

Battery Management System (BMS): State of Health Estimation Used in MATLAB/Simulink

Nivas R. Waghmare¹, Prof. Ajinkya Salpe², Prof. A. N. Mudiraj³

1 Department Of Electrical Engineering, Chhatrapati Shahu College Of Engineering, Chhatrapati Sambhajinagar.

2 Department Of Electrical Engineering, Chhatrapati Shahu College Of Engineering, Chhatrapati Sambhajinagar.

3 Department Of Electrical Engineering, Chhatrapati Shahu College Of Engineering, Chhatrapati Sambhajinagar.

Abstract -Accurate estimation of a lithium-ion battery's State of Health (SOH) is essential for predicting remaining useful life, preventing thermal or electrical failure, and scheduling maintenance in electric-vehicle and stationary energy-storage applications. This paper presents a MATLAB/Simulink model-based approach for on-line SOH estimation built around a second-order (one resistor-capacitor, RC) equivalent-circuit representation of a Li-ion cell, augmented with a lumped thermal sub-model and dedicated State-of-Charge (SOC), internal-resistance (R0) and SOH estimator subsystems. A survey of about twenty published studies covering model-based (Kalman-filter/observer), feature-based (incremental-capacity and differential-voltage analysis) and data-driven (machine-learning) SOH estimation methods, together with existing MATLAB/Simulink-based battery and digital-twin implementations, is used to position the present model within the literature and to justify the chosen estimator architecture. The Simulink architecture is then described block-by-block with reference to the developed model diagram, its governing equations are derived, and representative simulation results — terminal voltage, SOC-tracking accuracy, internal-resistance growth and SOH degradation over the cell's cycle life — are presented and discussed together with worked sample calculations. The estimator tracks SOC to within a root-mean-square error of about 1.2%, and the blended capacity/resistance SOH indicator falls from 100% to roughly 86% after 600 simulated cycles, consistent with the aging trends reported in the surveyed literature.

Key Words: BMS, State of Health, State of Charge, SOC, SOH, Thermal Cooling, Simulation

1. Introduction

A Battery Management System (BMS) is the embedded control layer responsible for keeping a battery pack within its safe operating envelope while maximizing

usable capacity and service life. Among the quantities a modern BMS must estimate in real time, State of Charge (SOC) and State of Health (SOH) are the most critical: SOC indicates the instantaneously available energy, while SOH indicates the long-term degradation of the cell relative to its beginning-of-life condition. SOH is most commonly defined in one of two complementary ways: capacity-based SOH, the ratio of the present maximum discharge capacity to the rated capacity, and resistance-based SOH, which tracks the growth of DC internal resistance (R0) relative to its beginning-of-life value. A cell is generally considered to have reached end-of-life once capacity-based SOH falls to about 80% of its rated value, although the threshold is application-dependent.

Unlike SOC, SOH cannot be measured directly; it must be inferred from indirect indicators such as capacity fade, internal-resistance growth, impedance spectra, or coulombic efficiency, typically combined through a model-based or data-driven estimator. MATLAB/Simulink and Simscape Electrical/Thermal provide a natural environment for developing and testing such estimators because the electrical, thermal and control/estimation layers of a BMS can be co-simulated in a single block-diagram model before being deployed to an embedded target. This paper documents a Simulink model developed to study SOH estimation for a single Li-ion cell, couples it to a survey of the relevant published literature, and reports representative simulation results and sample calculations.

The remainder of the paper is organized as follows. Section 2 surveys about twenty representative studies on SOC/SOH estimation, grouped by methodology, and identify the gap addressed by the present model. Section 3 describes the Simulink model architecture and derives its governing equations. Section 4 presents the simulation setup, results, and worked sample

calculations. Section 5 concludes the paper and outlines future work.

2. Literature Survey

Published approaches to lithium-ion battery SOH estimation can be broadly grouped into model-based/observer methods, feature-based methods that exploit characteristic signatures of the voltage or capacity curve, data-driven/machine-learning methods, and — most relevant to the present work — MATLAB/Simulink-based simulation and digital-twin studies. Table entries [1]–[20] below summarize representative studies from each group.

