35th International Electric Vehicle Symposium and Exhibition (EVS35)
Oslo, Norway, June 11-15, 2022

Systematic Battery State Estimation Algorithm Assessment – a Model-in-the-Loop Approach

Dominik Jöst[1,2], Katharina Quade[1,2], Franziska Berger[1,2], Dirk Uwe Sauer[1,2,3,4]
[1]*Chair for Electrochemical Energy Conversion and Storage Systems, Institute for Power Electronics and Electrical Drives (ISEA), RWTH Aachen University, Jägerstrasse 17-19, 52066 Aachen, Germany*
[2]*Juelich Aachen Research Alliance, JARA-Energy, Germany*
[3]*Institute for Power Generation and Storage Systems (PGS) @ E.ON ERC, RWTH Aachen University, Germany*
[4]*Helmholtz Institute Münster (HI MS), IEK-12, Forschungszentrum Jülich, Germany*

Executive Summary

Lithium-ion battery systems require an efficient battery management, the respective design of which must fit the different requirements of the specific application. To achieve this, various types of algorithms have been designed in academia and industry. In this work, a Model-in-the-Loop approach is presented to evaluate and compare such algorithms under realistic and reproducible conditions across the entire operating range. This allows to choose the most suitable set of algorithms for an application.

Keywords: battery, battery management, BMS (Battery Management System), diagnosis, state of charge, testing processes

1 Introduction

In recent years, rapid improvements in battery technologies, in addition to decreasing prices, have led to their widespread use in various applications [1]. Lithium-ion batteries have become established in the vast majority of sectors, due to their high energy and power density, efficiency and service life. In addition to power tools and multimedia applications, this includes stationary applications of various sizes, as well as all levels from micro hybrid to fully electric vehicles. Depending on the application needs, lithium-ion batteries, therefore, cover a wide range of energy and power densities as well as cyclic and calendar life [1].

Regardless of the application, it is crucial to accurately determine various states of the battery while it is in use. This task is performed by a Battery Management System (BMS). Diagnostic algorithms on the BMS determine values like the State of Charge (SOC), State of Health (SOH) and State of Power (SOP) of the battery in order to ensure its safety and optimal utilization [2]. The widespread use of lithium-ion batteries in various applications requires a comprehensive set of different diagnostic functions and methods. Consequently, numerous diagnostic algorithms have been developed and published for lithium-ion batteries. Typically, these are designed, parameterized and validated for a specific application and certain boundary conditions [3][4]. However, the accuracy, robustness and computational speed of most algorithms is affected by different load profiles, cell types, and BMS hardware, among other factors [2][4][5][6]. Therefore, a systematic assessment and direct comparison of the performance of algorithms from literature is not possible. However, in order to make a suitable selection of algorithms for an application, it is necessary to assess them under preferably equal conditions [6].

In order to investigate the aforementioned effects, this work presents a Model-in-the-Loop (MiL) toolchain for BMS that has been developed and implemented. A structural overview of the toolchain is given in Fig. 1. To demonstrate the benefit of the proposed method and to validate the toolchain, a basic set of SOC estimation algorithms is investigated within this work. A large number of simulations is carried out under systematically selected boundary conditions e.g. varying in load profile, temperature, and initial battery state. In addition, different cell chemistries, cell sizes and pack topologies can be considered. Key figures like estimation accuracy, drift, and transient response, as well as noise and offset stability are determined automatically in each case. These key figures are then evaluated across all boundary conditions and converted into scores based on user-definable threshold values. These can then be visualized in radar plots, as shown in Fig. 11. This achieves the set goal of evaluating algorithms systematically, across the entire operating range, and appropriately for the application.

