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Embedded fiber-optic sensing for accurate internal monitoring of cell state in advanced battery management systems part 2: Internal cell signals and utility for state estimation

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HIGHLIGHTS

- Embedded battery sensors critical for accurate cell state, safer/fuller utilization.
- Value of internal cell signals obtained with fiber-optic (FO) sensors demonstrated.
- Intercalation strain and electrode temperature key cell parameters monitored.
- Advanced algorithms enable <2.5% accurate cell state estimation with FO signals.

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ABSTRACT

A key challenge hindering the mass adoption of Lithium-ion and other next-gen chemistries in advanced battery applications such as hybrid/electric vehicles (xEVs) has been management of their functional performance for more effective battery utilization and control over their life. Contemporary battery management systems (BMS) reliant on monitoring external parameters such as voltage and current to ensure safe battery operation with the required performance usually result in overdesign and inefficient use of capacity. More informative embedded sensors are desirable for internal cell state monitoring, which could provide accurate state-of-charge (SOC) and state-of-health (SOH) estimates and early failure indicators. Here we present a promising new embedded sensing option developed by our team for cell monitoring, fiber-optic (FO) sensors. High-performance large-format pouch cells with embedded FO sensors were fabricated. This second part of the paper focuses on the internal signals obtained from these FO sensors. The details of the method to isolate intercalation strain and temperature signals are discussed. Data collected under various xEV operational conditions are presented. An algorithm employing dynamic time warping and Kalman filtering was used to estimate state-of-charge with high accuracy from these internal FO signals. Their utility for high-accuracy, predictive state-of-health estimation is also explored.

1. Introduction

As explained in part 1 of this two-part paper, a better understanding and real-time monitoring of internal cell state with accurate sensors is of critical need for effective control by battery management systems (BMS). This can play a key role in accelerating adoption of Lithium (Li)-ion batteries for clean energy technologies [1–3]. BMS for Li-ion cells perform a variety of functions such as cell balancing, state-of-charge (SOC), state-of-health (SOH) and state-of-power (SOP) estimation, failure prevention, and battery protection. BMS today typically monitor parameters such as voltage, current, and temperature externally to estimate cell state parameters. Common contemporary methods include Coulomb counting, open circuit voltage (OCV)-based approaches, and dynamical

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model-based approaches.

In Coulomb counting, the current is integrated over time and divided by the battery capacity to estimate SOC. This can be challenged in fielded packs as the low-cost current sensors typically used there have measurement drift errors that accumulate over time. The uncertainty in initial SOC and changing battery capacity over time can further complicate this method. In Ref. [4], an enhanced Coulomb counting method for SOC estimation was presented that uses derived empirical relationships between initial SOC, voltage and current, and dynamically re-calibrating the battery capacity. Using this approach, the maximum SOC estimation error was approximately 3%. It is not clear, however, whether that level of accuracy holds for more aggressive xEV-relevant battery loading profiles.

OCV can be computed by letting the battery rest for a sufficient duration of time ([5–7]). SOC can then be estimated using the pre-calibrated SOC-OCV relationship for that cell chemistry (or obtained using a very slow constant current charge). However, this method is of limited utility in real-world applications with real-time estimation requirements.

The dynamical model-based approach can broadly be classified into equivalent electrical circuit modeling and electrochemical modeling. The equivalent electrical circuit modeling approach is by far the most popular. There is a large body of research in this area. In Ref. [8], the authors employ an impedance spectroscopy approach to develop a non-linear electric-circuit model of an absorbent glass mat lead-acid battery. In Ref. [9], the authors evaluate and compare different electric circuit equivalent models of lithium-ion battery. According to their studies, the dual-polarization model, i.e. modeling independently the concentration and electrochemical polarizations, is the most accurate in estimating SOC.

In Ref. [10], the authors use a reduced order model of a Li-ion battery in conjunction with an Extended Kalman Filter (EKF) to estimate the SOC. To account for model errors, the measurement noise covariance in the EKF is modified based on the estimated SOC, the current, and the dynamics of diffusion, charge transfer and double layer. In Ref. [5], the authors address the problem that in practice there is some variation in the OCV versus SOC relationship from one Li-ion cell to the other. A new definition of capacity is proposed to minimize the variation across different cells. This leads to different capacities across different cells. A dual EKF is implemented that simultaneously estimates both capacity and SOC. As in Ref. [10], the measurement noise covariance is adaptively changed to account for model errors.

