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Maximum pulse current estimation for high accuracy power capability prediction of a Li-Ion battery

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ABSTRACT

This study gives insight to the design and implementation of the dual extended Kalman filter (dual EKF)-based maximum pulse current estimation for high accuracy power capability prediction of a Li-Ion battery. The information on the lumped resistance, which represents the magnitude of the voltage variance during the predefined time, can be obtained using numerical equations based on two values of the state-of-charge (SOC) and series resistance R_i estimated by the dual EKF. These obtained lumped resistances are properly compared with those extracted by the hybrid pulse power capability prediction (HPPC) technique and the direct current internal resistance (DCIR) technique. Through experimental results that shows little difference between the estimated lumped resistance and those extracted by the HPPC and the DCIR techniques, it can be certainly mentioned that this work sufficiently provides an outstanding solution related to the available maximum pulse current estimation of a Li-Ion battery to be operated within the safety discharging/charging range. Consequently, our proposed dual EKF-based approach is clearly appropriate for providing information regarding the reliable power capability prediction.

1. Introduction

Currently, rechargeable Li-Ion batteries have become a more and more attractive selection for power electronics applications, portable devices, and renewable energy storage systems (RESSs) [1–3]. In particular, Li-Ion batteries have been gradually recognized as a promising resolution for electric-powered transportation, such as electric vehicles (EVs) and hybrid electric vehicles (HEVs) [4–10]. These activities require accurate and reliable information on the electrochemical characteristics in order to assure the overall system performance; that is, they require a battery management system (BMS) [11–15]. The role of the BMS is to measure the experimental voltage, current and temperature of the Li-Ion battery and pack and specifically to manage the opening and closing of high/low voltage relays related to sequences and protections. In this case, failure to accomplish a well-designed BMS, leading to over-charging and over-discharging, may result in permanent internal degradation of the battery [15]. Therefore, in recent years, much research work has been performed to attempt to find an optimal BMS that can resolve the above weakness. Above all, great attention has been shown regarding the question of the state-of-charge (SOC) and state-of-health (SOH), which are considered as representative factors in the BMS for supporting optimal battery performance and safety in EVs and HEVs [16–40]. Specifically, current BMSs should have well-established SOC estimation and SOH prediction algorithms. In practical applications, precise SOC and SOH information is crucial for efficient battery management, for example, where it is necessary to determine how long the battery will last in order to predict a reliable operating range, and when to stop charging and discharging in order to prevent the batteries in EVs and HEVs from over-charging and over-discharging [30].

Nowadays, the SOH implementation can be achieved by capacity-based [31–38] and pulse power-based predictions [39–42]. In the case of capacity-based prediction, the authors in Refs. [31–33] presented that this analysis, the most common method, can provide real information, but can suffer from cycle-life testing which is time-consuming, costly, and labor intensive, and that the life prediction from such tests often has limited applicability under the assumption that the fading mechanisms in the course of testing remain the same. On the other hand, the other method, pulse power-based prediction, is known to be an implementation of power capability prediction under a charging/discharging pulse current. Examples of this approach are the hybrid pulse power characterization (HPPC) technique and the direct current internal

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Nomenclature

Subscripts, superscripts

k	time step index
chg	charge
dis	discharge
max	upper limit value
min	lower limit value
^–	a posteriori estimation value
^+	a priori estimation value

Symbols

R_i	series resistance of the ECM
R_d	diffusion resistance of the ECM
C_d	diffusion capacitance of the ECM
V_d	diffusion voltage of the ECM
V_k	terminal voltage of the ECM
C_n	discharge capacity
$\boldsymbol{x}_k$	state vector (SOC and V_d in the ECM)
$\boldsymbol{\theta}_k$	parameter vector (capacity and series resistance R_i in the ECM)
y_k	measurement vector (terminal voltage in the ECM)
w_k	process noise (of the state $\boldsymbol{x}$/weight filter $\boldsymbol{\theta}$)
υ_k	measurement noise
$\boldsymbol{Q}_k$	process noise covariance of the state $\boldsymbol{x}$/weight filter $\boldsymbol{\theta}$
$\boldsymbol{R_k}$	observer noise covariance
$\boldsymbol{P}_k$	covariance matrix of the state estimation uncertainty
$\boldsymbol{H}_k$	measurement sensitivity matrix
$\boldsymbol{K}_k$	Kalman gain

resistance (DCIR) technique. Unfortunately, these tests are generally implemented at a specific SOC range, therefore, it may be almost impossible to provide correct information of the power capability for the entire SOC range. Ref. [43] showed that the magnitude of the internal resistance at the middle SOC range is smaller than at the low and high SOC ranges. Moreover, due to the differences in the electrochemical characteristics among Li-Ion batteries, repeated parameter measurements for power capability prediction of an arbitrary Li-Ion battery is generally inevitable [44].

