Impact of Parameter Estimation Accuracy on State of Charge Estimation Using Extended Kalman Filter

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Abstract. The Extended Kalman Filter as been shown to be highly effective in estimating the battery State of Charge, however its performance strongly depends on battery model accuracy and on precise knowledge of the battery model parameters. This work investigates the correlation between inaccuracies in the battery model and the resulting error in the State of Charge estimation using the Extended Kalman Filter.

1 Introduction

With the Green Deal, the European Union has set climate neutrality as a goal by 2050 through a transition towards a sustainable economy. Battery technology can facilitate the transition to a decarbonized society, through the integration of renewable energies with the electricity grid. Zero-emission mobility Lithium batteries are among the most used energy storage systems because of their excellent performance, which is related to their high energy density, power efficiency, and long life. Furthermore, with a mass diffusion of electric vehicles, the battery recharges will have a great impact on the configuration and operation of smart grids, considering the high power needed for recharge in acceptable time [1-2].

The Battery Management System (BMS) uses advanced control algorithms for State of Charge (SoC) and State of Health (SoH) estimation with electrical models that fully reflect the actual performance and cycle life characteristics of batteries [3-6]. Extended Kalman Filter (EKF) has been widely used for battery SoC estimation [7-12]. The accuracy of the EKF in the SoC estimation has been proven to be high, but it strongly depends on the accuracy of the parameters of the battery model [13-15]. Furthermore, Unscented or Extended Kalman Filter has been used for the estimation of the State of Health or Capacity degradation or Remaining Useful Life [16].

In this work the correlation between the inaccuracies of the battery model and the resulting error of the SoC estimation obtained through the EKF has been investigated.

2 Battery model and Simulink implementation

The electric model of the single cell used in this work is reported in Figure 1. It consists of a voltage source OCV in series with a resistance R_0 and up to three parallel connected resistors and capacitance $R_1, C_1, R_2, C_2, R_3, C_3$.

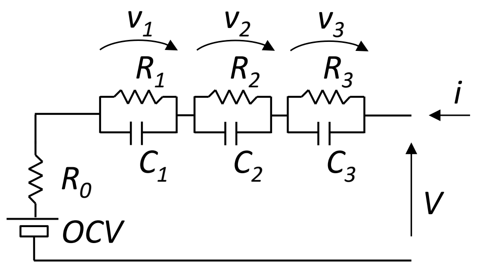

Fig. 1. Electric model of a single battery cell.

The 6 parameters have a piecewise linear dependence on SoC and temperature, and they must be estimated from experimental measurements. The equations describing the circuit of Figure 1 are the following

$$\dot{v}_1 = \frac{i}{C_1} - \frac{v_1}{R_1 C_1} \tag{1}$$

$$\dot{v}_2 = \frac{i}{C_2} - \frac{v_2}{R_2 C_2} \tag{2}$$

$$\dot{v}_3 = \frac{i}{C_3} - \frac{v_3}{R_3 C_3} \tag{3}$$

$$SoC = SoC_{init} - \frac{1}{Q}\int_0^t i(\tau)d\tau \tag{4}$$

$$V = OCV + iR_0 + v_1 + v_2 + v_3 \tag{5}$$

The discrete-time state space representation required by the Kalman filter is reported in the following

$$\begin{bmatrix} SoC(k+1) \\ v_1(k+1) \\ v_2(k+1) \\ v_3(k+1) \end{bmatrix} =$$

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & e^{-\frac{\Delta t}{\tau_1}} & 0 & 0 \\ 0 & 0 & e^{-\frac{\Delta t}{\tau_2}} & 0 \\ 0 & 0 & 0 & e^{-\frac{\Delta t}{\tau_3}} \end{bmatrix} \times \begin{bmatrix} SoC(k) \\ v_1(k) \\ v_2(k) \\ v_3(k) \end{bmatrix} + \begin{bmatrix} -\Delta t/Q \\ R_1(1 - e^{-\frac{\Delta t}{\tau_1}}) \\ R_2(1 - e^{-\frac{\Delta t}{\tau_2}}) \\ R_3(1 - e^{-\frac{\Delta t}{\tau_3}}) \end{bmatrix} \times i(k) + \omega(k) \tag{6}$$

$$V(k) = OCV(k) + i(k)R_0 + v_1(k) + v_2(k) + v_3(k) + \epsilon(k) \tag{7}$$

where $\tau_1 = R_1C_1$, $\tau_2 = R_2C_2$, $\tau_2 = R_3C_3$, $\omega(k)$ is the system state input error, $\epsilon(k)$ is the observation error.

