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Combined electrochemical, heat generation, and thermal model for large prismatic lithium-ion batteries in real-time applications

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HIGHLIGHTS

- A simplified combined electrochemical, heat generation and thermal model is proposed.
- Heat generation model that accounts for different loss mechanisms is developed.
- A real-time thermal model of a large format prismatic cells is proposed.
- Model parameterization under isothermal and non-isothermal operating conditions.
- Model validation using experimental data for broad C-rates, and temperature ranges.

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ABSTRACT

Real-time prediction of the battery's core temperature and terminal voltage is very crucial for an accurate battery management system. In this paper, a combined electrochemical, heat generation, and thermal model is developed for large prismatic cells. The proposed model consists of three sub-models, an electrochemical model, heat generation model, and thermal model which are coupled together in an iterative fashion through physicochemical temperature dependent parameters. The proposed parameterization cycles identify the sub-models' parameters separately by exciting the battery under isothermal and non-isothermal operating conditions. The proposed combined model structure shows accurate terminal voltage and core temperature prediction at various operating conditions while maintaining a simple mathematical structure, making it ideal for real-time BMS applications. Finally, the model is validated against both isothermal and non-isothermal drive cycles, covering a broad range of C-rates, and temperature ranges [−25 °C to 45 °C].

1. Introduction

In the past decade, lithium-ion batteries have gradually gained acceptance in the automotive sector as electric energy storage due to their high specific energy, low self-discharge rate, and non-memory effect. In order to efficiently integrate the lithium-ion batteries in electric vehicles (EV), different cell sizes have been introduced. Depending on the method of packing, the cells can be shaped into a pouch, cylindrical, or prismatic form. Prismatic lithium-ion batteries have become one of the most attractive options for energy storage systems due to their optimal use of space and light weight. However, abnormal operating conditions such as over discharge, overcharge, or high operating temperature can accelerate their aging and degradation and may lead to thermal runaways in extreme cases. To fully benefit from a lithium-ion energy storage system and avoid its physical degradation, an accurate battery management system (BMS) is required. The BMS is responsible for the battery state of charge (SOC), state of health (SOH), state of power (SOP), and thermal management. It uses state estimation algorithms for monitoring, as well as operating the battery within a range that is considered as nominal in order to ensure safety and performance as well as preserving its projected useful life. One of the main requirements for a successful BMS implementation is the development of a high fidelity battery model

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that includes thermal and aging dependent parameters. The battery model needs to be dynamically significant while being computationally efficient, robust, and accurate. Of particular interest is the prediction of the terminal voltage which is affected by the cell's core temperature. As such, an accurate thermal model is needed to predict the core temperature and estimate its dynamics. The inclusion of a thermal model within the overall battery model is necessary as it enables the BMS to operate the battery safely and preserve its performance effectively.

Battery models are broadly classified under three categories: equivalent circuit [1–4], behavioral (or black-box) [5–8], and electrochemical (physics-based) models [9–11]. The equivalent circuit models are widely used in BMS due to their acceptable accuracy, complexity, and fidelity. Most of the electrochemical modeling approaches found in the literature are based on the electrochemical pseudo-two-dimensional (P2D) model further developed following the Doyle-Fuller-Newman model [12,13]. The physics-based P2D model is very accurate; however, it is excessively computationally complex, thereby burdening its real-time implementation. Therefore, many model reduction methods have been proposed to reduce its complexity while maintaining its accuracy. The model reduction methods commonly used can be divided into two categories. One category focuses on reducing the computational complexity involved in solving the concentration of lithium in the solid particles of the electrodes by either simplifying the concentration profile or assuming it to be constant as presented by Refs. [14–16]. Another category focuses on reducing the electrochemical model as a whole, such as to avoid the solution of large sets of differential-algebraic equations (DAEs) of the Li^+ concentration distribution and the potential distribution of the electrolyte phase. Examples of the latter can be found in Refs. [17–19].

In order to investigate the dynamic behavior of the cell, two main approaches are discussed in the literature: (i) electrochemical impedance spectroscopy (EIS) and (ii) measurement of a voltage response using controlled input currents and then applying optimization techniques to determine the model parameters. The general principle of the EIS method is to apply an input signal either current (galvanostatic) or voltage (potentiostatic) and then measure the characteristic response of the cell which depends on the cell impedance. In the scope of this publication, the model is parameterized and validated using the second approach. The battery under test was subjected to charging, charge-sustaining and charge-depleting phases at six different temperature in order to determine the temperature dependency of the parameters. The genetic algorithm (GA) was then used to optimize the model parameters.

