Hardware-in-the-Loop Test Rig for Rapid Prototyping of Battery Management System Algorithms

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***Abstract*—Testing the performance of a battery management system (BMS) is extensive and crucial due to its importance for the overall battery safety and performance. In this paper, a hardware-in-the-loop (HiL) test bench is presented for rapid prototyping, testing and evaluation of BMS algorithms in real-time. The system is designed to work with real cell packs without any additional electronics or casing. This approach avoids the high cost and effort of building a full battery system and therefore simplifies algorithm testing on different cell types and cell pack topologies. An extended Kalman Filter based state-of-charge-algorithm is developed and compiled in C-Code in MATLAB/Simulink to run on a digital signal processor (DSP) in real-time. The capabilities and advantages of the setup are shown with experimental HiL tests of the developed BMS algorithm in comparison to software-in-the-loop (SiL) tests.**

***Index Terms*—BMS, Hardware-in-the-Loop, real cells, rapid prototyping, real-time**

I. Introduction

Lithium-ion batteries (LIBs) are currently the most suitable energy storage devices for powering electric vehicles (EV) due to their attractive properties like high energy efficiency, lack of memory effect, long service life, and high energy and power density. Nevertheless, LIBs have to be operated within predefined limits to ensure safe and efficient operation. For this purpose, battery management systems (BMSs) are developed. BMSs are embedded systems, which carry out measurements from battery and run specific BMS-algorithms. The main functions of BMS are data collection, state monitoring, safety protection, charging control, energy management, balancing management, thermal management and communication management. Internal states such as state-of-charge (SOC) or state-of-health (SOH) of the battery cannot be measured directly and have to be estimated with the help of advanced algorithms. The BMS provides important state information to the vehicle control unit (VCU) for energy management and power distribution control of an EV. Therefore, performance of BMS algorithms plays a key role for the complete EVs' performance [1].

Developing more accurate estimation algorithms is the core challenge in BMS development. In the last decade, numerous algorithms, especially for SOC and SOH estimation were proposed [2], [3]. Testing is an integral and inseparable part of this software development process. Parallel execution of tests in each phase of the development process allows to identify and fix erroneous software earlier. Therefore, development efforts, time and costs are reduced tremendously. At different stages of the development process, different testing environments as Model-in-the-Loop (MiL), Software-in-the-Loop (SiL) or Hardware-in-the-Loop (HiL) are used respectively [4]. HiL test systems with battery emulators are well established and widely used to evaluate BMSs. In that case, instead of real batteries, a battery emulator mimics the behaviour of cells with the help of online cell models. Therefore, test costs and testing time are decreased and critical states of the battery beyond the allowed range of operation can be tested more safely. Battery emulators have some limitations related to the accuracy, resolution and iteration rate of the battery model and emulation hardware [5]. Mathematical modelling of LIBs is a challenging task and there are no perfect mathematical models to mimic all complex features of a LIB, such as hysteresis, relaxation and the effects of temperature and aging on parameters [6]. In [7], a Cell-in-the-Loop approach is proposed where a single physical cell is integrated within a battery model. However, upscaling challenges like manufacturing tolerance of cells or thermal imbalance in the battery are not handled in this approach.

The state-of-the-art estimation algorithms are model based. While evaluating their performance, testing a model based algorithm in the loop with a model based emulator is misleading. This effect can be crucial especially during benchmarking of artificial intelligence based state algorithms, which can cover battery characteristics in depth. The reliability of state algorithms can be validated using real battery cells [8]. Hence, a new concept for a HiL test environment for evaluation of BMS algorithms with real cell packs without any additional battery electronics or casing is presented. The proposed HiL-System avoids the high costs and efforts of building a full battery system and allows straightforward algorithm testing with different cell types and cell pack topologies. Relying on measurements of a real cell pack, the effects of battery emulators on test results are ruled out by getting one step closer to real-life conditions without disproportionately high effort.

First, the system structure with hardware and software design is described. Second, exemplary experimental test results of an extended Kalman filter (EKF) based SOC-Algorithm with a $36\,\mathrm{V}$ cell pack are presented to demonstrate the capabilities of the proposed system. In the final section the conclusions are given.

II. System Structure

Figure 1 shows the structure of the proposed HiL-System. The system consists of five main parts: an environmental test chamber, programmable power supplies and electronic loads to charge and discharge the cell packs, a DSP-System to run the BMS-algorithms in real-time, two independent parallel DAQ-Systems for sensing and a host PC with a HiL-Software which is developed in MALTAB to control and monitor the test process, record test data and evaluate the results. This modular concept allows intensive and fast testing and validation of advanced estimation algorithms under realistic conditions.

