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Structural analysis based sensors fault detection and isolation of cylindrical lithium-ion batteries in automotive applications

Zhentong Liu [a,*], Qadeer Ahmed [b], Jiyu Zhang [b], Giorgio Rizzoni [b], Hongwen He [a]

[a] *National Engineering Laboratory for Electric Vehicles, Beijing Institute of Technology, 5 South Zhongguancun Street, Beijing 100081, China*
[b] *Center for Automotive Research, The Ohio State University, 930 Kinnear Rd., Columbus, OH 43212, USA*

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ABSTRACT

The battery sensors fault diagnosis is of great importance to guarantee the battery performance, safety and life as the operations of battery management system (BMS) mainly depend on the embedded current, voltage and temperature sensor measurements. This paper presents a systematic model-based fault diagnosis scheme to detect and isolate the current, voltage and temperature sensor fault. The proposed scheme relies on the sequential residual generation using structural analysis theory and statistical inference residual evaluation. Structural analysis handles the pre-analysis of sensor fault detectability and isolability possibilities without the accurate knowledge of battery parameters, which is useful in the early design stages of diagnostic system. It also helps to find the analytical redundancy part of the battery model, from which subsets of equations are extracted and selected to construct diagnostic tests. With the help of state observes and other advanced techniques, these tests are ensured to be efficient by taking care of the inaccurate initial State-of-Charge (SoC) and derivation of variables. The residuals generated from diagnostic tests are further evaluated by a statistical inference method to make a reliable diagnostic decision. Finally, the proposed diagnostic scheme is experimentally validated and some experimental results are presented.

1. Introduction

With the development of Electric Vehicles (EVs) in recent years, the lithium-ion batteries, as the energy storage device, are gaining more and more attentions due to its inherent benefits of high energy and power density, low self-discharge rate and long lifespan (Tie & Tan, 2013). To guarantee the battery safety, performance, reliability and life, a well-designed battery management system (BMS) is required to perform the functions such as thermal management to ensure the batteries work at optimal average temperature and reduced gradient, State-of-Charge (SoC) and State-of-Health (SoH) estimations, as well as over-current, over-/under-voltage protections (Lu, Han, Li, Hua, & Ouyang, 2013; Hu, Yurkovich, Guezennec, & Yurkovich, 2009; Plett, 2004; Zhang, Grube, Shin, Salman, & Conell, 2011; Fang, Wang, Sahinoglu, Wada, & Hara, 2014). These critical functions are mainly dependent on the current, voltage and temperature sensor measurements.

The sensors in the battery system may present various kinds of faults due to the manufacturing flaws, degradation, and external shock or vibrations (Balaban, Saxena, Bansal, Goebel, & Curran, 2009). If the current or voltage sensor is faulty, the SoC and SoH estimation performance will be degraded. The inaccurate estimated SoC maybe result in the battery suffering from over-charge and/or over-discharge, which would accelerate the process of battery aging (Lu et al., 2013; Plett, 2004; Marcicki, Onori, & Rizzoni, 2010). Moreover, the current and voltage protection circuitries may not work properly in the sensor faulty cases. If the temperature sensor cannot work normally, the performance of thermal management will deteriorate, thus decreasing the battery performance and life (Mikolajczak, Kahn, White, & Long, 2011). Therefore, it is critical to develop a reliable sensor fault detection and isolation (FDI) scheme for the battery system.

Few studies have been conducted regarding the battery fault diagnosis. A bank of reduced order Luenberger observers was used to isolate a single fault for a three-cell battery string, and the major problem of this scheme is that the Luenberger observer cannot achieve a satisfactory performance for system with measurement noise (Chen, Chen, Saif, Li, & Wu, 2014). Nonlinear parity equation based diagnostic scheme was applied to detect the current or voltage sensor fault in the simulation environment, but assuming the temperature sensor must be in no-faulty case (Marcicki et al., 2010). A multiple model-based diagnostic scheme was presented for the lithium-ion battery to detect the over-charge and over-discharge with the use of EKFs, but along with the complexity and

* Corresponding author.
E-mail address: zhentongliu87@gmail.com (Z. Liu).

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difficulty of identifying various models and running a bank of EKFs (Sidhu, Izadian, & Anwar, 2015). From the best of our knowledge, the topic of battery sensor FDI has been rarely addressed.

In this paper, a systematic model-based FDI scheme is proposed for the lithium-ion battery to detect and isolate the current, voltage and temperature sensor fault based on *structural analysis* theory. The proposed methodology could be applied for any other battery system faults. One advantage of this methodology is that it could pre-analyze the battery sensor fault detectability and isolability without the accurate knowledge of battery parameters, but just depending on the structural information of battery dynamics (Svärd & Nyberg, 2012; Svärd, Nyberg, Frisk, & Krysander, 2013). This is useful in the early design stages of diagnostic system. A further advantage of the structural analysis method is that it could decompose the coupled battery dynamics that has many internal interactions into smaller subsystems, which allows the design and implementation of efficient and effective diagnostic algorithms. The basic idea is that through analyzing the analytical redundancy part of structural model, structural analysis helps to extract various subsets of battery dynamics to construct diagnostic tests. In each diagnostic test, the unknowns are calculated sequentially using the known variables, and then a redundant equation (or consistency relation) is checked to generate a residual. To address different issues like unknown initial SoC and derivation of battery variables in different diagnostic tests, some efficient and effective diagnostic algorithms are designed based on the state observers and other advanced techniques. Further, in order to make a more accurate diagnostic decision, the residuals are evaluated by a statistical inference method, instead of just using fixed alarm thresholds for the residuals. Finally, the effectiveness of the proposed FDI scheme is experimentally validated and some experimental results are presented.