The conventional dual extended Kalman filter (dual EKF)-based approaches facilitated an improved SOH prediction from the suppression of the above drawbacks, in addition to providing SOC estimation [43,44]. In these approaches, the experimental results obviously showed that two factors such as SOC and capacity for degraded Li-Ion batteries were well estimated [43,44]. However, because of the use of an identical value for lumped resistance for the entire SOC range, these works cannot provide a sufficient satisfaction in the pulse power-based SOH prediction. As a result, it has been further shown that these approaches were slightly vulnerable to over-voltage and under-voltage operating conditions. In general, the Li-Ion battery has an allowable operating voltage range (which is narrow) between the fully charged voltage and the case of over-voltage. When the battery is operated in the over-voltage range, it suffers from irreversible deterioration or permanent damage. Therefore, at a high SOC, the battery must be prevented from being operated at the over-voltage range through the power flow control of the energy management algorithm of a vehicle controller. For the same reason, the battery must be prevented from being operated in the under-voltage range [45]. From this overall perspective, a definitive answer that uses a lumped resistance properly varied depending on the SOC range should be considered in the exist the dual EKF approaches for efficient pulse power-based SOH prediction.

This research aims to introduce a new approach for the design and implementation of the dual EKF-based parameter identification for high accuracy power capability prediction. The nonlinear equivalent circuit model (ECM) earlier considered in Ref. [43,44] is applied to this work (Fig. 1). Through this work, the SOC and series resistance R_i can be concurrently estimated. The estimated SOC and R_i are initially applied to numerical equation and used to obtain the lumped resistance, which represents the magnitude of the voltage variance during the predefined time. For reference, the RC-ladder that is comprised of the diffusion resistance R_d and the diffusion capacitance C_d is sensitive to the battery degradation. Fortunately, because of the characteristics of the HEV driving current profile which includes a frequent charging/discharging process, it can be assumed that there is little influence on the RC-ladder, therefore, the constant values of R_d and C_d are applied to this work. For verification of this approach, the obtained lumped resistances are compared with those extracted by the HPPC technique and the DCIR technique. The comparison clearly shows that there are little differences between the obtained lumped resistances and the extracted values. The lumped resistances are intimately linked with the available maximum charging/discharging pulse current considered as an essential prerequisite for improved power capability prediction. The experimental results showed the clearness of the dual EKF-based approach for reliable power capability prediction. This work has been extensively verified by the experimental results conducted on 18,650 Li-Ion batteries that had a rated capacity of 1.3 Ah [46].

The remainder of this approach is organized as follows. This approach is divided into six parts, including this introduction section. To begin with, a review of the theoretical background on the dual EKF applied to the ECM is presented in Section 2. Section 3 shows the experimental setup for the implementation of the charging/discharging cycle for Li-Ion batteries. In the following section, the proposed approach for achieving the significant purpose of the maximum charging/discharging pulse current estimation is explained. The experimental results that show the robustness of the proposed approach are presented in Section 5. In the final section, some conclusions and final remarks are given.

2. Theoretical background on the dual EKF applied to the ECM

2.1. Basic concept of the dual extended Kalman filter (dual EKF)

The dual extended Kalman filter (dual EKF) [43,44,47–50,18,51–54], which makes use of two EKFs running in parallel, is extensively used for simultaneous state and model parameter estimations. In contrast with the Kalman filter applied for linear

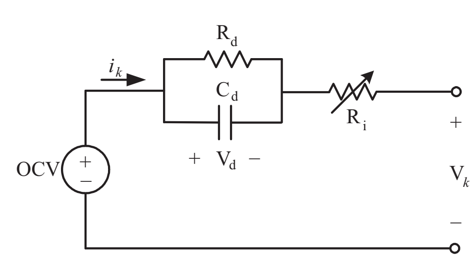

Fig. 1. Nonlinear equivalent circuit model (ECM) including the open-circuit voltage (OCV), a series resistance R_i in series with a parallel diffusion resistance R_d and diffusion capacitance C_d.