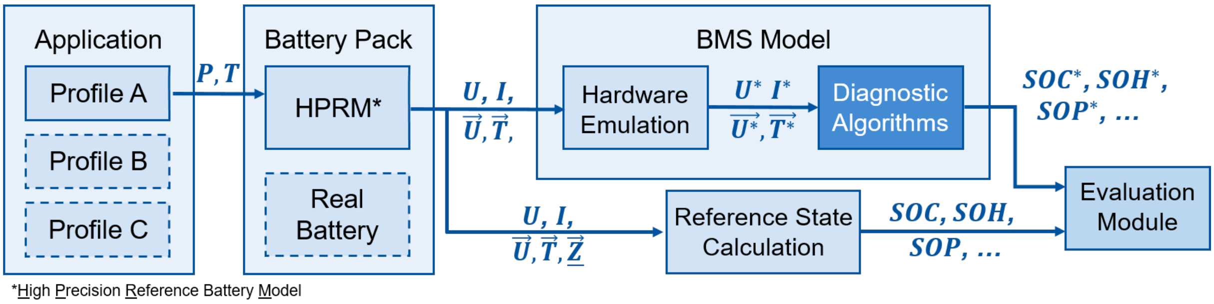

Figure 1: Structural overview of the simulation and validation environment

2 Lithium-ion battery diagnostics

Compared to other technologies, lithium-ion batteries offer high performance, yet only operate in a comparably small safe operating area. In order to allow safe operation, a BMS is required to determine the state of the battery, to keep it in the safe operating area and to utilize the full battery capacity and power. This not only guarantees safety, but also ensures that the battery life does not prematurely end. The use of appropriate, often model based diagnostic algorithms allows the battery to be better utilized, thus improving the cost-benefit ratio.
The first and foremost task of a BMS system is to maintain the safe operating area of the battery. This is usually achieved by applying fixed voltage, current and temperature limits, the exceeding of which leads to the system being shut down [2]. A further task is the determination of different battery states for optimized control and utilization of the battery system or visualization for the user. These include the state of charge (SOC), the state of available power (SOP) as well as the state of health (SOH) and the estimation of the remaining useful life (RUL) [5]. With the knowledge about the battery states, many algorithms, e.g. for charge equalization between the cells and for optimized charging can be executed more precisely.

3 Simulation and validation environment

3.1 Overview

The implemented Model-in-the-Loop simulation and validation environment is structured as shown in Fig 1. It covers the parts described below and marked in bold in the text. In addition to real, recorded load profiles from various applications, simulated profiles of various vehicle topologies, as well as synthetic current profiles, can be used as **Application** input data. A high precision equivalent circuit **Battery Pack** model parameterized by both, electrochemical impedance spectroscopy and time domain pulse measurements and modelled on cell level is used as the reference. The output of the battery pack model consists of high resolution pack (U, I) and single cell $(\vec{U}, \vec{I})$ voltages and currents, temperatures at defined sensor points $(\vec{T})$ and the impedance of the cells $(\underline{\vec{Z}})$. Based on the toolchain, the diagnostic algorithms using more simplified battery models are tested against the reference. The **BMS Model** includes the simulation of the entire signal path through the BMS hardware and software as detailed in Fig. 5. It converts the data into digital values with limited accuracy, as it happens in a real system. The resulting digital data values $(U^*, I^*, \vec{U}^*, \vec{T}^*)$ are then processed by the diagnostic algorithms. Various diagnostic algorithms can be implemented to estimate battery states such as state of charge (SOC^*), state of health (SOH^*) or state of power (SOP^*) of the battery system. In the **Reference State Calculation** the reference battery states (SOC, SOH, SOP) are determined in parallel with maximum resolution of the signals and taking into account additional information from the battery model (i.e. impedance, capacity, overvoltages). At the end of the signal chain, the **Evaluation Module** compares the determined battery states with the reference states. Further external processing of the data also allows the comparison between different implementations or algorithms the diagnostic tasks. Thus, it is possible to investigate and compare diagnostic algorithms under equal but freely definable boundary conditions.

3.2 Application Model

The application model is the starting point of the toolchain. In this block a certain application profile is selected and scaled according to the specific battery chosen. A possible origin for such a application profile is a recorded data set from the application, e.g. a stationary storage system used for primary control reserve or a drive cycle of a BEV. Alternatively, two types of synthetic profiles can be used with the toolchain. The first type of synthetic profiles is generated from standardized operating or driving profiles utilizing a simulation model of the application. This can be, for example, the WLTP cycle known from combustion vehicles, or cycles adapted for electric vehicles and their recuperation capability as described in [7]. For this purpose, a vehicle model was integrated into the toolchain, which makes it possible to convert specified speed profiles with different vehicles and vehicle topologies (full electric vehicle, serial and parallel hybrid vehicle, mild hybrid vehicle) into power profiles, as shown in Fig 2.

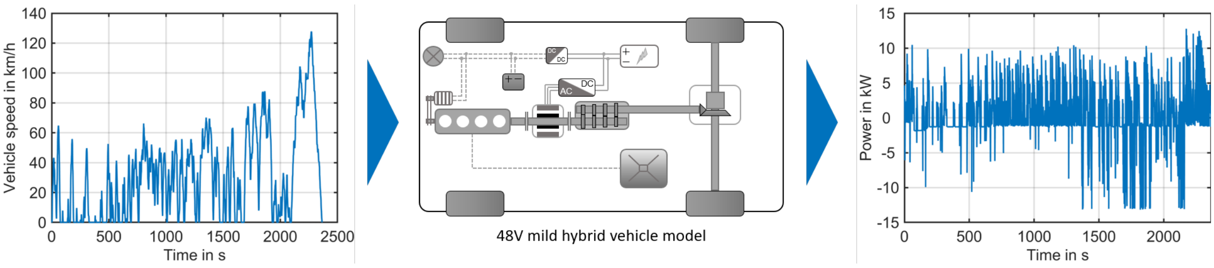

Figure 2: Load cycle Sporty Mid Daily Use from [7] transformed into battery power of 48V mild hybrid vehicle by a vehicle model

