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Online multi chemistry SoC estimation technique using data driven battery model parameter estimation

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Abstract

Kalman filters have shown to be a very accurate and robust method for SoC estimation. However, their performance depends heavily on the accuracy of the used battery model and its parameters. These battery model parameters have shown to vary with the SoH, cell chemistry, temperature and load current. This paper proposes a data driven battery model parameter estimation technique based on the recursive least squares method as an alternative to extensively characterizing every cell of interest with time consuming test procedures, reducing offline characterization time by up to 70%. This allows the parameter estimation model to be applied, in cooperation with a SoC estimation model, to create a data driven multi chemistry SoC estimation module.

Keywords: Battery model, Battery Management System , Electric Vehicle, Modeling, State of Charge

1 Introduction

Determining SoC of a battery accurately poses a challenge as it cant be measured directly and is influenced by various factors such as temperature and cell aging. Furthermore, the very dynamic load profile of batteries in automotive applications adds to the complexity of accurate SoC estimation. Some of the most commonly used SoC estimation methods include coulomb counting, various applications of Kalman filters and adaptive methods based on machine learning [2] - [6]. Coulomb counting, the most straight forward method, has some major drawbacks: it's heavily dependent on initial SoC accuracy and being an open-loop method means that it is susceptible to accumulated errors due to measurement errors on the load current [7]. Kalman filters on the other hand, have shown to be a very accurate and robust method for SoC estimation [3]-[6]. However, their performance depends heavily on the accuracy of the used battery model and its parameters. These battery model parameters have shown to vary with the aging level of the cell, cell chemistry, temperature and load current [8]. It is common practice to determine these battery model parameters by performing an extensive Hybrid Pulse Power Characterization (HPPC) test at different ambient temperatures on the desired cell, which will correlate the parameter values to current rate and temperature at a specific SoC. This elaborate, time consuming procedure has to be carried out for every different cell of interest, which can have varying formats, designs, chemistries and aging levels. In this paper the extensive characterization procedure is bypassed by proposing an online adaptive parameter estimation technique based on the recursive least squares method with adaptive forgetting factor. Furthermore, this method is implemented in a SoC estimator model to allow online SoC estimation independent of cell aging and chemistry.

2 Data driven battery model

2.1 Battery model

Modelling the electrical behaviour of a battery accurately from its measurable values (i.e. voltage, current and temperature) is paramount for model-based battery management systems, which often implement SoC estimation algorithms based on Kalman filters. While Kalman filters have shown to weaken the influence of white noise and initial SoC error, they cannot eliminate the existing error of the battery model itself. Furthermore, it has been shown that the accuracy of SoC estimation is directly related to the accuracy of the battery model [9]. In order to obtain an accurate battery model with acceptable complexity the second order Thevenin model or dual polarization model is selected. Its electrical behaviour is described by equation 1, where U_{pa} denotes the polarization voltage over the first RC network, U_{pc} denotes the diffusion voltage over the second RC network, U_{OC} represents the OCV and U_{bat} is the terminal voltage. The values of the ideal electrical components R_o, R_{pa}, C_{pa}, R_{pc} and C_{pc} define the electrical behavior of the battery and have shown to vary with cell chemistry, temperature, load current and state of health (SoH).

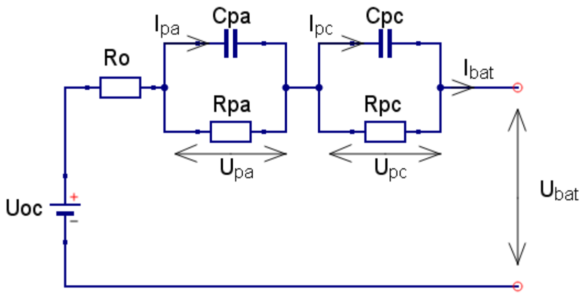

Figure 1: Schematic diagram of second order battery model [8]

$$\begin{cases} \dot{U}_{pa} = -\dfrac{U_{pa}}{R_{pa}C_{pa}} + \dfrac{I_{bat}}{C_{pa}} \\ \dot{U}_{pc} = -\dfrac{U_{pc}}{R_{pc}C_{pc}} + \dfrac{I_{bat}}{C_{pc}} \\ U_{bat} = Uoc - U_{pa} - U_{pc} - I_{bat}R_o \end{cases} \tag{1}$$

