Voltage-Controlled SoC Estimation in Lithium-Ion Batteries: A Comparative Analysis of Equivalent Circuit Models

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Published in:
The 26th European Conference on Power Electronics and Applications

Publication date:
2025

Voltage-Controlled SoC Estimation in Lithium-Ion Batteries: A Comparative Analysis of Equivalent Circuit Models

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***Abstract*—This paper applies voltage-controlled methods introduced in [1] to regulate battery voltage and extract state of charge (SoC) in lithium-ion batteries, comparing three equivalent circuit models (ECMs): a simple resistance model, an RC model, and an RC-Diffusion model. Their simulated responses are evaluated against the experimental dataset reported in [2] in order to assess their relative accuracy.**

***Index Terms*—State of Charge, Equivalent Circuit Models, Voltage-Controlled Method, Lithium-ion Battery, Model-Based, Battery Management Systems (BMS).**

I. Introduction

Accurate State of Charge (SoC) estimation in lithium-ion batteries is essential for managing battery systems in applications like electric vehicles, portable electronics, and renewable energy storage. It serves as a key metric for understanding remaining battery energy, guiding decision-making that affects performance, safety, and lifespan [3]. Reliable SoC diagnosis provides precise information for advanced energy management, optimizing capacity, extending battery life, and improving efficiency [4]. In large-scale applications like electric vehicles and grid storage, precise SoC estimation supports predictive maintenance and warranty assessments and enhances BMS performance [5].

Various methods have been developed for SoC estimation, including empirical, model-based, and data-driven (AI-based) approaches. While AI-based methods, such as neural networks and support vector machines, model complex and nonlinear battery behavior using large datasets [6], they often require extensive training data and may struggle with generalization across different battery types and operating conditions [7]. Additionally, these methods can suffer from a lack of interpretability and high computational demands [8].

Model-based methods, especially those using equivalent circuit models (ECMs), have gained popularity due to their balance between simplicity and accuracy [9], [10]. ECMs represent the battery's electrical behavior with resistive, capacitive, and sometimes inductive elements [11]–[13]. The RC model improves on the basic R model by adding a capacitor, better capturing the battery's voltage response to changes in current [15], [16].

However, traditional model-based methods often rely on current-controlled estimation, which can be prone to errors due to inaccuracies in current measurement and SoC drift. To overcome these limitations, voltage-controlled methods have emerged as a novel approach for SoC estimation [1]. Unlike current-controlled models, voltage-controlled methods use battery voltage as the primary input for determining SoC. This approach offers robustness against current sensing errors, provides a direct relationship between voltage changes and SoC, and is advantageous where accurate current measurement is difficult or when the battery operates under variable loads [1].

This paper evaluates three different ECMs for SoC estimation: a simple resistance (R) model, an RC model, and an extended RC model that incorporates diffusion effects within battery electrodes [17], [18]. The study explores the application of voltage-controlled methods across these models to assess their effectiveness in accurately estimating SoC under various operational conditions, including full cycling at a 1C rate, shallow cycling between 25% and 75% SoC, and dynamic operation based on the WLTP.

The authors would like to acknowledge Smart Battery Villum Investigator Grant (222860) from Villum Fonden, Denmark.

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II. METHODOLOGY

This study investigates the SoC estimation in lithium-ion batteries using three different ECMs: an R-only model, an RC model, and an RC-Diffusion model. Each model is evaluated under various conditions, using a voltage-controlled estimation method to ensure precise SoC determination. The methodology includes the parameterization of the models, the experimental setup, and the comparison of the models using Coulomb counting as a benchmark.

