

# Influence of change in open circuit voltage on the state of charge estimation with an extended Kalman filter



Christian Campestrini\*, Stephan Kosch, Andreas Jossen

Institute for Electrical Energy Storage Technology (EES), Technical University of Munich (TUM), Arcisstr. 21, 80333 Munich, Germany

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## ABSTRACT

The Kalman filter is a commonly used state of charge estimation algorithm for lithium-ion cells. Therefore, the filter uses the correlation between the open circuit voltage and the state of charge as reference. The aforementioned relationship is largely affected by temperature and ageing. However, the effect of cell ageing on the filter accuracy is often neglected in literature. In this work we show the influence of an ageing dependent open circuit voltage on the state estimation with an extended Kalman filter. Therefore, the open circuit voltage (OCV) determined by constant current charge/discharge, and the OCV determined by charge/discharge steps, at four different temperatures in the range from 0 °C to 40 °C are considered. For each temperature, the open circuit voltage of cells with a state of health of 98.3%, 90.4% and 82.5% is changed during the validation process. Based on our measurements, we observed a root mean square error of approximately 3.5% in state of charge when the open circuit voltage of the new cell is compared to the aged cell. This value increases to a state of charge estimation error of up to 6.5% when the extended Kalman filter is applied. However, the open circuit voltage dependency on the estimation can be influenced by the filter tuning. In consequence, the open circuit voltage has to be adapted to the cell condition to fulfil the requirements of an accurate and reliable state estimation with open circuit voltage based algorithms.

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## 1. Introduction

To date, a large variety of state of charge (SOC) and state of health (SOH) estimation algorithms for lithium-ion batteries are presented in literature [1,2]. One of the most common algorithms is the extended Kalman filter (EKF) [3–6]. In the field of battery SOC estimation, the filter is commonly used to predict the battery output voltage based on an equivalent circuit model (ECM) and a coulomb counter. Therefore, the filter considers the relationship between the SOC and the OCV. Here the OCV can be represented by a model or look-up table (LUT) in the filter. This may lead to large deviations compared to the measured OCV resulting in high estimation errors or unstable estimation behaviour. Nevertheless, the influence of the OCV on the SOC estimation is rarely investigated in literature.

In [7] the influence of the temperature-dependent OCV of a lithium-iron-phosphate (LFP) cell on the SOC estimation with an EKF is investigated. Here, high errors resulting from an incorrect

OCV–SOC correlation are shown. To resolve this problem, different OCVs at different temperatures are implemented in the battery model.

Zheng et al. [8] showed, that the temperature dependency is influenced by the OCV determination method. Here, the OCV, determined by a constant charge/discharge with a current of C/20, and the OCV, determined by 10% charge/discharge steps followed by a 2 h relaxation time are compared and the influence on the SOC estimation with an EKF is investigated. In their work, the OCV shows a high deviation from the reference at lower temperatures, and therefore, the estimation of the EKF is more accurate when the incremental (IC)–OCV is used. However, at 0 °C both the constant-current (CC)–OCV and the IC–OCV method lead to high estimation errors, whereas the regions lower than 10% and higher than 90% are not considered.

The relationship between SOC and OCV is often assumed to be constant over the lifetime of a lithium-ion battery (LIB) [9]. However, a change in shape of the OCV due to degradation effects is observed in more recent publications [10–12]. These variations can be explained by a change in the electrode morphology due to the formation of dendritic deposits [13], loss of cycable lithium-ions [14] or loss of active materials [14–16]. As a consequence, the correlation between OCV and SOC changes during ageing [17] and

\* Corresponding author.

E-mail address: [c.campestrini@tum.de](mailto:c.campestrini@tum.de) (C. Campestrini).

URL: <http://www.ees.ei.tum.de>

the relationship has to be updated for an accurate state estimation based on the OCV [18]. In [19,20] the SOC of an aged cell is derived from the OCV–SOC correlation of a new cell. In both cases an SOC error of approximately 10% is observed.

As one can see, the OCV not only depends on the determination method and cell temperature, but also on the ageing state of the cell. Regarding the SOC estimation with EKFs, this behaviour is often not considered in literature [1]. To address this issue, we investigate the influence of OCVs at different ageing states on the SOC estimation with an EKF at different temperatures in this paper. Therefore, we take the two OCV determination methods into account.

The work presented here is structured as follows: in Section 2 the cell model is explained and the used ECM is discussed. Furthermore, OCV characteristics and the EKF are introduced. The experimental of our work is presented in Section 3. Here, the measurement setup, the ECM parameter identification and the OCV determination methods are shown. Furthermore, this section summarises the validation method from our previous work [21] and the filter tuning of the EKF. In Section 4, the dependencies of the ECM parameters and the OCV are shown and the results regarding the influence of the OCV on the estimation with an EKF are discussed. To summarise our work, a conclusion is given in Section 5.