2.2 Data driven parameter identification based on RLS with adaptive forgetting factor

In order to obtain and maintain an accurate SoC estimation, a data driven adaptive electrical model is developed that is able to identify and update the model parameters from the measurable values, i.e. voltage and current, during operation. The developed data driven model is based on the well-known Recursive Least Squares (RLS) method with adaptive forgetting factor. In order to implement the RLS method on the battery model, the auto regressive exogenous (ARX) model of the second order thevenin model has to be constructed. Based on equation 1, the transfer function H(s) of the electrical model in the frequency domain can be obtained [10]:

$$H(s) = \frac{R_o s^2 + \frac{1}{R_{pa}C_{pa}R_{pc}C_{pc}}[(R_o + R_{pc})R_{pa}C_{pa} + (R_o + R_{pa})R_{pc}C_{pc}]s + \frac{R_o+R_{pa}+R_{pc}}{R_{pa}C_{pa}R_{pc}C_{pc}}}{s^2 + \frac{R_{pa}C_{pa}+R_{pc}C_{pc}}{R_{pa}C_{pa}R_{pc}C_{pc}}s + \frac{1}{R_{pa}C_{pa}R_{pc}C_{pc}}} \tag{2}$$

The transfer function is discretized using the bilinear transform shown in equation 3, to obtain the discretized transfer function H(z) in equation 4.

$$s \leftarrow \frac{2}{T_s}\frac{1 - z^{-1}}{1 + z^{-1}} \tag{3}$$

$$H(z) = \frac{b_0 + b_1 z^{-1} + b_3 z^{-2}}{1 - a_1 z^{-1} - a_2 z^{-2}} \tag{4}$$

This allows to rewrite equation 1 as equation 5, where $U_{t,k}$ is the measured terminal voltage at timestep k and $I_{bat,k}$ is the measured current at timestep k. Hereafter, we can acquire the ARX form of the battery model in equation 6.

$$U_{t,k} = (1 - a_1 - a_2)U_{OC} + a_1 U_{t,k-1} + a_2 U_{t,k-2} + b_0 I_{bat,k} + b_1 I_{bat,k-1} + b_2 I_{bat,k-2} \tag{5}$$

$$y_k = \theta_k^T.\phi_k \tag{6}$$

where the measurement data vector ϕ_k and the parameter vector θ_k at timestep k are given by

$$\begin{cases} \phi_k = [U_{OC}, U_{t,k-1}, U_{t,k-2}, I_{bat,k-1}, I_{bat,k-2}] \\ \theta_k = [1 - a_1 - a_2, a_1, a_2, b_0, b_1, b_5] \end{cases} \tag{7}$$

The recursive set of calculations of the RLS with adaptive forgetting factor are implemented as shown in equation 8. Where λ_k represents the adaptive forgetting factor at timestep k, L_k represents the updated gain of the parameter vector at timestep k and P_k represents the covariance error of the parameter vector at timestep k. Finally, the battery model parameters can be retrieved from the updated parameter vector θ_k.

$$\begin{aligned} \lambda_k &= 1 - \frac{1}{1 + \frac{c}{\phi_k^T P_{k-1}\phi_k}} \\ L_k &= \frac{P_{k-1}\phi_k}{\lambda_k + \phi_k^T P_{k-1}\phi_k} \\ P_k &= \frac{P_{k-1} - L_k \phi_k^T P_{k-1}}{\lambda_k + \phi_k^T P_{k-1}\phi_k} \\ \theta_k &= \theta_{k-1} + L_k(y_k - \phi_k^T \theta_{k-1}) \end{aligned} \tag{8}$$

3 Validation Process

In order to validate the proposed data driven battery model parameter estimation technique, several tests were performed using a 24-channel SBT0550 battery tester on three cells of different chemistries: a 20Ah NMC cell, a 14Ah LFP cell and a 5Ah LTO cell. The battery tester allows voltage measurements between -3V and 5V DC with a resolution of 100μV and an accuracy of $\pm 0.03\%$. Current measurements are possible between 0A and 50A DC with an accuracy of $\pm 0.02\%$. The performed test cycles for the validation process are a Dynamic Discharge Performance Test (DDPT) and the more dynamic World harmonized Light vehicles Test Cycle (WLTC). Three variables were accurately logged throughout the duration of these tests using the SBT0550 battery tester: current I, terminal voltage V and temperature T. Hereafter, the variables were used as an input for the data driven parameter estimation model, which estimates the battery model parameters for a second order Thevenin model, as can be seen in figure 2. Validation is finally performed by observing the difference between the measured voltage and the simulated voltage.

