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An Improved Impedance-Based Temperature Estimation Method for Li-ion Batteries ⋆

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Abstract: In order to guarantee safe and proper use of Lithium-ion batteries during operation, an accurate estimate of the (internal) battery temperature is of paramount importance. Electrochemical impedance spectroscopy (EIS) can be used to estimate the (internal) battery temperature and several EIS-based temperature estimation methods have been proposed in the literature. In this paper, we argue that all existing EIS-based temperature estimation methods implicitly distinguish two steps: experiment design and parameter estimation. The former step consists of choosing the excitation frequency (or frequencies) and the latter step consists of estimating the battery temperature based on the measured impedance resulting from the chosen excitation(s). By distinguishing these steps and by performing Monte-Carlo simulations, all existing estimation methods are compared in terms of accuracy (mean-square error) of the temperature estimate. The results of the comparison show that, due to different choices in the two steps, significant differences in accuracy of the temperature estimate exist. More importantly, by jointly selecting the parameters of the experiment-design and parameter-estimation step, a more accurate temperature estimate can be obtained. This novel more-accurate method estimates the temperature with an rms bias of 0.4°C and an average standard deviation of 0.7°C using a single impedance measurement for the battery under consideration.

Keywords: Lithium-ion batteries, Electrochemical Impedance Spectroscopy, Internal battery temperature, Monte-Carlo simulations

1. INTRODUCTION

Due to properties such as high energy density, Lithium-ion (Li-ion) batteries are used in various applications such as battery packs in (hybrid) electric vehicles. For safety and control purposes, temperature estimation of Li-ion batteries is of vital importance. For example, high battery temperatures can induce thermal runaway, which may cause fire or explosions, and accelerate ageing of the battery, thus reducing its lifetime and performance. A relatively new field of temperature estimation methods is based on electrochemical impedance spectroscopy (EIS), where a temperature relation is inferred from the electrochemical battery impedance. Using EIS for temperature estimation is often referred to as "sensorless temperature estimation", since no intrusive or surface-mounted temperature sensors are needed. Another advantage is that the internal average battery temperature is gauged. Therefore, there is no heat transfer delay due to the thermal mass of the battery as with measurements of the surface temperature.

A number of studies have presented temperature estimation methods (Raijmakers et al., 2014; Schmidt et al., 2013; Srinivasan, 2012; Richardson et al., 2014; Zhu et al., 2015; Howey et al., 2014). It can be argued that the presented methods can be broken down into two components: how to choose the excitation signal for the battery and how to estimate the battery temperature based on the measured output resulting from the chosen excitation signal. In Fig. 1, a general block diagram is shown that can be used to describe existing temperature estimation methods. Here, the frequency f defines the excitation signal and the measured output Z is the battery impedance. Choosing the excitation frequency f is referred to as *experiment design*, whereas estimating the battery temperature based on the measured impedance Z is referred to as *parameter estimation*. The real battery temperature and estimated battery temperature are denoted by T and $\hat{T}$, respectively, and v denotes measurement noise on the measured impedance Z. Furthermore, a battery impedance model is employed to establish a relation between the measured battery impedance Z and the battery temperature T. In Fig. 1, this is captured by the modelled battery impedance $\hat{Z}$, which is computed by using a battery impedance model and the excitation frequency f.

In general, the modelled battery impedance $\hat{Z}$ is compared to the measured battery impedance Z, using some established temperature relation, in order to obtain a temperature estimate $\hat{T}$. This comparison is defined by the *parameter-estimation* component by means of settings given by m. For example, one existing estimation method

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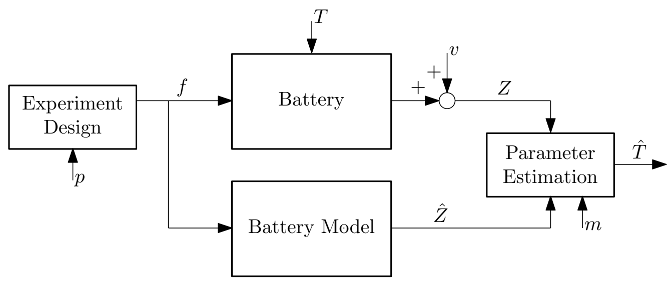

Fig. 1. Top level block diagram of measurement system.

(Schmidt et al., 2013) relates the real part of the battery impedance Z to the battery temperature T. Therefore, the parameter m induces the setting "real part of Z" on the *parameter-estimation* block and the battery temperature T is estimated by comparing the real part of the measured battery impedance to the real part of the modelled battery impedance at the excitation frequency f. The settings for *experiment design*, p, should yield a certain frequency f that causes the output Z to have the right information for the *parameter estimation* to give accurate results. For example, a sensitivity analysis in Schmidt et al. (2013) reveals that a high variation of impedance Z with temperature T can be found for low frequencies f. However, also a high variation of the impedance Z with the State-of-Charge (SoC) is found in this frequency region. The combination of both sensitivity analyses can be seen as choosing the *experiment-design* parameter p, which resulted for Schmidt et al. (2013) in a compromise in the excitation frequency f. Also, p can hold information as to how many measurements are taken and averaged in order to obtain a temperature estimate.

