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 ˆT, 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 ˆZ, which is computed by using a battery impedance model and the excitation frequency f.

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

$$Z(j\omega) = \frac{\mathbf{v}(j\omega)}{\mathbf{I}(j\omega)},$$

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 database 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

$$Z = g(f, T, \text{SoC}, w) + v,$$  \hspace{1cm} (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

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

for some $\text{SoC}_j \in [0, 100]$ 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 $\text{SoC} = 50\%$, since the behaviour of the battery impedance might be asymmetric with respect to SoC.

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 $T$. This accuracy is defined as the mean-square estimation error (MSE) of the temperature estimate $T$, where the MSE can be broken down into bias (i.e., systematic error) and standard deviation (i.e., random error) of the temperature estimate $T$. 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
3. IMPEDANCE-BASED TEMPERATURE ESTIMATION

Given the relation between the battery impedance $Z$ and the temperature $T$ in (2), the question now is, how to obtain the most accurate estimate of the temperature $T$ for a measured impedance $Z$ using EIS? Fig. 1 and (3) show that this question can be treated by considering two separate questions with the joint objective of obtaining the most accurate temperature estimate $\hat{T}$: how to determine the excitation frequency $f$ (or multiple frequencies $f_i, i \in \{1, \ldots, N\}$) and how to obtain the temperature estimate $\hat{T}$ from the measured impedance $Z$ for a certain $f$? Referring back to Fig. 1, what should $p$ and $m$ be?

The second question will be answered directly below, using existing literature on parameter estimation (Yates and Goodman, 2005). For answering the first question, better understanding is needed of the sensitivity of the temperature estimate with respect to the excitation frequency. This will eventually allow us to make a comparison of existing EIS-based estimation methods and it will allow us to devise a more accurate method.

3.1 Temperature Estimation

An EIS measurement with a certain excitation frequency $f$ and measured impedance $Z$ may be used to estimate the internal battery temperature $T$ by computing appropriate inverse functions of the battery impedance model (3). However, given the measured battery impedance $Z$, uncertainty in the estimated temperature $\hat{T}$ exists due to the measurement noise $v$, averaging over SoC and unmodelled effects $w$. Still, for some $f$ the inverse of (3) may be computed, leading to

$$\hat{T} = \tilde{g}_j^{-1}(Z) \quad \text{with} \quad \tilde{g}_j(T) = \tilde{g}(f, T).$$

(4)

The inverse in (4), like Fig. 1, shows that in order to obtain a temperature estimate $\hat{T}$ with the smallest MSE value, a proper value of the excitation frequency $f$ (i.e., experiment design) and suitable settings for using $\tilde{g}$ (i.e., parameter estimation) need to be chosen.

Instead of approximating the inverse as given in (4), a nonlinear least-squares estimator is proposed to estimate the battery temperature. This estimator is given by

$$\hat{T}(f, N, \alpha, Z) = \arg\min_T \frac{1}{N} \sum_{i=1}^{N} \alpha \tilde{g}_1^2(f_i, T, Z_i) + (1 - \alpha) \tilde{g}_2^2(f_i, T, Z_i),$$

(5)

where $N$ is the number of EIS measurements, $f$ is the vector of excitation frequencies $f = [f_1, \ldots, f_N]^T$ with a frequency $f_i$ for each EIS measurement, $Z$ is the vector of measured battery impedance values $Z = [Z_1, \ldots, Z_N]^T$ obtained through EIS, and $\alpha \in [0, 1]$ denotes a selector variable. In Cartesian coordinates, $\tilde{g}_1$ and $\tilde{g}_2$ are given by

$$\tilde{g}_1(f_i, T, Z_i) = \text{Re} (\tilde{g}(f_i, T) - Z_i)$$

(6a)

$$\tilde{g}_2(f_i, T, Z_i) = \text{Im} (\tilde{g}(f_i, T) - Z_i)$$

(6b)

while for polar coordinates, we have

$$\tilde{g}_1(f_i, T, Z_i) = \text{arg} (\tilde{g}(f_i, T)) - \text{arg} (Z_i)$$

(7a)

$$\tilde{g}_2(f_i, T, Z_i) = |\tilde{g}(f_i, T)| - |Z_i|.$$  

(7b)

In absence of noise $v$, unmodelled phenomena $w$ and for accurate information of SoC and any excitation frequency $f_i$ for which the model in (3) becomes bijective, the objective function in the minimisation problem in (5) becomes exactly zero and its result is exactly equal to (4). Note that the model in (3) is obtained through averaging a number of $K$ EIS measurements, and the result from (5) is obtained with a number of $N$ EIS measurements using the same model.