The second type of synthetic profiles are test profiles especially designed for the validation of BMS algorithms. One implemented example is the symmetrical, mean value-free signal of characteristic frequencies of the application, adapted from [6] and shown in the upper half of Fig 3. Among others, it can be used to analyze possible drifts in the SOC estimation. Such a profile is either directly simulated at various battery states or integrated in a master profile and therefore executed at different battery states, e.g. different SOCs as shown in Fig 3 at the bottom.

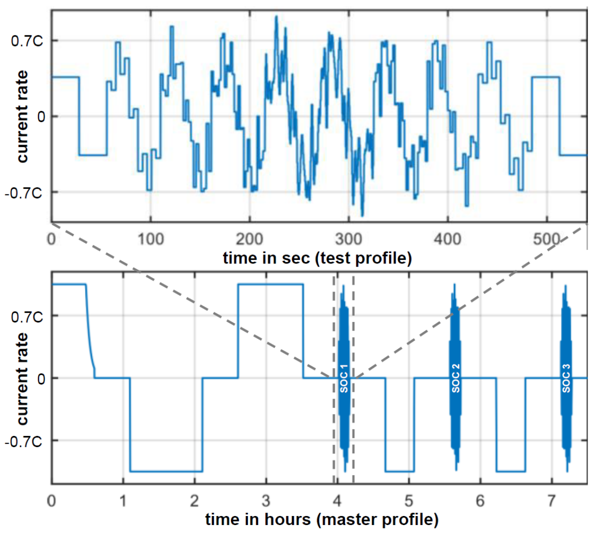

Figure 3: Top: Example synthetic load profile, Bottom: Master profile with integrated synthetic load profile at three SOCs

3.3 Battery System Model

The battery system model is used to simulate the behavior of the interconnected battery cells, not taking into account the electronics. The basic part for this work consists of a physico-chemically motivated electric equivalent circuit battery cell model shown in Fig 4 and described in [8] and [9], but could also be replaced by other validated high precision models or for some cases single cell measurements with the specific application profile from a test bench. This battery cell model is run for all cells in a module with statistically slightly modified parameters. In order to be able to provide pack sizes, the simulated values are then scaled from module to pack according to a definable topology.

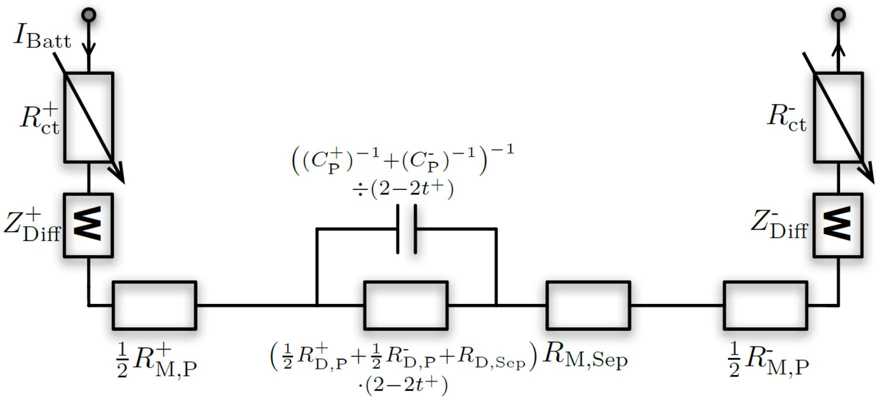

Figure 4: Physically motivated battery cell ECM from [9]

3.4 BMS Model

The BMS Model part covers the behavior of the battery pack electronics to ensure that the algorithms are tested under real life conditions. It divides into a BMS hardware emulation and the diagnostic algorithms.

3.4.1 BMS Hardware Emulation

The complete signal path of the measured values from the sensors to the algorithms running on the BMS is modelled (compare Fig 5). The BMS hardware emulation reproduces the signal path of the hardware developed at the authors institute, but can be adapted to other BMS hardware. Fig 5 shows in detail the processing of the cell voltages, which is similarly done for temperatures and pack values.

