Using Kalman filtering techniques to obtain a better State of Charge-estimation of the battery pack of a Solar Car

Complementary to thesis submitted for the degree of Master of Science in Electrical Engineering, option Information Systems and Signal Processing

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***Abstract*—This paper explains the steps that have been taken to go from commonly executed tests on battery cells to a new and better State of Charge estimation method for the Belgian Solar Team. The State of Charge (SoC) indicates how much energy the team has left to its disposition in the battery pack. The currently used method is a very static model, that compares one measurement with a predefined test, which makes it inaccurate and unreliable. Moreover, these issues get even worse in the case of Lithium-Iron-Phosphate (LFP) cells, since re-calibration is very hard.**

Therefore, in this thesis, a model-based SoC-estimation method was implemented. First, models were created that relate the current through the cell to its terminal voltage. The parameters were estimated on tests conducted on three sample cells using the same, general optimisation procedure.

Next, Kalman filtering techniques were implemented on the single cell systems. Since the systems are not linear, an Extended Kalman Filter and Unscented Kalman Filter were used. Both were able to accurately track the SoC.

As a battery pack consists of modules, that consist of cells in parallel, the single cell systems were translated to a module level. Real-life data from an actual solar race was used to assess this translation. Tt turns out to be hard to track the SoC from the modules correctly. Different sources of error are discussed.

It is concluded that Kalman filtering techniques have a lot of potential to accurately track the SoC of a battery pack of a solar car. More research effort still has to go into investigating the module level modelling.

***Index Terms*—System modelling, data-driven modelling, Kalman filters, state estimation, battery management, electric vehicles**

I. Introduction

This article is complementary to the thesis with the same title, submitted for the degree of Master of Science in Electrical Engineering, option Information Systems and Signal Processing at the KU Leuven. The full thesis, all models and demo scripts can be found on Github. [1]

The State of Charge (SoC) of a battery is the amount of charge that is still in the battery, relative to its nominal capacity (C_nom). It is a measure for the energy remaining in the battery. To the Innoptus Solar Team, it is a crucial parameter to predict, monitor and measure correctly during their races.

Especially for Lithium-Iron-Phosphate (LFP) cells, under scrutiny in this thesis, it is difficult to obtain an accurate estimate. This is caused by its extremely flat Open Circuit Voltage (OCV) curve, the yellow line on Figure 1. The OCV is the voltage measured at the terminal of the cell when no load is applied and no transients take place. The insensitivity of the OCV on the SoC makes it infeasible to use a voltage measurement as a trustworthy indicator of the SoC [1].

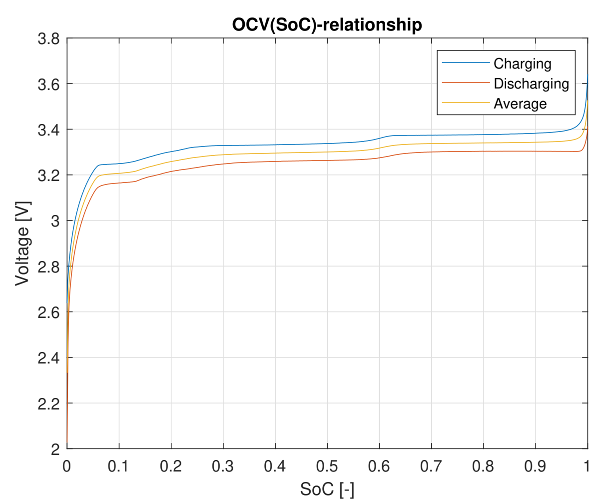

Fig. 1: OCV(SoC)-curve of the LFP sample cells in yellow. Since the sensitivity of the SoC on the OCV is extremely low for a wide range of SoC-levels, measuring the terminal voltage is no reliable way to estimate the SoC.

