Model-based parameter estimation of li-ion batteries

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Motivation

Online evaluation of the battery state is a basic function of a battery management system (BMS) in electric vehicles (EV). A common approach to estimate the internal parameters of the cell under investigation is the use of model-based methods like the Kalman Filter (KF). Thereby the mathematical model of the battery is adapted during operation to the measured cell terminal voltage. For EV-applications the algorithms have to be simple enough to be run on an embedded system.

Introduction

While most methods deal with the estimation of the state of charge (SOC), this work focuses on the parameter estimation of the internal resistance, which represents the available power of the battery. Two different adaption techniques, the Extended Kalman Filter (EKF) and the Unscented Kalman Filter (UKF) are applied to the estimation of the internal resistance of a commercial li-ion battery. For validation the UR18650ZT cell from Sanyo was used. This

Fig. 1: Cylindrical high-energy li-ion cell (Sanyo UR18650 ZT)

cylindrical NMC cell (see Fig. 1) has a nominal capacity of 2.7 Ah. Experimental data based on the European driving cycle ARTEMIS of an EV is used to compare the algorithms in terms of estimation accuracy.

Modeling

The model of the battery must be as simple as possible to be implemented on embedded applications but as accurate as possible to represent the main electrochemical phenomena. In order to derive a proper model structure, the characteristics of the li-ion battery are investigated using electrochemical impedance spectroscopy (EIS) and various pulse-current profiles covering the complete SOC range. In Fig. 2 the data of the EIS is compared to the results simulated with a model, which is based on an equivalent circuit (EC), that consists of

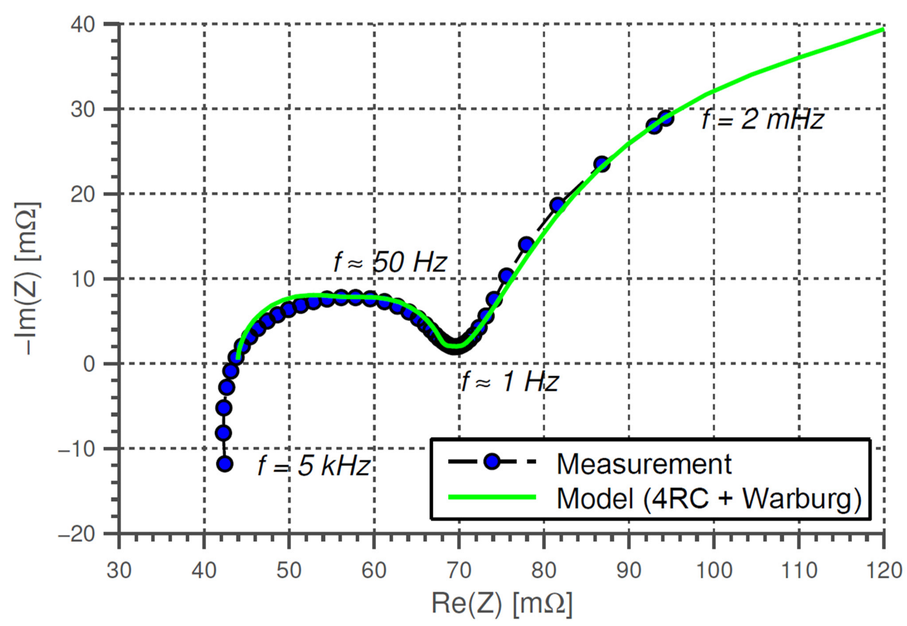

Fig. 2: Nyquist plot, f = 5 kHz ... 2 mHz, SOC=100 %

four RC-circuits and one Warburg Impedance.
In order to reduce the complexity, the model is adapted for EV-applications. It consists of an accurate open-circuit voltage source V_0, an internal resistance R_I and an element describing the diffusion effects, $R_D||C_D$ (see Fig. 3).
The internal resistance R_I combines the ohmic resistance R_Ω and the effects associated to the solid electrolyte interphase and charge transfer reactions. To determine its value, a current pulse ΔI is applied to the battery and the change of the terminal voltage is measured after a period Δt.

$$R_I = R_{DC}(\Delta t = 1\,s) = \frac{\Delta U(\Delta t)}{\Delta I} = \frac{U(t) - U(t+\Delta t)}{\Delta I}$$

Parameter identification of R_D *and* C_D as a function of the SOC is performed using nonlinear least squares fitting.

