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Model based condition monitoring in lithium-ion batteries

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HIGHLIGHTS

- Robust condition monitoring of Li-Ion cell using multiple model adaptive estimation.
- Equivalent circuit based model was updated with a nonlinear OCV–SOC relationship.
- The OCV–SOC equation was obtained via curve fitting of the experimental data.
- The model bank includes a normal cell and two distinctively over-discharged cells.
- RLS method was used to identify the model parameters from measured data.

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ABSTRACT

In this paper, a model based condition monitoring technique is developed for lithium-ion battery condition monitoring. Here a number of lithium-ion batteries are cycled using two separate over discharge test regimes and the resulting shift in battery parameters is recorded. The battery models are constructed using the equivalent circuit methodology. The condition monitoring setup consists of a model bank representing the different degree of parameter shift due to overdischarge in the lithium ion battery. Extended Kalman filters (EKF) are used to maintain increased robustness of the condition monitoring setup while estimating the terminal voltage of the battery cell. The information carrying residuals are generated and evaluation process is carried out in real-time using multiple model adaptive estimation (MMAE) methodology. The condition evaluation function is used to generate probabilities that indicate the presence of a particular operational condition. Using the test data, it is shown that the performance shift in lithium ion batteries due to over discharge can be accurately detected.

1. Introduction

Lithium ion (li-ion) batteries are the electrochemical energy source of choice today. A typical li-ion rechargeable cell with lithium metal oxide based positive electrode, graphitic carbon negative electrode, and lithium conducting organic electrolyte, offers great advantages over other battery chemistries [1,2]. With major advantages of high energy density, safer chemistries, low self-discharge, longer cycle life, broad temperature application, the li-ion batteries, availability in different form factors, are used in a range of applications like consumer electronics, automotive, space exploration, and medical implants [1,3], to name a few. With these growing applications in mind the health of the Li-ion battery becomes a critical factor in the combined system functionality of the device.

Faults occurring in the li-ion battery can be attributed to number of factors either individual, like structural failure, failure of thermal management, or more likely, a combination of factors involving manufacturing defects, over charge, over discharge, and short circuit. The currently available li-ion battery safety devices can be broadly divided into internal and external protection. The internal elements are implanted on the battery cell and provide protection against over current, high temperature, high pressure, over charge, and over discharge. The commonly used internal safety elements are the polymeric positive temperature coefficient (PPTC), charge interrupt devices (CID), and the printed circuit boards [4,5]. The external protection elements ensure the battery safety under over charge, overdischarge, and shorting through the use of devices like protection diodes, dedicated battery charging integrated circuit elements, temperature sensors, and more. Some of these devices are resettable while others are one time use, which later renders the battery useless. Furthermore, these protective devices fail to provide the user with any information regarding the condition of the battery, extent of the fault, fault identification, and battery

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health prognosis. Critical insight into the battery health can be obtained by implementing analytical redundancy. It involves reconstructing the process behavior on-line by using models which mimic the actual process under study. The application of analytical redundancy for li-ion battery condition monitoring, fault detection and diagnosis results in better understanding of the battery dynamics, and hence contributes towards safer batteries, which leads to the overall system safety.

The application of fault detection and diagnosis on li-ion batteries is not new, extensive work in this area has been done by researchers with focus on different faults and related techniques. The work on li-ion battery fault detection is based primarily on the state estimation, empirical techniques, parameter identification, data driven methods and others.

Substantial work in the field of fault detection and diagnosis, and prognosis in li-ion battery using data driven methods has been carried out by Saha et al. [6–8]. Related research by using support vector machine algorithm for state of health (SOH) and remaining useful life (RUL) was recently carried out by Nuhic et al. [9] and Wang et al. [10]. These methods involve the application of classification and regression algorithms found under the paradigm of machine learning. In Ref. [11], the author uses AC impedance spectroscopy (IS) along with auto regressive moving average (ARMA), neural network, and fuzzy logic techniques for parameter identification, estimation and eventually battery prognosis. Data driven techniques do not require in depth knowledge of the battery and its underlying mechanisms, hence their implementation does not involve expert knowledge of the process under study. The biggest hurdle in using data driven methods can be attributed to the computational expensiveness and requirement of extensive data for training, and the time involved in learning.

