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Characterization of a battery model using parameter estimation techniques

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Abstract

The rise of hybrid and electric vehicles involves some new technological challenges, especially when it comes to batteries. In these applications batteries will be loaded very dynamically and they have to perform under different conditions. In this research an electrical model of a lithium-ion battery is presented, which allows to predict the voltage response of the battery. The developed model consists of a voltage source, some resistors and some capacitors. The values of these components are influenced by temperature, current rate and State-of-Charge. To estimate the parameters under different conditions two parameter estimation techniques are implemented in Matlab/Simulink: the Parameter Estimation Tool and an Extended Kalman filter. Afterwards, the parameter values under different conditions are stored in look-up tables. A simulation model makes it possible to validate the results of the proposed model using different current profiles. The model error is defined as the difference between the measured and the simulated voltage. With both techniques a RMS value of the percent error was achieved with a maximum of 3.6 %. On the one hand the result can be improved by defining a more accurate algorithm to determine the State-of-Charge. On the other hand the parameter estimation process can be refined by optimizing the used load cycles.

Keywords: lithium-ion battery, parameter estimation, Extended Kalman filter, Randle model

1 Introduction

Nowadays batteries are an indispensable part of modern society. Different applications use this technology as mobile energy storage. The upswing of electric mobility poses new technological challenges for energy storage. An electric powertrain of an electric vehicles consist of a battery pack, an inverter and an electric motor. The battery pack is one of the most delicate components, because of its impact on the performance and range of the vehicle. Due to the modern lithium-ion technology, the power and energy density of batteries are increasing significantly. Nevertheless, further developments and research are needed.

Many applications draw a constant current or power out of the battery. Electric vehicle batteries on the contrary are loaded very dynamically due to accelerations and decelerations. Also the currents are relatively high and the batteries are subjected more to temperature variations. To develop a reliable electric vehicle an accurate battery model is desired, which predicts the voltage response under different circumstances. This model could be integrated in a Battery Management System (BMS) to protect the battery pack. In case of failure of the voltage measurement the model can be used to simulate the battery and hence allow the driver to safely stop near the road.

In literature battery behaviour has been studied from different fields of expertise. Mathematical models have been developed which are based on empirical equations. These models are often too abstract for practical use. They predict the capacity, runtime and efficiency. Major disadvantages are the limited accuracy (5-20%) and the fact that no dynamic behaviour can be predicted [5] [7]. Chemical models are used based on the electrochemical background of a battery.
To characterize these models, several aspects of the battery (e.g. chemical parameters, battery construction, material properties) have to be known [4]. Often complex differential equations and long calculation times are required. Its purpose is mainly to optimize the physical design of the battery [5]. Equivalent circuit models, or simply electrical models, use a combination of voltage sources, resistors, capacitors and inductors to model a battery. According to [5] the accuracy is 1-5%. Because of its intuitivity and applicability this type of model was used during this research.

For the study a second order Randle model is considered. The model consists of a voltage source and five other parameters, namely two capacitors and three resistors (Figure 1). Considered influences are the cell temperature (T), current (I) and State-of-Charge (SOC) [2] [8].