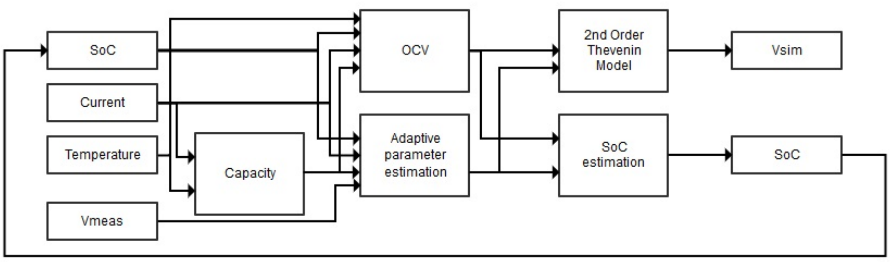

Figure 2: Flowchart of complete data driven battery model parameter estimation model

4 Results and Conclusion

The implemented SoC estimator during the validation process, of which the results are presented in this section, is the Extended Kalman Filter (EKF). While the data driven battery model has shown to work with varying other SoC estimation methods, such as coulomb counting and Unscented Kalman Filter, it is preferred to show the results of only one SoC method for the sake of clarity and compactness. Analogously, only the simulation results at 25°C are presented. The results shown in this section are structured as follows: section 4.1 deals with the validation results of the Dynamic Discharge Performance Test (DDPT) for the three tested chemistries, while section 4.2 deals with the validation results of the World harmonized Light vehicles Test Cycle.

Table 1: Mean absolute error (mV) and mean relative error (%) on simulated voltage for three chemistries

	Mean absolute error (mV)			***Mean relative error (%)***		
	NMC	**LFP**	**LTO**	**NMC**	**LFP**	**LTO**
DDPT	1.69 mV	5.29 mV	3.53 mV	0.04%	0.16%	0.17%
WLTC	1.99 mV	5.42 mV	0.62mV	0.06%	0.16%	0.03%

4.1 Dynamic Discharge Performance Test

The first performed validation profile is the Dynamic Discharge Performance Test at 25°C, of which the simulated voltages and error on these simulations can be observed in figures 3, 5 and 7 for the 20Ah NMC, 14Ah LFP and 5Ah LTO cell respectively. While all three chemistries show accurate simulation results with a mean relative error smaller than 0.2%, it is clear that the LFP chemistry poses the biggest challenge to model accurately. This can be attributed to the characteristic flat SoC-OCV relationship of LFP cells in the middle SoC range, which also explains why the estimated SoC shows a less linear trend, as can be seen in figure 5. It is observed that the simulation for the LFP cells is more accurate in the low SoC range, shown in figure 6, where the SoC-OCV relationship shows high linear behaviour. Furthermore, the OCV hysteresis is not negligible for LFP cells and should be included in future models to improve simulation accuracy and the reliability of the SoC estimation.

4.2 World harmonized Light vehicles Test Cycle

Secondly, the World harmonized Light vehicles Test Cycle was performed on the three selected cell chemistries at 25°C, of which the simulated voltages and error on these simulations can be observed in figures 9, 10 and 11 for the 20Ah NMC, 14Ah LFP and 5Ah LTO cell respectively. All three chemistries show accurate simulation results with a mean relative error smaller than 0.2%. While the data driven battery model benefits from a more dynamic load profile to identify and update the model parameters, the more dynamic nature of the profile also poses a bigger challenge to accurately simulate the voltage response. Similar to the DDPT, it is observed that the LFP cell shows the least accurate simulation result out of the three tested cell chemistries for the same reasons cited in section 4.1.

5 Conclusion

The data driven parameter estimation model based on the recursive least squares method with adaptive forgetting factor proposed in this paper, has shown to model battery behaviour of a 20Ah NMC cell, 14Ah LFP cell and a 5Ah LTO cell at 25 °C within an acceptable accuracy (mean relative error smaller than 0.2%) under load conditions of varying dynamic nature representative for EV applications. Furthermore, the validation results have shown that the data driven parameter estimation model also functions accurately under different temperatures, SoH and even chemistries of the cell. This allows the parameter estimation model to be applied, in cooperation with a SoC estimation model, to create an online multi chemistry SoC estimation module.