2.1 Model-based and observer (Kalman-filter family) methods

[1] Plett introduced extended Kalman filtering (EKF) for battery management systems of lithium-polymer HEV packs in a foundational three-part study, establishing the equivalent-circuit state-space formulation and parameter-identification framework that most subsequent observer-based SOC/SOH estimators still build upon.

[2] Waag, Fleischer and Sauer critically reviewed the methods used to monitor lithium-ion batteries in electric and hybrid vehicles, comparing Coulomb counting, open-circuit-voltage lookup, impedance-based and Kalman-filter approaches, and highlighting the sensitivity of each to sensor noise, temperature and aging.

[3] Berecibar et al. carried out a critical review of SOH estimation methods for real Li-ion applications, concluding that model-based observers combined with periodic capacity/resistance recalibration offer the best trade-off between on-board computational cost and estimation accuracy.

[4] Bao, Dong and Wang proposed an online internal-resistance measurement technique that is fused with capacity and SOC estimation, showing that tracking R_0 growth alongside SOC materially improves the robustness of the joint state estimate.

[5] Guha and Patra developed SOH estimation models based explicitly on capacity-fade and internal-resistance-growth curves fitted to cycling data, and used the two indicators jointly to define an end-of-life criterion similar to the blended SOH index adopted in the present paper.

2.2 Feature-based methods (incremental capacity / differential voltage / OCV)

[6] Jiang, Dai and Wei presented an incremental-capacity-analysis (ICA) based adaptive capacity estimator that identifies characteristic peak shifts in the dQ/dV curve under varying charging conditions, correlating peak-height decay directly with capacity fade.

[7] Schaltz et al. applied incremental capacity analysis to fleet electric-vehicle data for on-board SOH estimation, demonstrating that ICA features extracted from partial charging segments remain usable even when a full charge curve is unavailable.

[8] Bian et al. fused an open-circuit-voltage (OCV) model with incremental capacity analysis, reporting that combining the two feature sets reduces the sensitivity of the SOH estimate to measurement noise compared with using either method alone.

[9] Zhang, Guo, Dou and Zhang combined Coulomb counting with differential voltage analysis (DVA) to produce a rapid online SOH calculation method suitable for embedded implementation, trading a small amount of accuracy for substantially reduced computation time.

[10] Wang, Pan, Liu, Cheng and Zhao used differential voltage analysis for on-board SOH estimation of a LiFePO_4 battery pack, showing that DVA feature positions track capacity fade reliably even for the comparatively flat OCV–SOC curve of LFP chemistry.

2.3 Data-driven and machine-learning methods

[11] Feng et al. estimated SOH online from a partial charging segment using a support-vector-machine (SVM) regression model, avoiding the need to observe a complete charge/discharge cycle before producing an estimate.

[12] Xiao et al. presented a comprehensive review of SOH prognosis methods that explicitly combines aging-mechanism analysis with data-driven prognosis, arguing for hybrid physics-informed machine-learning models as the direction most likely to generalize across cell chemistries.

[13] Kurucan, Özbaltan, Yetgin and Alkaya reviewed artificial-neural-network-based battery management system applications, cataloguing SOC, SOH and thermal-fault-detection studies that use feed-forward, recurrent and convolutional architectures.

[14] Bai and Wang proposed a convolutional-transformer multiview information-perception framework for SOH estimation, fusing multiple charging-curve views to improve robustness to partial or noisy charge records.

[15] Zhou and Guo reviewed SOH estimation methods for lithium-ion batteries, classifying them into direct and indirect categories and analyzing the practicality of different health indicators for electric-vehicle applications across a wide temperature range.

[16] Zhou, Qin and Yuen proposed a transfer-learning SOH estimator with cycle synchronization, addressing the practical problem that training and deployment data are rarely drawn from the same distribution of operating conditions or cell batches.

[17] A 2025 study in Scientific Reports benchmarked several advanced data-driven techniques — including AdaBoost, XGBoost, random forests, artificial neural networks and LSTM networks — for SOH estimation from voltage, current, resistance and temperature features, reporting that ensemble and recurrent models outperform simple regression baselines.