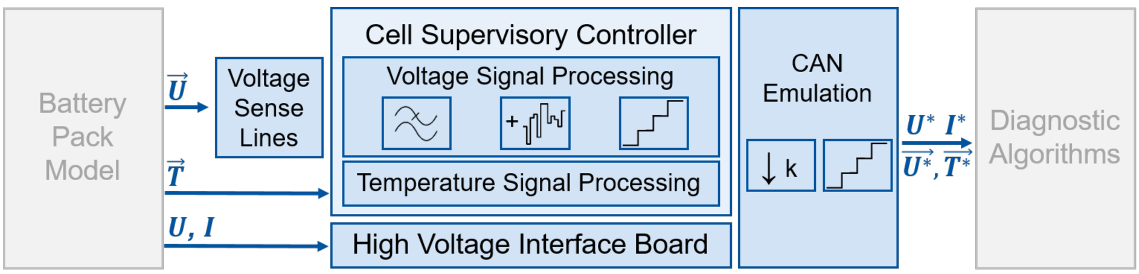

Figure 5: BMS emulation structure

In a first step, a simple resistance model of the voltage sense lines processes the cell voltage in order to consider a possible influence of balancing currents through the sense lines. Entering the printed circuit board of the Cell Supervisory Controller, often called "BMS Slave", the analog signal (which is represented in the simulation environment via maximum resolution) is low-pass filtered. The emulation further samples the resulting data, according to the specifications of the front-end chip, with 100 Hz. After applying additional noise and a possible sensor offset characterized from own measurements and datasheet values, the signal is quantized to the bit-length of 14 bit used in the BMS. In the CAN transceiver module the data is down-sampled once more to 10 Hz and in case of the single cell voltages converted to a lower resolution of 1 mV. The resulting values are used as input to the diagnostic algorithms.

3.4.2 Diagnostic Algorithms

The diagnostic algorithm environment is designed in a modular structure, which allows a simple exchange of individual algorithms. Fig 6 presents an overview of the considered BMS algorithm modules and is divided into the four domains ‘Battery Model’, ‘State Estimation’, ‘Aging Estimation’ and ‘Battery Control’.

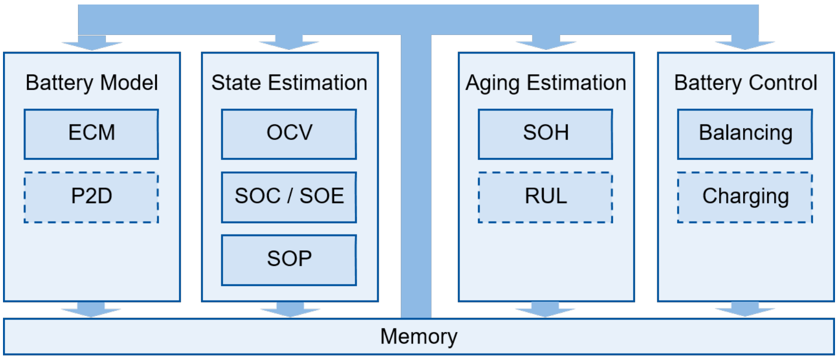

Figure 6: Overview of the modular diagnostic algorithm environment

In the ’Battery Model’ part different model variants can be implemented. In the simplest case, this is a static first order Thevenin model, but can also be replaced by higher order electrical models including online adaptation or even a physico-chemically motivated Pseudo-2-Dimensional Model (P2D) can be integrated. The algorithms summarized under ’State Estimation’ determine the states of the battery immediately influenced by the operation and thus cover relatively short periods of time. In contrast, the algorithms implemented under ’Aging Estimation’ depict the changes occurring in the battery over a longer time horizon. This mainly concerns the loss of capacity and the increase of the internal resistance. Additionally, an estimation of the remaining useful life (RUL) would be implemented in this part. Finally, the algorithms that have a retroactive effect on the battery are summarized under ’Battery Control’. This always includes a balancing strategy, but for example special model-based charging strategies could also be implemented. Modules with solid outlines are equipped with basic implementations, whereas modules with dashed lines indicate that they can be implemented optionally or are beyond state of the art. The data exchange between the algorithm modules is realized via a common buffer memory. This is necessary because some algorithms rely on the results of others. This structure can now be used for algorithm evaluation. To do so, one or more modules, provided as libraries, are replaced by alternative implementations and the results are compared with the reference states and the previous implementation.

3.5 Reference State Calculation

The reference state calculation uses the high-resolution data from the reference battery model to calculate as precisely as possible the battery states that are estimated by the diagnostic algorithms. For this, the data used in this block includes data which typically can not be measured (e.g. impedance, available capacity, overvoltages, internal potentials) and therefore is not available for the diagnostic algorithms, but is directly available in the reference model. The resulting states then serve as reference for the values generated with the diagnostic algorithms.