Electrochemical models attempt to build the model from first principles. Examples of these models include the pseudo two-dimensional model, the single particle model and the porous electrode model [11]. With such models, a trade-off exists between model realism and solution time. In Ref. [12], the authors develop a partial differential equation-based observer using the back-stepping control approach.

In part 1 of this paper, we made the case for direct internal monitoring with more informative embedded sensors to provide accurate SOC estimates and early indications of incipient failure for BMS. We presented fiber optic (FO) sensors as attractive candidates for embedding as sensors in Li-ion and other advanced batteries. The successful fabrication of high-performance large-format Li-ion pouch cells with embedded FO sensors (referred to as "FO-cells" in this paper) and assembly into commercial xEV modules by our team were discussed in part 1 of this paper. This second part of the paper focuses on the internal strain and temperature signals obtained from these fiber-optic sensors under various xEV operational conditions and their utility for high-accuracy SOC and SOH estimation algorithms.

The contributions and organization of this part of the two-part paper is as follows. In Section 2, we describe the various parameters that can be sensed or derived using FO sensing. These parameters include temperature, strain and current. We describe a novel computational approach for strain-temperature separation and experimentally validate the approach. In Section 3, we explain the relationship of strain with SOC in cell- and module-level tests and present our SOC estimation algorithm. The SOC estimation is based on a combination of FO based strain sensing and Coulomb counting. In Section 4, we describe the impact of aging on the strain-SOC relationship and our SOH estimation algorithm. In particular, we use measured strain to estimate the capacity of the battery and also predict the capacity up to 10 cycles into the future. Finally, we conclude with a summary and some thoughts for future research directions building on this work.

2. Sensing parameters of interest and strain-temperature separation

The details of the large-format FO-cells fabricated by our team were presented in part 1 of this paper. As mentioned and illustrated there, the FO cable within the cell shown there includes two elements of a particular class of FO sensors, fiber Bragg grating (FBG) sensors [13]. The FBG sensors are sensitive to strain and temperature, measured by monitoring their reflected wavelength shifts $\Delta\lambda$. The nominal cell capacity is approximately 15 Ah. The cell's anode material is graphite and cathode material is a blend of nickel-manganese oxide and manganese spinel.

It should be mentioned that while the FBG is monitoring the electrode around a single point, intuitively strain at a point in the electrode is not only affected by local SOC but also by expansion/contraction from lithiation/delithiation at other points in the electrode layer (since they are all mechanically part of the same electrode structure). Therefore, the strain measured at one point is expected to be indicative of SOC over a much larger area of the electrode rather than just the local SOC at that point.

One of the two FBG sensors was enclosed in a special tubing to allow it to slide freely and thereby make it selectively sensitive to thermal strain alone. The measured wavelength shift of the "reference" FBG sensor in the tubing is then subtracted from the wavelength shift of the adjacent FBG sensor sensitive to total electrode strain so that temperature variations are compensated. The compensation method is described next.

The reference FBG in the tubing, referred to herein as "loose" FBG, measures only the local temperature change ΔT [14]:

$$\Delta\lambda_{loose} = \overline{K}_T \Delta T \tag{1}$$

The adjacent FBG (referred to herein as "fixed") measures a combination of strain ε and temperature change [14]:

$$\Delta\lambda_{fixed} = K_\varepsilon \varepsilon + K_T \Delta T = \overline{\varepsilon} + K_T \Delta T \tag{2}$$

Equations (1) and (2) can be rewritten as follows:

$$\Delta\lambda_{fixed} = \overline{\varepsilon} + K_T^* \Delta\lambda_{loose} \tag{3}$$

We can recover the modified strain, $\overline{\varepsilon}$, if the constant K_T^* can be estimated. We refer to this constant as the "temperature compensation factor". This factor can be estimated in two ways.

2.1. Experimental approach to determining the temperature compensation factor

In this approach, a cell at rest is first heated to a certain temperature. The values of $\Delta\lambda_{fixed}$ and $\Delta\lambda_{loose}$ are recorded. Because the cell is at rest, the value of $\overline{\varepsilon}$ is zero. Therefore, the steady state ratio