This paper is organized as follows. Section 2 describes the battery modeling. Section 3 gives the background theory of structural analysis based fault diagnosis, while Section 4 presents the proposed FDI scheme. Section 5 illustrates the experimental design to extract the battery model parameters. The experimental diagnostic evaluation and resulting conclusions are given in Sections 5 and 7, respectively.

2. Coupled electro-thermal model

In this section, a coupled electro-thermal model is described for cylindrical lithium iron phosphate batteries. It is composed of: a second order equivalent circuit model to capture the battery terminal voltage, and a two-state thermal model used to estimate the battery surface and core temperatures. Each individual model is described in the following subsections.

2.1. Electrical model

Fig. 1 shows the electrical model, which consists of an open circuit voltage (OCV) V_{oc}, an ohmic resistance R, and two parallel resistor-capacitors ($R_1 - C_1$, $R_2 - C_2$). The model representation is given as,

$$\frac{dV_1}{dt} = -\frac{V_1}{R_1 C_1} + \frac{I}{C_1} \quad (1)$$

$$\frac{dV_2}{dt} = -\frac{V_2}{R_2 C_2} + \frac{I}{C_2} \quad (2)$$

$$V_t = V_{oc} - V_1 - V_2 - I \cdot R \quad (3)$$

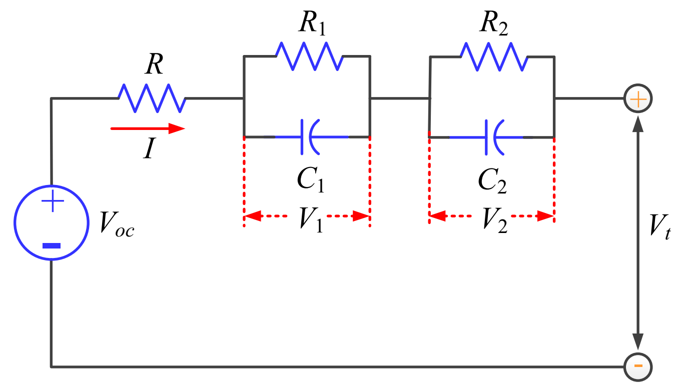

Fig. 1. Schematic of second order equivalent circuit model.

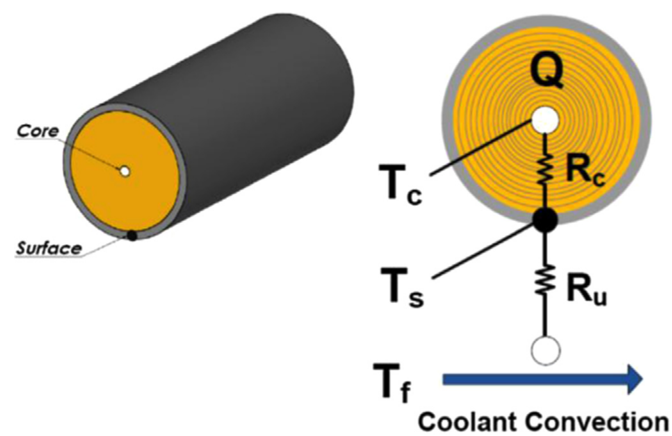

Fig. 2. Schematic of two-state thermal model (Adopted from Lin et al. (2014)).

where I is the current that is positive at discharge and negative at charge, V_1 is the voltage across capacitor C_1, V_2 is the voltage across the capacitor C_2, and V_t is the terminal voltage.

The battery OCV is usually a nonlinear function of SoC. The SoC is calculated by Coulomb counting as,

$$\frac{dSoC}{dt} = -\frac{I}{C_{bat}} \quad (4)$$

where C_{bat} is the battery available capacity. The equivalent circuit resistances and capacitances depend on the core temperature, SoC and current direction, and the effect of battery aging is not considered in this work. The battery capacity, OCV, parameters R, R_1, C_1, R_2, and C_2 will be identified in the following experimental design section.

2.2. Thermal model

The two-state thermal model, as sketched in Fig. 2, is used to model the radial thermal dynamics of a cylindrical battery (A123 26650) using the core and surface temperatures T_c and T_s, represented as,

$$\frac{dT_c}{dt} = \frac{T_s - T_c}{R_c\ C_c} + \frac{Q}{C_c} \quad (5)$$

$$\frac{dT_s}{dt} = \frac{T_f - T_s}{R_u C_s} - \frac{T_s - T_c}{R_c C_s} \quad (6)$$

$$Q = I\,(V_{oc} - V_t) \quad (7)$$