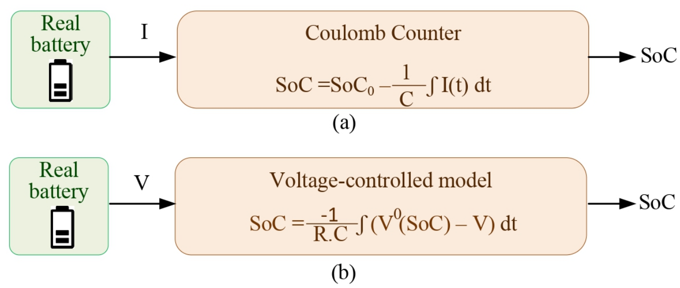

Fig. 1. Lithium-ion battery SoC diagnosis, (a) Coulomb counter, and (b) voltage-controlled algorithm.

A. Measurement and Diagnosis of SoC

SoC estimation in this study is performed using two primary methods: the Coulomb counter and the voltage-controlled model, as illustrated in Fig. 1. The Coulomb counter method estimates SoC by integrating the current over time, according to the equation:

$$SoC(t) = SoC_0 - \frac{1}{C_N} \int_{t_0}^{t} I_{exp}(\tau) d\tau \quad (1)$$

where $I_{exp}(t)$ is the experimentally measured current, C_N is the nominal capacity of the battery, SoC_0 is is the initial SoC. This method is straightforward, providing a direct relationship between the current flow and the SoC. However, it is susceptible to errors due to inaccuracies in current measurement, particularly during shallow cycling, where calibration points are not reached. Such errors can accumulate over time, leading to significant deviations in SoC estimation, especially under conditions where the battery does not undergo full charge and discharge cycles.

On the other hand, the voltage-controlled model estimates SoC using the battery's voltage as the primary input. In this approach, the relationship between SoC and the measured voltage $V_{exp}(t)$ is expressed through the ECMs. For the R-only model, the SoC estimation is governed by the equation:

$$\frac{dSoC_{sim}}{dt} = -\frac{1}{R.C_N}(V^0(SoC_{sim}) - V_{exp}(t)) \quad (2)$$

where $V^0(SoC_{sim}$ is the open-circuit voltage as a function of SoC, and R is the internal resistance of the battery. This model utilizes the voltage drop across the resistor, adjusting SoC based on changes in the observed voltage. The current output from this model is derived using:

$$I_{sim} = \frac{1}{R}(V^0(SoC_{sim}) - V_{exp}(t)) \quad (3)$$

This method offers a significant advantage as it does not rely on direct current measurement, thereby making it more robust against errors associated with current sensing. The voltage-controlled approach is particularly beneficial in scenarios where accurate current measurement is challenging or where the battery operates under varying loads, as it directly correlates voltage changes with SoC, providing a more stable and reliable estimation in real-time applications.

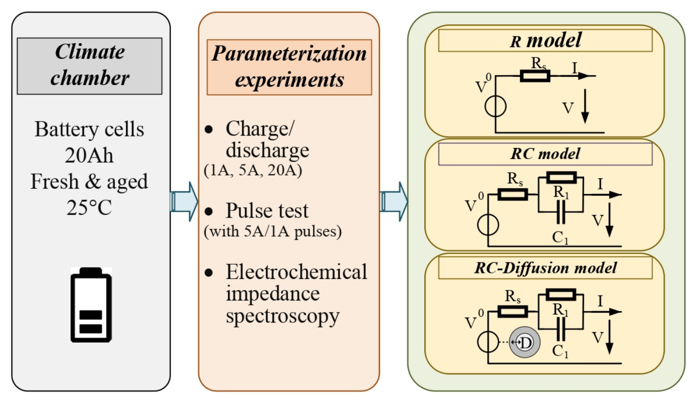

Fig. 2. Detailed process of SoC diagnosis using the proposed methods, based on ECMs.