1) Environmental test chamber: In order to get a realistic performance validation, tests have to be run under different environmental conditions such as temperature or humidity. These conditions can have a large influence on the state of the batteries. Real cells without integrated electronics, casing or cooling system are used. For this reason, an environmental test chamber with two layers of $3\,\mathrm{mm}$ thick stainless steel and thermal insulation in-between to protect personnel and equipment is utilized. A Huber Ministat 240 is integrated to manipulate the temperature. All electronic equipment of the HiL-System remains outside of the test chamber.

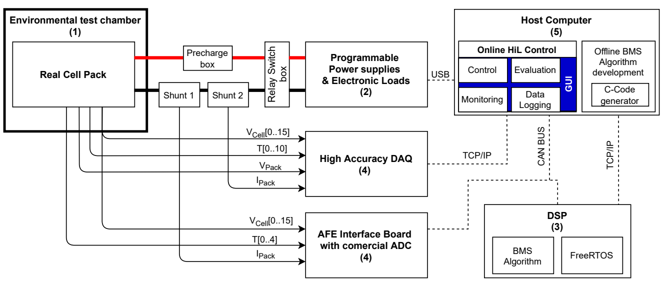


Fig. 1. Structure of HiL-System

2) Programmable Power supplies and electronic loads: To realize the test scenarios with dynamic charge and discharge, a high power, high accuracy test machine is necessary. In the presented test bench Elektro-Automatik programmable laboratory power supplies (PS) and electronic loads (EL) are used. The HiL-Software controls them in real-time via USB by standardized (IEC 60488-2-2004) instrumentation programming protocol SCPI [9]. The implemented setup supports currents up to $80\,\mathrm{A}$ and voltages up to $100\,\mathrm{V}$. This allows full scale testing of commercial light electric vehicle applications (LEV) as well as reduced mock-up testing of hybrid and battery electric vehicles [8]. Furthermore, the system can be easily upscaled with new equipment due to the usage of a standardized SCPI protocol. A relay switch box is installed to switch between test machines or to add new test machines to the system easily. The main test machine is a combined system of 4 power supplies (EA-PSI 91000-30 3U) and 4 electronic loads (EA-ELR 91500-30 HP 3U), which support up to $120\,\mathrm{A}$ current, $1000\,\mathrm{V}$ voltage and $40\,\mathrm{kW}$ power. In addition, two bidirectional test machines are integrated i.e. EA-PSB 9080-360 3U and EA-PSB 9100-40 3U to show the flexibility of the system.

3) DSP-System: The in-house developed DSP-System is based on a well-established System On Chip-Platform Zynq-7030 [10]. It enables rapid prototyping due to the automated code generation from MATLAB/Simulink to C-Code. The offline developed algorithms are compiled in C-Code and flashed onto the DSP. The DSP executes these algorithms in real-time and utilizes Control Area Network (CAN) Bus for communication. The measurement data of the cell pack and the results of the BMS-algorithm are received and transmitted via CAN-BUS, respectively.

4) Data acquisition (DAQ): Cell voltages, pack voltage, pack current and temperatures are the main measurements of a battery. The state-of-the-art BMS-algorithms are based on this information. Since the measurement quality has a direct effect on the algorithm performance, two parallel working data acquisition systems are implemented for comparison and safety reasons: A high accuracy DAQ-System [11] and an industry standard DAQ-IC based analog front end (AFE) interface board.

The high accuracy DAQ-System (HA-DAQ) communicates via TCP/IP and the HiL-Software logs the measured reference data with a $2\,\mathrm{kHz}$ sample rate. Based on the measured data and system limits, the HiL-Software ensures safe operation of the system. When a critical limit such as maximum cell temperature or minimum cell voltage is reached, the test is stopped. The implemented system supports up to 16 cell voltage and 11 temperature measurements. PT-100 sensors are used for temperature measurements. The reference current is measured over a precision Manganin shunt resistor ($\pm\,0.25\,\%$). The high sample-rate minimizes integration errors for the Coulomb-counting approach. This allows to calculate accurate reference values for SOC and SOH estimations.