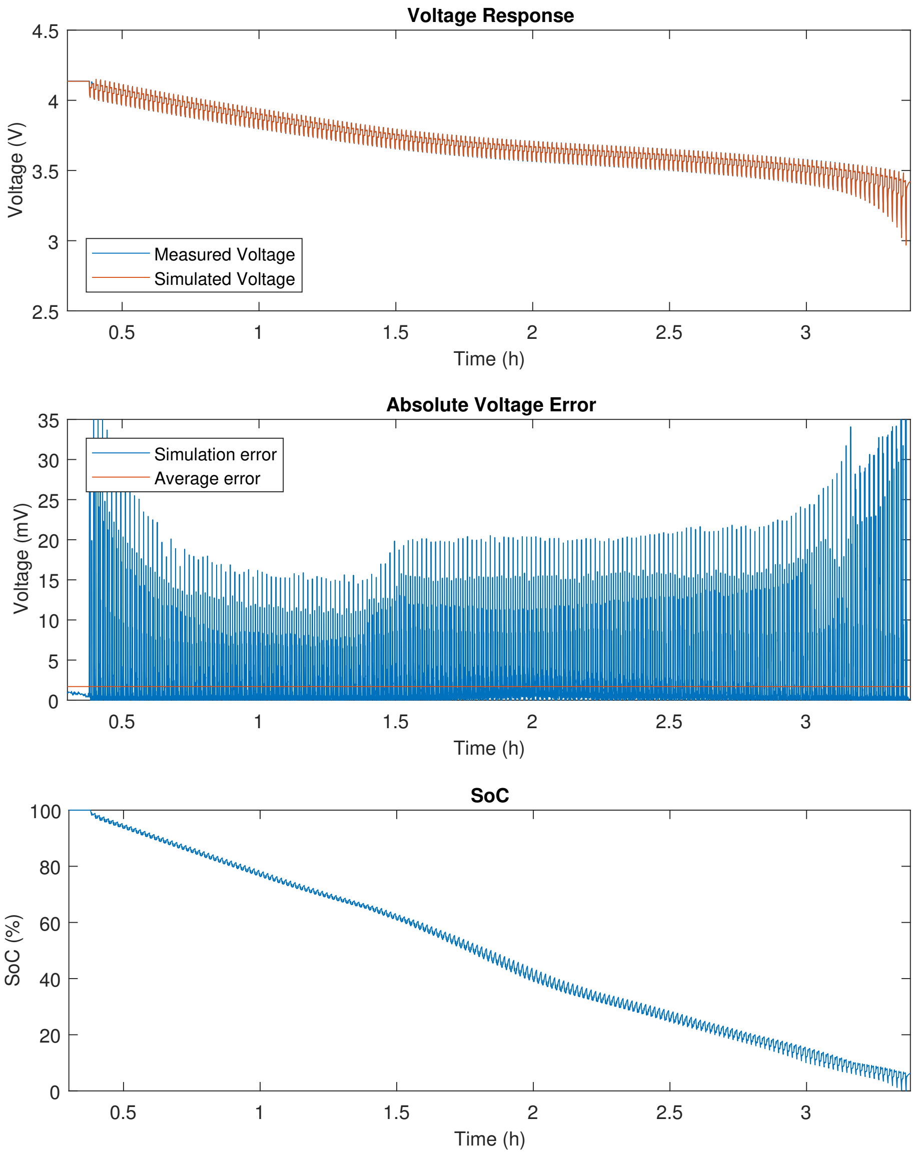

Figure 3: DDPT validation results on 20Ah NMC

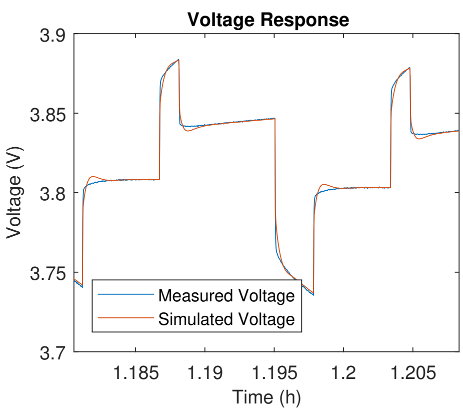

Figure 4: DDPT voltage response of 20Ah NMC at 70% SoC