In this paper, we analyse the accuracy of impedance-based temperature estimation and propose a method that yields a more accurate temperature estimate, when compared to the existing methods. To do so, we will carefully investigate both *experiment design* and *parameter estimation* of impedance-based temperature estimation by introducing several parameters, and explain how existing methods can be considered as having certain choices for these parameters. A Monte-Carlo approach will be taken to analyse how different choices in *experiment design* and *parameter estimation* will lead to a different accuracy of $\hat{T}$. This accuracy is defined as the mean-square estimation error (MSE) of the temperature estimate $\hat{T}$, where the MSE can be broken down into bias (i.e., systematic error) and standard deviation (i.e., random error) of the temperature estimate $\hat{T}$. This will allow for a thorough comparison of the achieved estimation accuracy of the state-of-the-art impedance-based temperature estimation methods. Moreover, the analysis allows for synthesising parameters p and m that yield a more accurate temperature estimate (in terms of a smaller MSE value). As a basis for the comparison, analysis and synthesis, a data-based approach is chosen. No prior knowledge about batteries or battery modelling is assumed and therefore this paper focuses on the estimation problem instead of battery modelling and related issues. This makes the framework widely applicable for data-based battery analysis.

The organisation of the paper is as follows. Some background on EIS is presented in Section 2, and the principle of temperature estimation and the proposed framework are introduced in Section 3. Subsequently, the results of this study are presented and discussed in Section 4 and the conclusions are drawn in Section 5.

2. BATTERY IMPEDANCE MODELLING

The battery impedance Z can be interpreted as the battery frequency response, where the battery takes a sinusoidal voltage or current input with frequency $f = \omega/(2\pi)$, and produces a sinusoidal current or voltage output, respectively, with the same frequency. The ratio between input and output can be described as a (complex) impedance

$$Z(j\omega) = \tfrac{V(j\omega)}{I(j\omega)}, \tag{1}$$

where the magnitude of the excitation signal should be sufficiently small in order to guarantee local linearity of the system, yet not too small to prevent a poor signal-to-noise ratio (SNR). The technique of obtaining the frequency response of the battery is known as EIS and is widely used for gathering information about a non-linear system such as a battery (Orazem and Tribollet, 2008). In this study, EIS measurements are conducted in galvanostatic mode by superimposing a sinusoidal current with an amplitude of $100\sqrt{2}$ mA on the load current of the battery (whether or not a load current is present).

Based on the focus of the paper, as discussed in the Introduction, modelling efforts are limited to defining a data-based model instead of using modelling approaches such as first-principles modelling or equivalent-circuit modelling (Bergveld et al., 2002; Buller et al., 2003). In particular, we model the battery by a function $g : \mathbb{R}^4 \to \mathbb{C}$, that depends on excitation frequency f, temperature T, State-of-Charge (SoC) and other effects w such as cycling history and (dis)charge current. If also additive measurement noise $v \in \mathbb{C}$, induced by the measurement device, is considered, the battery impedance is given by

$$Z = g\,(f, T, \mathrm{SoC}, w) + v, \tag{2}$$

where $v = a + jb$ with $[a, b]$ a joint zero-mean Gaussian distribution. In this paper, we do not take into account the dependencies denoted by w and we shall assume $w = 0$ from now on. Introducing other dependencies than f, T and SoC can be seen as an extension on this work without changing the approach presented in this paper.

Based on the relation in (2) and EIS measurements, a battery model can be made, e.g., by storing impedance data in look-up tables. Since the measurement noise v and the SoC are assumed to be unknown, for simplicity, a model $\hat{g}$ of the battery impedance Z is constructed by averaging over SoC and v in order to make the model independent of these influences. As a result of these assumptions, the model is given by

$$\hat{g}\,(f, T) = \frac{1}{KM} \sum_{j=1}^{M} \sum_{i=1}^{K} g\,(f, T, \mathrm{SoC}_j, 0) + v_i \tag{3}$$

for some $\mathrm{SoC}_j \in [0, 100]$ and $j \in \{1, \ldots, M\}$, where $M \in \mathbb{N}$ is the number of SoC values at which the battery impedance is measured and $K \in \mathbb{N}$ is the number of measurements taken per SoC. It should be noted that the averaged model (3) is not necessarily equivalent to a model based on SoC = 50%, since the behaviour of the battery impedance might be asymmetric with respect to SoC.