It should be noted that for the case of using polar coordinates, two quantities with different units are compared, making it difficult to give a physical interpretation to the resulting quantity. However, from an analysis point of view it provides valuable insights and therefore this notation is adopted. Furthermore, the physical interpretation for $\alpha = 1$ in (5) in combination with (6) is that only $\text{Re}(Z)$ is used in estimating the temperature. For $\alpha = 0$, only $\text{Im}(Z)$ is used. In case (5) is used in combination with (7), $\alpha = 1$ can be interpreted as using only $\text{arg}(Z)$ and $\alpha = 0$ as using only $|Z|$.

Now, for given experiment-design settings $f$ and $N$, the estimation method in (5) provides a structured approach for comparing, analysing, and finally, improving the parameter-estimation settings, $\alpha$ with a certain coordinate system, (6) or (7), for temperature estimation. These parameter-estimation settings can be seen as a concrete example of $m$ in Fig. 1.

3.2 State-of-the-Art Temperature Estimation Methods

Currently, there are a number of studies presenting EIS-based temperature estimation methods, see Table 1. In the design of the estimation method, these studies do not clearly differentiate between experiment design and parameter estimation. Table 1 shows the corresponding differentiation of the existing estimation methods. For each method, the estimation parameters $f, \alpha$ and the coordinate system, (6) or (7), can be identified to fit (5). This allows for a comparison of methods in Section 4 for a fixed $N$.

As indicated in Table 1, Schmidt et al. (2013) relate $\text{Re}(Z)$ at a fixed frequency to the battery temperature. It is stated that this fixed frequency is chosen at the high-frequency end of the impedance spectrum below the intersection with the real axis, showing only low inductive behaviour with a slight dependence on SoC. Also, Richardson et al. (2014) relate $\text{Re}(Z)$ at a fixed frequency to the battery temperature. However, they also use a thermal-impedance model combined with measurements of the surface temperature.

For the sake of comparing estimation methods in terms of

| Method                        | Experiment Design | Parameter Estimation |
|-------------------------------|-------------------|----------------------|
| Schmidt et al. (2013)         | fixed $f, N$      | Cartesian (6), $\alpha = 1$ |
| Richardson et al. (2014)      | fixed $f, N$      | Cartesian (6), $\alpha = 1$ |
| Srinivasan (2012)             | fixed $f, N$      | Polar (7), $\alpha = 1$ |
| Rajmakers et al. (2014)       | varying $f$ such that $\text{Im}(Z) = 0$, fixed $N$ | Cartesian (6), $\alpha = 0$ |
their EIS-based temperature estimation, this is not taken into account. The measurement frequency is chosen in the high-frequency semicircle, where the impedance is found to be on the edge of becoming SoC dependent. Srinivasan (2012) uses an equivalent measurement frequency to the one used by Richardson et al. (2014), but instead of relating temperature to $\text{Re}(Z)$, Srinivasan (2012) infers a relation from $\text{arg}(Z)$. Lastly, Rajmakers et al. (2014) do not employ a fixed frequency but define the so-called zero-intercept frequency, i.e., the frequency for which $\text{Im}(Z)$ is zero. This implies that a relation based on $\text{Im}(Z)$ is used. The estimation parameters for the improved method, which we will propose below, will be obtained by choosing the estimation parameters which achieve an improved accuracy (in terms of a smaller MSE of the estimated temperature) based on the results of the analysis also presented below.

4. RESULTS

To analyse and compare the accuracy of the temperature estimate $\hat{T}$ for existing estimation methods in literature, as well as to synthesise a more accurate estimation method, EIS measurements have been conducted for a single type of battery cell. Based on these measurements and by using (5), Monte-Carlo simulations have been conducted.

4.1 Comparison of Temperature Estimation Methods

Given foreseeable use of impedance-based temperature estimation in battery packs of (hybrid) electric vehicles, a large-capacity (90 Ah) LiFePO$_4$ cell has been chosen for the experiments. The EIS measurements were conducted with a dedicated measurement setup in combination with Maccor cycling equipment and a climate chamber. The measurement settings for the experiments are given in Table 2. The frequency range is based on a lower bound, where the battery impedance becomes SoC-dependent. The upper bound is chosen at a frequency where no noticeable temperature dependency is found. The temperature range includes temperatures expected during normal operating conditions of battery cells and also, it approximately covers the temperature ranges used in other studies.

For each combination of the measurement settings in Table 2, $K = 64$ measurements have been conducted for $M = 4$ values for SoC. Results from these measurements at SoC $= 40\%$ are shown in a Nyquist plot in Fig. 2. Due to the measurement noise $v$, for each measurement setting, a distribution of $K = 64$ data points can be seen in the Nyquist plot. The inset shows five distributions for five temperatures at a single frequency. Analysis yields that the measurement points are normally distributed with zero mean and a standard deviation in the real and imaginary part of $\sigma = 14 \mu \text{Ω}$. Using the measurement data, a model $\hat{g}$ of the battery impedance can be obtained through (3). The model comprises a lookup-table with a temperature-frequency grid. A finer temperature-frequency grid than the measurement grid in Table 2 is obtained using spline interpolation.