The accuracy of the BMS-Hardware in practice is lower than laboratory measurements. Compensation of measurement

TABLE I
COMPARISON OF MEASUREMENT ACCURACY OF THE IMPLEMENTED DATA ACQUISITION-SYSTEMS

	HA-DAQ System	AFE-Board DAQ-System
Current	$\pm$ 0.29 %	$\pm$ 1.03 %
Cell voltage	$\pm$ 2.0 mV	$\pm$ 10.0 mV
Temperature	$\pm$ 0.75 K	$\pm$ 3.4 K

errors is another important challenge of the BMS development process. Validation based on laboratory measurements can be also misleading. Therefore, an analog front end interface board with an industrial battery monitor is developed. The AFE is based on the IC BQ76952 by Texas Instruments. The developed AFE circuit board (AFE-board), shown in Figure 2, substitutes the BMS-slave board in a distributed master-slave BMS architecture and provides real measurement information to the tested BMS-algorithms via CAN-BUS.

Simultaneously, the HiL-Software logs all these measurements. The AFE supports 3 to 16 cell voltage and 5 temperature measurements with 4 Hz sampling rate [12]. The current is measured using a compact shunt resistor ($\pm$ 1 %) and the temperature with NTC thermistors. Table I summarizes the accuracy of the both systems with mentioned sensors.

5) Host computer and HiL-Software: The HiL-Software is developed using the MATLAB Parallel Computing Toolbox. The main tasks controlling, monitoring and data logging are run asynchronously but simultaneously on different CPU-cores of the host PC. During the test, all data is collected and logged via TCP/IP and CAN-Bus protocol. The limits of the cells and cell packs are monitored continuously and the test is stopped immediately in critical states.

A graphical user interface (GUI) is developed with the help of the MATLAB App Designer to enhance the user experience. Figure 3 shows the main screen of the developed GUI. The user can select the desired test machine, load cell parameters and set the pack topology to configure the battery. Predefined testing procedures as CCCV-charging, CC-charging, capacity test, WLTP, NEDC and DST are provided to specify the test scenario. Additionally, user can load time- or SOC-dependent custom current profiles. All the test procedures are limited according to configured battery and are down scaled if necessary. In idle mode, live measurements are shown and test results can be analyzed.

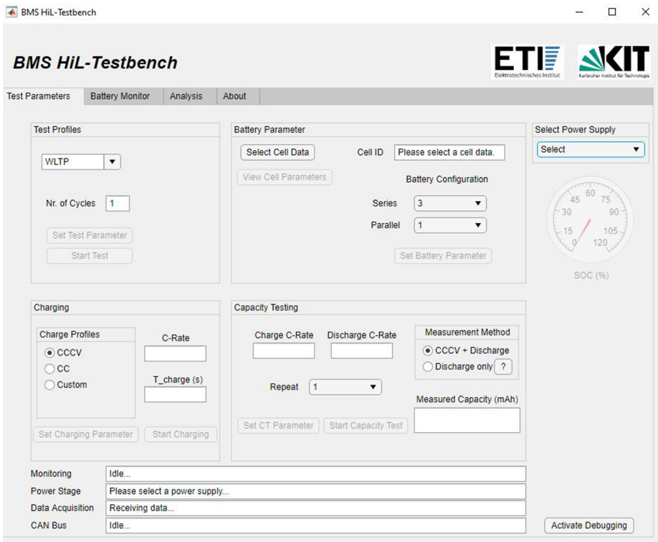


Fig. 3. Main screen of the developed GUI

Figure 4 shows the implemented laboratory HiL-Sytem test bench.

III. EXPERIMENTAL RESULTS

A state-of-the-art SOC estimator to introduce the HiL-test bench is developed and tested for a 36V cell pack. The pack is built with commercial 18650 type cylindrical Li-NMC cells. Figure 6 shows the cell pack at the test bench. The estimation algorithm is based on an extended Kalman Filter (EKF), one of the most commonly used methods to estimate the SOC.