B. Parameterization Experiments

The ECMs are parameterized using exclusively the experimental dataset reported in [1], which comprehensively captures the battery's performance under controlled conditions. In [1], the lab setup utilizes commercial lithium-ion battery cells tested at a stable ambient temperature of 25 °C within a climate-controlled chamber to ensure consistency and accuracy in the results. The experimental setup consists of commercial high-power 20 Ah lithium-ion pouch cells placed inside the climate chamber and connected to a battery cycler. During the parameterization experiments, constant-current/constant-voltage (CCCV) charge and discharge curves are measured at different C-rates, together with additional pulse-current tests, as described in. EIS is employed at 50% state of charge to characterize the battery's impedance across a wide frequency range (approximately 1 mHz–100 kHz). These EIS measurements provide detailed insights into the internal resistance and capacitive behavior of the battery, which are critical parameters for the ECMs. The model parameters and experimental dataset employed in this study are therefore directly taken from [1], [2].

C. Equivalent Circuit Models

This study utilizes three ECMs, as shown in Fig.2, each with increasing levels of complexity:

1) R-Only Mode: Consisting of a single resistor R, this model represents the internal resistance of the battery, providing a basic approximation of SoC based on the voltage drop across the resistor.

2) RC Model: This model adds a capacitor C_1 in parallel with the resistor R_1 to capture the transient response of the battery. The RC model provides improved accuracy during dynamic operations where the current fluctuates.

3) RC-Diffusion Model: The RC-Diffusion model is the most complex among the models used in this study. It extends the RC model by incorporating an additional resistor-capacitor (R_1C_1) circuit to account for solid-state diffusion effects within the battery. This enhancement allows the model to capture the slower dynamic responses associated with the diffusion of lithium ions between different regions within the battery, specifically the shell and core regions of the electrode particles.

In this model, the SoC is divided into two components: SoC_{shell} and SoC_{core}. The SoC_{shell} refers to the state of charge in the outer (shell) region of the electrode particles, where the lithium-ion concentration changes more rapidly due to its proximity to the electrolyte. Conversely, SoC_{core} refers to the state of charge in the inner (core) region of the electrode particles, where lithium ions diffuse more slowly. The diffusion current I_D is a critical element of this model, representing the rate at which lithium ions move between the shell and core regions, driven by the concentration gradient between these regions. The diffusion coefficient D determines the rate of this inter-region transfer.

The equations for the RC-Diffusion model are as follows:

$$V = V^0(SoC_{shell}) - R_s.I - V_{R_1C_1} \quad (4)$$

$$\frac{dV_{R_1C_1}}{dt} = \frac{1}{C_1}\left(I - \frac{V_{R_1C_1}}{R_1(I)}\right) \quad (5)$$

$$\frac{dQ_{core}}{dt} = I_D \quad (6)$$

$$\frac{dQ_{shell}}{dt} = -I - I_D \quad (7)$$

$$I_D = D.(SoC_{shell} - SoC_{core}) \quad (8)$$

$$SoC_{core} = \frac{Q_{core}}{C_N.(1 - f_{shell})} \quad (9)$$

$$SoC_{shell} = \frac{Q_{shell}}{C_N.f_{shell}} \quad (10)$$

$$SoC = \frac{Q_{core} + Q_{shell}}{C_N} \quad (11)$$

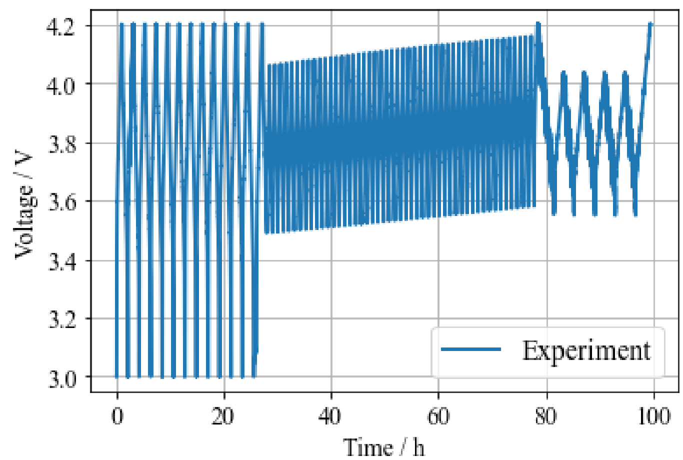

Fig. 3. Measured voltage as a function of time.