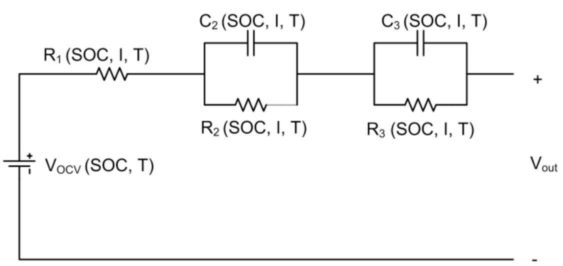

Figure 1: Proposed model

To characterize a battery a programmable testing infrastructure is used, together with a climate chamber to keep the battery at a constant temperature. This allows to determine the model parameters under all conditions. The parameter estimation is done using two different techniques: an offline estimation method based on the Parameter Estimation Tool of Matlab/Simulink and a real-time estimation method, an Extended Kalman filter. The estimated parameter sets are then stored in look-up tables. A simulation model allows simulating the voltage response for any time series current input. To validate the model four different self-defined discharge tests are used. The error is defined by the difference between the measured voltage and the simulated voltage for each time step. For both estimation techniques a Root Mean Square (RMS) error was achieved with a maximum of 3.6 %. The obtained errors with the look-up tables from the Extended Kalman filter are generally larger than those with the Parameter Estimation Tool. For the Extended Kalman filter the complexity can be found in the way of storing the different parameters. Accurately defining how and when to save the parameters could possible improve the overall results.

2 Methodology and development

2.1 Test conditions

All tests were performed on a lithium iron phosphate battery, with a nominal capacity of 40 Ah and a nominal voltage of 3.3 V. The limits used for this study are shown in Table 1.

Table 1 : Used battery limits

Limits	Value
Min. Voltage (V)	2.5
Max. Voltage (V)	3.75
Min. Temperature (°C)	-10
Max. Temperature (°C)	70
Max. Charge (A)	120
Max. Discharge (A)	120

To load the cell according to a certain pattern, a PEC test infrastructure (SBT0550) was used. The tests were carried out in a climate chamber on constant temperatures of 10 °C, 20 °C and 30 °C.

2.2 Terminology

- *Capacity:* The amount of electricity delivered expressed in Ampere-hours (Ah). It expresses how long a battery can deliver a certain current. A battery of 20 Ah is able to deliver for one hour approximately 20 A. If 40 A is required, the battery will be depleted in less than half an hour. The discharge time is not exact because the delivered capacity of a battery depends on the required current rates, temperature and other factors. The capacity is determined by coulomb counting, i.e. taking the integral over time of the current.

$$\text{capacity}\,(Ah) = \frac{1}{3600}\int_0^t I\,dt$$

- *State-of-Charge (SOC):* SOC is defined as the available capacity relative to the nominal capacity (40 Ah). The available capacity is calculated by subtracting the initial capacity with the depleted capacity throughout the test [13].

$$SOC(\%) = \frac{C_{initial} + \frac{1}{3600}\int_0^t I\,dt}{C_{nominal}} \cdot 100$$

- *C rate:* A commonly used method for expressing the charge and discharge currents relative to the nominal capacity of the battery. It's a multiplication or fraction of the nominal capacity. For a cell of 40 Ah, a discharge current of 2C means currents of 80 A.

- *Open Circuit Voltage:* When a battery is at rest, it still has a potential voltage. This is called the Open Circuit Voltage (OCV). This voltage depends on temperature and SOC. At low SOC, the OCV is lower than at high SOC. The OCV is not dependent on the current, as it is determined at rest.

2.3 Proposed model

Figure 2 shows the voltage response of a battery loaded with a current step. It can be seen that there is an instantaneous voltage drop followed by a transient behaviour with two time constants [5].

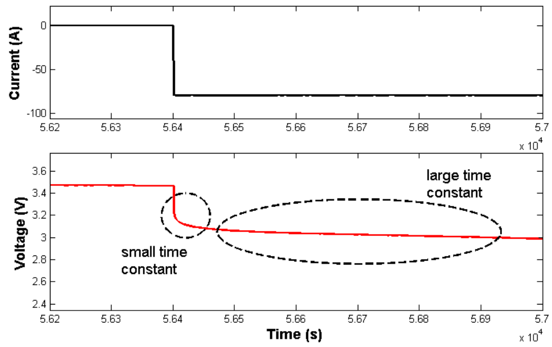

Figure 2: Battery behaviour in detail

The proposed model contains electrical components to model this behaviour. It uses a resistor (R_1) to model the instantaneous voltage drop and two parallel chains (C_2 & R_2 and C_3 & R_3) to account for the time constants. The parameters are actually linked to chemical phenomena, e.g. different forms of polarization [3] [4].