Finding the temperature estimate requires solving (5). To evaluate the EIS-based temperature estimation methods, Monte-Carlo simulations are carried out over a range of $f$, $N$, $\alpha$ and for (6) and (7). Subsequently, for a certain point in which the accuracy of the temperature estimate $\hat{T}$ is evaluated, i.e., at some $f$, $T$, and SoC, an input distribution of measured impedance values $Z$ for (5) is generated by adding a distribution of the measurement noise $v$ to the modelled impedance value $g$ in (2). The sample size of the Monte-Carlo simulations (i.e. the number of realisations for $Z$) is taken $N_{\text{MC}} = 10^4$, which results in a $\geq 95\%$-confidence bound for temperature estimates being within $\pm 0.2 ^\circ \text{C}$ of the actual value, see, e.g., (Yates and Goodman, 2005). The quality of the temperature estimate $\hat{T}$ can be described in terms of the MSE, see also, e.g., (Yates and Goodman, 2005).

The Monte-Carlo simulations allow us to make an assessment of the accuracy of the temperature estimate $\hat{T}$ for any given estimation parameters $f$, $N$, and $\alpha$ for (5). Since the existing EIS-based temperature estimation methods (Rajmakers et al., 2014; Schmidt et al., 2013; Srinivasan, 2012; Richardson et al., 2014) can all be described by a particular choice for $f$, $N$, and (6) or (7), see Table 1, the Monte-Carlo simulations allow the aforementioned methods to be compared. In our comparison and analysis, $N = 1$ is chosen. Certainly, $N > 1$ will give a smaller estimation error, but it will also take more time to gather measurement data (depending on the chosen measurement frequency $f$). In order to avoid the discussion on a trade-off between a short measurement time and a small estimation error, we take $N = 1$ in the comparison and analysis.

Finally, due to the use of a different battery cell than the ones used in the various studies (Rajmakers et al., 2014; Schmidt et al., 2013; Srinivasan, 2012; Richardson et al., 2014), an equivalent excitation frequency $f$ is chosen, satisfying the description of the estimation methods in Section 3. Note that for the method of Rajmakers et al. (2014), a frequency range is given since they use the concept of zero-intercept frequencies, implying a different frequency for each temperature.

Table 2. EIS-measurement settings for constructing $\hat{g}$.

| Temperature $T$ | $-20, -10, +10, +30, +50 ^\circ \text{C}$ |
|----------------|---------------------------------------------|
| Frequency $f$  | 25 log-spaced freqs. in range 50 Hz to 5 kHz |
| SoC values    | 20, 40, 60, 80%                            |
4.2 Analysis of the Temperature Estimation Methods

Fig. 3 shows the results of the analysis of temperature-estimation accuracy for Cartesian coordinates in terms of the MSE of the temperature estimate in °C-squared. Owing to space limitation, a separate discussion of the estimation accuracy for Cartesian coordinates in terms of the bias values and standard deviation on the estimate, as well as the MSE values, is omitted. Fig. 3 is divided into three rows and two columns with contour plots. The horizontal axis shows the frequency $f$ on a logarithmic scale whereas the vertical axis shows the value for $\alpha$. The colour corresponds to the colorbar to the right of each plot. The columns show two different SoC values and the rows show the real temperatures in ascending order from $-10^\circ$C to $30^\circ$C.

From Fig. 3, it can be concluded that for higher frequencies, the MSE is larger than for lower frequencies. This is particularly true for $\alpha = 0$ and for high temperatures. It can also be observed that the smallest estimation error can be found in the range of 50 Hz – 300 Hz. Selection of an $\alpha$ value in this range is less clear. Nevertheless, for $\alpha = 0$, the MSE is typically larger at higher frequencies than for $\alpha = 1$, as can be noticed from the bottom-right corner of each plot. Furthermore, all plots are in agreement on the fact that the smallest estimation error is found for $\alpha = 0.5$, i.e., by equally weighting the real and the imaginary part of the impedance.

The analysis of Fig. 3 can be used to propose an improved method for temperature estimation that yields the smallest estimation error for this type of cell. Namely, analysis of Fig. 3 indicates that, in Cartesian coordinates, the estimation error increases for higher frequencies and higher temperatures. Therefore, frequencies up to 300 Hz are suitable and we decide to choose 50 Hz. For the parameter $\alpha$, the estimation error is typically smallest for $\alpha = 0.5$, which is likely due to the fact that two measurements of the impedance, namely the real and imaginary part, are combined when $\alpha = 0.5$. Note that all conclusions drawn here are specific for the cell under consideration. Still, the proposed methodology and analysis is general and can be extended towards, and repeated for, different battery cells.