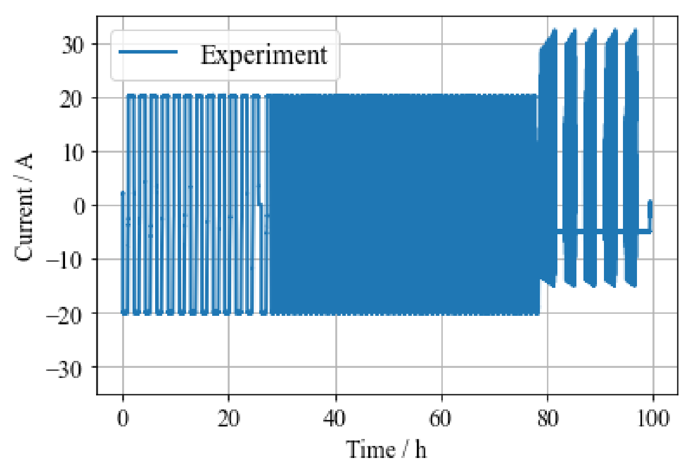

Fig. 4. Measured current as a function of time.

In these equations, V represents the terminal voltage of the battery while $V^0(SoC_{shell})$ denotes the open-circuit voltage as a function of the SoC in the shell region. The parameter R_s corresponds to the series resistance that accounts for the ohmic drop in the battery. The term $V_{R_1C_1}$ represents the voltage across the R_1C_1 diffusion network, which captures the diffusion-related potential drop. Additionally, $R_1(I)$ is the current-dependent resistance associated with the diffusion process, and C_1 is the capacitance of the R_1C_1.

III. Results and Analytics

The models are evaluated under three specific conditions:

- Full Cycling at 1C Rate
- Shallow Cycling at 1C Rate (25% to 75% SoC)
- Dynamic Operation Based on WLTP

As illustrated in Fig. 3, the measured voltage and current profiles during these three operational modes provide a comprehensive basis for evaluating the performance of different SoC estimation models.

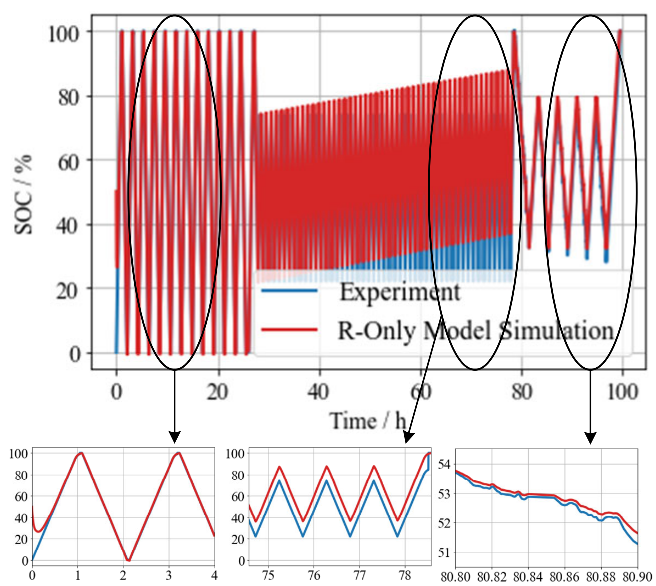

Fig. 5. Comparison of estimated SoC across three operational modes using the R-only model and the current-controlled Coulomb counter (Experiment).