The method currently used by the Solar Team is based on current integration on the full pack. During the race, the current that flows through the pack gets integrated. This implies that if the current integration sensor brakes down, a module within the pack gets damaged or some drift arises on the sensor, this is not noticed until the module hits the

[1] https://github.com/frederikvanmaele/KalmanFilteringLFP.git

lower cell voltage boundary. When this happens, the Team has to radically slow down. No other parameters of the cells are taken into account, which makes it very prone to human error as well (Innoptus Solar Team, 2023).

The goal of the thesis is to obtain a more accurate and reliable SoC-estimation, by taking other measurement than the integrated current, that are already available, into account as well. Three steps have to be undertaken to achieve this in the following structure.

First, better models, that accurately describe a single cell system's behaviour, are developed. The input of this system is the current; the output is the terminal voltage. All parameters in the models depend on the SoC. The state vector of the system will therefore contain the SoC, but this cannot be directly measured in any way. The same applies to the other values in the state vector, which differ according to the model. The state vector is therefore called a hidden state vector. Two types of models will be implemented: the so-called electrical equivalent networks, consisting of electrical components, and the polarisation models.

Second, after good models have been obtained, Kalman filtering is applied to the system. A regular, Linear Kalman Filter (LKF) is the best estimator for the state vector of a linear system [2]. Since the system of a battery cell is not linear, due to the specific shape of the OCV(SoC)-curve, a LKF cannot capture this behaviour. More advanced Kalman filtering techniques are needed. The two Kalman filtering techniques implemented are the Extended Kalman Filter (EKF) and the Unscented Kalman Filter (UKF). The performance of the two filters on the five models is assessed and discussed.

To obtain a good estimation of SoC of the full battery pack, a single cell Kalman Filter does not suffice. Since the battery pack consists of modules in series, which contain cells placed in parallel, the Kalman filter has to be translated to this level and multiplied. An assessment, based on real-life data from a solar race, will be made and the results investigated. This is the third step in the process.

II. Modelling

The first goal is to develop a model that accurately describes the input-output behaviour of a single battery cell. The input in this system is the current that flows through the cell; the output is the voltage measured at the terminal of the cell.

A. Testing

The cell models' parameters have been determined in a data-driven way, based on tests that took place on three sample cells. Four types of tests have been conducted, all at room temperature.

1) Capacitance tests took place to determine the exact capacitance and the coulombic efficiency (η_C) of the sample cells. This parameter models the loss of charge due to processes internal to the battery. $\eta_C = 1$ was chosen, based on the tests and the characteristic retention rate of LFP-cells [3].
2) OCV(SoC)-tests, in which the cell gets charged and discharged at very low currents, were conducted to determine this relationship. These tests led to Figure 1.
3) Hybrid Pulse Power Characterisation (HPPC) tests, in which pulses are applied to the cell at different, equally spaced levels of SoC, took place. These will be discussed further on in more detail.
4) Race tests, in which the cells are submitted to a load profile based on a race day of an actual solar race, have been conducted as well. This dataset is used to validate the performance of the models after optimisation and to test the SoC-estimation of the single cell Kalman filtering.

B. Estimating the parameters

The HPPC-test exists of a sequence of pulses that is repeated at different levels of SoC, as can be seen on Figure 2. Between sequences, the cell is discharged to the next level of SoC and rests for a predefined time. Between pulses within the same sequence, the cell rests as well for a shorter time. By letting the cell rest between sequences, it is hoped to avoid signal leakage from one sequence into the next one. It is shown that the test procedure is not entirely adequate for the cells under scrutiny and that some leakage does take place. The HPPC-tests were used to optimise all the parameters of the models, except the OCV, which is determined via the specific test.