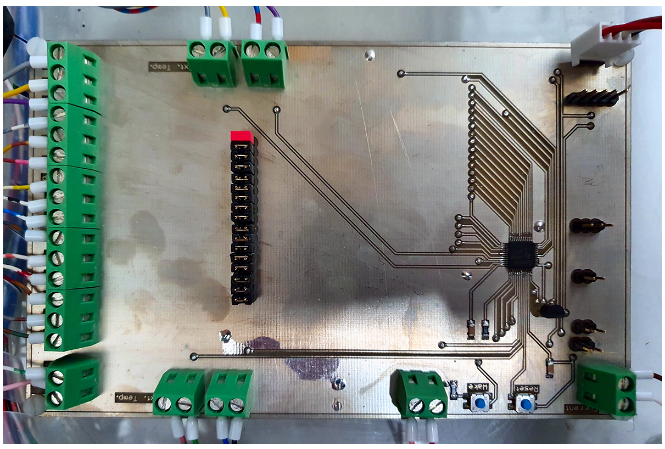


Fig. 2. AFE-Board with TI BQ76952 BMS-Chip

Fig. 4. Implemented HiL-System

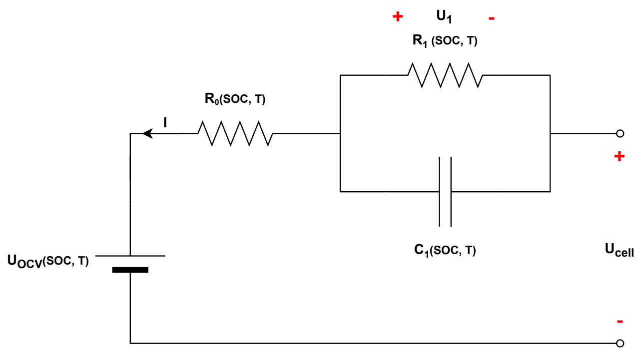


Fig. 5. Thevenin ECM with 1 RC branch

A. Cell modeling and parameter identification

Thevenin equivalent circuit model (ECM) with 1 RC branch is used to mimic the electrical behaviour of the LIB and to develop the model-based SOC estimator. Figure 5 visualizes the well-known Thevenin model, where U_{OCV} is the cell open circuit voltage (OCV), U_{Cell} the cell terminal voltage, U_1 the polarization voltage, R_0 the ohmic resistance, R_1 the polarization resistance and C_1 is the polarization capacitance. I is the cell current with negative value for discharging and positive for charging. Equations (1) and (2) can be deduced from the Thevenin model with the help of Kirchoff's current and voltage laws to describe the electrical behaviour mathematically. The implementation in MATLAB/Simulink is realized based on these equations.

$$U_{Cell} = U_{OCV} + U_1 + R_0 I \tag{1}$$

$$\dot{U_1} = \frac{-U_1}{C_1 R_1} + \frac{I}{C_1} \tag{2}$$

The state of charge of LIB can be expressed as a function of time as follows:

$$SOC(t) = SOC(t_0) + \frac{1}{C_N}\int_{t_0}^{t} I(\tau)d\tau, \tag{3}$$

where C_N is the nominal capacity and $SOC(t_0)$ indicates the initial SOC.

The cell parameters are identified using capacity tests and hybrid pulse power characterization (HPPC) tests [13]. The tests are performed by use of a BaSyTec XCTS battery cycler and repeated under 6 different temperatures i.e. $5\,°C$, $15\,°C$, $25\,°C$, $35\,°C$, $45\,°C$, $55\,°C$ to capture the thermal dependencies. The hysteresis effect on the parameters is modeled by testing in charge and discharge direction. HPPC tests are executed with $10\,\%$ SOC steps. The extracted values are saved in 3-D lookup tables.

The implemented model is validated with measurement data at $25\,°C$. The root mean squared error (RMSE) of the simulation voltage is $18.4\,\mathrm{mV}$ and the maximum absolute error is $48\,\mathrm{mV}$.

B. State of Charge Estimation

EKF is a well-established variation of the standard Kalman filter for state estimation of nonlinear systems. EKF linearizes nonlinear systems like LIB at each time step with first order Taylor approximation. Plett [14] adapted for the first time the EKF method for state estimation of LIBs. EKF uses a discrete-time cell model and measurement signals of current, voltage and temperature. As a model-based recursive algorithm, it can handle the main problems of SOC estimation i.e. measurement noise, online estimation and initial value problem [15]. Hence, many scholars have been focused on the development of EKF based SOC estimators [16] [17] [18].