In this work we developed a Simulink model implementing the battery model (1-5) and EKF (6-7). The Simulink model is reported in Figure 2.

A variable number of RC can be implemented in the EKF. Three EKFs for SoC estimation have been implemented with 1RC (considering $R_2 = R_3 = 0$ in (6)), 2RC (considering $R_3 = 0$ in (6)) and 3RC. The SoC estimation is compared with the SoC obtained by the battery model described by (4). The EKFs can evaluate the voltage error as the difference between its estimated voltage reported in (7) and the battery model described by the (1-5) or the experimental measurements.

A detail of the Simulink model implementing the generic Extended Kalman Filter is reported in Figure 3.

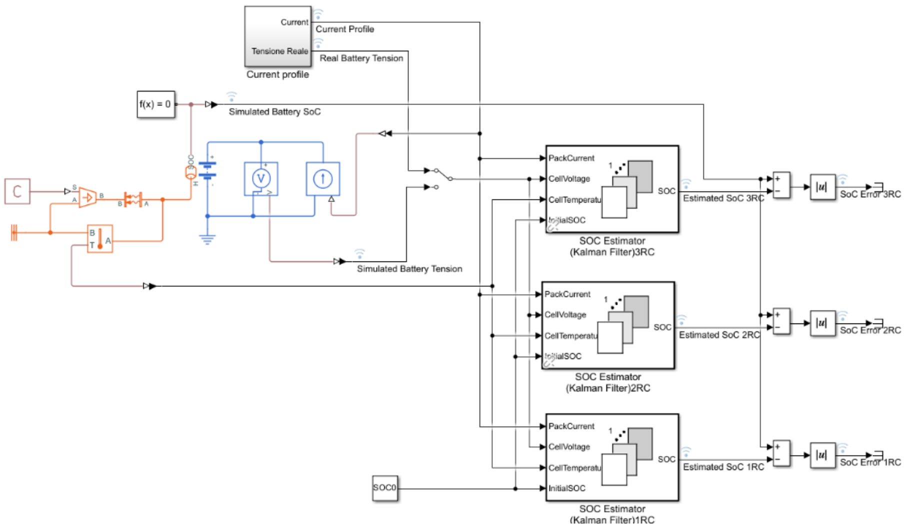

Fig. 2. Simulink model of a single cell with 3 EKFs: 1RC, 2RC, 3RC.

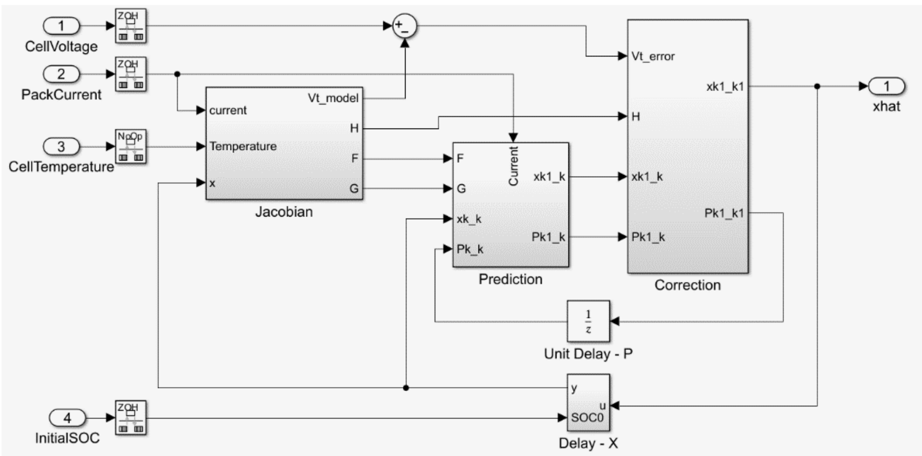

Fig. 3. Extended Kalman Filter implementation in Simulink.