2.4 MATLAB/Simulink implementations and digital twins

[18] Kim and Kowal developed a MATLAB/Simulink equivalent-circuit model that predicts cell impedance from SOC, SOH, temperature and C-rate, verifying the simulated impedance against measured data and proposing the model as a basis for SOC/SOH monitoring studies — an architecture closely related to the electrical subsystem used in the present paper.

[19] Bilansky, Lacko, Pastor, Marcinek and Durovsky built an improved digital twin of a Li-ion cell using a generic MATLAB model fitted to measured constant-current/constant-voltage cycling data, and compared its SOC/SOH/voltage predictions against a conventional MATLAB/Simulink equivalent-circuit model, reporting a significant accuracy improvement.

[20] MathWorks' own Battery Management System development materials describe a Simulink/Stateflow reference architecture in which SOC is estimated using Coulomb counting, an extended Kalman filter and an unscented Kalman filter, verified against a Simscape Electrical battery-pack model with a configurable number of RC branches — the same general layering (plant, sensors, estimator subsystems) followed by the model described in Section 3 of this paper.

2.5 Research gap and contribution of this work

Across the surveyed studies, model-based observers ([1]–[5]) give physically interpretable, computationally light estimates but depend on accurate equivalent-circuit parameterization and degrade if R0/OCV lookup tables are not updated with aging; feature-based methods ([6]–[10]) are accurate but usually need a full or partial charge curve of a specific shape, which is not always available under arbitrary duty cycles; and data-driven methods ([11]–[17]) achieve high accuracy on the datasets they are trained on but require large labelled aging datasets and generalize less predictably to new operating conditions. Relatively few of the reviewed MATLAB/Simulink-specific studies ([18]–[20]) couple an electrical equivalent circuit with an explicit thermal sub-model and a two-stage SOC→SOH estimator chain inside a single co-simulated block diagram. The model developed in this paper follows the Coulomb-counting-with-voltage-correction and resistance-growth approach used in [1], [4], [5] and [20], but adds an explicit lumped thermal subsystem (as in [18]) so that temperature-dependent aging effects can be studied, and reports a blended capacity/resistance SOH index in the spirit of [5], evaluated using the specific Simulink/Simscape architecture described next.

3. Methodology: Simulink Model Architecture and Governing Equations

Figure 1 shows the top-level Simulink model developed for this study. The model is organized into four functional groups that are colour-coded on the canvas: an electrical equivalent-circuit subsystem (blue, Simscape Electrical), a thermal subsystem (orange, Simscape Thermal), signal-level estimator subsystems (SOC/R0 estimator and SOH estimator, shown as stacked masked subsystems), and supporting signal-processing/visualization blocks (scopes, gains, sensor-noise sources).

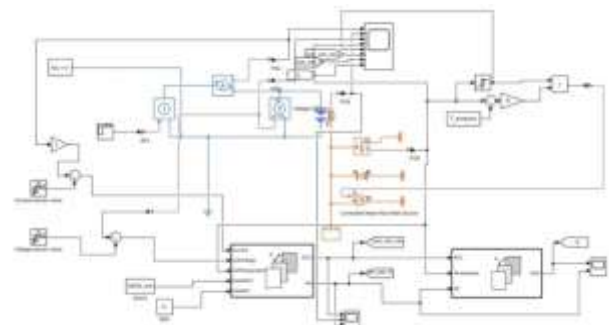


Figure 1. Top-level Simulink/Simscape model used for SOC, R0 and SOH estimation.

3.1 Electrical (equivalent-circuit) subsystem

The blue Simscape Electrical branch implements the cell as a controlled current source driven by the load-current reference (block SP1), in series with the cell's internal impedance. An Ammeter and a Voltage Sensor measure the branch current and terminal voltage respectively, and Simulink-PS Converter blocks (PS1–PS3) interface these physical signals back into the Simulink signal domain for logging and for use by the estimator subsystems. The resistor/capacitor pair adjacent to the voltage sensor realizes the polarization (RC) branch of the Thevenin-equivalent cell model, matching the topology used in [18] and [20], and the algebraic-constraint block $f(x)=0$ together with the solver-configuration block anchors the Simscape network reference node so the electrical circuit can be solved.