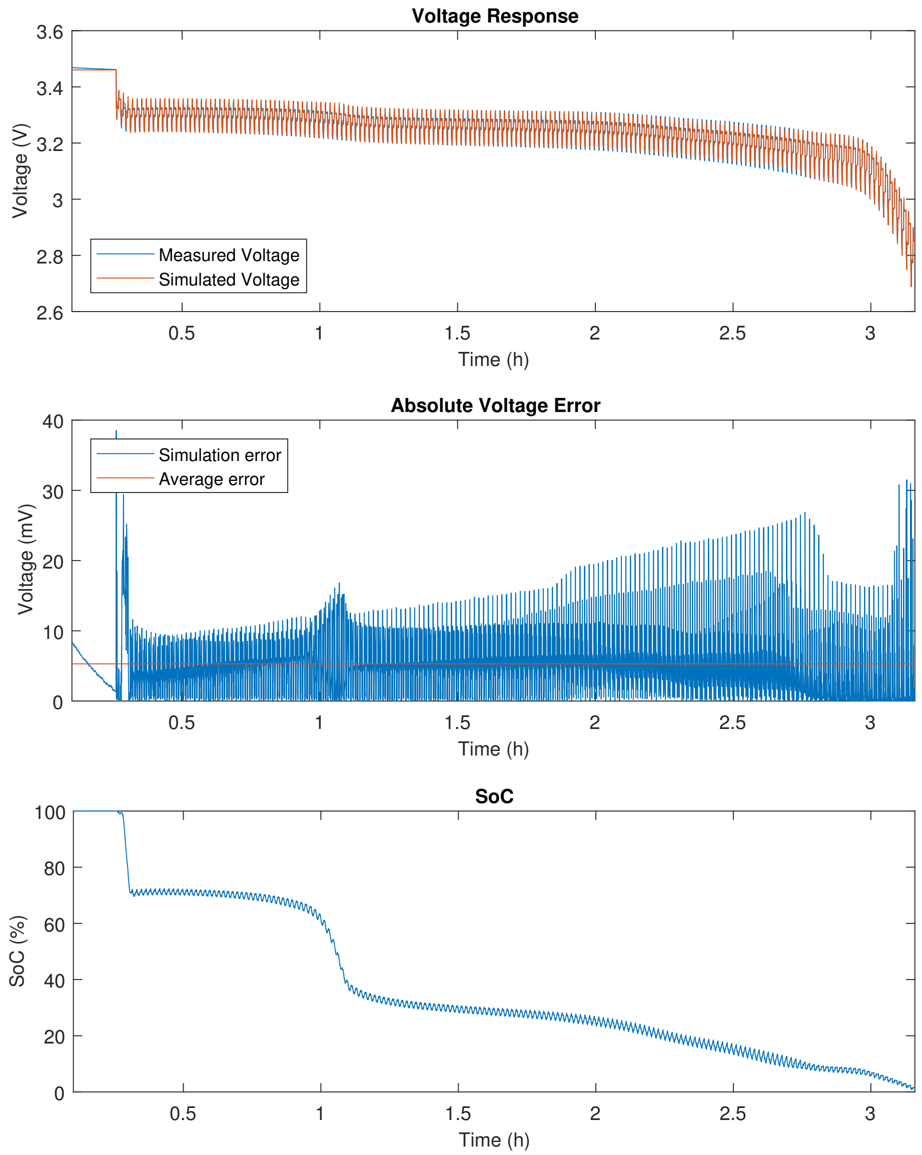

Figure 5: DDPT validation results on 14Ah LFP

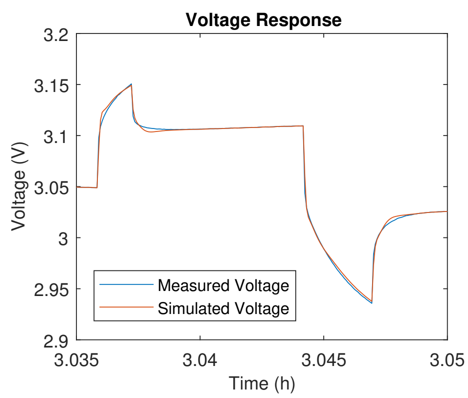

Figure 6: DDPT voltage response of 14Ah LFP at 5% SoC