The process (4) and measurement (5) equations of EKF can be expressed for LIB in discrete time domain as (6) and (8), respectively, according to (1), (2) and (3) [19].

$$x_k = f(x_{k-1}, u_{k-1}) + w_{k-1}, \tag{4}$$

$$y_k = h(x_k, u_k) + v_k, \tag{5}$$

where k is discrete-time instant.

$$\begin{aligned} x_k = \begin{bmatrix} U_{1,k} \\ SOC_k \end{bmatrix} &= \underbrace{\begin{bmatrix} 1 - \frac{\Delta t}{R_1 C_1} & 0 \\ 0 & 1 \end{bmatrix}}_{A} \begin{bmatrix} U_{1,k-1} \\ SOC_{k-1} \end{bmatrix} \\ &+ \underbrace{\begin{bmatrix} \frac{\Delta t}{C_1} \\ \frac{\Delta t}{3600 C_N} \end{bmatrix}}_{B} \underbrace{I_{k-1}}_{u_{k-1}} + w_{k-1}, \end{aligned} \tag{6}$$

$$h(x_k, u_k) = U_{OCV,k} + U_{1,k} + R_0 I_k, \tag{7}$$

$$y(x_k, u_k) = U_{OCV,k} + U_{1,k} + R_0 I_k + v_k, \tag{8}$$

where x_k is the state vector, $f(x_k, u_k)$ the state transition function, y_k the cell voltage measurement vector, v_k the measurement noise, w_k the process noise, $h(x_k, u_k)$ the nonlinear measurement function, Δt is the sampling time in seconds, A the state transition matrix, B the control input matrix and u_{k-1} is the input vector. EKF considers w_k and v_k as independent zero-mean Gaussian noise with covariance matrices Q and R, respectively.

According to the parameter identification results, the impact of SOC on model parameters R_0, R_1 and C_1 is limited. Therefore U_1 and R_0 are treated as constant in (7) for sake of simplicity. The extracted U_{OCV} behaviour is expressed with a six-order polynomial equation for each temperature level to ensure the calculation of partial derivatives.

Jacobian matrix C_k is involved for the linearization. In this work, the estimated values are denoted with a hat sign ($\hat{.}$) and a priori predictions with a minus sign ($.^-$).

$$C_k = \left. \frac{\partial h(x_k, u_k)}{\partial x_k} \right|_{\widehat{x_k^-}, u_k} \tag{9}$$

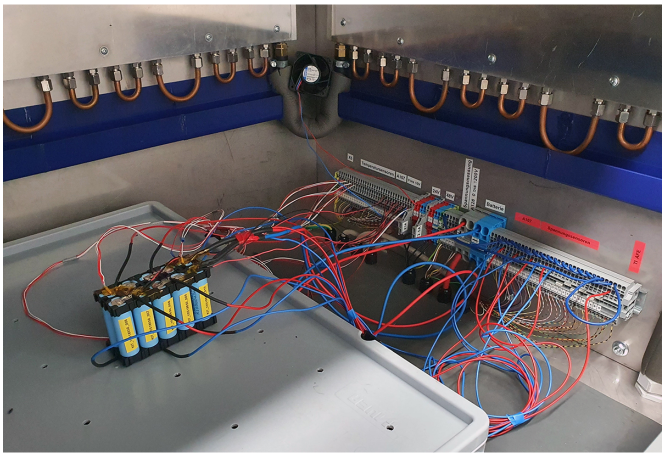


Fig. 6. 36V cell pack at HiL test rig

EKF is a recursive iterative algorithm with two main steps: Time update (prediction) and Measurement update (correction).

In the time update step the state $\widehat{x}_k^-$ is predicted by (10) for the current time step k and the estimation error covariance P_k^- by (11) [20].

$$\widehat{x}_k^- = A\widehat{x}_{k-1} + BI_{k-1} \tag{10}$$

$$P_k^- = A_k P_{k-1} A_k^T + Q \tag{11}$$

In the measurement update step the state estimation $\widehat{x}_k$ and the predicted error covariance P_k will be corrected with the help of calculated Kalman gain K_k.

$$K_k = P_k^- C_k^T [C_k P_k^- C_k^T + R]^{-1}, \tag{12}$$

$$\widehat{x}_k = \widehat{x}_k^- + K_k(y(k) - \widehat{y}(k)), \tag{13}$$

$$P_k = [1 - K_k C_k] P_k^-. \tag{14}$$

The EKF based SOC estimator is implemented with the help of the introduced equations and extracted cell parameters in MATLAB/Simulink.