To disregard the background of the battery, a number of standard charge and discharge cycles are done to test stability (Figure 3). Because the initial state of the battery is unknown, it is first fully discharged. Charging is done according to the principle of CC/CV. During the constant current (CC) phase the battery is charged until it reaches the maximum voltage of 3.75 V, after which a constant voltage (CV) of 3.75 V is retained. The charging process ends when the current only amounts to 2.5% of the initial charging current.

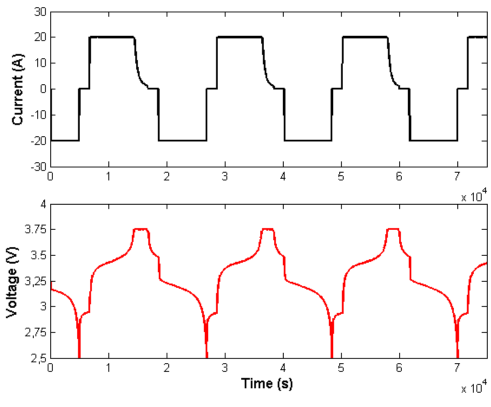

Figure 3: Preconditioning cycles

2.4 Defined test profile

The proposed model includes a voltage source, which is considered to model the OCV of the battery. To determine the OCV a pulsed load test including rest periods is chosen. The battery is charged in different stages of each time 12% SOC.

After each charge period the battery has several hours to stabilize, so that the measured voltage will approach the OCV. Next, another charge pulse follows together with a pause to determine the OCV for another SOC value. The same principle was handled for discharging. This method is already demonstrated in literature [1], [2] [12]. This method was chosen because it has a short duration and it also allows to integrate a sequence of pulses after each pause (Figure 4). It was decided to use this sequence only at the discharge phase of the test. Later on, the data retrieved from these dynamic sequences of pulses will be used to estimate parameters at different SOC. The test uses one sequence of pulses performed three times at different currents of 1C, 2C and 3C. The test was performed for all three different temperatures.

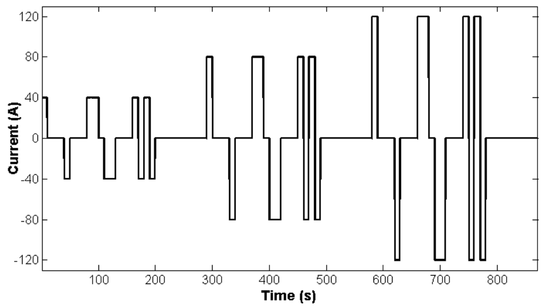

Figure 4: Load cycles for parameter estimations

An overview of the entire test can be found in Figure 5.

During the charge phase the voltage measurements of the OCV will be higher than during discharge.

This is due to the very long time to completely stabilize to OCV (more than 24 hours). The OCV curve is finally obtained by taken the average of the measured points during charge and discharge [1].

2.5 Parameter estimation

Based on the defined test profile all the data can be collected to estimate the parameters for all the conditions. In this section two parameter estimation techniques are considered: Parameter Estimation Tool and Extended Kalman filter.

2.5.1 Parameter Estimation Tool

The Parameter Estimation Tool allows to calibrate the response of a model based on the physical behaviour of a dynamical system. In literature few publications can be found which use this method [8] [11]. The response of the model is optimized by an iterative estimation of the parameters. This optimization is done by applying the nonlinear least squares method.

For each combination of current value, temperature and SOC an estimation of the different parameters can be made. Due to the large number of required estimations, the estimation procedure was automated via Matlab. Since the average current during this the test profile is low, the cell temperature will not rise significantly. When running the test at 10°C the cell temperature increased only 3.4°C. When applying the test with other temperatures, this temperature difference was even lower.