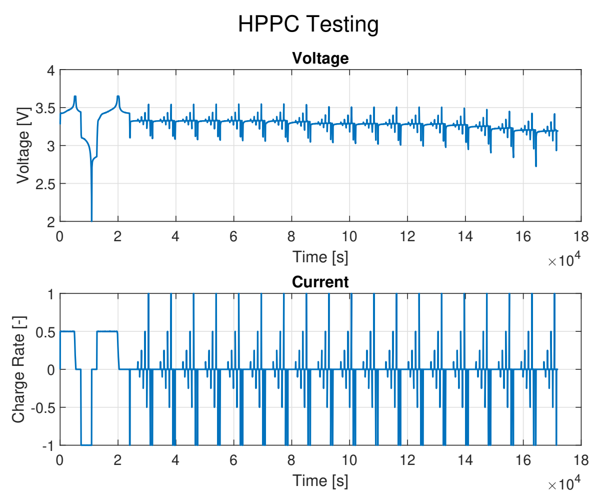

Fig. 2: A current pulse sequence is repeated at different levels of SoC that are, in this case, 5 % apart. The voltage is the output of the system and should be modelled as good as possible. The cell rests between sequences, to assure all transient effects have vanished to make sequences independent from each other.

Simulink models have been created for every model and the optimisation has taken place in Matlab, using the Matlab Optimisation Toolbox handle Nonlinear Least Squares [4]. All the default parameters have been maintained. The search space has been limited by bounding every parameter in the process.

Based on the reaction of the cell's terminal voltage on the current pulses, the parameters of the models are estimated. As there is a lot of freedom to estimate the parameters, it is worthwhile to consider desirable characteristics of the model. Since, after optimising the parameters at each level of SoC, interpolation will take place, a desirable feature is to have smoothly varying parameters. Two measures have been taken to stimulate this:

1) The HPPC-sequences have been split with and without overlap between the sequences. By having overlap between different levels of SoC, the parameters will be optimised partially on the same data. This is expected to improve the similarity of the parameters, but might compromise the model's accuracy. Therefore, both types of splitting the data have been investigated.
2) The parameters obtained at the previous level of SoC are used as initialisation of the optimisation algorithm for the next level of SoC. This has been inspired on the layered approach proposed in [5].

After the optimisation at every level of SoC, an additional optimisation over all data at once took place. The preprocessing, that took place before the actual HPPC-tests, was included in some cases to see whether this additional data improved the model's parameters.

C. Models

1) Electrical Equivalent Networks: The electrical equivalent networks aim to accurately capture the cell's behaviour by adding RC-blocks to the simple Rint model, which consists of an OCV and an internal resistance [6]. Every RC-block adds a time-dependency to the model. This way, different phenomena within the cell can be represented. Models with 2 and 3 RC-blocks have been implemented and are respectively called the 2RC and 3RC-model.

These models are found to accurately model the dynamics of the cell. However, the models are unable to accurately predict the terminal's voltage of convergence after relaxation. These models expect the terminal voltage to converge to the OCV, but this is not always the case in real life, as can be observed on Figure 4. To counter this phenomenon, the polarisation models have been implemented.

2) Polarisation Models: In these models, the model-dependent block is an offset to the OCV [7]. Two models have been implemented. The P0-model has a SoC-dependent offset that does not depend on any other parameters and exhibits Schmitt-trigger behaviour. The P1-model is more sophisticated in the sense that its offset voltage is determined by a first-order differential equation. Both models have been optimised following the same procedure as for the equivalent electrical networks.

3) Combination Model: Since the polarisation models focus on getting the offset to the OCV right and the electrical equivalent models focus on the dynamic behaviour of the cell, they have been combined as well. This led to the 3RC-P0-model, which aims to combine the best of two worlds.

This cell model is depicted on Figure 3. It consists of three 3RC-blocks, with distinct time constants τ_1 to τ_3, an internal resistance and a P0-polarisation block.

In this paper, only the 3RC-P0-model will be discussed in detail, since it incorporates both the electrical equivalent networks and the polarisation models and was found to be the most accurate model.