3.6 Evaluation Module

The evaluation module compares the respective signals from the BMS algorithms and the reference state calculation. For this, typical comparison values for the estimation accuracy, such as the absolute error (AE), mean squared error (MSE), the mean signed deviation (MSD) and the average deviation (AD) are calculated. To address the issue of comparability, the estimation algorithms are further evaluated systematically for drift, offset stability, noise stability, transient behaviour as well as temperature stability by multiple simulations and their analysis. For this purpose, drift is defined as a measure that determines the tendency of the estimated values to deviate from the reference values over time. Since the estimated values typically are non-linear for batteries, the regression line of the estimation error is used to determine the drift score. Offset stability is derived by analyzing the influence of different errors of the measurement system (i.e. current sensor offset, voltage sensor offset, temperature sensor offset) and changes in the battery (i.e. cell resistance, cell capacity) on the estimated values. Noise stability is tested by adding multiple levels of normal distributed, mean value-free signal noise to the values determined by the different sensors. To analyze the transient behaviour, the algorithms are initialized with a false initial value and the time until a threshold of acceptable accuracy is reached, is investigated. Test profiles

are conducted at different surrounding as well as initial temperatures to investigate the stability of the diagnostic algorithms against normal as well as harsh environmental conditions.
Even if a direct analysis of the simulation results in terms of accuracy and stability is relatively easy if only a few simulation results are to be evaluated, there are too many simulations to be analyzed in a systematic approach like the one presented here. Therefore, in order to evaluate the results comprehensively in a simply way, while still assuring comparability among the estimation algorithms, a benchmarking method based on a error-limit score is used. In this approach, a score point system from 0 (worst) to 5 (best) is applied. For visualization, the benchmark scores of the estimation algorithms in each test profile are averaged and depicted in a radar plot as shown in Fig 7.

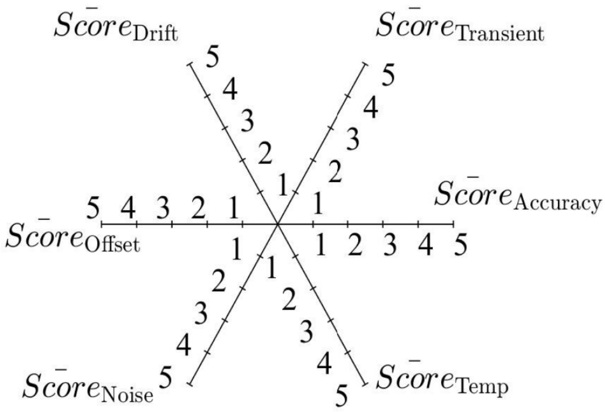

Figure 7: Radar plot for visualization of averaged algorithm scores

4 Exemplary results and discussion

4.1 Testset description

In this section exemplary results and scores of three SOC estimation approaches for a full electric vehicle application are showcased. All simulations are carried out using a high precision reference model of a lithium-ion 13.15 Ah battery cell with NMC vs. graphite chemistry. For this work a total of 224 simulations have been executed and analyzed to cover the different combinations of evaluation aspects and surrounding temperatures.
Three different input profiles (low dynamic load, high dynamic load, long-term stability) were used for this, of which the low dynamic load profile variant is depicted in Fig 3. Prior to the validation experiment, the modeled battery is initialized at a SOC value of 50% for the low dynamic profile and long-term stability profile. Whereas for the high dynamic profile, the battery cells are initialized at 100%. The resulting reference SOC course for all three profiles is shown in Fig 8.

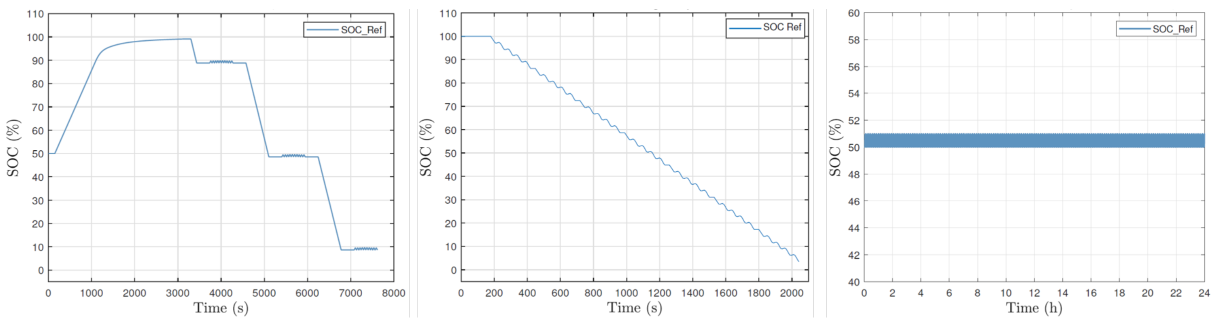

Figure 8: Reference SOC course for low dynamic (left), high dynamic (middle) an long-term stability (right) profiles