A. Simulation Results for the R-Only Model

The R-Only model employs a basic approach to SoC estimation by considering the voltage drop across a single resistor. This model effectively captures the general SoC trend over time, as illustrated in Figs. 5 and 6. However, as shown in Fig. 5, which depicts the SoC estimation during different operational modes (full cycling, shallow cycling, and dynamic conditions), the R-Only model exhibits substantial deviations from the

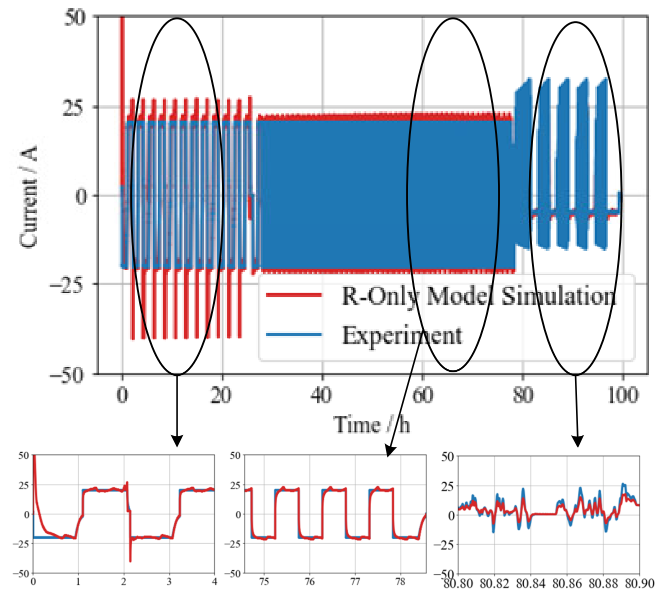

Fig. 6. Comparison of current across three operational modes using the R-only model and the current-controlled Coulomb counter (standard algorithm).

actual SoC, particularly during dynamic and shallow cycling conditions. These discrepancies arise due to the model's inability to account for transient and diffusion effects, which are critical in accurately representing rapid current and voltage fluctuations during dynamic operations. Similarly, Fig. 6 demonstrates the current comparison across the three modes, highlighting the model's limitations in accurately reflecting the battery's current response under these conditions. Consequently, while the R-Only model offers computational simplicity, it lacks the precision required for applications involving frequent load variations or transient states.

B. Simulation Results for the RC Model

The RC model introduces a capacitor in parallel with the resistor, significantly enhancing SoC estimation accuracy over the R-Only model, as shown in Figs. 8 and 9. Fig. 8 illustrates the estimated SoC across different operational modes, where the RC model shows a marked improvement in accuracy, particularly during dynamic cycling conditions. The addition of the capacitor enables the RC model to effectively manage sudden voltage changes, thereby reducing the impact of transient conditions. This improvement results in a closer alignment with experimental data, especially under dynamic cycling conditions, where the model better captures the battery's real-time dynamics. Fig. 9 presents the current comparison, demonstrating that the RC model more accurately follows the experimentally measured current, proving its effectiveness in both steady and dynamic state operations.

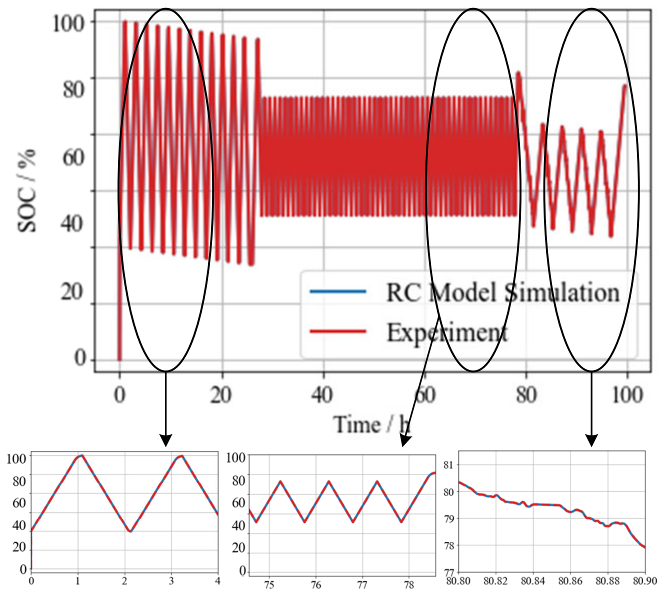

Fig. 7. Comparison of estimated SoC across three operational modes using the RC model and the current-controlled Coulomb counter (Experiment).