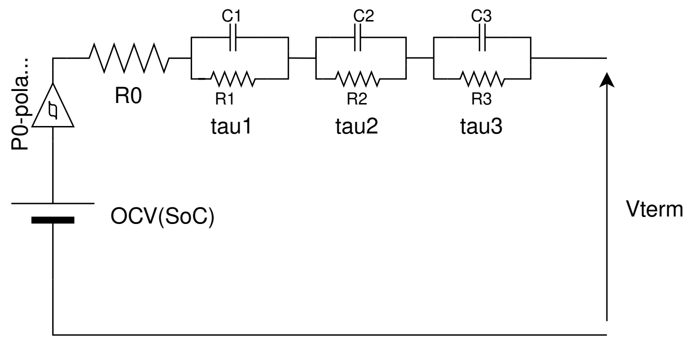

Fig. 3: The 3RC-P0-model consists of 3 RC-blocks, in series with an internal resistance and a P0-polarisation block, which exhibits the behaviour of a Schmitt trigger. It models the offset to the OCV.

D. Generalisation of the models

Since only three sample cells are available and a battery pack consists of many more, it is important to have an indication whether the cell models are representative for all these other cells.

It has been shown in the thesis that the parameters obtained for the different sample cells are accurate in describing the other sample cells' behaviour as well, for each model. This is logical, since this is more of a cell characteristic than of the model.

Since the cells' parameters within one model are similar, it was chosen to create a final set of parameters that is the average of the three cells. The performance of this parameter set is in line with the ones optimised on a specific cell. Since the models are not linear, it is not trivial that the linear averaging operation still leads to good results.

E. Results & Discussion

The final assessment of the models is made on the race data. The metric is the RMSE of the error between the measured voltage during the tests and the voltage obtained by feeding the input of the tests to the model. In Table I the results for the different models are listed. The second column shows the error voltage at the end of the day, indicating whether the target voltage converges to the modelled one.

In general, the error is quite limited for all models, but the electrical equivalent networks outperform the polarisation models. The 3RC-P0-model combines the good dynamic modelling of the electrical equivalent networks with a lower error at the end of the day. It outperforms all the other models on the race data.

Model	RMSE [mV]	Final Error [mV]
2RC	7.85	-3.82
3RC	7.60	-2.87
P0	13.01	-0.40
P1	10.75	8.63
3RC-P0	6.71	1.26

TABLE I: The RMSE on the race data and the error at the end of the race data. The electrical equivalent network model the dynamic behaviour of the cells better, but lead to an error at the end of the day. The P0-model models this final voltage better; the P1-model does not. The 3RC-P0-model effectively combines the good dynamics of the 3RC-model with the lower error at the end of the day of the P0-model.

The offset between the target and modelled voltage is mitigated by the simple P0-model, compared to the equivalent electrical networks. This is visible on Figure 4, where the 3RC-P0-model accurately captures the voltage at the end of the day, due to its P0-component. The target voltage and modelled voltage lay closely to each other. The yellow line, the predicted OCV, is the voltage of convergence for the equivalent electrical networks.

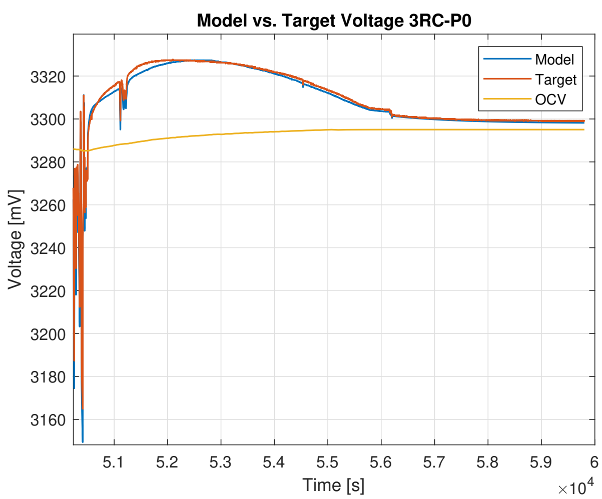

Fig. 4: Target voltage and predicted voltage at the end of the race data for the 3RC-P0-model. The error between the modelled voltage and the target voltage is almost negligible. In the electrical equivalent models, the expected voltage of convergence is always the OCV.