A combination of rule based signal monitoring and probability based Li-ion battery fault detection and diagnosis was explored by Xiong et al. [12], these methods rely heavily on the thermal signatures of the battery which in turn depend on the rate of charge/discharge applied on the cell. Further, there is little information regarding the initial state of the cell under test; as it is difficult to achieve an over discharge cell failure in $LiFePO_4$ cell chemistries after two cycles. In Ref. [13], the open circuit voltage (OCV) is analyzed along with model based approach to detect the cell nominal capacity fade due to cycling. This technique gives good results for offline applications where the load can be disconnected and there is enough time to accurately access the OCV of a given cell.

Sate estimation involves the evaluation of the state of the battery, while the choice of technique can differ based on the requirements, the aim is to access the information related to the Li-ion battery that is not readily available through measurement [14]. The choice of state variable depends on the model of the system, but for Li-ion batteries, SOC among others is a natural candidate. Application of Luenberger observers (LO) for fault detection and diagnosis can be found in Ref. [15], here the authors implement fault diagnosis on a string of Li-ion batteries using a bank of reduced order observers. LO is a good candidate for fault detection and diagnosis in systems with little or no measurement noise, but with presence of noise, this setup will face inherent difficulties especially under subtle but important performance variation. The use of Kalman filters under the paradigm of observer based fault diagnosis for fault detection and diagnosis in Li-ion batteries is given in Ref. [16]. Where the optimal filter shows strong robustness to noise and the adaptive nature of the algorithm ensures accurate fault detection.

The use of observer based fault diagnosis under the paradigm of model based fault diagnosis offers inherent benefits like the decoupling of faults of interest from other faults, and minimizing the effects of unknown disturbances and model uncertainties [17]. These advantages are further utilized in the multiple model adaptive estimation (MMAE) technique; a special type of observer based fault diagnosis technique. MMAE employs a Kalman filter bank of n filters, where one observer represents the healthy condition of the process being monitored while the remaining $n-1$ observers represent the fault conditions of the process [16,18,19]. In addition to this apparent extension to the single observer case, MMAE also provides the added advantage of including a probabilistic approach to fault detection and diagnosis.

This paper is organized as follows: Section 2 describes the battery model, Section 3 describes the model-based fault diagnosis using nonlinear observers for residual generation and probability evaluation. Section 4 discusses the design of the experiment, and Section 5 provides the discussion of the results obtained. The conclusion of the work is captured in Section 6.

2. Battery modeling

Li-ion batteries can be modeled using different techniques namely electro chemical, neural networks, empirical, experimental and equivalent circuit [20,21]. The choice of modeling technique is a tradeoff between capturing cell dynamics and computational demand. For real time application the equivalent circuit model approach is adopted because it gives good representation of cell dynamics while maintaining low computational resource usage.

The Li-ion battery can be modeled as a third order system using lumped electrical elements like resistors and capacitors. The equivalent circuit model is shown in Fig. 1.where, R_b is the ohmic resistance, which accounts for the limited conductance of the metallic contacts, inter cell connections, electrode material and the bulk electrolytic resistance to electron and ion migration [1,22], constant phase element (CPE) C and resistance R are used to model the distribution of reactivity depicting the local property of the electrode., charge transfer resistance R_{ct} and double layer capacitance C_{dl} represent the interfacial impedance of the cell [23] and V_{OCV} represents the battery cell OCV. The CPE captures the distribution of reactivity at the electrodes which can be attributed to variation in surface properties. The impedance function of the combined RC pair is given by Refs. [23,24],

$$Z_{CPE}(\omega) = \frac{R}{1 + (j\omega)^{\alpha} QR} \tag{1}$$

where, α is the depression factor associated with the CPE and is assumed to be unity. As a result Q can be replaced by C and the CPE then behaves like a normal capacitor [22,23].

The circuit parameters depend on the SOC, temperature and capacity fade effects [25]. For this study, parameter dependency on these factors is assumed to be small. The effect of non-linear element in the equivalent circuit namely Warburg impedance representing the diffusion phenomenon is considered to be negligible [26].

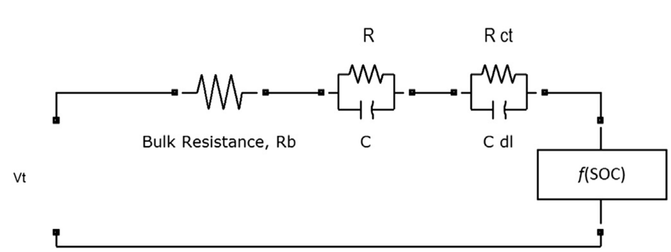

Fig. 1. Li-ion battery equivalent circuit model.