Improving the functional safety of automotive batteries using in-situ impedance spectroscopy

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Abstract

Safe operation of Li-ion traction batteries in electric cars is one of the main requirements for a broad acceptance of this technology. Safety critical factors such as over-temperature conditions must be reliably monitored and captured. Increasingly strict safety regulations in the automotive sector imply rising challenges to both car manufacturers and battery system suppliers and hence resilient, reliable yet inexpensive tools for battery state diagnosis are necessary to address these topics. The approach presented here is a battery diagnosis tool based on in-situ galvanostatic electrochemical impedance spectroscopy which can be integrated into a standard battery management system. The algorithms which are used to convert the impedance measurements into valuable battery temperature estimations are based on numeric correlations between the impedance and these state variables. This method improves the safety in electric cars during the usage of a battery pack by redundant monitoring of the battery temperature.

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1. Introduction

Safe operation of Li-ion traction batteries in electric cars is one of the main requirements for a broad acceptance of this technology. Safety critical factors such as ageing effects and over-temperature conditions must be reliably monitored and captured. Increasingly strict safety regulations in the automotive sector imply rising challenges to both car manufacturers and battery system suppliers and hence resilient, reliable yet inexpensive tools for battery state diagnosis are necessary to address these topics.

State of the art battery monitoring in electric vehicles mainly consists of battery voltage, direct current and temperature measurements comprehensively shown by Waag et al. (2014). The interpretation of the measured data depends on the algorithms which are implemented in the battery management system. There exists a variety of algorithms which differ in their kind of data analysis, accuracy and required computational power.

In recent years efforts have been made to determine battery states like temperature, state of health or state of charge by means of electrochemical impedance spectroscopy. Numerous solutions for battery temperature estimation were presented by Spinner et al. (2015) and Richardson et al. (2014) using correlations between cell temperature and single-frequency impedance measurement data or broad frequency band impedance measurement data. The latter approach was introduced by Schmidt et al. (2013), Zhu et al. (2015) and Rajmakers et al. (2014). Similar methods were also used for state of health estimation by Eddahech et al. (2012) and Barre et al. (2013) and state of charge estimation by Xu et al. (2013). It could be shown that these techniques lead to reasonable results on laboratory scale. However, the implementation of hardware and appropriate algorithms into automotive battery management systems which are needed for impedance measurements is still a challenge due to the ambitious functional safety requirements of automotive industry. Furthermore, the cited approaches are all based on impedance measurements performed while the batteries were in equilibrium state meaning that no direct current (DC) was applied during or before the impedance measurements but especially a temperature estimation is only useful during current loads in order to monitor the increase of the battery temperature.

The approach presented here is a battery diagnosis tool based on in-situ galvanostatic electrochemical impedance spectroscopy which can be embedded into a standard battery management system. It is designed for on-line battery state estimation. In this work it is shown that impedance measurements can be successfully applied for battery temperature estimation during charge and discharge processes as well as dynamic current loads.

2. Experimental details

In this study 21 Ah Li(NMC)O₂ automotive grad pouch cells were characterized. Regarding the data sheet these cells can be charged with up to 3 C between 0 °C and 55 °C and discharged with up to 5 C between -20 °C and 55 °C. Impedance measurements were performed in galvanostatic mode with an excitation amplitude of 200 mA in a frequency range from 10 kHz to 10 mHz using a Gamry IF1000 galvanostat. To investigate the influence of a DC-offset on the impedance measurements a DC-offset of 0.5 A was superimposed on the AC-excitation in charge as well as in discharge direction. The ambient temperature was adjusted from 0 °C to 50 °C using a Binder MK53 temperature chamber.

3. Results and discussion

Estimating the battery temperature via in-situ impedance measurements requires a correlation between both values being unique for each cell. Getting this numerical correlation out of impedance measurements in equilibrium state of the respective battery can be achieved easily (see Chapter 1). For practical applications detailed information about the dependence of this correlation from the DC-load and the DC-profile is necessary in order to monitor the temperature also during these non-equilibrium states.
3.1. Impedance measurements

Figure 1 shows the experimental sequence of the impedance measurements. The reference measurement (1) was carried out over the full frequency range and under electrochemical and thermal equilibrium conditions meaning that the DC-offset was $I_{DC} = 0$ A. Non-equilibrium measurements were performed over the full frequency range with a DC-offset of $I_{DC} = 0.5$ A (2) and $I_{DC} = -0.5$ A (3). Each measurement took about 35 minutes. The state of charge variation between the beginning and the end of both measurements was about 1.5% meaning that the expected change in the impedance spectra between the equilibrium and non-equilibrium measurements could rather be attributed to the DC-offset than to the state of charge dependency of the impedance itself. Measurement (4) and (5) are single frequency impedance measurements determining the impedance of the cells right after a current pulse of 1 A and -1 A for 10 s, respectively. After each measurement the cells were stored for three hours to achieve electrochemical and thermal equilibrium again.