The P1-model is not able to lower the error at the end of the day compared to the other models, despite that being its main reason of creation. It is believed this is caused by a lack of suitable data. Since the pulses in the HPPC-tests are very short, their influence on the polarisation voltage might be insufficient to accurately estimate the P1-model parameters.

III. Single Cell SoC-estimation

Next, the Kalman Filters are implemented and their ability to accurately estimate the SoC of the battery cells investigated. The reader is referred to the thesis or the introductory work of Welch and Bishop [8] for an introduction in Kalman filtering.

A. Kalman filtering

A Linear Kalman Filter (LKF) works on a linear system, with the state update equation and output equation given in Equation 1. w_k and v_k are the process and measurement noise respectively, with covariance matrices Q_k and R_k.

$$\begin{cases} x_{k+1} &= Ax_k + B\mathrm{I_k} + w_k \\ y_k &= Cx_k + D\mathrm{I_k} + v_k \end{cases} \tag{1}$$

The Linear Kalman Filter is a filter that estimates the hidden state vector, x_k, of such a linear system optimally, in a minimum square error sense. It compares the output of a model with the actually measured output and iteratively adapts its hidden state based on the error between these two values. Hereby, it gains confidence about this state [9].

The model equations for the single battery cell that have been developed are all linear in the update equation, but they are not in the output equation. This is caused by the non-linear OCV(SoC)-curve, which makes it impossible to define the C matrix. Therefore, more advanced Kalman filtering techniques must be used.

For the 3RC-P0-model, the state vector is the following. The state of the Schmitt trigger of the P0-model is also tracked, but is not estimated by the Kalman filtering and not included in the state vector. I_1 to I_3 are the currents that flow through the corresponding resistances in the model.

$$x_k = \begin{bmatrix} SoC \\ I_1 \\ I_2 \\ I_3 \end{bmatrix} \tag{2}$$

The state update and output equations are given by Equations 3 and 4. I_k is the current measured through the cell at time index k. ΔV is the offset voltage of the P0-polarisation block.

$$\begin{aligned} x_{k+1} = &\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & exp(\frac{-\Delta t}{\tau_1}) & 0 & 0 \\ 0 & 0 & exp(\frac{-\Delta t}{\tau_2}) & 0 \\ 0 & 0 & 0 & exp(\frac{-\Delta t}{\tau_3}) \end{bmatrix} x_k \\ &+ \begin{bmatrix} \frac{\eta_C \Delta t}{C_{nom}} \\ 1 - exp(\frac{-\Delta t}{\tau_1}) \\ 1 - exp(\frac{-\Delta t}{\tau_2}) \\ 1 - exp(\frac{-\Delta t}{\tau_3}) \end{bmatrix} I_k \end{aligned} \tag{3}$$

$$y_k = OCV(SoC) + \Delta V + R_1 \cdot I_1 + R_2 \cdot I_2 + R_3 \cdot I_3 + R_0 \cdot I_k \tag{4}$$

B. Extended Kalman Filter

In terms of Taylor factorisation of a polynomial, the Extended Kalman Filter (EKF) can be considered to use the first-order approximation of the non-linear function in order to obtain the C matrix [10]. Hence, the error on this approximation is linear to the deviation between the tangent and the actual function. Good results can thus be expected when the function is nearly linear in the region of interest. This is the case for the largest part of the non-linearity under scrutiny, namely the OCV(SoC)-curve.

C. Unscented Kalman Filter

The Unscented Kalman Filter (UKF) handles the non-linearity in a more sophisticated way. It takes several points around the estimate of the state. The spacing of these so-called sigma points depends on the uncertainty on the states; a higher uncertainty means the points will lay further away. By calculating the update equation and output equation and a weighed summation, the influence of the non-linearity should be taken into account better [11].