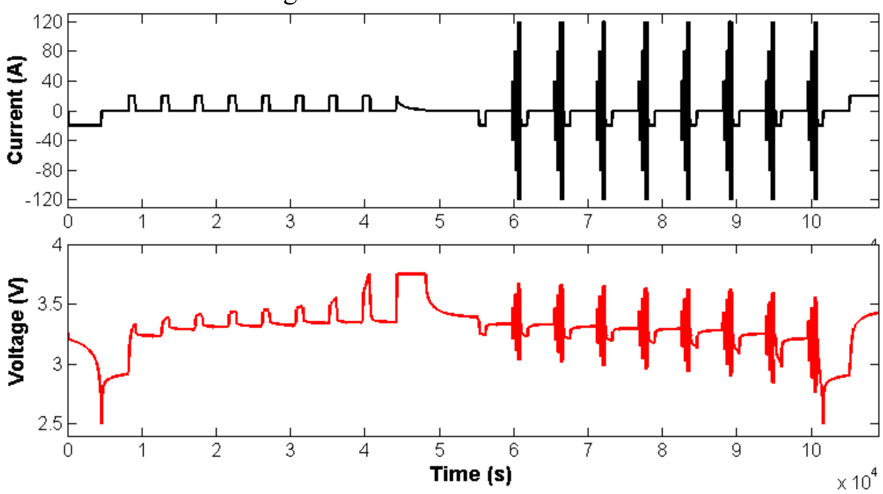

Figure 5: Overview of the test profile

It is therefore assumed that the parameters are estimated at constant temperatures of 10 °C, 20 °C and 30 °C. The result of an estimation with currents of 2C during the fourth sequence at 20 °C is shown in .

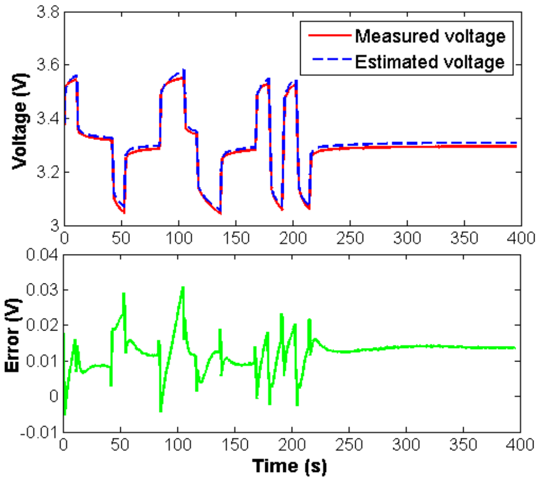

Figure 6: Result of a pulse estimation

The estimation error is calculated by taking the difference between the simulated and measured voltage. In this case, the error appears to have a maximum of 30.8 mV. One by one each pulse is estimated. These estimations showed that the range of the maximum absolute error is between 6.4 mV and 156.7 mV. After the estimation process, all parameter values were implemented in look-up tables.

2.5.2 Extended Kalman filter

The Extended Kalman filter is a derivative of the Kalman filter, which is only applicable for linear systems. The filter uses stochastic 'a priori' assumptions and translates this after every new observation in a revised assumption, the 'a posteriori' estimation. The 'a priori' and 'a posteriori' assumptions can be found in the form of time-dependent and measurement-dependent update equations. The assumption is adjusted based on new measurements. When performing the time-dependent update equations, the filter tries to make a prediction of the different state variables (1) and the covariance of the result is calculated (2). The prediction is based on a linearized model (1). The 'a priori' estimations are represented using a tilde (~). When performing the measurement-dependent update equations (3), (4), and (5), the estimation is being adjusted based on information obtained from the recent measurement. Here, the state variables will be adjusted so that the difference between reality and simulation is minimized. The covariance of the parameters is then calculated again (6). The 'a posteriori' estimates are represented using a caret (^).