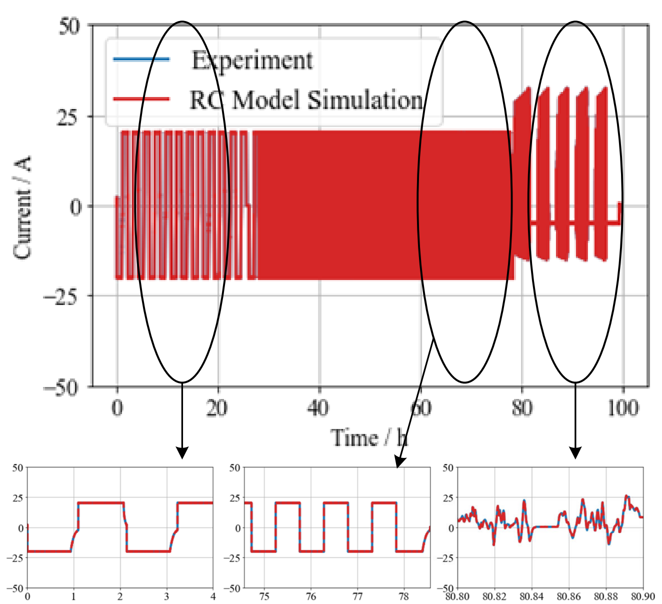

Fig. 8. Comparison of current across three operational modes using the RC model and the current-controlled Coulomb counter (standard algorithm).

C. Simulation Results for the RC-Diffusion Model

The RC-Diffusion model, presented in Figs. 10 and 11, further enhances SoC estimation by incorporating diffusion effects, which are particularly significant during prolonged charge and discharge cycles. Fig. 10 shows the estimated SoC across various modes, emphasizing the model's ability to account for both rapid and slow battery responses, closely aligning with Coulomb counting data to provide a highly accurate SoC estimation. As illustrated in Fig. 11, the RC-Diffusion model closely matches the experimentally measured current, effectively capturing the complex behavior of the battery under diverse cycling conditions. This high level of fidelity makes the RC-Diffusion model particularly suitable for applications demanding precise SoC estimation, such as electric vehicles operating under varying environmental and load conditions.

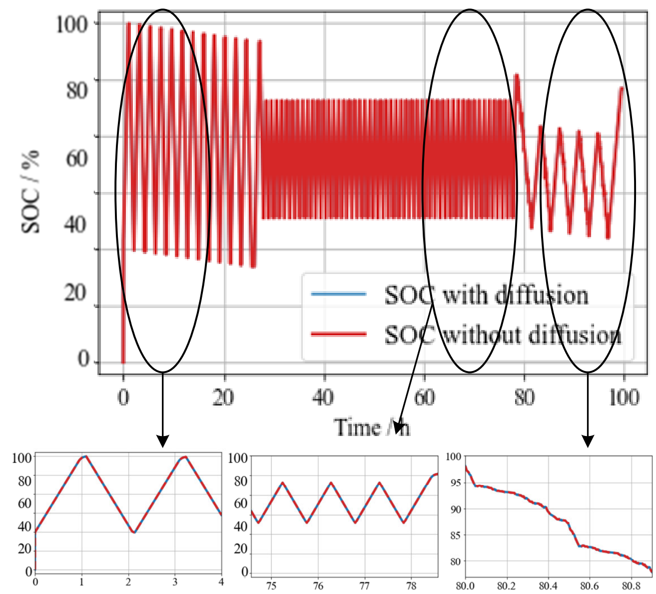

Fig. 9. Comparison of estimated SoC across three operational modes using the RC-Diffusion model, and the current-controlled Coulomb counter (Experiment).