## 2. Basics in cell modelling and Kalman filtering

### 2.1. Cell modelling

To investigate the ageing influence of the OCV on the estimation with an EKF, an one RC term model (Fig. 1) is used as this ECM provides the best compromise between accuracy and complexity [22,23]. In this work the ECM model consists of one resistor  $R_{dc1s}$  and one RC term.  $U_T$  and  $I_T$  corresponds to the terminal voltage and current. Here,  $R_{dc1s}$  is the resistance calculated one second after a 0.25 C current pulse from the voltage drop and the applied current. Due to the short pulse time, the  $R_{dc1s}$  contains fast processes of the charge transfer reactions in the cell. Instead of using the ohmic resistance  $R_i$  as usually, the  $R_{dc1s}$  is used due to the state of charge estimation algorithm sample time of one second ( $t_{step} = 1\text{ s}$ ) [23]. The RC term ( $R_1$ ,  $C_1$ ) describes diffusion effects consisting of the diffusion capacitance and the diffusion resistance [24].

The OCV is defined as the difference between the half-cell potentials of the cathode and anode when the applied cell current is cut off and all polarisation effects are completely decayed. Here, the half-cell potential is related to the amount of lithium intercalated in each electrode. Consequently, the cell SOC changes with the SOC of both electrodes [25]. Fig. 2 shows the OCV of different commercial 18650 cells at 25 °C with common cathode materials such as nickel–cobalt–aluminium (NCA), nickel–manganese–cobalt (NMC) or lithium–iron–phosphate (LFP) and graphite as the anode material. Therefore, the material composition of the active materials defines the characteristic potential curves of the OCV for the chemistry [14,26].

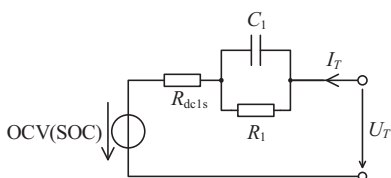


Fig. 1. ECM consisting of one resistor  $R_{dc1s}$ , one RC term ( $R_1$ ,  $C_1$ ) and the SOC-dependent OCV.

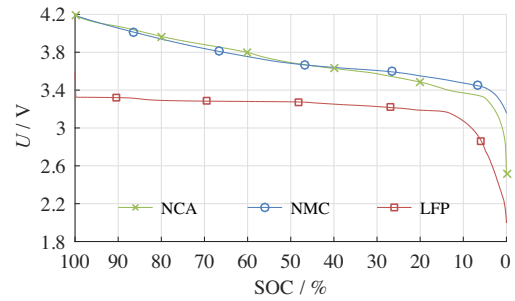


Fig. 2. OCVs of commercial 18650 lithium-ion cells with graphite vs. different conventional cathode materials at 25 °C, measured by averaging the cell voltage at a constant current charge and discharge.

The high voltage drop at SOC lower than approximately 10% can be explained by the increasing potential of the delithiated anode [17]. In applications this region is often avoided due to practical reasons [15].

To determine the OCV two common methods are established in practise [27]. The first method is the measurement of the cell voltage at a CC charge and discharge (CC-OCV). The OCV–SOC correlation is then calculated by averaging the charge and discharge curve. Due to averaging, hysteresis effects and impedance influences are minimised [10]. Hysteresis effects arise from mechanical stress and different thermodynamic states at the same SOC [28]. This effect is predominantly observed in LFP cells. The charge throughput is normalised to the actual cell capacity [25]. In literature, the applied current to measure the OCV varies from C/20 [15] to C/40 [14,25]. In general, a lower applied current leads to a lower cell polarisation [29,27], thus, the OCV can be measured more accurately. However, as the cell impedance can increase significantly at very low and very high SOC, a low cell polarisation may not be ensured during measurement [14,29,27]. Therefore, the CC methods can lead to high voltage errors and imprecise OCV values in these regions. This effect increases at lower temperatures [19] as well. To minimise the voltage error, the OCV can be determined by the so-called incremental-OCV (IC-OCV). Here, the cell is charged and discharged stepwise to different SOC. After each step, the applied current is cut off and the OCV is measured when the cell reached nearly equilibrium. The relaxation time is dependent on SOC, temperature and cell age [30]. In literature, the relaxation time varies from 1 h [31,29,12] to 24 h [19] and the step size from 4% [19] to 10% [8]. If the same SOC for each cut-off phase can be guaranteed [29], the charge and discharge OCV can be averaged to minimise hysteresis effects [31].

### 2.2. Kalman filter

As shown in our previous work [23] a similar behaviour of different Kalman filters (KF) can be observed. Thus we choose a EKF for the analysis carried out in this work. In this work, the adaptive approach of the EKF is not considered. As the adaptive extended Kalman filter (AEKF) only adapts to the measurement noise and to the model uncertainty, but not to changes in OCV.

The EKF belongs to the prediction–correction method. It first predicts a state  $\hat{x}_k^-$  (SOC and  $U_1$ ) in its state-space representation and the corresponding covariance matrix  $\mathbf{P}_k^-$ , considering a linearised system  $\mathbf{A}_k$  and the transition matrix  $\mathbf{B}_k$ . In the next step, the Kalman gain  $\mathbf{K}_k$  is computed. Then, the EKF corrects the prediction ( $\hat{x}_k^+$  and  $\mathbf{P}_k^+$ ) by weighting the difference between the real measurement  $U_k$  and the predicted measurement result  $y_k$  with the  $\mathbf{K}_k$ . Therefore,  $y_k$  is calculated considering the linearised measurement matrix  $\mathbf{H}_k$  and the straight-way matrix  $\mathbf{D}_k$ . This calculation sequence [33,36] with the covariance of the

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