Time-dependent update equations:

$$\tilde{x}_k = A\hat{x}_{k-1} + B u_{k-1} \quad (1)$$

$$\tilde{P}_k = A\hat{P}_{k-1}A^T + Q_{k-1} \quad (2)$$

Measurement-dependent update equations:

$$S_k = R_k + H_k \tilde{P}_k H_k^T \quad (3)$$

$$K_k = \tilde{P}_k H_k^T S_k^{-1} \quad (4)$$

$$\hat{x}_k = \tilde{x}_k + K_k(z_k - H_k \tilde{x}_k) \quad (5)$$

$$\hat{P}_k = (I - K_k H_k)\tilde{P}_k \quad (6)$$

The proposed model is a nonlinear system. Therefore, an Extended Kalman filter is used. The dynamic model (7) and observation model (8) are linearized each iteration in the most recent estimate. Consequently the update equations are changed slightly compared to the original Kalman filter.

$$x_k = f(\hat{x}_{k-1}, u_{k-1}) + \left.\frac{\delta f}{\delta x}\right|_{\hat{x}_{k-1}}(x_{k-1} - \hat{x}_{k-1}) + \rho_p \quad (7)$$

$$z = h(\tilde{x}) + \left.\frac{\delta h}{\delta x}\right|_{\tilde{x}}(x - \tilde{x}) + \rho_m \quad (8)$$

While going through the iterative process, the filter tries to estimate new values of the various components of the model. The filter also tries to minimize the variance of the estimations. To gain valuable information from this filter, it is necessary that a good model is represented that follows the reality well and that good initial estimates are given by the user. Both the observation model and the dynamic model are considered to have a certain level of noise using the respective covariance matrices R and Q. Both are user defined. The covariance matrix R relates to the measurement error (noise) of the measuring devices and is therefore easy to determine. It can be considered as the variance measured at a constant measurement. The covariance matrix Q is more difficult to determine and provides the ability to tune the filter. Here, a diagonal matrix is defined which defines for each parameter a certain minimum variance. By adjusting these values, the filter can be affected to give better estimations.

To compare the two parameter estimation techniques, the estimations of the Extended Kalman filter were also integrated in look-up tables. Here, only the look-up tables for currents of 1C are considered. Due to the realtime estimation method, the look-up tables will always be updated with the latest values of the system.

2.6 Developed simulation model

To simulate the proposed model a simulation model was developed in Matlab/Simulink. The model consists of a voltage source namely, the OCV, and the transfer function of the internal impedance. This research requires variation in the parameter values during the simulation. Therefore a second order transfer function was used, where variables A, B, C, D, E and F represent terms of products consisting of the different parameters (Figure 7).

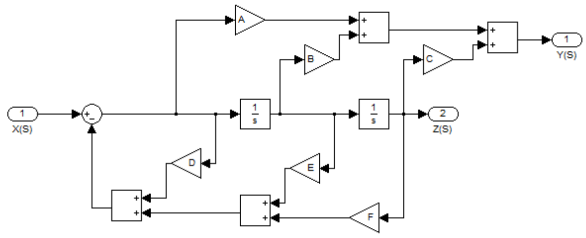

Figure 7: Scheme of transfer function

The simulation model considers as input variables: current time series, temperature time series and initial capacity. During each simulation step of 100 ms the output voltage and SOC are calculated based on parameters for corresponding conditions.

The parameters at that moment are derived from the earlier generated look-up tables. The correct value for the OCV is derived from the OCV-SOC relationship. The SOC is calculated by coulomb counting.

3 Results

In order to validate the developed simulation model four validation test were conducted. The first test was performed in a climate chamber at a temperature of 25°C. The other three tests were not performed in a conditioned room. For these tests the variation of the temperature was taken into account.

3.1 Parameter Estimation Tool

The results of the simulation for the first validation test are shown in Figure 8. As can be seen discharge and charge sections and pauses are considered. The initial capacity for this validation was set to the maximum charge capacity derived from previous tests. The simulation ends with a final capacity of 1.6 Ah. The RMS error is 1.4% and a maximum error of 10.8% is reached. Assuming that batteries used in automotive will only work within a range of 20-80% SOC, a decrease of the maximum RMS error can be found. The results of the validation tests are summarized in Table 2. The second validation test is extremely dynamic and consists of discharge pulses and pauses (Figure 9). The third validation regime consists of discharge pulses with different current values and the fourth and last test is a variant of the first validation regime, without any breaks.

