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Review article

A systematic review of lumped-parameter equivalent circuit models for real-time estimation of lithium-ion battery states

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HIGHLIGHTS

- Ten lumped-parameter lithium-ion battery models are systematically reviewed.
- Two variations of lithium-ion cells are used for experimental verifications.
- Real-time system identification is realised using dual Extended Kalman filtering.
- Modelling accuracies are compared for online state-of-charge and power predictions.
- Resistor-capacitor network models are shown to have better dynamic performances.

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ABSTRACT

This paper presents a systematic review for the most commonly used lumped-parameter equivalent circuit model structures in lithium-ion battery energy storage applications. These models include the Combined model, Rint model, two hysteresis models, Randles' model, a modified Randles' model and two resistor-capacitor (RC) network models with and without hysteresis included. Two variations of the lithium-ion cell chemistry, namely the lithium-ion iron phosphate ($LiFePO_4$) and lithium nickel-manganese-cobalt oxide (LiNMC) are used for testing purposes. The model parameters and states are recursively estimated using a nonlinear system identification technique based on the dual Extended Kalman Filter (dual-EKF) algorithm. The dynamic performance of the model structures are verified using the results obtained from a self-designed pulsed-current test and an electric vehicle (EV) drive cycle based on the New European Drive Cycle (NEDC) profile over a range of operating temperatures. Analysis on the ten model structures are conducted with respect to state-of-charge (SOC) and state-of-power (SOP) estimation with erroneous initial conditions. Comparatively, both RC model structures provide the best dynamic performance, with an outstanding SOC estimation accuracy. For those cell chemistries with large inherent hysteresis levels (e.g. $LiFePO_4$), the RC model with only one time constant is combined with a dynamic hysteresis model to further enhance the performance of the SOC estimator.

1. Introduction

Due to the growing concerns over the emissions of greenhouse gasses, together with the volatile and ever-increasing cost of fossil fuels, a global shift towards hybrid electric vehicles (HEVs), plug-in hybrid electric vehicles (PHEVs) and battery electric vehicles (BEVs) is apparent. The uptake of these electrified vehicles (EVs) within the transport system not only improves the air quality in dense urban areas, but can also provide a distributed energy storage solution for the implementation of the rapidly evolving smart grid [1]. However, without significant improvements on traction battery technologies and battery management systems (BMSs), the adoption of EVs by consumers is not feasible.

A key function of the BMS is to assess and monitor the performance of the traction battery through accurate characterisation of various battery states. These states include the state-of-charge (SOC—quantity of deliverable ampere-hour charge at any time), state-of-health (SOH—ability of a battery to provide its nominal capacity over its service lifetime), state-of-power (SOP—a quantity describing the battery's power capability) and the state-of-function (SOF—a binary yes/no parameter indicating the battery's ability to complete a task) [2–4].

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Whilst direct measurement techniques such as coulomb-counting (integration of battery current over the charge or discharge period) are easy to implement for SOC estimation, they suffer largely from erroneous initialisation of SOC, drifts caused by current sensor noise and battery capacity variations due to temperature and SOH. Moreover, the direct measurement of the other battery states of interest (i.e. SOH, SOP and SOF) for real-time applications is somewhat impossible. Hence, battery models are often utilised within the BMS to indirectly infer and monitor the battery's operation through the measurement of its terminal voltage, current and surface temperature. In addition to accurate characterisation of the battery states, a candidate model is also desired to be computationally efficient. In other words, there should be a balance between model accuracy and complexity so that it can easily be embedded on a simple and inexpensive microprocessor unit (MCU), similar to those found in EV BMS hardware.

The battery models presented in literature mainly fall into one of the following categories:

1. Electrochemical or physics-based models,
2. Empirical or data-based models, and
3. Equivalent electrical-circuit based models.

Electrochemical models (e.g. Refs. [5–9]) that aim to capture the dynamic behaviour of battery cells on a macroscopic scale often can achieve high accuracies. These models are defined by a high number of partial differential equations (PDEs) that must be solved simultaneously. The complexity of any electrochemical model is directly related to the number and order of the governing PDEs, which can lead to tremendous requirements for memory and computational power. Another issue that often precludes these models from real-time applications is that due to the large number of unknown variables, they are likely to run into over-fitting problems, increasing the uncertainty in the model's output. Alternatively, these models can be represented by a lower number of 'reduced order' PDEs and by substituting boundary conditions and discretisation, real-time applications may become achievable (e.g. Refs. [10–12]). However, this comes at the expense of reduced SOC accuracy and yet the computational burden on the MCU remains questionable.