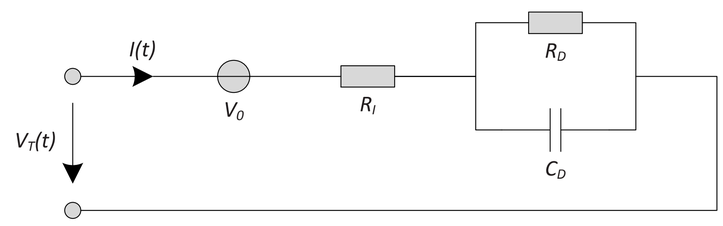

Fig. 3: Reduced equivalent circuit model (1RC)

The model is used for online-estimation of the internal resistance of a li-ion battery. Therefore it is transforemd into the discrete state-space representation and applied to the dual estimation approach of both the EKF and UKF. Hereby the sampling period ΔT is 1 s. The state vector $\underline{x}_k$ consists of V_{RC} , the over-voltage at the R_DC_D-element, and the SOC. The parameter vector $\underline{w}_k$ is made up by the internal resistance R_I and the diffusion parameters R_D *and*T_D.
The model has been validated using experimental data based on various current profiles. There is a very close agreement between the simulated cell terminal voltage V_T and the measured cell terminal voltage. The root-mean-squared (RMS) error of the voltage for a complete discharge cycle is 12.62 mV.

Results

The EKF and the UKF are applied to the adaption of the internal resistance R_I and the diffusion parameters R_D and $T_D = R_DC_D$ and compared in terms of estimation accuracy and computational complexity based on the ARTEMIS urban driving cycle. The UKF predicts the parameters of the battery more precisely than the EKF, especially if the model behaviour is highly nonlinear. The RMS internal resistance estimation error of the UKF is 1.87 mΩ, of the EKF ist is 4.27 mΩ. However, the EKF outperforms the UKF in terms of computational complexity.
Fig. 4 shows the estimated internal resistance and the measured direct-current resistance R_{DC} *(Δt = 1 s)*.

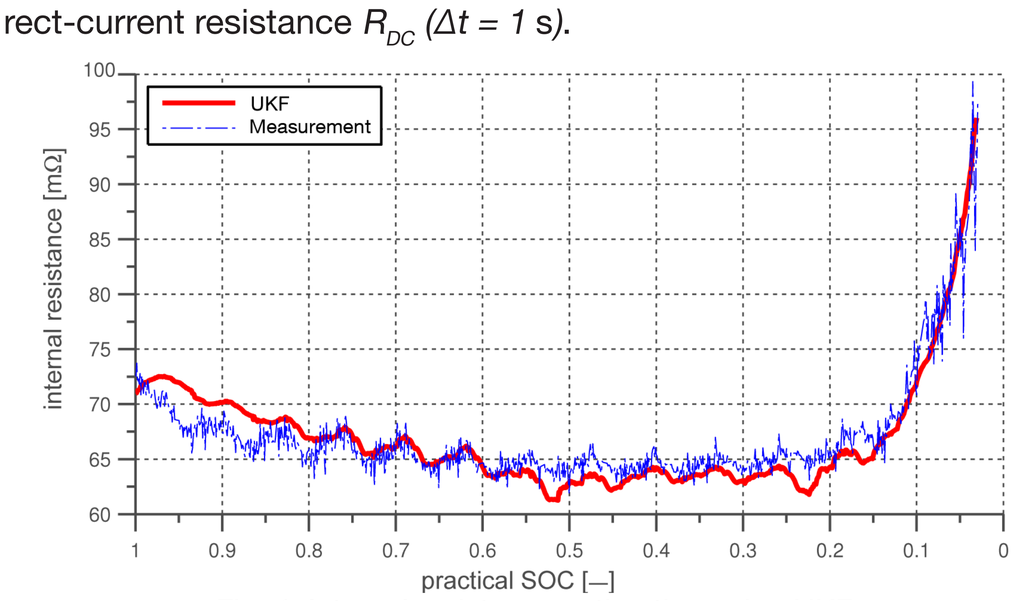

Fig. 4: Internal resistance estimation using UKF

References

[1] Andre, D. ; Meiler, M. ; Steiner, K. ; Walz, H. ; Soczka-Guth, T. ; Sauer, D. U.: Characterization of high-power lithium-ion batteries by electrochemical impedance spectroscopy In: Journal of Power Sources 196 (2011)
[2] Jossen, A.; Weydanz, W.: Moderne Akkumulatoren richtig einsetzen, Inge Reichardt Verlag, Neusäß, 2006
[3] van der Merwe, R.: Sigma-Point Kalman Filters for Probabilistic Inference in Dynamic State-Space Models, Dissertation, Oregon Health & Science University, 2004