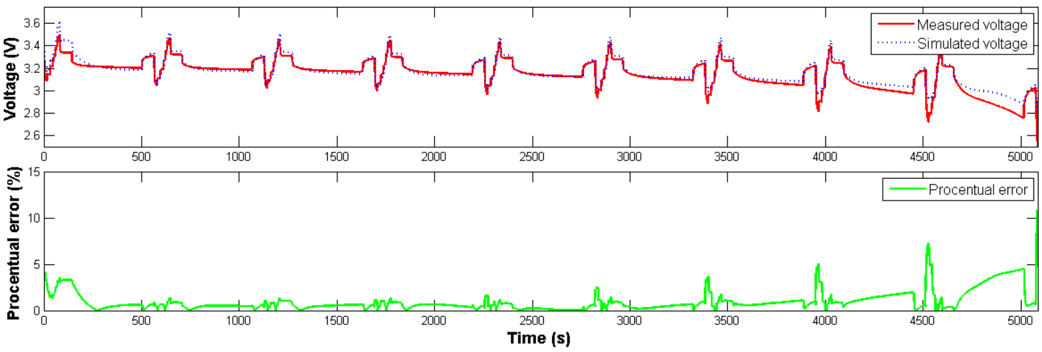

Figure 8: Validation test 1 with Parameter Estimation Tool parameters

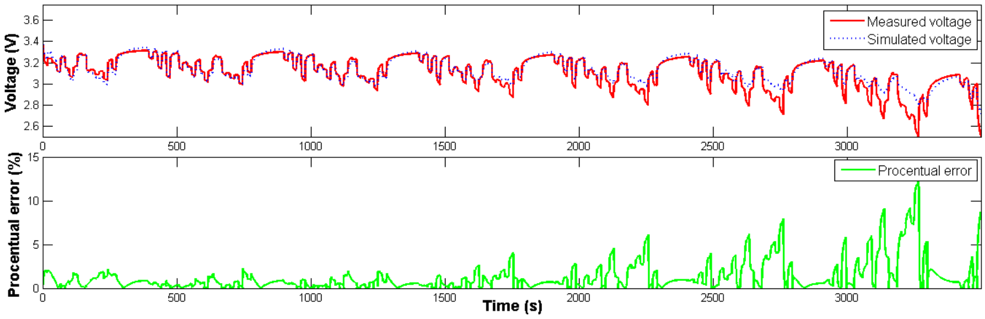

Figure 9: Validation test 2 with Parameter Estimation Tool parameters

Table 2: Information of tests with Parameter Estimation Tool parameters

	Val. test 1	Val. test 2	Val. test 3	Val. test 4
Temperature (°C)	25	room	room	room
Initial capacity (Ah)	44.3	44.1	43.6	43.8
Final capacity (Ah)	1.6	1.2	1.1	0.6
RMS error (%)	1.4	2.1	0.8	1.5
Maximum error (%)	10.8	12.3	7.7	8.5
Time 100_20 (s)	466 - 4326	226 - 2958	263 - 2417	339 - 3148
RMS error 100_20 (%)	0.8	1.5	0.6	1.1
Maximum error 100_20 (%)	5	8	4.6	5.2

3.2 Extended Kalman filter

Results derived with the look-up tables (generated by the Extended Kalman filter) are shown in Figure 10 and Figure 11. In comparison to the results of the Parameter Estimation Tool, the errors are generally higher. The results of the validation tests are summarized in Table 3.

Note that the results of the fourth validation regime are not present. During this test, the results diverged, resulting from an extrapolation of the look-up tables. The available look-up tables have a range of 10-30°C. During the fourth validation regime, however, a maximum cell temperature of 38°C was reached.