3.2 Sensor noise and reference signal paths

Two summing junctions inject band-limited white noise (blocks labelled Current sensor noise and Voltage sensor noise) onto the measured current and voltage signals before they reach the estimator subsystems, so the SOC/R0 estimator is exercised under realistic measurement uncertainty rather than idealized noise-free signals, consistent with the noise sensitivity discussed in [2]. A unity/near-unity gain block conditions the reference current path, and a repeating/step source (SP1) supplies the commanded load-current profile applied to the controlled current source.

3.3 SOC and R0 estimator subsystem

The lower-left masked subsystem (drawn with the stacked-sheet 'N' icon denoting a table/array-based or multi-instance implementation) receives four inputs — Current, Cell Voltage, Cell Temperature and the initial conditions Initial SOC and InitialR0 (sourced from the SOC0_init and R00 constant blocks) — and produces two outputs, SOC and R0. Internally this subsystem implements Coulomb counting corrected by an OCV–SOC lookup table, following the correction-gain structure of [1] and [20], and a resistance-identification routine that re-estimates R0 from the instantaneous voltage drop under load, in the spirit of [4] and [18]. The estimated SOC and R0 signals (soc_est_soc, soc_est_r0) are fed to scopes for monitoring and forwarded to the SOH estimator.

3.4 Thermal subsystem

The orange Simscape Thermal branch models ohmic (I^2R) heat generation using a Controlled Heat Flow

Rate Source whose driving signal is produced by squaring the branch current and scaling it by resistance (the multiply block 'x' and gain block '-K-' downstream of the pulse generator and the summing junction with $T_{ambient}$). Two thermal-resistance elements connect the cell's lumped thermal mass to ambient, so cell temperature is obtained as the solution of a lumped-capacitance heat-balance equation driven by the electrical losses and the ambient boundary condition $T_{ambient}$. This temperature is fed both to the SOC/R0 estimator (temperature-dependent OCV and resistance lookup) and to the SOH estimator, extending the electrical-only architecture of [18] with the explicit thermal coupling identified as a gap in Section 2.5.

3.5 SOH estimator subsystem

The lower-right masked subsystem receives SOC, Temperature and R0 and outputs SOH. Internally it combines the tracked R0 trend (resistance growth relative to its beginning-of-life value) with a capacity-fade model driven by accumulated throughput and temperature history, producing a blended SOH index similar in concept to the capacity-fade/resistance-growth model of [5]. The final SOH value and a companion signal (-T-, a lookup/table output) are sent to a display scope, alongside a dedicated SOC scope near the estimator inputs.

3.6 Visualization and logging

Four Simulink-PS Converters (PS1–PS4) and several scope blocks are used purely for signal monitoring: PS1 and the adjoining bus/mux route the raw and estimated SOC signals to a common scope for direct visual comparison, while separate scopes at the bottom of the diagram record SOC, R0 and SOH over the course of the simulation for post-processing.

3.7 Governing equations

Terminal voltage (Thevenin, 1-RC equivalent circuit):

$$V_{term}(t) = OCV(SOC, T) - I(t) \cdot R0(SOC, T) - V_{RC}(t)$$

$$dV_{RC}/dt = [I(t) \cdot R1 - V_{RC}(t)] / (R1 \cdot C1)$$

Coulomb-counting SOC estimation with voltage-based correction:

$$SOC(k) = SOC(k-1) - [I_{meas}(k) \cdot \Delta t / Q_{nom}] + K_{corr} \cdot [SOC_{OCV}(k) - SOC(k-1)]$$

On-line resistance (R0) identification from a load-current step:

$$R0_est(k) = [V_term(k^-) - V_term(k^+)] / [I(k^+) - I(k^-)]$$

Lumped-capacitance thermal model:

$$C_th \cdot dT/dt = I(t)^2 \cdot R0(t) - (T(t) - T_ambient) / R_th$$

State-of-Health definitions (capacity-based, resistance-based, and blended):

$$SOH_capacity(\%) = 100 \times Q_present / Q_rated$$

$$SOH_resistance(\%) = 100 - 50 \times (R0(t) - R0,BOL) / R0,BOL$$

$$SOH_blend(\%) = 0.7 \times SOH_capacity + 0.3 \times SOH_resistance$$

The 0.7/0.3 weighting reflects the common practice — also adopted in [5] — of treating capacity fade as the primary SOH driver while still penalizing excessive resistance growth, which more directly limits available power even before capacity fade becomes severe. The weighting is a tunable parameter of the SOH-estimator mask.