3 Measurements and Simulation Results

The experimental results have been carried out using batteries with nominal capacity of 50 Ah and nominal voltage of 3.2 V.

The parameters have been estimated with experimental measurements using the HPPC technique, as reported in [17]. The current profile used for the characterization is reported in Figure 4. It consists in a sequence of discharge current pulses starting from a fully charged battery.

The parameters of the battery model and of the three EKFs with 1RC, 2RC and 3RC have been estimated and the simulations have been compared with the experimental results. Figure 5 reports the cell voltage obtained from experimental measurements in yellow and the simulations of the battery model after parameter optimization in green. The maximum error between model and measurements is 30 mV.

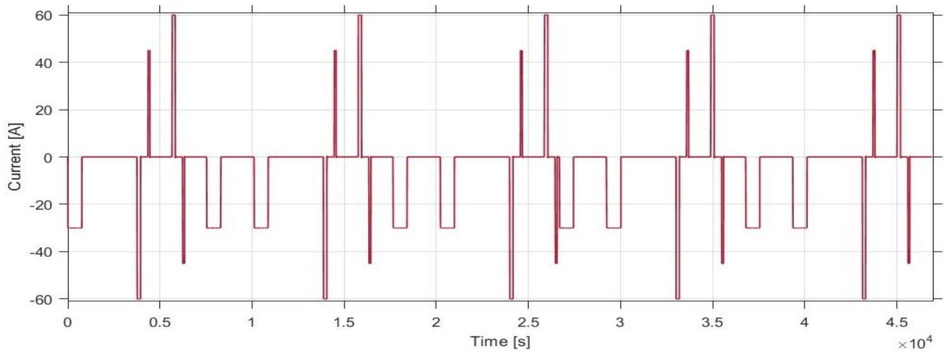

Fig. 4. Current pulse sequence used for parameter estimation.

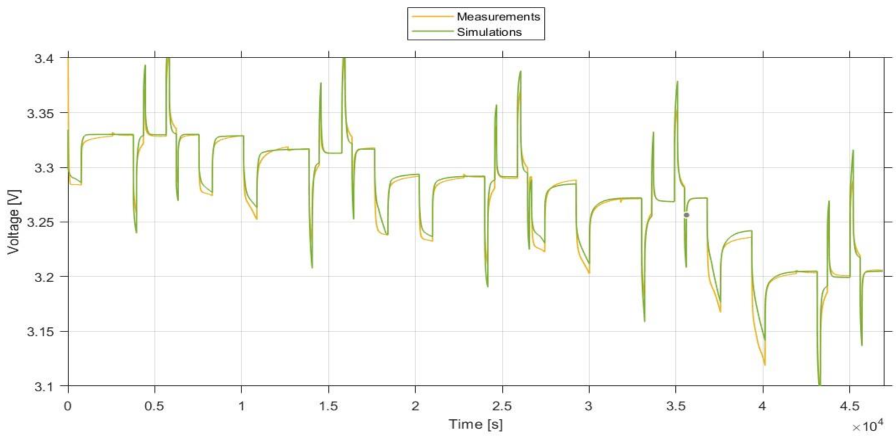

Fig. 5. Experimental voltage obtained applying to the battery cell the current profile reported in Figure 4 and the battery model.

The next step is the comparison between the SoC evaluated using the battery model and the SoC estimations obtained by the three EKFs (1RC, 2RC and 3RC). The initial SoC and the initial charge in the capacitors in a battery cell are not known by the filters. A good estimation algorithm can recover from bad initialization.