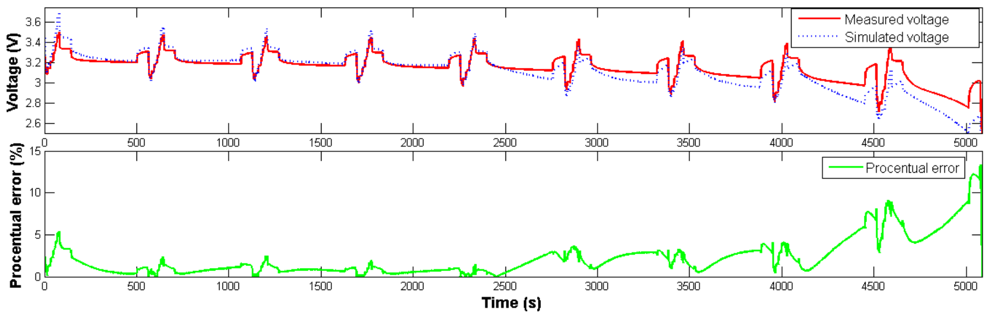

Figure 10: Validation test 1 with Extended Kalman filter parameters

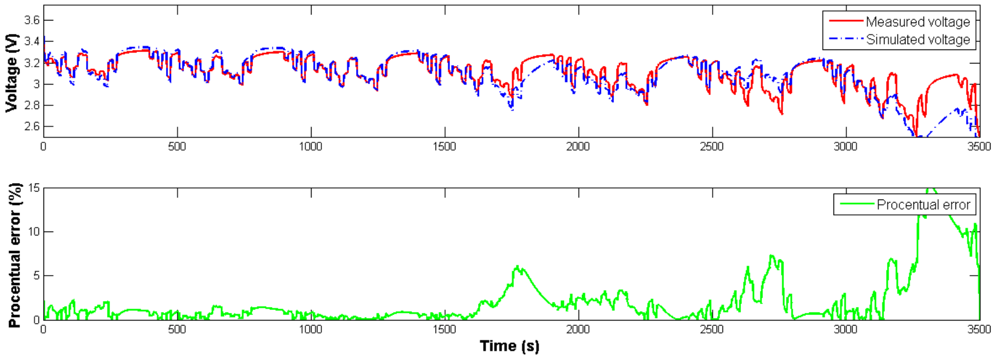

Figure 11: Validation test 2 with Extended Kalman filter parameters

Table 3: Information of tests with Extended Kalman filter parameters

	Val. test 1	Val. test 2	Val. test 3	Val. test 4
Temperature (°C)	25	room	room	room
Initial capacity (Ah)	44.3	44.1	43.6	43.8
Final capacity (Ah)	1.6	1.2	1.1	0.6
RMS error (%)	3.11	3.63	0.96	--
Maximum error (%)	13.31	15.23	5.28	--
Time 100_20 (s)	466 - 4326	226 - 2958	263 - 2417	339 - 3148
RMS error 100_20 (%)	1.85	2.00	0.52	--
Maximum error 100_20 (%)	5.09	6.87	5.14	--

4 Discussion

An important factor in the model seems to be the relationship between the State-of-Charge and the Open Circuit Voltage. The SOC is defined based on the remaining energy in the cell and calculated with coulomb counting. It was assumed that the gained capacity during charging can be fully obtained at discharge with an efficiency of 100%. In reality this is not the case and the difference can be defined as the Coulombic efficiency. This efficiency factor allows to determine the maximum discharge capacity when the charge capacity is known.