The following three SOC estimation algorithms have been investigated in this work:
At first, a standard coulomb counting approach, extended by full charge detection and OCV recalibration. A very basic way of SOC estimation with low computational cost, in which the measurement values from the current sensor are integrated, divided by the capacity of the battery to obtain a relative value, and lastly summed with the initial SOC level to gain the current SOC level of the battery. Secondly, a model

based approach with low computational effort, utilizing a 2-RC model and a Recursive Least Squares (RLS) algorithm with two forgetting factors. It is a mathematical optimization method to predict the parameters of an over-determined linear equation-system based on previous data with minimal quadratic error between predicted and measured values as constraint. In this implementation, the OCV is estimated using the RLS algorithm on the equivalent circuit model and the SOC is then determined based on a OCV-SOC lookup table. Lastly, a Dual Unscented Kalman Filter (DUKF) approach on a 3-RC model, with much higher complexity as well as computational effort. In this implementation, two Unscented Kalman Filters being responsible for for the parameter estimation and the state estimation respectively are coupled in such a way that estimation of the SOC is possible with better accuracy, while the computational costs remain at the level of a single UKF.

4.2 Results

In this section the accuracy scores for the RLS based SOC algorithm are exemplary shown. For a better understanding of the scores, some examples of the SOC estimation courses over time at different temperature levels with the low dynamics profile are also given. Table 1 shows the estimation accuracy score ($Score_{Accuracy}$), offset stability score ($Score_{Offset,Accuracy}$) and noise stability score ($Score_{Noise,Accuracy}$) of the RLS algorithm for all temperatures and test profiles.

Table 1: Resulting accuracy scores for the RLS algorithm

SOC_RLS		-10°C	0°C	10°C	25°C	40°C	60°C	80°C	$Score_{\text{Temp,Accuracy}}$
Low Dynamic	$Score_{\text{Accuracy}}$	1.8	1.9	2.4	3.0	3.1	3.1	3.1	3.9
	$Score_{\text{Offset,Accuracy}}$	4.9	4.9	4.8	4.7	4.6	4.6	4.6	
	$Score_{\text{Noise,Accuracy}}$	4.8	4.8	4.6	4.5	4.4	4.4	4.4	
High Dynamic	$Score_{\text{Accuracy}}$	1.1	1.2	1.3	1.4	1.4	1.4	1.4	4.8
	$Score_{\text{Offset,Accuracy}}$	4.8	4.7	4.7	4.7	4.6	4.6	4.6	
	$Score_{\text{Noise,Accuracy}}$	4.9	4.9	5.0	5.0	5.0	5.0	5.0	
		$25\,°C \rightarrow 80\,°C \rightarrow -10\,°C \rightarrow 25\,°C$							
Long-term Stability	$Score_{\text{Accuracy}}$	3.3							-
	$Score_{\text{Offset,Accuracy}}$	4.3							
	$Score_{\text{Noise,Accuracy}}$	4.3							

From Table 1 we can observe that the RLS method has relatively poor estimation accuracy and their estimation accuracy scores vary under the influence of ambient temperature. The $Score_{Accuracy}$ is in the range of 1.8 to 3.1 in the low dynamic profile and 1.1 to 1.4 in high dynamic profile respectively. It is visible that the estimation accuracy reduces with decreasing temperature, this can also be observed in Fig 9. This behaviour is caused by the higher impedance values at lower temperatures, which are not adequately adjusted by the implemented RLS algorithm. The spread of this result yields in a $Score_{Temp,Accuracy} = 3.9$ in low dynamic profile and $Score_{Temp,Accuracy} = 4.8$ in high dynamic profile. The estimation algorithm behaves comparably stable against offset and noise influences. Its $Score_{Offset,Accuracy}$ and $Score_{Noise,Accuracy}$ are consistently above 4.6 in both low dynamic and high dynamic profiles. Although its $Score_{Accuracy}$ in the long-term stability profile is not as high as in the coulomb counting algorithm, its stability scores in this profile are still higher than those of the coulomb counting algorithm, with $Score_{Offset,Accuracy} = Score_{Noise,Accuracy} = 4.3$ for the RLS algorithm.
In Fig 9, the SOC results in low dynamic profile under normal operation (without offset and noise errors) and under operation with voltage offset are depicted. The SOC results in long-term stability profile under normal operation as well as current offset are depicted in Fig 10.

The mean scores of the SOC algorithms are calculated from the tables like Table 1 and transformed into radar plots as described in Subsection 3.6. The resulting radar plots for all three algorithms and profiles are shown in Fig 11.