In addition, various strategies have been proposed in the literature for modeling the temperature profile inside a cell during its operation. These include coupled partial differential equations (PDE) models, linear parameter-varying state-space models, three-dimensional Finite Element Analysis (FEA) models and relatively simple lumped capacitance zero-dimensional thermal models. Smyshlyaev et al. [20] proposed an analytic solution for solving the thermal model PDEs. Whereas, Hu et al. [21] reduced the PDEs computational complexity by fitting a more complicated computational fluid dynamics (CFD) model to a linear parameter-varying state-space model. Guo et al. [22] presented a three-dimensional FEA thermal model, while Baba et al. [23] developed a full 3D thermal model that takes into account local heat generation and the spatial dependencies to obtain a full 3D temperature distribution of the cell. The FEA thermal models are very accurate; however, they require excessive computational power and specific material properties, which limit their real-time implementation especially when fluid dynamics are considered in the cooling process. Damay et al. [24] developed a lumped capacitance, zero-dimensional thermal model. The model included one heat capacitor coupled with different modes of heat transfer throughout the cell to represent the thermal behavior of a prismatic cell. Similarly, Forgez et al. [25] employed the same technique for cylindrical cells using two heat capacitors. Further to the above, the lumped capacitance modeling approach will also be considered in this work due to its low computational complexity and acceptable accuracy. An accurate set of parameters is required for obtaining a high-fidelity thermal model. The thermal parameters are either determined analytically or experimentally. Lin et al. [26] used detailed information about the material and geometry of the cell for analytically determining the parameters. Perez et al. [27] used the least squares optimization algorithms to fit the model to the experimental data. Lin et al. [28] proposed an online estimation algorithm. Sastry et al. [29] developed a surrogate-based modeling and dimension reduction techniques to assess the role of design variables on multiple competing objectives for a wide range of engineering problems [30,31].

In this publication, an experimental method involving optimization will be used instead of the analytical methods as they suffer from a high level of uncertainty.

This paper proposes three unique contributions for improving battery modeling. The first contribution is a combined electrochemical, heat generation, and thermal model capable of accurately predicting the cell's terminal voltage and core temperature. The second contribution is an accurate yet computationally simple four-node thermal model (4NTM). The 4NTM helps in estimating the battery's core temperature leading to an increase in the terminal voltage accuracy within a broad range of temperatures [-25 °C–40 °C]. The four-node structure constitutes a reduced order form that renders the model suitable for real-time applications. The third contribution is a model parameterization scheme that allows identification of each sub-model parameters separately.

1.1. Paper structure

In section 2, the combined electrochemical, heat generation and thermal model is illustrated. Section 3, 4 and 5 presents the reduced-order electrochemical model (ROM), the heat generation model, and the thermal model respectively. In section 6, the parameter identification procedure and the experimental setup are explained. The ROM, 4NTM, and the combined ECHTM are then validated using battery voltage, current, and temperature measurements against different driving cycles. Finally, the conclusion, results, and future work are presented.

2. The combined model

This sections will present the main contribution of this paper, the formulation of a combined electrochemical, heat generation, and thermal model (ECHTM) that allows the BMS to effectively operate the battery in safe conditions and improve its terminal voltage, SOC, and SOH estimation accuracy. Fig. 1 shows a schematic representation of the combined ECHTM and its sub-models. The combined ECHTM is capable of estimating the cell's SOC, terminal voltage, and core temperature and it is divided into three different sub-models. First, the electrochemical model estimates the cells' terminal voltage V_t, SOC, open circuit potential $U_{p,n}$, and Li-ion concentration gradients $C_s^{n,p}$ as a function of the cell's core temperature T_c using physicochemical temperature dependent parameters. The cell's core temperature is calculated using a specific thermal model and fed back to the electrochemical model as an input. The heat losses are the most difficult elements to model due to the nonlinear nature of the heat sources. Thus, a specific model is developed for heat generation Q_{gen}, which computes reversible,