IV. Conclusion and Future Work

The novelty of this study lies in the application of the voltage-controlled method for SoC estimation across different equivalent circuit models. By using voltage rather than current as the primary input, this method enhances robustness against errors associated with current sensing, which is particularly advantageous in scenarios with variable loads or where accurate current measurement is challenging. This innovative approach is integrated into a comprehensive evaluation of three equivalent circuit models—the R-Only model, the RC model, and the RC-Diffusion model—for State of Charge (SoC) estimation in lithium-ion batteries. The study evaluates the performance of these models under various cycling conditions,

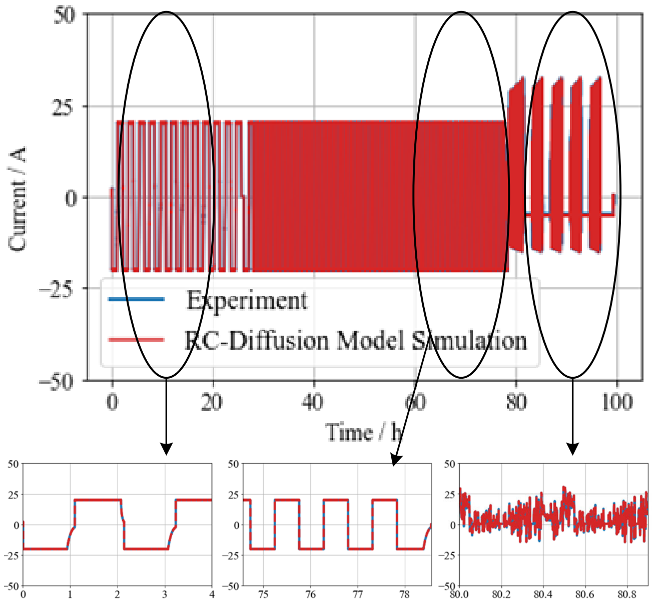

Fig. 10. Comparison of current across three operational modes using the RC-Diffusion model and the current-controlled Coulomb counter (standard algorithm).

including full cycling at a 1C rate, shallow cycling between 25% and 75% SoC, and dynamic operation based on the Worldwide Harmonized Light Vehicles Test Procedure (WLTP). The results show that while the R-Only model offers computational simplicity, its accuracy is insufficient for dynamic applications. The RC model, with its ability to account for transient responses, improves SoC estimation and is suitable for applications involving varying loads. The RC-Diffusion model provides the highest accuracy by incorporating diffusion effects, making it well-suited for scenarios requiring precise SoC estimation. In conclusion, the choice of the SoC estimation model should be based on the specific requirements of the application, balancing between computational efficiency and estimation accuracy. For applications with high dynamic loads or where precision is critical, the RC-Diffusion model and RC model are recommended.

Future work will focus on optimizing these models for real-time applications and integrating them with AI-based methods to combine the strengths of both model-based and data-driven approaches, thereby further enhancing SoC estimation accuracy.

V. Acknowledgement

This work is supported by the Villum Investigator Smart Battery Project at Aalborg University, Department of Energy.

The authors gratefully acknowledge that the experimental data used in this study was obtained from the open-access repository provided by Braun et al. [1], [2].

References

[1] Jonas A. Braun, René Behmann, David Schmider, Wolfgang G. Bessler, State of charge and state of health diagnosis of batteries with voltage-controlled models, Journal of Power Sources, Volume 544, 2022, 231828, ISSN 0378-7753, https://doi.org/10.1016/j.jpowsour.2022.231828.

[2] J. A. Braun, R. Behmann, D. Schmider, and W. G. Bessler, "Research data for 'State of charge and state of health diagnosis of batteries with voltage-controlled models'," Zenodo, 2022, doi: 10.5281/zenodo.6817725.

[3] Hoda Sorouri, Arman Oshnoei, Yunhong Che, Remus Teodorescu, A comprehensive review of hybrid battery state of charge estimation: Exploring physics-aware AI-based approaches, Journal of Energy Storage, Volume 100, Part B, 2024, 113604, ISSN 2352-152X.