As one can see in Fig 11, the implemented coulomb counting method delivers the best overall performance in comparison with the implemented DUKF and RLS methods, because it has the largest coverage area in all three radar plots. However, it shows the poorest $\overline{Score_{Offset}}$ and $\overline{Score_{Noise}}$ in both low dynamic as well as long-term stability profile. Although the DUKF algorithm is less accurate and has larger drift in comparison to the coulomb counting method and exhibits slowest transient behaviour, it performs relatively consistent in all three test profiles with sufficiently good stability against offset and noise influences. On the other hand, the RLS algorithm obtains fairly similar mean scores as the DUKF algorithm in most aspects. However, its drift scores fluctuate in different test profiles. In the radar plot

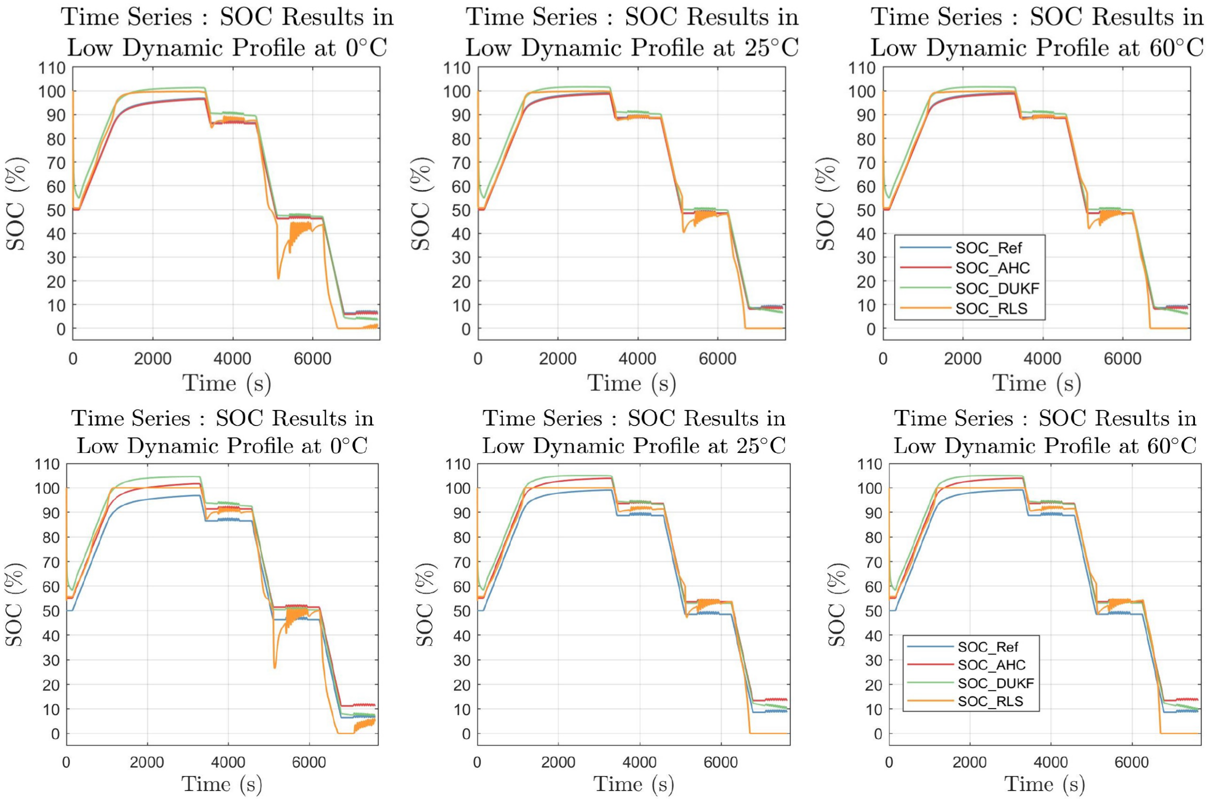

Figure 9: Results in low dynamic profile at three temperature levels with no offsets and noise (top row) and 30 mV voltage offset (bottom row)