Data-based models (e.g. Refs. [13–15]) often adopt empirically derived equations from experimental data fittings to infer relationships between various battery parameters such as the terminal voltage, throughput current, surface temperature and SOC. Although these models benefit from simplicity and ease of implementation, they often suffer from inaccuracies of 5–20% mainly due to the highly non-linear behaviour of a battery under a dynamic load profile. In Refs. [16,17], the authors took a multiple-model approach to battery modelling using the local model networks (LMN). This technique interpolates between different local linear models to capture the battery's non-linearity due to SOC variations, relaxation, hysteresis, temperature and the battery current effects. One downside of the LMN modelling approach is the excessive requirements for different experiments to train the model in first place. Generally, the data-based model parameters are not physically interpretable, which drops their popularity for *in situ* estimation and tracking of SOH and SOP. Furthermore, a large cell sample of the same chemistry is required to create a dataset for identification and training of data-based models.

In Refs. [18–20], Plett used a series of models including the combined, simple, zero-state hysteresis, one-state hysteresis and a non-linear enhanced self-correcting (ESC) model to adaptively estimate the battery's SOC. The latter model took into consideration the effects of the current direction, the SOC dependency of open-circuit-voltage (OCV) hysteresis and the relaxation or the charge-recovery effect to improve the model accuracy for dynamic load profiles. In an attempt to model the OCV hysteresis behaviour together with the charge recovery effects, Roscher et al. [21] developed an empirical model whose parameters required off-line identification. In Refs. [22], Huria et al. proposed a mathematical model to describe the dynamics of the large hysteresis levels that exist amongst high-power lithium-ion cells. Further on in the paper, this model structure will be referred to as the adaptive hysteresis model.

The lumped-parameter equivalent circuit models have gained a lot of interest amongst EV designers for real-time battery state estimation and power management purposes. This is due to their simplified mathematical and numerical approaches that minimise the necessity for computationally intensive procedures. Furthermore, there is often a strong physical relation between the constituent model parameters and the underlying electrochemical processes that occur within the battery cells. These models use passive electrical components, such as resistors and capacitors, to mimic the behavioural response of a battery. The simplest equivalent circuit model is in the form of an ideal voltage source in series with a resistor [23]. This model assumes that the demand current has no physical influence on the battery, i.e. no core temperature variations or undesired transition effects. More complicated equivalent circuit models include resistor-capacitor (RC) networks to characterise the battery transient responses with different time-constants associated with the diffusion and charge-transfer processes. Depending on the dynamics of the load profile and the required modelling accuracy, the number of the parallel RC branches may vary from one-RC (e.g. Refs. [24–27]) to two-RC (e.g. Refs. [28–30]). Higher order Models of up to fifth-order have also been used previously in literature (e.g. Ref. [31]) to improve the model's impedance response under higher frequencies of operation.

In literature, there are no studies that compare the accuracy and universality of the reported battery models for real-time estimation of SOC and SOP together. Therefore, this review paper aims to carry out a systematic study of a number of selected lumped-parameter battery models for two variations of the lithium-ion cell chemistry, namely the lithium-ion iron phosphate ($LiFePO_4$) and the lithium nickel-manganese-cobalt oxide (LiNMC). The models of interest in this paper include the combined model, Rint model, One-state hysteresis model by Plett, Huria et al. hysteresis model, one- and two-RC models and one- and two-RC models combined with the hysteresis model proposed by Huria et al. [22]. These models were nominated based on the number of their appearances in the literature. The Kalman filter (KF) algorithm is then applied to simultaneously estimate and identify the model parameters in real time. Nevertheless, for those models that are non-linear in parameters (e.g. one- and two-RC models) the extended Kalman filter (EKF) algorithm is adopted.

This paper is organised as follows. Section 2 describes the experimental configuration for gathering an accurate dataset for both training and verification purposes. Section 3 gives a quantitative definition for the SOC, SOP and SOF. Section 4 provides an overview of the battery model structures of interest in this work. Section 5 describes the real-time system identification technique based on the dual-EKF algorithm for both model parameter identification and battery state estimation. Section 6 compares the voltage prediction and SOC estimation capabilities of the nominated model structures. Furthermore, an optimum model structure will be put forward for real-time SOP and SOF estimation. And finally section 7 concludes this paper.

2. Battery dataset generation

2.1. Experimental setup

The experimental setup features a multi-channel Maccor battery