In the first simulation the EKF compares the estimated voltage obtained with (7) with the voltage obtained by the battery model. The SoC estimation of the EKF is compared with the SoC obtained by the battery model. Figure 6 reports the SoC error obtained by the three EKFs (1RC, 2RC and 3RC). The simulation starts with an initial SoC of 80% while the Kalman initial estimation has been fixed to 50%. Therefore, initial error is 30%. After an initial transient the SoC estimation with the 3RC EKF is close to the model, while the maximum error is 5% for the 2RC EKF and 10% for the simplified 1RC EKF. The error increases when the input current pulse cause a rapid variation on the cell voltage, while the error is reduced in steady state conditions. The speed in the SoC approximation starting from an initial strong error increases as the dimension of the EKF decreases.

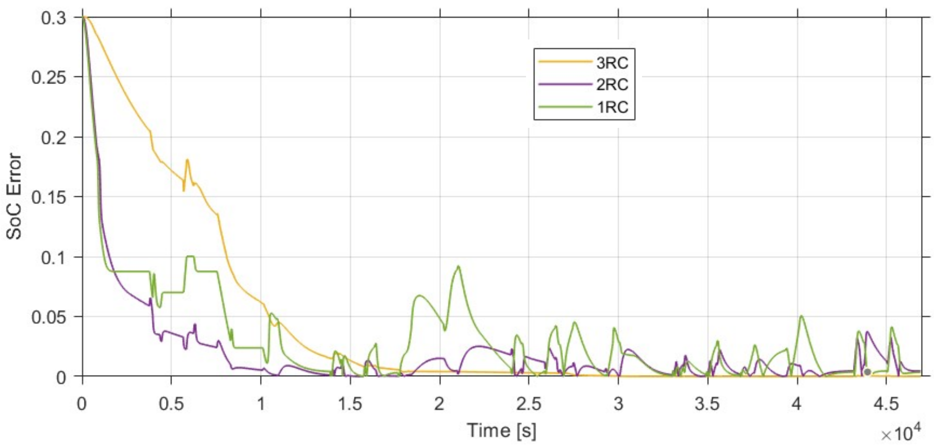

Fig. 6. Reference SoC error between simulation model and three EKFs (1RC, 2RC, 3RC).

A second simulation compares the voltage estimated by the EKF with the measured voltage, as in a real case of a hardware implementation of the BMS. On the other hand, the SoC estimation using EKF is compared with the SoC obtained by the battery model, since the SoC cannot be directly measured. Figure 7 reports the SoC error obtained by the three EKFs (1RC, 2RC and 3RC).

The simulation starts with an initial error 30% as in previous simulation. After an initial transient the SoC error is reduced, with the maximum error is 5% for the 3RC EKF, 10% for the 2RC EKF and 15% for the 1RC EKF. Even if the battery model is accurate enough, as shown in Figure 5, the SoC estimation error is about 1% in steady state conditions.

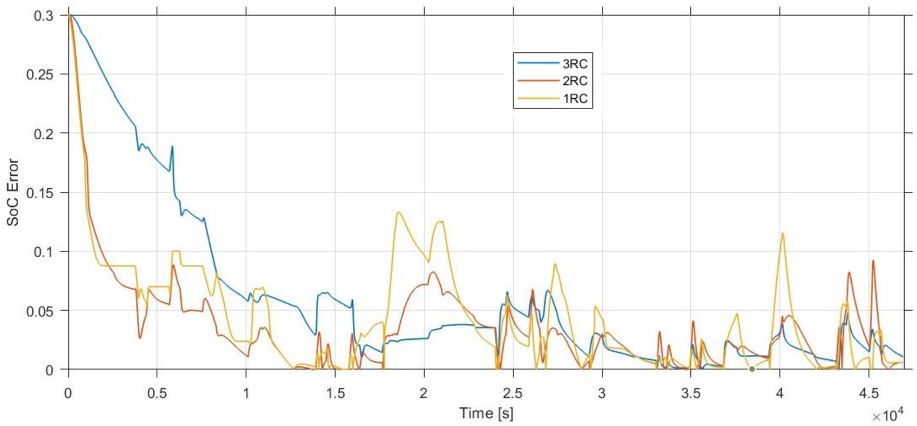

Fig.7. SoC error between coulomb counting model and three EKFs (1RC, 2RC, 3RC). The EKFs compare the calculated voltage with the measured voltage.

