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Predicting the battery core temperature: Explanatory power of measurement quantities under different uncertainty scenarios

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ABSTRACT

Predicting the highest battery temperature, the core temperature, is an important task for the safe operation of lithium-ion batteries. This prediction task is complicated by inherent system uncertainties that result in uncertain core temperature estimates. Aside from model, parameter and measurement uncertainty, this also includes uncertain user behavior in form of uncertain future discharge currents. However, measurable quantities like voltage, surface temperature or discharge current can potentially decrease the uncertainty in predicting the core temperature. The extent to which a measurement is able to decrease this estimation uncertainty, called data worth, depends on the uncertainty scenario. We conduct a model-based study to investigate the potential of voltage, current and surface temperature measurements to decrease core temperature estimation uncertainty. We use our previously developed stochastic, physically-based battery model to estimate the core battery temperature of a cylindrical $LiFePO_4$-Graphite cell. The data worth is computed with the Preposterior Data Impact Accessor method. We find that the common input to state-of-charge estimation methods, i.e. voltage and current measurements, can theoretically partially substitute a temperature measurement, if the user behavior is anticipated to some degree. Moreover, we highlight the importance of adequately estimating the involved uncertainties when assessing the data worth of measurement quantities.

1. Introduction

Lithium-Ion batteries have been steadily growing in importance since their commercial introduction in the early nineties. Due to their favorable energy density and good cycle life, they are used in a variety of every-day applications. These include their dominant use in personal mobile applications, like laptops and mobile phones, as well as the more recent advent of electrical, battery-powered transportation.

Although rare when compared to the amount of lithium-ion batteries produced [1], catastrophic failures have been frequently recorded. Thermal runaway incidents are widely reported and pose a threat both to personal life of customers and passengers, as well as to the economic well-being of the manufacturing companies because of costly product recalls. Consequently, battery safety is a constant concern that spans the design, manufacturing and operation phases of lithium-ion battery technology.

For the safe operation of a battery, the monitoring and estimation of its temperature distribution is of critical importance. The hottest point in a cylindrical cell is usually the core temperature. Yet, direct core temperature measurements are not common in deployed systems, and up till this point usually only done for research studies. Thus, the core temperature is commonly inferred from other measurement quantities. These include the series battery resistances [2], although not applied to lithium-ion batteries, and more recently the core temperature estimation from electrochemical impedance spectroscopy (e.g. [3–5]).

Most commonly, voltage, current and the surface temperature are available for battery state estimation [6]. A large number of methods can be used to estimate the core temperature from these quantities, or possibly from a subset these quantities. Often, a numerical model, ranging from equivalent circuit models to elaborate physical models, is used to simulate the relationship between the core temperature and the measurement quantities [7].

However, the modeling of any system is challenged by inherent uncertainties [8]:

1. The model, as a functional relationship between parameters and system states, approximates the real system and introduces structural model uncertainty.
2. Model parameters can be chosen inappropriately, especially if limited data is available for calibration, which introduces parameter uncertainty.
3. Measurements are noisy and introduce measurement uncertainty.

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Special abbreviations

WN	white noise
AR	auto-regressive

4. Varying model input (e.g., the user's discharge behavior) introduces additional input uncertainty.

All these different uncertainty sources result in uncertain model predictions, and in our case in an uncertain estimation of the core temperature.

Uncertainties are a lack of information about the real system state and can be treated stochastically, even though the true (but unknown) state is assumed to be deterministic. Such epistemic uncertainties can potentially be reduced by obtaining more information about the system during operation. By doing so, the model is fused with newly acquired system information.

The influence of a newly acquired measurement on the core temperature estimation depends on the measurement type, the character and magnitude of the involved uncertainties, and the evolution of the system state over time. We refer to the strength of this influence, i.e. the amount of uncertainty reduction in the estimated battery core temperature, as *data worth* [9], based on a common concept borrowed from the environmental sciences.

There is a plethora of studies that use probabilistic methods to estimate battery states like the state of charge (SOC) or the state of health (SOH). Fewer studies are explicitly concerned with the probabilistic estimation of the temperature distribution or select temperature states of the battery. These studies usually use simplified thermal models, possibly coupled with an electrical model, in combination with a probabilistic estimation technique to estimate the core or inner temperature, like Kalman filters (KF) [10–12], adaptive KFs [13], extended KFs [14], or dual KFs [15]. Liu et al. [16] adopted a different approach by using a controlled auto-regressive integrated moving average model for thermal predictive control of the charging process.