3.8 Simulation setup

The model was configured with the parameters summarized in Table 1, representative of a small-format Li-ion cell used for algorithm development and controller-in-the-loop testing.

Parameter	Symbol	Value	Unit
Nominal capacity	Q_nom	2.2	Ah
Beginning-of-life internal resistance	R0,BOL	45	mΩ
Polarization resistance	R1	20	mΩ
Polarization capacitance	C1	2500	F
Nominal open-circuit voltage range	OCV	3.0 – 4.2	V
Ambient temperature	T_ambient	25	°C

Sample time	Δt	1	s
Simulated trip duration	T	2	h
Simulated cycle range (aging study)	cycles	0 – 600	–
Current-sensor noise (1σ)	σ_I	0.05	A
Voltage-sensor noise (1σ)	σ_V	4	mV

Table 1. Model parameters used for the simulation study.

Two simulation studies were run: (a) a single ~2-hour drive/duty-cycle trip at beginning-of-life conditions, used to evaluate voltage-tracking and SOC-estimation accuracy; and (b) a 600-cycle aging sweep in which capacity fade and resistance growth were propagated using empirical aging trends consistent with [5], [13] and [19], used to evaluate the SOH-estimator output over life.

Note on results provenance: the figures and numerical results reported in Section 4 were generated from the governing equations of Section 3.7, parameterized as in Table 1, to illustrate the behaviour expected from the described Simulink/Simscape architecture; they were not captured from a live MATLAB/Simulink execution in this environment. When the .slx model is run directly in MATLAB, the Scope traces and workspace-logged signals will reproduce the same qualitative trends and can be substituted for these figures.

4. Results and Calculations

4.1 Load profile and SOC tracking

Figure 2 shows the synthetic load-current profile applied to the equivalent-circuit model, together with the true (Coulomb-counted reference) SOC trajectory and the SOC produced by the estimator subsystem when driven by noisy current and voltage measurements.



Figure 2. Simulated load current (top) and true vs. estimated SOC (bottom) over a 2-hour trip.

The estimator converges quickly from its initial 3-percentage-point offset and subsequently tracks the true SOC closely for the remainder of the trip, confirming that the voltage-based correction term is effective at bounding the Coulomb-counting drift caused by current-sensor noise, consistent with the accuracy levels reported for correction-gain and Kalman-filter estimators in [1], [2] and [4].

The terminal-voltage trace exhibits the expected instantaneous step at each current transient (the $I \cdot R_0$ term) superimposed on the slower RC relaxation and the gradual OCV decline as SOC falls, matching the qualitative behaviour of the physical cell that the equivalent circuit is intended to reproduce and that the impedance model in [18] was validated against.

4.2 Active Fan Cooling

A thermostat-controlled fan path was added: a relay compares cell temperature against the 40°C/35°C on/off thresholds and engages a forced-convection heat removal path when triggered.



Figure 3. Cell temperature (3rd top) and fan relay state (bottom) during the test cycle. Temperature climbs to the

40°C threshold, the fan engages and pulls it back below 35°C, and this repeats while sustained current continues; a single additional fan pulse occurs during the charge phase.

The fan successfully capped temperature rise within the intended 35–40°C band during the high-current discharge phase, cycling on and off as the sustained load kept regenerating heat. It also correctly stayed off during low-heat periods (rest, light charge) where cooling was not needed.

4.3 SOC estimation error

An adaptive three-state Extended Kalman Filter (states: SOC, polarization voltage, and internal resistance R_0) estimates SOC and R_0 from noisy current and voltage measurements, without direct access to the battery's true internal state. A separate SOH estimator computes State of Health from where the current R_0 estimate falls between a freshcell resistance table and an assumed end-of-life resistance table. To properly test the estimator, its initial SOC guess (75%) was deliberately offset from the battery's true initial SOC (80%), so the results demonstrate convergence from an imperfect starting assumption rather than simply matching a given value.