[4] R. Korthauer, Lithium-ion Batteries: Basics and Applications, Springer, Berlin, Heidelberg, 2018.

[5] A. Kulkarni et al., "Li-ion Battery Digital Twin Based on Online Impedance Estimation," 2023 IEEE 17th International Conference on Compatibility, Power Electronics and Power Engineering (CPE-POWERENG), Tallinn, Estonia, 2023, pp. 1-6.

[6] J.P. Meyers, M. Doyle, R.M. Darling, Newman, J. The impedance response of a porous electrode composed of intercalation particles, J. Electrochem. SoC. 147 (2000) 2930–2940.

[7] M. Mayur, S.C. DeCaluwe, B.L. Kee, W.G. Bessler, Modeling and simulation of the thermodynamics of lithium-ion battery intercalation materials in the open-source software Cantera, Electrochim. Acta 323 (2019), 134797, https://doi.org/ 10.1016/j.electacta.2019.134797.

[8] G.L. Plett, Equivalent-circuit Methods, in: Battery Management Systems, vol. 2, Artech House, Boston, London, 2016.

[9] W. Waag, C. Fleischer, D.U. Sauer, Critical review of the methods for monitoring of lithium-ion batteries in electric and hybrid vehicles, J. Power Sources 258 (2014) 321–339.

[10] M. Piras, V. De Bellis, E. Malfi, Jose M. Desantes, R. Novella, M. Lopez-Juarez, Incorporating speed forecasting and SoC planning into predictive ECMS for heavy-duty fuel cell vehicles, International Journal of Hydrogen Energy, Volume 55, 2024, Pages 1405-1421, ISSN 0360-3199.

[11] Jinxin Xu, Kai Xiong, Taoran Tang, Yuanjie Chen, Dongfang Hu, Dexin Hou, Mingming Yu, Jiong Ding, Precise determination of the continuous entropic coefficient profile of lithium-ion batteries using frequency-domain method, Measurement, Volume 240, 2025, 115578, ISSN 0263-2241.

[12] Niccolò Nicodemo, Roberto Di Rienzo, Marco Lagnoni, Antonio Bertei, Federico Baronti, Estimation of lithium-ion battery electrochemical properties from equivalent circuit model parameters using machine learning, Journal of Energy Storage, Volume 99, Part A, 2024, 113257, ISSN 2352-152X.

[13] Jonas A. Braun, René Behmann, Daniel Chabrol, Frederik Fuchs, Wolfgang G. Bessler, Single-cell operando SoC and SOH diagnosis in a 24V lithium iron phosphate battery with a voltage-controlled model, Journal of Energy Storage, Volume 85, 2024, 110986, ISSN 2352-152X.

[14] Zhen Tao, Zhenyu Zhao, Changdong Wang, Lantao Huang, Huamin Jie, Hong Li, Qianying Hao, Yuhang Zhou, Kye Yak See, State of charge estimation of lithium batteries: Review for equivalent circuit model methods, Measurement, Volume 236, 2024, 115148, ISSN 0263-2241.

[15] [20] C. Campestrini, T. Heil, S. Kosch, A. Jossen, A comparative study and review of different Kalman filters by applying an enhanced validation method, J. Energy Storage 8 (2016) 142–159.

[16] M. Tutuianu, et al., Development of a world-wide World-wide harmonized Light duty driving test cycle (WLTC). Technical report UN/ECE/WP.29/GRPE/WLTP-IG, in: UNECE Working Party on Pollution and Energy, GRPE), 2013.

[17] P. Shrivastava, T.K. Soon, M.Y.I.B. Idris, S. Mekhilef, Overview of model-based online state-of-charge estimation using Kalman filter family for lithium-ion batteries, Renew. Sustain. Energy Rev. 113 (2019), 109233.

[18] M. Doyle, T.F. Fuller, Newman, J. Modeling of galvanostatic charge and discharge of the lithium/polymer/insertion cell, J. Electrochem. SoC. 140 (1993) 1526–1533.