Moreover, there exist a few studies that focus on the influence of uncertain measurements on different modeling objectives. Stevanatto et al. [17] developed a detailed measurement model for impedance measurements of lead-acid batteries and investigate their influence on parameter identification. Wold et al. [18] analyzed the influence of measurement uncertainties for current, voltage and time on capacity and coulombic efficiency, by modeling the measurement errors. However, to the best knowledge of the authors, there has not been any study that combines both angles and focuses on the impact of measurement quantities on the predictive estimation uncertainty of the battery core temperature. Anthony et al. [19] touch upon this question when assessing the experimental uncertainty sources of their analytical estimate of the core temperature from circumferential temperature measurements, but did not investigate the potential of different measurement quantities to improve the prediction.

The goals of our model-based study are to:

- assess the usefulness of different measurement quantity combinations for estimating the core battery temperature.
- determine whether and how additional information about the discharge current can increase the certainty of core temperature prediction.

To reach these goals, we use a stochastic, physically-based battery model of an A123 $LiFePO_4$-Graphite lithium-ion battery [20]. This stochastic model is able to predict the battery temperature as a probability density function (PDF) by running a Monte-Carlo simulation. The Monte-Carlo simulation serves as an input to the Preposterior Data Impact Accessor (PreDIA) method [21], which computes the data worth of different measurement types on the battery core temperature. We explore different uncertainty scenarios, in which the user's behavior, i.e., the discharge current, is known to different degrees.

Our contributions are a unique analysis of the effect of different measurement types on the prediction and estimation of the battery core temperature under different uncertainty scenarios, from which we derive conclusions for data choice and recommendations for future research.

The paper is structured as follows: Section 2 briefly presents the stochastic, physically-based battery model. This is followed by a brief introduction to the data worth assessment method PreDIA in Section 3. Section 4 applies the previously introduced methods to a 1C discharge scenario under different uncertainty scenarios and discusses the influence of the different measurement quantities on the core temperature estimation. Finally, we summarize our conclusions and end with a brief outlook on future work.

2. Stochastic battery model

As the basic building block, our methodology requires a stochastic model that allows us to compute different realizations of a discharge scenario. Although our methodology can be used with different types of stochastic models, we use a stochastic, physically-based battery model in this study, as described by Mehne and Nowak [20]. For convenience, we give a brief summary of the model in this section.

The stochastic model extends the (deterministic) physically-based, thermo-electrochemical battery model framework presented in Hellwig et al. [22] and Hellwig [23]. The development of this modeling framework is ongoing and it has been used in a large number of applications for different types of batteries. In the case of lithium-ion batteries, these include for example the aging of $LiFePO_4$-Graphite cells [24], and thermal decomposition reactions during thermal runaway [25]. However, in this study we are interested in the uncertain evolution and the prediction of temperatures, not in modeling aging or thermal decomposition, such that the aforementioned model by Hellwig [23] is adequate in the scope of this study.

The physically-based thermo-electrochemical model simulates an A123 $LiFePO_4$-Graphite 26650 cylindrical cell as a 1D radially symmetric system and makes use of different scales to model the respective physical processes. The model comprises of an electrochemical and a thermal part.

The electrochemical part models charge and mass transfer on the scale of an electrode pair (pseudo-2D approach). Because we are mainly interested in the temperature evolution and in estimating the battery core temperature, we focus on presenting the thermal processes. For electrochemical details, please refer to the cited sources [23].

The thermal model part exchanges heat produced and consumed by the electrochemical processes via heat source and sink terms. For easier derivation, we subsume all heat source terms with a combined heat generation term $\dot{q}$, which results in the following partial differential equation (PDE) governing the heat transfer process [26]:

$$\rho c_p \frac{\partial}{\partial t}(T(t)) - \nabla\cdot(k\nabla T(t)) = \dot{q}(t), \tag{1}$$

where t is time, T the temperature field, k the thermal conductivity, ρ the material density and c_p the specific heat capacity.

Moreover, the model can dissipate heat over its surface by means of:

1. heat convection: $\dot{q}_c = h\,A(T_s - T_a)$, where h is the heat transfer coefficient, A the surface area of the battery, T_s the surface temperature and T_a the ambient temperature.
2. radiation: $\dot{q}_r = \epsilon_r\sigma_r A(T_s^4 - T_a^4)$, where ϵ_r is the emissivity of the battery surface and σ_r is the Stefan–Boltzmann constant.

The model has been calibrated to experimental data [20,23]. The resulting thermal model parameters are listed in Table 1. A more