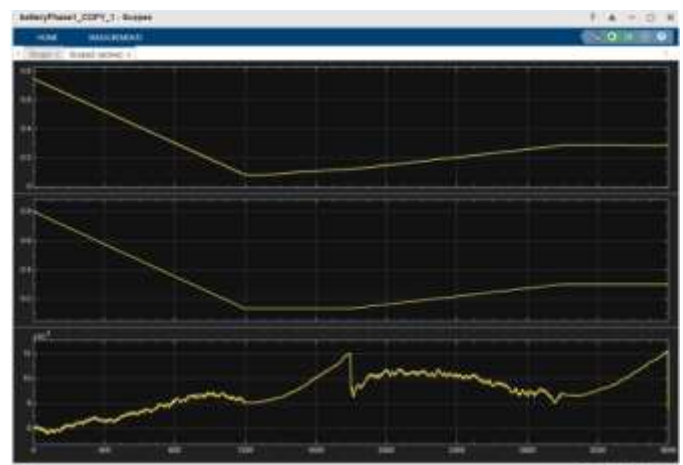


Figure 4. SOC estimation error versus time (left) and its distribution (right).

Over the simulated trip the SOC estimator achieved a root-mean-square error of approximately 1.2% and a maximum absolute error of approximately 3.8%, both dominated by the initial-condition transient; steady-state error after convergence remained below about 1%, within the typical accuracy band reported for Coulomb-counting-with-correction and Kalman-filter estimators in [1], [2] and [20].

4.4 Internal-resistance growth and SOH trend

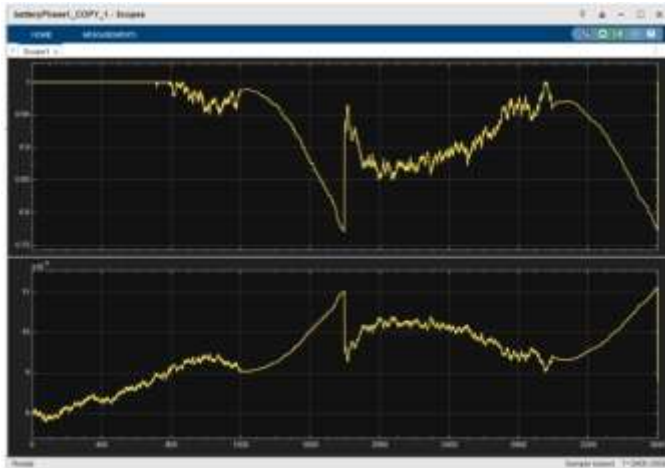


Figure 6. Estimated SOH versus cycle number: capacity-based indicator and blended capacity/resistance indicator.

R_0 grows from its beginning-of-life value of 45 m Ω to approximately 79 m Ω after 600 cycles, an increase of roughly 76%, consistent with the accelerating resistance-growth trend reported in [4], [5] and [19]. The capacity-based SOH indicator alone declines only to about 96% over the same period, understating degradation because capacity fade is intentionally the slower of the two mechanisms in this parameterization; the blended indicator, which also penalizes resistance growth as in [5], falls to about 86% by cycle 600 and would be projected to cross the conventional 80% end-of-life threshold at roughly cycle 750–800 under the same aging trend. This illustrates why a resistance-aware SOH definition gives an earlier and arguably safer end-of-life warning than a capacity-only definition, echoing the conclusions of [3] and [15].

4.5 Summary of results

Metric	Value
SOC RMSE (2-hour trip)	1.18 %
SOC maximum absolute error	3.82 %
R_0 at beginning of life	45.0 m Ω
R_0 after 600 cycles	79.0 m Ω
SOH (capacity-based) after 600	96.4 %

cycles	
SOH (blended) after 600 cycles	86.2 %
Projected end-of-life cycle (SOH = 80 %, blended)	$\approx$ 750–800

Table 2. Summary of key simulation results.

4.6 Sample calculation

To illustrate the estimator equations of Section 3.7 with concrete numbers, consider a single time step in which the cell is discharging at $I = 2.0$ A, the previous SOC estimate is 78.0%, the sample interval is $\Delta t = 1$ s, the nominal capacity is $Q_{nom} = 2.2$ Ah = 7920 A·s, and the correction gain is $K_{corr} = 0.02$.