D. Tuning and Initialisation

A lot of attention has gone to finding suitable parameters for the Kalman Filters. In case of the EKF, the following parameters have to be tuned:

1) R_k is the covariance of the measurement noise. For a single cell system, only one output is observed. The measurement noise is thus reduced to a scalar. It can be seen as the noise on the measurement.
2) Q_k is the covariance of the state noise, so a measure for the uncertainty of the model dynamics. This parameter is more difficult to tune, since the state is hidden. It is a vector of length n.
3) The covariance matrix of the state vector needs to be estimated. It is assumed that there is no initial correlation between the values in the state vector, which leads to a diagonal matrix of dimensions n×n.
4) The state vector, $x_{k|k}$, is initialised with the best guess for the different states in the system and is therefore a vector of length n. However, the first element of this vector (the SoC) will be deliberately initialised incorrectly in some tests to evaluate the correcting behaviour of the Kalman filter.

The calculation of Q_k has been implemented as given by Equation 5. This is based on [12], who have been inspired by Plett [13]. All matrices (A, B, C, D) in the system are SoC-dependent, which means they are time-varying as well. Therefore, the subscript k is used.

$$Q_k = B_k \cdot \rho^2 \cdot B_k^T \tag{5}$$

A grid search has been executed to find suitable parameters for R_k and ρ, which eventually led to $R_k = 10^5$ and $\rho = 10$. The values in the state vector are initialised after a simulation with the model. The first value, which is the SoC, can be subject to a deliberately incorrect initialisation. The values on the diagonal of the state error covariance matrix are set high, in order to account for possible incorrect initialisation of the state vector.

In the UKF algorithm, additional parameters have to be defined. The reader is referred to the thesis for a more thorough discussion.

E. Results & Discussion

The EKF and UKF have been implemented on all developed models. The performance is then assessed by comparing the estimated SoC with the measured SoC during the tests with the race data.

In comparison to the currently used method, one of the main advantages of Kalman filtering is its ability to correct its hidden state, which contains the SoC, based on new information. Therefore, three scenarios are studied. In the first scenario, the SoC is, on purpose, initialised with a negative offset of 5 %. In the second scenario, it was initialised correctly and in a third, a positive offset of 5 % was added.

It is observed that the Kalman filtering on the 3RC-P0-model performs best. Figure 5 shows the performance of the Extended Kalman Filter after the SoC has been initialised incorrectly. After a short time, the SoC converges to the correct value.

This behaviour is observed for both the EKF as the UKF. On the best models, namely the 3RC and 3RC-P0-model, the EKF and UKF perform very similarly.

IV. Full pack SoC-estimation

The battery pack as a whole consists of a number of modules in series. One module consists of a number of cells in parallel. Due to the parallel connection between cells, the terminal voltage between the cells will always be equal to each other. The SoC of the full battery pack is then calculated as the minimum of the SoC over all modules.

A. Translation to module level

To use Kalman filtering to determine the SoC in a real race, the single cell models must be translated to a module level, since the voltage measurements happen at this level. The current can only be estimated to be the measured current divided by the number of cells in parallel, since no measurement per cell is available.

Five possible sources of error when translating the single cell Kalman Filter to the full battery pack have been identified.

1) The current might not be symmetrically distributed between the cells inside a module due to a mismatch in the internal resistance [14]. Therefore, the input current used for the Kalman filter is an approximation. Performing a HPPC-test on the battery pack as a whole, measuring the voltage of each module, or performing HPPC-tests on each module separately might be a valid alternative to the per-cell approach that has been used in this thesis. This way, specific parameters for each module can be obtained.