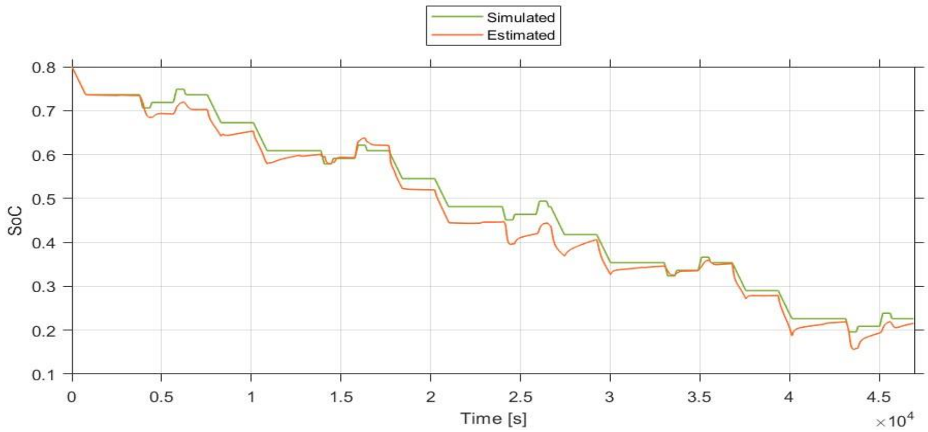

Fig.8. Reference SoC obtained from the model with 3 RC and Extended Kalman Filter estimation with 3RC.

To evidence the possible correlation between the voltage error and the SoC error, we performed a third simulation with the same current profile reported in Figure 4 and with the initial SoC estimation of the accurate 3RC EKF identical to the real value 80%. The EKF compares the estimated voltage with the measured voltage. Figure 8 reports the SoC obtained from the battery model and 3RC EKF estimation. The model error causes a SoC estimation error, especially immediately after a current pulse, but even at the end of the transient the error of the Kalman estimation is not zero.

The relation between the Voltage error and SoC error during time is evidenced in Figure 9.

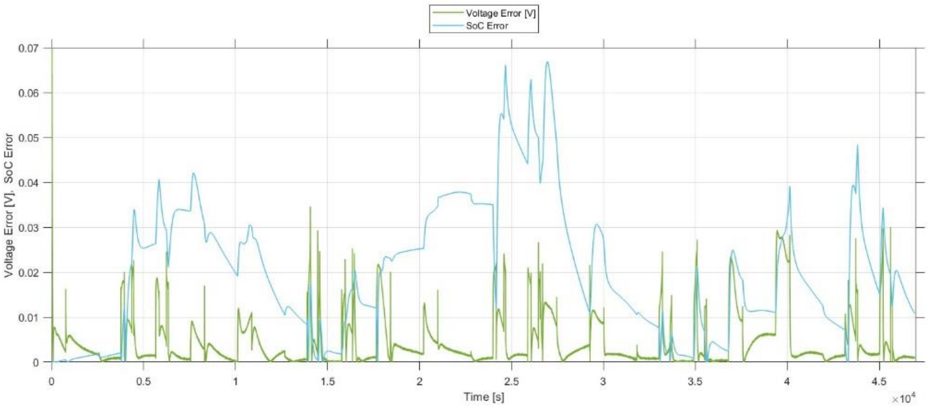

Fig.9. Voltage error and SoC error.

4 Conclusions

Three Extended Kalman Filter with different internal models was tested. The EKF with 1RC uses a less accurate model, especially when the battery voltage is subject to rapid variations. This model inaccuracy causes an error in the estimation of the SoC by the EKF. The SoC estimation error can reach 15%, as shown in the simulations. Conversely, a more accurate internal model, as in the case of the EKF with 3RC with a maximum error of 30 mV in the estimation of the battery voltage, allows a maximum error of 5% in the SoC estimation.

An inaccurate model or an inaccurate estimation of the parameters of the model cause an inaccurate estimation of the SoC performed by the Extended Kalman Filter.

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