented in Section 2. The EMPC formulation and its ingredients are described in Section 3. The proposed algorithm is then numerically implemented in Section 4, followed by a concluding summary in Section 5.

2. General problem statement

In the course of charge/discharge operation, the power capability of a lithium-ion battery is influenced by various factors, such as SoC, SoH, voltage, cell temperature, and ambient temperature. These factors are typically interrelated during lithium-ion intercalation/de-intercalation process, diffusive transport, and electrochemical reactions. In response to changes in battery ambient environment and internal dynamics, the maximum available power will therefore vary in the time domain. Knowing the SoP available in the near future, one can safely operate the battery around its power limits, giving enhanced performance and prolonged battery lifetime.

The available power of a battery cell is defined as the product of current and voltage. Its current and voltage are related through the dynamic battery system and are usually considered as the system input and output, respectively. This means that, for a given current, the voltage can be derived as an output of a dynamic battery model.

Based on the above discussions, the general problem of online battery SoP prediction can be stated as:

Problem Statement. *The prediction of SoP for a lithium-ion battery is to determine the input current on the future time interval,* $[t, t+T]$, *that gives the maximum average power while the transient current, voltage, SoC, and temperature all stay within their allowable operating ranges, given some in-situ measurements of current, voltage, and surface temperature at the current time, t.*

The above problem statement for SoP prediction can be mathematically formulated as a constrained finite-horizon optimization problem

$$\max_{I(\tau)} \int_t^{t+T} \left| \mathscr{P}(I(\tau), V(\tau)) \right| d\tau \tag{1a}$$

$$s.\ t.\quad \dot{x}(\tau) = F(x(\tau), I(\tau), p) \tag{1b}$$

$$V(\tau) = H(x(\tau), I(\tau), p) \tag{1c}$$

$$I(\tau) \in \mathscr{I}(\tau) \subset \mathbb{R} \tag{1d}$$

$$V(\tau) \in \mathscr{V}(\tau) \subset \mathbb{R} \tag{1e}$$

$$x(\tau) \in \mathscr{X}(\tau) \subset \mathbb{R}^n \tag{1f}$$

$\forall\, \tau \in [t, t+T]$, where I, V denote the input current and terminal voltage; x represents a vector of n state variables; p is a vector of parameters in the battery system; $F(\cdot)$, $H(\cdot)$ are nonlinear functions; and $\mathscr{I}$, $\mathscr{V}$, and $\mathscr{X}$ define the constraints.

The objective function, (1a), is established to directly maximize the available power on the prediction horizon T with the definition of

$$\mathscr{P}(t) = I(t)V(t). \tag{2}$$

The optimization variable, $I(\tau)$ for $\tau \in [t, t+T]$, is the current, and