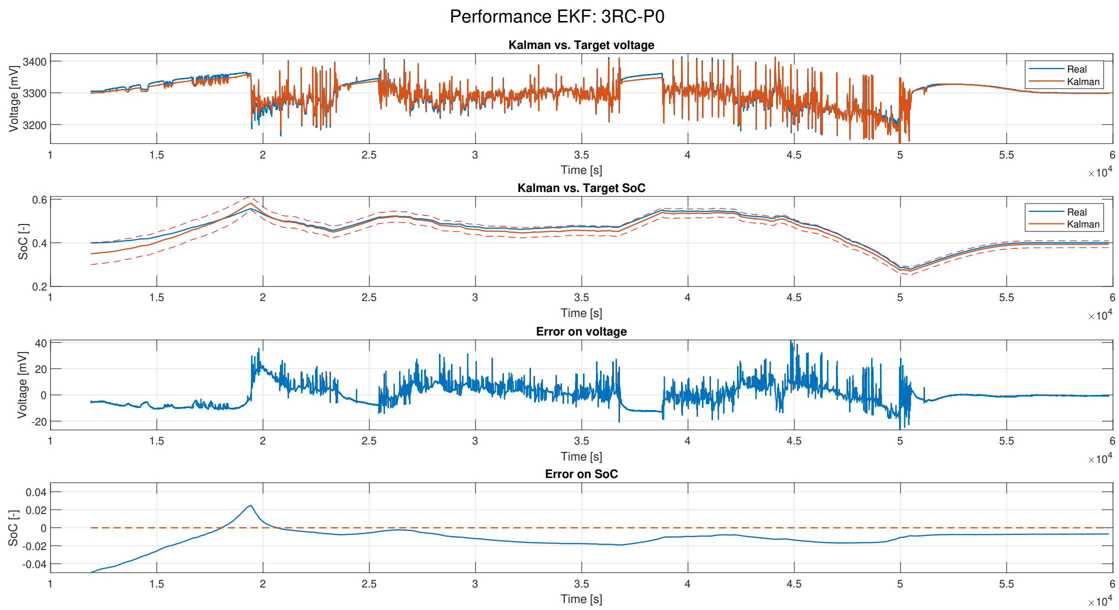

Fig. 5: After deliberate incorrect initialisation of the SoC, quick convergence is achieved for most test cases with the 3RC-P0-model, with both Kalman filtering techniques. The red dotted lines show one-sigma confidence interval, which is obtained via the state error covariance matrix.

2) Using the same, generalised, set of parameters for every cell will lead to errors. For the three sample cells, this error has been shown to be limited.
3) No information on the degradation of the cells or its influence on the cells' parameters is available. This might cause an additional error to the model of the cells [15].
4) The capacitance of every cell has been assumed to be 15000 mAh, since no capacitance tests for every cell are available.
5) The influence of temperature on the cells' behaviour is not taken into account.

B. Results & Discussion

Even though it is expected that errors will arise during the transfer, the performance of the SoC-estimation on the modules has been assessed. To this end, data from the Solar Challenge Morocco 2021 was used. In this race, the Solar Team effectively participated with the battery cells under scrutiny.

Results for the EKF on the first day are shown on Figure 6. The Real SoC is the estimation made by the Solar Team during the race. The results are exemplary for the performance of the SoC-estimation on the following days as well. The algorithm underestimates the SoC consistently.

On the final day, the SoC drops drastically, as shown on Figure 7. Ideally, it would reach zero at some point. Due to the uncertainty on the SoC-estimation methods, the Solar Team took a margin of 4.5 % on the SoC. This means that it was

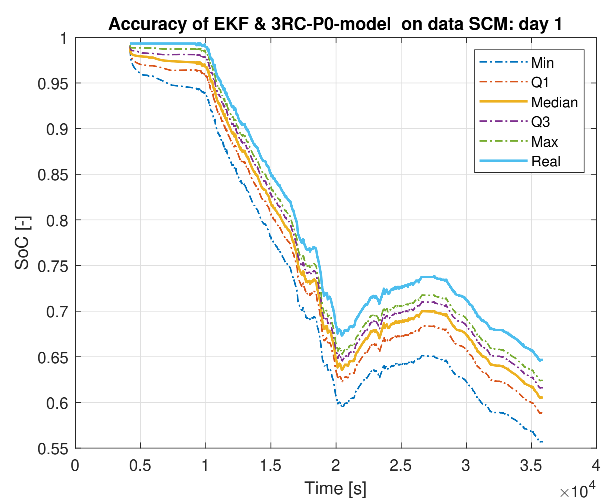

Fig. 6: Using real-life race data, the EKF, in combination with the 3RC-P0-model, underestimates the SoC for all modules, when the SoC is in a region where the terminal voltage is very insensitive to it.

estimated that at a SoC of 4.5 %, the effective SoC would be 0 %. The minimum SoC effectively reached was around 5 %. During the race, it was estimated that, at this point, the actual SoC was between 2 and 2.5 % and so the margin was taken 2 to 2.5 % too high (Innoptus Solar Team, 2023).