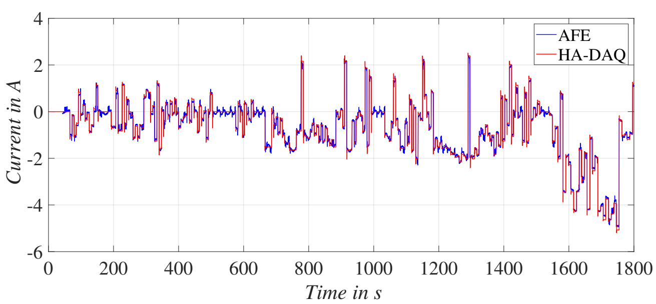
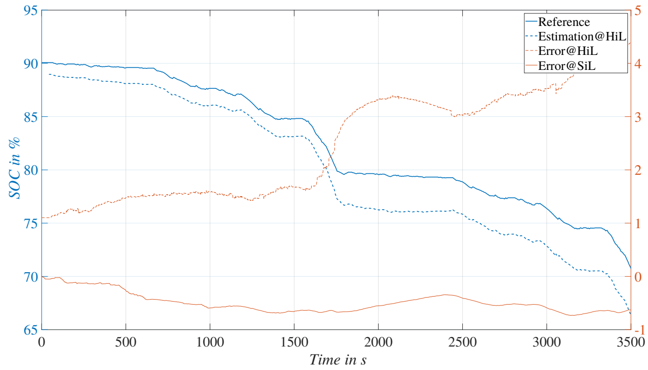
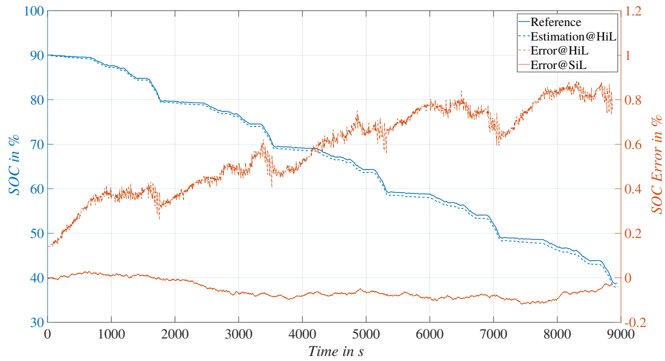


Fig. 7. Downscaled WLTP Current Profile measurements by HA-DAQ-System and AFE- DAQ-System



(a) First test



(b) Second test

Fig. 8. SiL- and HiL-Test results of an EKF based SOC estimator by testing at 25 °C with WLTP

C. Tests and Results

To present the benefits of the proposed test bench, the developed algorithm is tested first in a SiL environment with battery simulation. Second, the algorithm is compiled in C-Code and downloaded on DSP to be executed in real-time. Finally, the SOC estimator is evaluated on the developed HiL test rig with a cell pack with 10 serial connected cells.

The cell pack's nominal voltage is 36 V and its capacity is 3.3 A h. The maximum charging current is limited to 2.3 A and the maximum discharging current is limited to 5 A. The worldwide harmonized light vehicles test procedure (WLTP) is used to simulate a dynamic driving scenario and to see the realistic performance of the algorithm. WLTP current profile is downscaled by HiL-System according to the cell pack limits. Figure 7 shows the AFE-DAQ-System and HA-DAQ-System measurements of the applied WLTP current profile.

The pack is charged with CCCV and discharged with WLTP at 25 °C. The test is executed twice on SiL and HiL. A white Gaussian noise is added to the current input on SiL-Tests to get closer to the real operating conditions. The performance of the SOC estimator is analyzed after each test and the parameters Q and R of the estimator are tuned iteratively.

Figure 8(a) and Figure 8(b) visualize the estimated SOC on the HiL-System compared to the reference SOC and the estimation error on HiL- and SiL-Testing in the two executed tests. In the first test the RMSE of the SiL based validation is about $0.5\,\%$ while the RMSE of the HiL is about $2.8\,\%$, which shows the discrepancy between emulation and hardware. After manipulating the parameters Q and R, a second test is executed. In this case, the performance of the estimator on HiL is improved significantly with an RMSE error of about $0.6\,\%$ and the RMSE of the SIL reduced under $0.1\,\%$. Thus, the performance of the algorithm is identified in an early stage of the development process and improved in a more agile way. Benchmarking and testing of a BMS with emulation leads to an overestimation of performance. In turn, this shows the outstanding benefit of a hybrid test bench over a pure software solution.

IV. Conclusion

This paper presents a new HiL test rig, which enables rapid-prototyping of BMS-algorithms on real cells. In addition to improving the BMS development process, the system can also be used to benchmark different algorithms. The proposed HiL-System is verified with an exemplary case. Therefore, an SOC estimator is developed, implemented and tested to demonstrate the capabilities of the setup. In the future, the system will be extended with a custom balancing board to be able to test balancing algorithms in real-time.

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