Figure 2 shows some Nyquist plots of equilibrium and their corresponding non-equilibrium. The intersection of the graphs with the x-axis represent the total ohmic resistance of the cell mainly determined by the resistance of the electrolyte. Following Ohm’s law the electrolyte resistance decreases from about 1.6 mΩ at 10 °C to 1.2 mΩ at 50 °C. The structure of the inductive part of the spectra in the high frequency range ($Z_{im} > 0$ mΩ) is basically independent of the temperature. The suppressed semicircles in the mid frequency range representing the charge transfer kinetics at the electrode/electrolyte interface show a strong temperature dependence which can be expressed by the Butler-Volmer-equation.

The sloping lines in the low frequency region can be attributed to diffusion processes. The slopes are almost equal for the equilibrium and non-equilibrium spectra, respectively. This indicates that the measurements were performed under reproducible conditions. Applying a DC-offset during the impedance measurements leads to a changing slope indicating that the direct current influences the diffusion kinetics.
3.2. In-situ temperature estimation

The precise quantification of the correlation between the battery temperature and its impedance is the most important requirement for an accurate temperature estimation. Besides a quantification of this correlation for electrochemical and thermal equilibrium state a massive amount of characterization effort as well as increased model complexity would arise if the correlation has to be quantified separately for all non-equilibrium states. Thus, the excitation frequencies at which the correlation is quantified should be carefully chosen in a way that the influence of the non-equilibrium states is minimized. This would only lead to the necessity of the numerical correlation gathered during equilibrium state. Using this correlation in non-equilibrium conditions leads to an error of the temperature estimation depending on the deviation of the battery impedance between equilibrium and non-equilibrium states which will be discussed below.

The upper part of Fig. 3 shows the temperature dependence of the impedance \( Z \) measured at a chosen frequency under the different load conditions described in Chapter 3.1. The relations between the impedance and the temperature can be accurately fitted by polynomial functions whereas \( Z_{eq}(T) \) is the correlation function obtained in equilibrium state and \( Z_{neq}(T, I_{DC} \ldots) \) are the correlation functions for different non-equilibrium conditions. The deviation between the impedances obtained at equilibrium and non-equilibrium states are shown in the lower part of Fig. 3. It can be seen that the current load which was superimposed to the impedance measurement leads to a deviation of less than 4% in a temperature range from 10 to 50 °C and about 7% at 0 °C. Applying a current pulse right before an impedance measurement with \( I_{DC} = 0 \) A leads to a deviation of less than 4% with respect to the equilibrium impedance in the full temperature range.

An estimation of the battery temperature via impedance measurements can be performed using the inverse correlation function \( T_{eq}(Z) \) even for impedance values obtained under non-equilibrium conditions. As a consequence thereof the error \( \Delta T \) of this estimation is given by the difference between \( T_{eq}(Z(I_{DC} \neq 0)) \) and \( T_{eq}(Z(I_{DC} = 0)) \) for the measured value of the impedance. Due to the small deviation between \( Z_{eq}(T) \) and \( Z_{neq}(T, I_{DC} \ldots) \) as shown in Fig. 3 this procedure seems suitable for an accurate in-situ temperature estimation.
4. Conclusion

In this work an impedance measurement study on automotive-grade Li(NMC)O₂ batteries was presented. Impedance measurements in equilibrium and non-equilibrium states were performed at different temperatures. It could be shown that a numerical correlation between the impedance and the battery temperature exists for the examined cell type. The impedance values at chosen frequencies measured at non-equilibrium states showed only a small deviation from those measured at equilibrium state. However, the behavior of the impedance at higher DC-offsets has to be further investigated in order to fit application-related circumstances. Thus, temperature estimation with impedance values measured at non-equilibrium conditions can be made using the numerical correlation between the impedance measured in equilibrium state and the battery temperature. This correlation can be generated experimentally in a short period of time saving lots of experimental efforts. This procedure allows to determine the battery temperature by an impedance measurement during dynamic charge and discharge processes which occurs for example in electric cars. The presented approach can be used in such applications as a redundant method for battery temperature estimation which has the potential to increase the functional safety of the whole battery pack.

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