The minimum SoC estimated by the EKF is approximately this value. In this case, the EKF estimates the SoC better than the current method. The reason is that at low SoC, the sensitivity of the OCV, and therefore the terminal voltage, is much higher than at other SoC-levels. This makes it easier for the Kalman Filter to accurately determine the SoC, even with the errors that are introduced by the translation to a module level included.

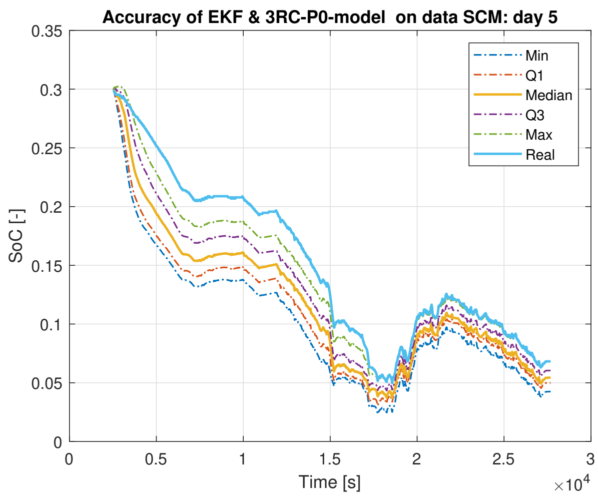

Fig. 7: On the last race day, so reaching very low SoC, the EKF, in combination with the 3RC-P0-model, estimates the minimum voltage better than the currently used method. It is believed this is caused by the higher sensitivity of the terminal voltage on the SoC.

In general, the results for the EKF and the UKF are again very similar. Therefore, other plots have been left out of this report, but can be found in the thesis.

V. Conclusion

The three steps taken to obtain a better SoC-estimation method using Kalman filtering techniques have been discussed in this article.

The first step, modelling a single battery cell's input-output behaviour, has been a success. Five models have been implemented and their parameters estimated. For all models, good parameter sets have been found, using a simple and effective optimisation method. It is believed that it is generally applicable to other cell technologies as well, due to the complexity of the LFP-cells. The thesis may act as a manual on how to derive good single cell models from commonly used tests. The models are ready for reuse and provided to the reader.

The second step, implementing Kalman filtering on these models, has been successful as well. The algorithms have been applied on all models using a standardised framework. Both the EKF as the UKF are well capable of tracking the SoC using the best models, even in regions where the sensitivity of the terminal voltage on the SoC is extremely low, due to the OCV(SoC)-curve, that is characteristic LFP-cells. Therefore, it is reasonable that for other cell technologies, equally good or even better results might be obtained.

Using these single cell models to implemented Kalman filtering on a full battery pack, consisting of modules in series, has proven to be a challenge. The performance of the Kalman filtering has not been reproduced on the real-life race data. Several possible sources of errors have been discussed, but is unclear what causes the error. In a region with higher sensitivity of the terminal voltage on the SoC, so at low SoC, it is however estimated more accurately than using the current method.

In general, the thesis provides a framework to implement cell models and Kalman filtering on battery cells, for any cell technology. By focusing on LFP-cells, which are known for their extremely flat OCV(SoC)-curve and long time constants, the results are expected to be easily reproducible on other cell technologies.

VI. Future Work

To obtain a reliable SoC-estimate for the full battery pack, more research and effort must be put into the translation from the single cell models to module level, in order to accurately identify the source(s) of error and to mitigate the issue(s). Another approach to the problem would be to start modelling at the module level straight away.

It is hoped that future researchers can reuse much of the work done in this research and take into account the insights given here from the beginning.

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