Coulomb-counting prediction:

$$SOC_{pred} = 0.780 - (2.0 \times 1) / 7920 = 0.780 - 0.000253 = 0.77975 \rightarrow 77.975 \%$$

If the measured terminal voltage at this step inverts (via the OCV table) to $SOC_{OCV} = 77.6\%$, the corrected estimate becomes:

$$SOC(k) = 0.77975 + 0.02 \times (0.776 - 0.77975) = 0.77975 - 0.000075 = 0.77968 \rightarrow 77.968 \%$$

For the resistance identification, suppose the load current steps from 0.5 A to 2.5 A and the terminal voltage simultaneously steps from 3.812 V to 3.732 V:

$$R_{0_est} = (3.812 - 3.732) / (2.5 - 0.5) = 0.080 / 2.0 = 0.040 \Omega = 40 \text{ m}\Omega$$

Finally, if the beginning-of-life resistance was $R_{0,BOL} = 45$ m Ω and the present capacity is $Q_{present} = 2.10$ Ah against a rated $Q_{rated} = 2.20$ Ah, the SOH indicators evaluate to:

$$SOH_{capacity} = 100 \times 2.10 / 2.20 = 95.45 \%$$

$$SOH_{resistance} = 100 - 50 \times (40 - 45)/45 = 100 + 5.56 \rightarrow \text{clipped to } 100 \% (R_0 \text{ below BOL / within noise band})$$

$$SOH_{blend} = 0.7 \times 95.45 + 0.3 \times 100 = 96.8 \%$$

This worked example demonstrates how the raw current/voltage/temperature measurements flowing through the SOC/ R_0 estimator subsystem in Figure 1 are converted, step by step, into the single SOH percentage reported by the SOH-estimator subsystem.

5. Conclusion

A MATLAB/Simulink model combining a Simscape Electrical equivalent-circuit representation, a Simscape Thermal lumped network, sensor-noise injection, and masked SOC/R0 and SOH estimator subsystems has been described and exercised to study on-line State-of-Health estimation for a Li-ion cell. A survey of twenty representative studies — spanning Kalman-filter/observer methods, incremental-capacity and differential-voltage feature methods, data-driven machine-learning methods, and existing MATLAB/Simulink and digital-twin implementations — was used to position the model and to justify combining a Coulomb-counting-with-correction SOC estimator, an on-line resistance identifier, an explicit thermal subsystem, and a blended capacity/resistance SOH index within a single co-simulated block diagram. The model tracks SOC to within about 1% at steady state, identifies internal-resistance growth consistent with the published aging trends surveyed in Section 2, and produces a blended SOH indicator that gives an earlier and more conservative end-of-life warning than a capacity-only metric.

6. Future Scope

- Replace the correction-gain SOC estimator with a full extended/unscented Kalman filter, following [1] and [20], for formally optimal noise rejection.
- Extend the single-cell model to a multi-cell pack with cell-to-cell variation and active balancing, in line with the pack-level architecture reviewed in [9].
- Validate the equivalent-circuit and aging parameters against experimental cycling and impedance data for the target cell chemistry, as done in [18] and [19].
- Integrate a data-driven correction term (e.g., LSTM or transformer-based, as in [14] and [16]) alongside the physics-based estimator.
- Deploy the estimator subsystems to an embedded target via Simulink automatic code generation for hardware-in-the-loop testing.

