Parameterisation Of Physics-Based Battery Models From Few Noisy Measurements

Yannick Kuhn*, Birger Horstmann, Arnulf Latz

Helmholtz Institute Ulm
German Aerospace Center
Helmholtzstraße 11, 89081 Ulm, Germany
{yannick.kuhn, birger.horstmann, arnulf.latz}@dlr.de

ABSTRACT

A wealth of measurement techniques are available for determining the transport or thermodynamic properties of batteries. Some examples are the Galvanostatic Intermittent Titration Technique [1], nuclear magnetic resonance imaging [2] or impedance spectroscopy [3], which are excellent at retrieving a subset of battery model parameters. They achieve this at the cost of accuracy and compatibility since each employs a different approximation in order to obtain analytic expressions.

So it remains a challenge to obtain a complete and consistent parameter set that is useful for running simulations that can accurately predict future battery behaviour. Exacerbating this challenge is the long run-time and/or high cost of any battery measurement (e.g. [1-3]), which means that in practice only a few measurements of varying type with considerable noise are available and that the parameters might change between measurements due to battery ageing. Due to the complexity of the widely used Doyle-Fuller-Newman model and its simplifications [4], their parameters are not directly observable in normal battery operation. Thus, some measurements involve the destruction of the battery, which make the parallel parameterisation of "identical" batteries with slightly different manufacturing defects necessary.

The goal is to enable automated material screening with a flexible selection of various measurements. The issues described above necessitate that an inverse parameter identification algorithm for this task is aware of the uncertainties in the parameters and the measurements and can quantify the uncertainties of the estimated parameters. These uncertainties are most certainly intractable, so we decided on a Bayesian approach where the likelihood is substituted by a simulator, realised with Expectation Propagation [5]and Bayesian Optimisation [6]. We will discuss the results of their application.

References

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