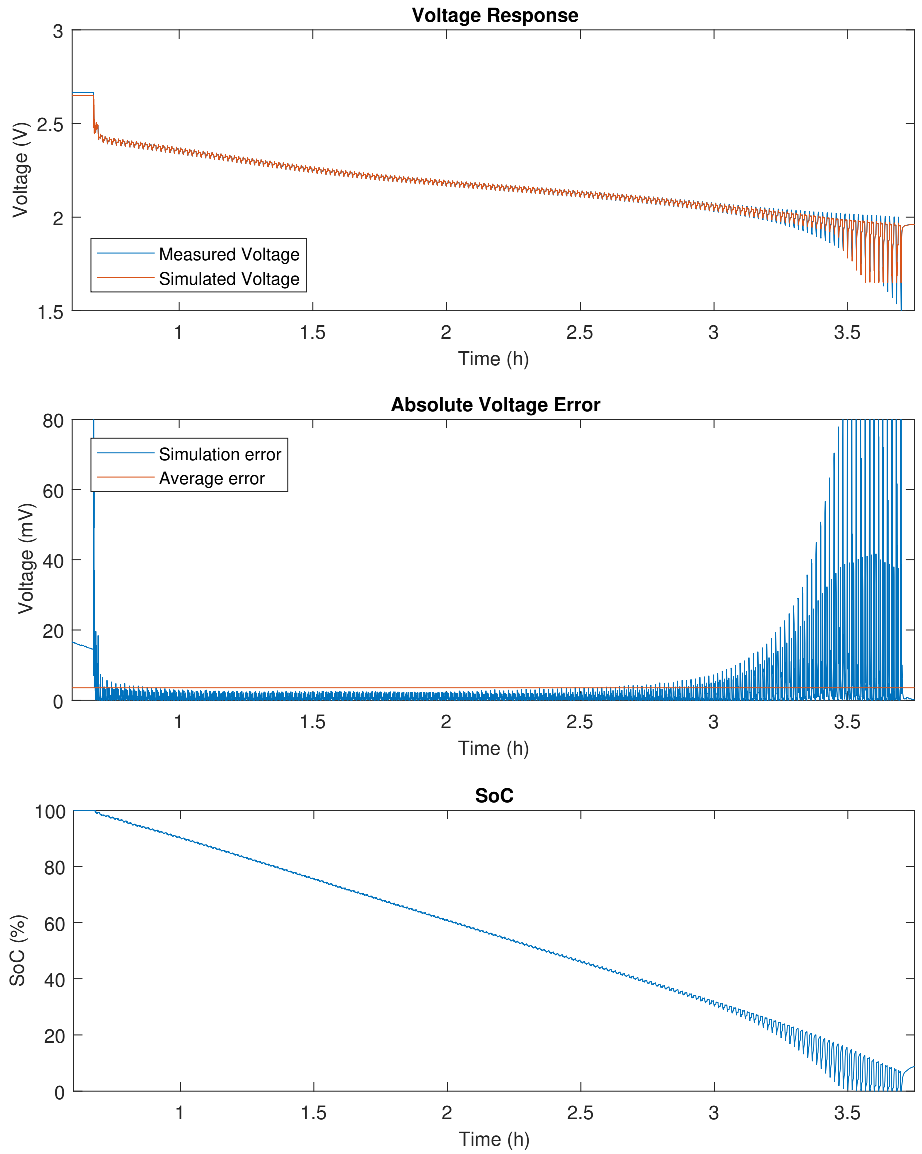

Figure 7: DDPT validation results on 5Ah LTO

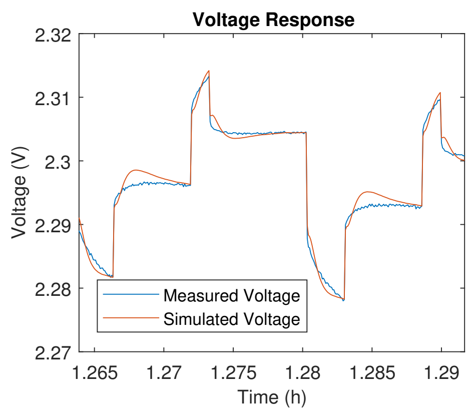

Figure 8: DDPT voltage response of 5Ah LTO at 80% SoC

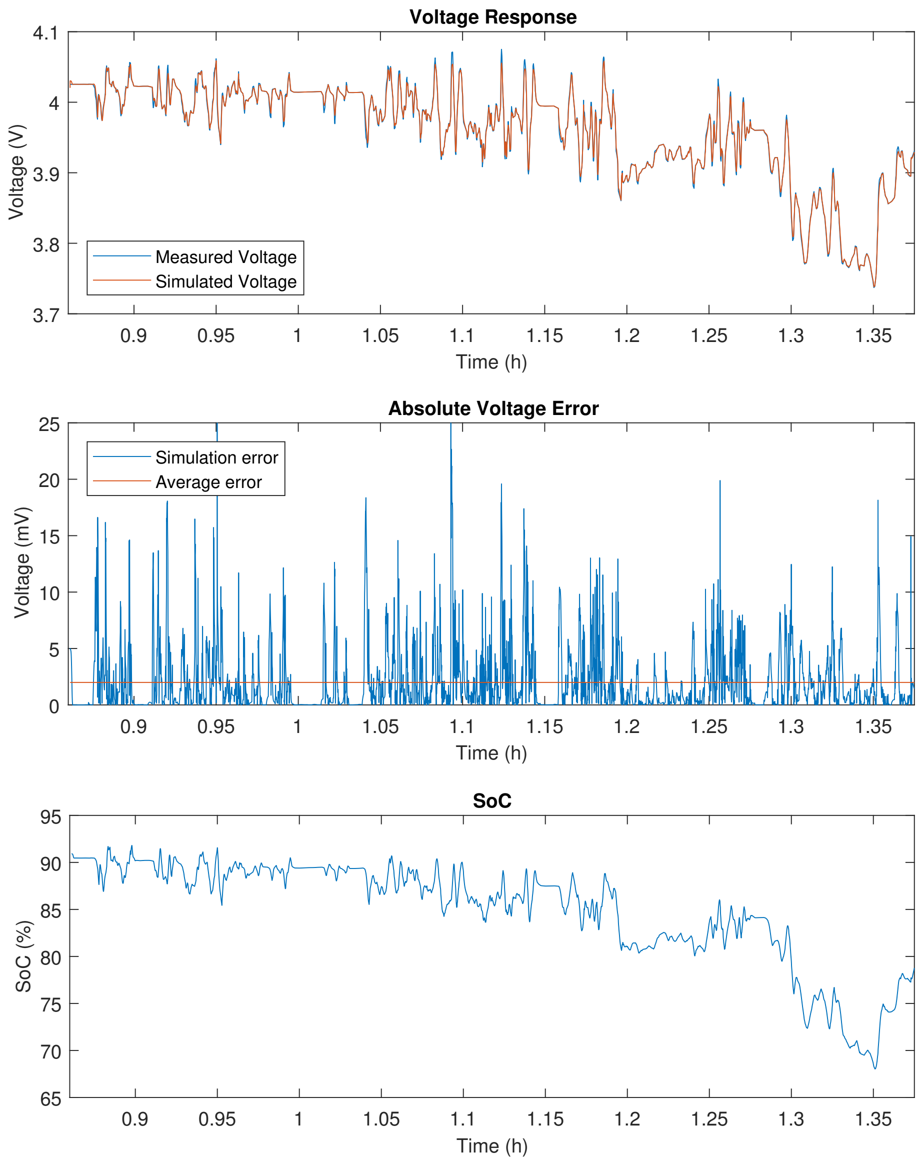