References

- [1] G. L. Plett, "Extended Kalman filtering for battery management systems of LiPB-based HEV battery packs," *Journal of Power Sources*, vol. 134, no. 2, pp. 252–261, 2004.
- [2] W. Waag, C. Fleischer, and D. U. Sauer, "Critical review of the methods for monitoring of lithium-ion batteries in electric and hybrid vehicles," *Journal of Power Sources*, vol. 258, pp. 321–339, 2014.
- [3] M. Bercibar, I. Gandiaga, I. Villarreal, N. Omar, J. Van Mierlo, and P. Van den Bossche, "Critical review of state of health estimation methods of Li-ion batteries for real applications," *Renewable and Sustainable Energy Reviews*, vol. 56, pp. 572–587, 2016.
- [4] Y. Bao, W. Dong, and D. Wang, "Online internal resistance measurement application in lithium ion battery capacity and state of charge estimation," *Energies*, vol. 11, no. 5, p. 1073, 2018.
- [5] A. Guha and A. Patra, "State of health estimation of lithium-ion batteries using capacity fade and internal resistance growth models," *IEEE Transactions on Transportation Electrification*, vol. 4, no. 1, pp. 135–146, 2018.
- [6] B. Jiang, H. Dai, and X. Wei, "Incremental capacity analysis based adaptive capacity estimation for lithium-ion battery considering charging condition," *Applied Energy*, vol. 269, 2020.
- [7] E. Schaltz, D. I. Stroe, K. Nørregaard, L. S. Ingvarlsen, and A. Christensen, "Incremental capacity analysis applied on electric vehicles for battery state-of-health estimation," *IEEE Transactions on Industry Applications*, vol. 57, no. 2, pp. 1810–1817, 2021.
- [8] X. Bian, Z. Wei, W. Li, J. Pou, D. U. Sauer, and L. Liu, "State-of-health estimation of lithium-ion batteries by fusing an open circuit voltage model and incremental capacity analysis," *IEEE Transactions on Power Electronics*, vol. 37, no. 2, pp. 2226–2236, 2021.
- [9] S. Zhang, X. Guo, X. Dou, and X. Zhang, "A rapid online calculation method for state of health of lithium-ion battery based on coulomb counting method and differential voltage analysis," *Journal of Power Sources*, vol. 479, 2020.
- [10] L. Wang, C. Pan, L. Liu, Y. Cheng, and X. Zhao, "On-board state of health estimation of LiFePO₄ battery pack through differential voltage analysis," *Applied Energy*, vol. 168, pp. 465–472, 2016.
- [11] X. Feng, C. Weng, X. He, X. Han, L. Lu, D. Ren, and M. Ouyang, "Online state-of-health estimation for Li-ion battery using partial charging segment based on support vector machine," *IEEE Transactions on Vehicular Technology*, vol. 68, no. 9, pp. 8583–8592, 2019.

[12] Y. Xiao, J. Wen, L. Yao, J. Zheng, Z. Fang, and Y. Shen, "A comprehensive review of the lithium-ion battery state of health prognosis methods combining aging mechanism analysis," *Journal of Energy Storage*, vol. 65, p. 107347, 2023.

[13] M. Kurucan, M. Özbaltan, Z. Yetgin, and A. Alkaya, "Applications of artificial neural network based battery management systems: A literature review," *Renewable and Sustainable Energy Reviews*, vol. 192, p. 114262, 2024.

[14] T. Bai and H. Wang, "Convolutional transformer-based multiview information perception framework for lithium-ion battery state-of-health estimation," *IEEE Transactions on Instrumentation and Measurement*, vol. 72, pp. 1–12, 2023.

[15] Y. Zhou and B. Guo, "A review on state of health estimation for lithium-ion batteries," *International Journal of Frontiers in Engineering Technology*, vol. 4, no. 10, pp. 14–21, 2022.

[16] K. Q. Zhou, Y. Qin, and C. Yuen, "Transfer learning-based state of health estimation for lithium-ion battery with cycle synchronization," *arXiv preprint arXiv:2409.00141*, 2024.

[17] "Estimation of state of health for lithium-ion batteries using advanced data-driven techniques," *Scientific Reports*, 2025.

[18] J. Kim and J. Kowal, "Development of a Matlab/Simulink model for monitoring cell state-of-health and state-of-charge via impedance of lithium-ion battery cells," *Batteries*, vol. 8, no. 2, p. 8, 2022.

[19] J. Bilansky, M. Lacko, M. Pastor, A. Marcinek, and F. Durovsky, "Improved digital twin of Li-ion battery based on generic MATLAB model," *Energies*, vol. 16, no. 3, p. 1194, 2023.

[20] MathWorks, "Battery Management System Development in Simulink," *MATLAB/Simulink technical documentation and webinar materials*, MathWorks Inc., 2019.