The Coulombic efficiency depends on the current, temperature, SOC, self-discharge and ageing [9] [14]. When implementing Coulombic efficiency into the simulation model, the SOC will therefore be lower, hence the OCV during simulation will also be lower. At low SOC it is noticed that the simulated voltage for the Parameter Estimation Tool always remains higher than the actual voltage. When taking the Coulombic efficiency into account, the SOC will lower, which will result in a smaller error in the region of 20% till 0% SOC. So an accurate determination of SOC will increase the accuracy of the model for low and high SOC. The influence of the SOC calculation was demonstrated by taking a Coulombic efficiency of 97% into account during the simulation of the first validation test. The simulation ended at a capacity of 0.09 Ah. The RMS minimum error is now only 0.7% and the maximum error is 6.6%. In simulations, this Coulombic efficiency is not known, but the results do show that the model can be improved. It is therefore important to predict the remaining capacity by means of an algorithm or look-up tables. It should also be noted that there are different definitions of SOC in literature. One can define that a cell is empty when it reaches its minimum voltage. Using a correct algorithm the final SOC should be 0%. However, it appears that a cell after a time break still has some usable capacity [10]. In this case, the above mentioned theory is no longer correct and the SOC will not be 0%.It can be concluded that an accurate SOC determination is important for the model. Currently, there are many studies on alternatives for Coulomb counting to determine SOC. One example is the estimaton of SOC using an Extended Kalman filter [6]. This study also attempted to estimate the OCV, as it is related to SOC. A small voltage error on the estimation of the OCV, however, quickly gave an error of 10% in the determination of the SOC.

As the SOC decreases, the estimation error increases during simulation. The parameter estimations with Parameter Estimation Tool show that the error increases as the current rises. A possible explanation for this may be due to the assumption of a constant OCV during the parameter estimations. When estimating a pulse, this pulse will affect the SOC. Discharge pulses of 120 A for 20 seconds, correspond to an extraction of 0.67Ah. At high and low SOC, the path of the OCV curve is no longer flat, so here it can't be assumed that OCV is constant during the estimation. This concept is illustrated in Figure 12.

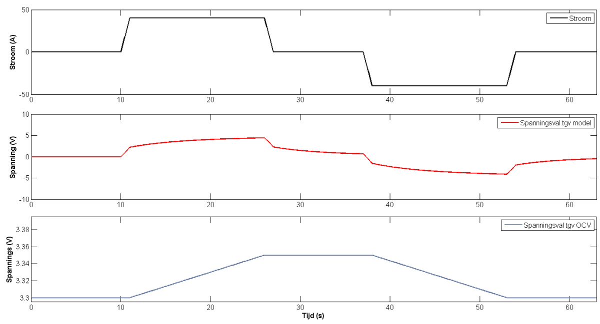

Figure 12: Influence of a pulse on OCV

During this research the implemented Extended Kalman filter was also estimating the OCV. This study shows that the OCV is a very important factor because of the slope at high and low SOC. The results of the Extended Kalman filter could probably be improved by not taking OCV into account during the estimation.

The accuracy of the model can be further improved by optimizing the defined pulse sequence. The pulses have a duration of ten or twenty seconds with rest periods of thirty seconds. This consideration has an impact on both of the estimations. Because a break takes only thirty seconds, it is difficult to estimate the largest time constant. The value of the second time constant appears to be about forty seconds. Therefore it is proposed to increase the duration of the pulses and rest periods. There is also a rest period between the cycles of different loads (1 C, 2 C and 3 C). Optionally the initial pause of three minutes can also be increased. This original break is currently not long enough for the battery to stabilize. So pulses at 1C are also affecting the voltage behaviour at 2 C and 3 C is. Another option is to redefine the pulse sequence with only one load current. Therefore the test will need to be performed three times

In addition, the accuracy of the model can be increased by avoiding extrapolation of the look-up tables. For example, introducing a higher resolution of the lookup tables and an extended temperature range. It is also possible to refine the model further e.g. a distinction of parameters for charge and discharge.

The estimations are showing the complexity of deciding when to store certain parameter under a certain condition. In fact, when storing the estimations of the Extended Kalman filter a lot of information is lost. Nevertheless, the Extended Kalman filter is interesting for further research. It could be used for example to estimate the State-Of-Health (SOH) of a battery by studying the change of internal impedance as the battery ages.

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