4.3 Results of the Comparison

The results of the comparison of estimation methods, as defined in Table 1, are depicted in Fig. 4. In this figure, the plots show a comparison of bias values, standard deviation values and MSE values in the top, middle and bottom plots, respectively. The left and right column show these results for SoC = 40% and SoC = 80%, respectively. In order to make a comparison, the estimation methods are evaluated at temperatures $T \in \{-15, -10, ..., +35, +40\}$ °C. Since the battery cell under investigation is not the same as the one used in the studies presenting the various estimation methods, an equivalent frequency, complying with the description of the methods in Section 3, is chosen in the frequency spectrum of the LiFePO$_4$ cell. Also, the proposed improved method has been evaluated. For Fig. 4, the selected excitation frequencies can be found in Table 3.
Results in terms of bias can be compared with Figs. 4a,b. It can be seen from these figures that the bias of all estimation methods varies with the real battery temperature $T$ and SoC. Due to the fact that the SoC is assumed unknown, the influence of SoC in the estimation is relatively large. In terms of standard deviation in Figs. 4c,d, the methods by Schmidt et al. (2013) and Richardson et al. (2014) show an increasing standard deviation towards higher temperatures. The method by Srinivasan (2012) shows opposite results with a decreasing standard deviation towards higher temperatures. The standard deviation for the method by Raijmakers et al. (2014) is around 3$^\circ$C over the complete temperature range. The improved method yields a small standard deviation over the whole frequency range. For the MSE in Figs. 4e,f, similar observations can be made.

Table 3 shows results for the comparison of estimation methods in terms of the root-mean-square (rms) bias and the average standard deviation, calculated over the same frequencies and temperatures as in Fig. 4 and SoC $\in \{20, 40, 60, 80\}$%. For this type of battery cell, it can be seen that the improved method yields the best performance for both the rms bias as well as the average standard deviation. The methods by Richardson et al. (2014) and Schmidt et al. (2013) yield a comparable rms bias, but the standard deviation is at least twice as large as the one for the improved method. For the method of Srinivasan (2012), the rms bias is the largest of all methods, also the average standard deviation has, together with the method by Schmidt et al. (2013), the largest value found for all methods. Finally, the rms bias and standard deviation for the method by Raijmakers et al. (2014) are relatively large.

To summarise, the improved method and the method by Richardson et al. (2014) show the most accurate results in terms of overall bias and standard deviation for SoC $\in \{20, 40, 60, 80\}$%, as well as in terms of the MSE in Figs. 4e,f. It should be noted that some methods yield better performance at high temperatures whilst other methods perform better at low temperatures. Therefore, the rms bias and average standard deviation do not give full details, but overall, the improved method outperforms the other methods.

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### Table 3. Comparison of estimation methods.

| Method                  | equivalent $f$ | rms$_{bias}$ | average $\sigma$ |
|-------------------------|----------------|--------------|------------------|
| Schmidt et al. (2013)   | 1300 Hz        | 0.6$^\circ$C | 3.3$^\circ$C     |
| Richardson et al. (2014)| 150 Hz         | 0.6$^\circ$C | 1.9$^\circ$C     |
| Srinivasan (2012)       | 150 Hz         | 1.0$^\circ$C | 3.4$^\circ$C     |
| Raijmakers et al. (2014)| 200 – 650 Hz   | 0.9$^\circ$C | 3.2$^\circ$C     |
| Improved method         | 50 Hz          | 0.4$^\circ$C | 0.7$^\circ$C     |

Through the combination of these components, an improved and more accurate estimation method has been deduced. The estimation parameters within the approach can also be used to describe existing estimation methods. Given the fact that no prior knowledge of batteries or battery modelling is assumed, the framework is a promising tool for analysis of impedance-based temperature estimation.

Using experimental data from a Li-ion cell, the accuracy of temperature estimates is analysed with a Monte-Carlo method for a large set of frequencies and temperatures. Results are evaluated in terms of the MSE of the estimate $\hat{T}$. These results show that suitable estimation parameters can be found at low frequencies, using both the real and the imaginary part of the impedance. Also, a quantitative comparison of estimation methods, including the improved method, is performed. Overall, differences in choices of estimation parameters are found to result in significant differences between estimation methods. It has been verified that the improved method yields the best overall performance in terms of bias and standard deviation.

### 5. CONCLUSIONS

For safety and control purposes, internal battery temperature information is essential. Temperature estimation methods based on EIS can be broken down into two steps: choosing the excitation frequency $f$ (i.e., experiment design) and estimating the temperature $T$ based on the measured impedance $\hat{Z}$ (i.e., parameter estimation). This paper presents a novel, data-based approach in which experiment design and parameter estimation are combined in order to find the most accurate temperature estimate.