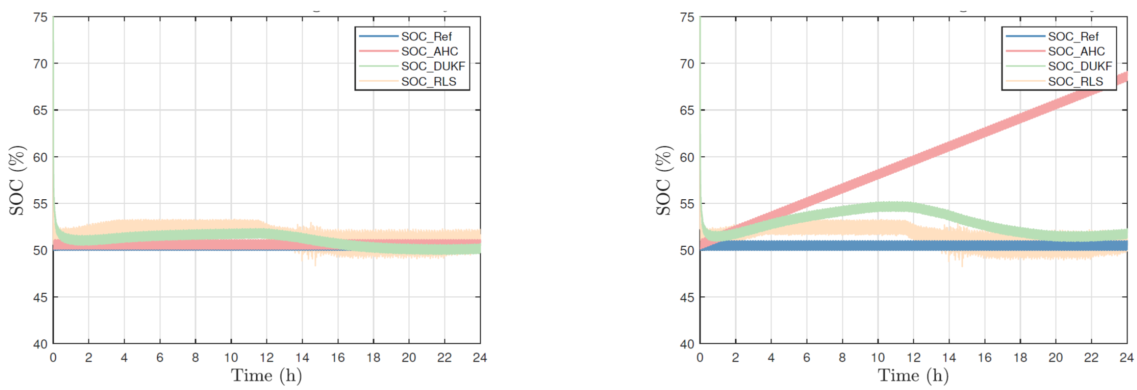

Figure 10: Results in long-term stability profile without offsets and noise (left) and 0.5% current offset (right)

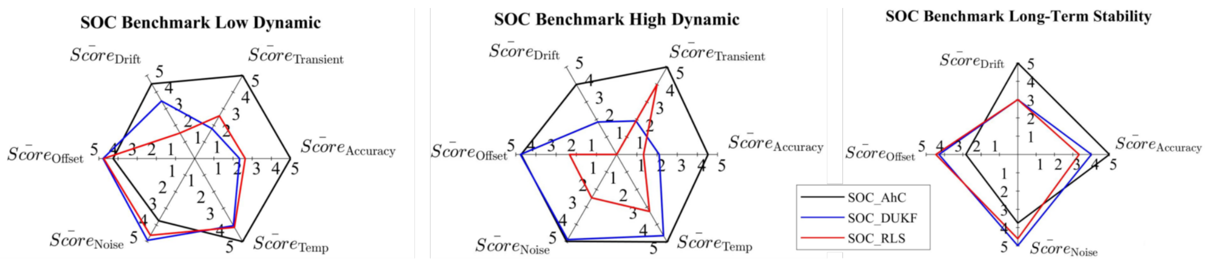

Figure 11: Radar plot of SOC benchmark scores for all three profiles

of the high dynamic profile, it is observed that the RLS estimation has $\overline{Score}_{Drift}$ = 0 and relatively low $\overline{Score}_{Offset}$ as well as $\overline{Score}_{Noise}$. This is because the drift score of the RLS method fails for high dynamic profile because its estimation error at $t_{0.5h}(\epsilon_{0.5h})$ is beyond the highest error bound (10%). This leads to no further investigation of offset stability and noise stability of the algorithm regarding drift. The $Score_{Offset}$ is calculated from the mean of both $Score_{Offset,Accuracy}$ and $Score_{Offset,Drift}$, whereas the $Score_{Noise}$ is calculated from the mean of $Score_{Noise,Accuracy}$ and $Score_{Noise,Drift}$. Hence, with the absence of $Score_{Offset,Drift}$ and $Score_{Noise,Drift}$, the $\overline{Score}_{Offset}$ and $\overline{Score}_{Noise}$ of the RLS algorithm are significantly lower than those of the other two methods.

5 Conclusion and outlook

In this work, a methodology and a toolchain to test and compare BMS diagnostic algorithms are presented and elaborately described. The toolchain takes into account the complete signal path through the BMS hardware from the application to the BMS algorithms. It can be adapted to the specific needs of the user, like a certain application, battery or BMS system. The functionality of the toolchain has been validated with a large set of simulations including different input profiles, temperature levels, sensor offsets and exemplary results have been discussed for a RLS based SOC estimation algorithm. The proposed method makes it possible to compare different algorithms for the same task, select the most suitable algorithms for a given application and to evaluate their interaction under realistic conditions.
In future work, the toolchain will be used to validate and compare the performance of different diagnostic algorithms for each battery management task and for different applications. Also, the performance of various algorithms on different cell chemistries, i.e. lithium iron phospate (LFP) will be investigated. In addition, the toolchain will be improved to sufficiently compare not only the precision and robustness of the algorithms, but also the necessary computing power.

Acknowledgments

This work was supported by the European Union's Horizon 2020 research and innovation program under the project 3beLiEVe (Grant Agreement 875033).

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Presenter Biography

Dominik Jöst from RWTH Aachen University in the very west of Germany is a research associate and head of the section Storage System Technology and Vehicle Integration at Dirk Uwe Sauers lab of Electrochemical Energy Conversion and Storage Systems. He studied electrical engineering at RWTH Aachen University and completed his master's degree in 2016. His current work focuses on the analysis of battery management algorithms and their necessary properties for different applications, as well as their validation through a model-in-the-loop toolchain.