Figure 9: WLTC validation results on 20Ah NMC

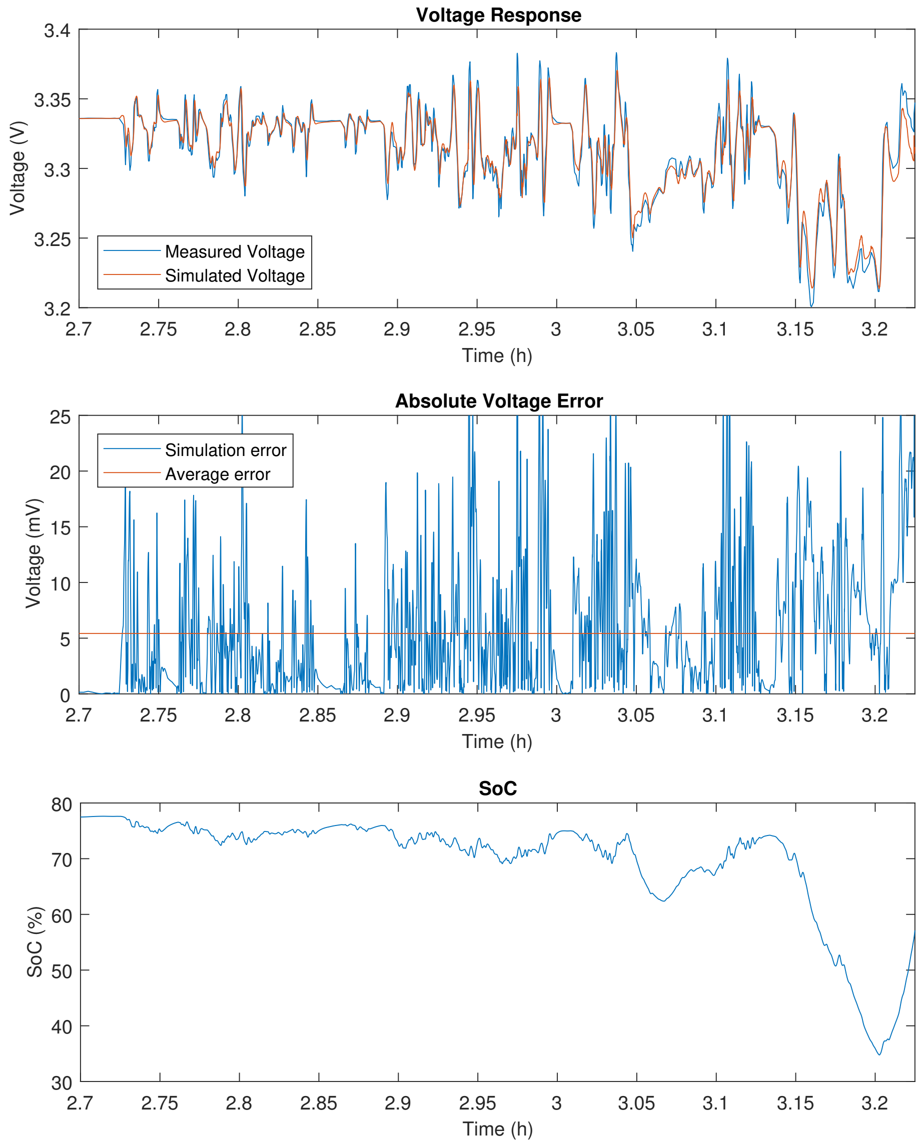

Figure 10: WLTC validation results on 14Ah LFP

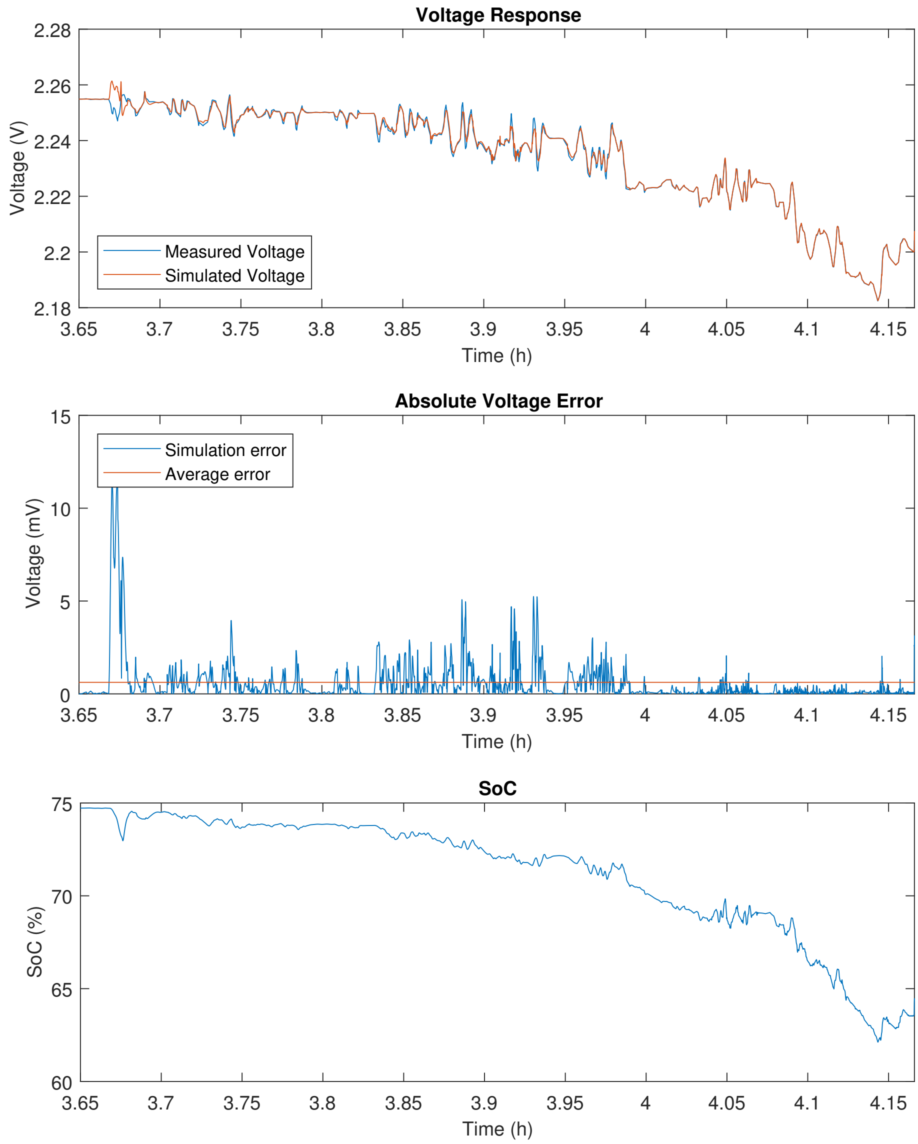

Figure 11: WLTC validation results on 5Ah LTO

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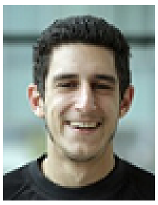

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