

Article

Validation of Electrical Equivalent Circuit Models for Second-Life Regenerated Lithium-Based Traction Batteries

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Abstract

This study aims to verify and improve the Electrical Equivalent Circuit Model (EECM) for a regenerated VW e-Golf cell and to develop a verification and optimization framework that enhances simulation accuracy. The model is based on an identified set of EESB elements derived from enhanced measurements of the regenerated cell and is compared with the original cell. A global EESB model is implemented in the PLECS environment, comprising a charge/discharge block and a Voc versus SOC evaluation. Parameters are obtained from measurements of the regenerated VW e-Golf cell and augmented with SOC-dependent polynomial relationships for individual model components. The methodology was applied to identify EESB elements for the regenerated VW e-Golf cell and to produce an EESB model aligned with the identification results. Verification compares simulated and experimental curves in critical SOC regions (0–10%, around 30%, and during relaxation) and cross-validates regenerated versus original cells. Results show that SOC-based polynomial estimates extend the valid range of EESB elements to 0–10% SOC and improve agreement with measured trajectories. Optimization reduces the computational load and improves accuracy, particularly in critical SOC regions, supporting a robust verification framework for regenerated battery cells and guiding further research and implementation in BMS and simulation environments.

Keywords: traction electrochemical cell; electrical equivalent circuit; simulation; modeling; optimization

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1. Introduction

The global transition toward sustainable transportation has accelerated the deployment of electric vehicles (EVs), placing unprecedented demands on battery management systems (BMSs) and real-time system-level simulation architectures. To ensure operational safety, optimize state estimation, and prevent premature thermal degradation, advanced simulation platforms—such as PLECS (Plecs 5.0.2) and MATLAB/Simulink (Matlab R2025b)—require battery models that balance computational efficiency with high fidelity. While physics-based electrochemical frameworks, such as Pseudo-Two-Dimensional (P2D) models, provide microscopic insights into solid-state diffusion and interfacial kinetics, their high order of partial differential equations introduces substantial computational overhead. Consequently, Electrical Equivalent Circuit Models (EECMs)—

typically configured with an Open-Circuit Voltage (OCV) source, a series ohmic resistance (R_0), and two distinct polarization branches (R_1C_1 and R_2C_2)—remain the industry standard for real-time BMS implementation and Hardware-in-the-Loop (HIL) testing [1–6].

However, the fidelity of an EECM relies heavily on capturing the complex, non-linear dependencies of its parameters across the operational space, particularly as a function of the State of Charge (SOC) and dynamic current profiles. While parameter identification protocols are well-established for pristine lithium-ion cells, significant gaps remain in modeling cells that have undergone regeneration processes or secondary life conditioning [7–10]. Cell regeneration—whether induced via electrochemical reconditioning, extreme pulse protocols, or second-life sorting—fundamentally alters the localized transport dynamics within the porous electrode matrix. Changes in the Solid Electrolyte Interphase (SEI) thickness, the micro-cracking of active material particles, and non-uniform lithium plating modify the kinetic resistance and interfacial capacitance of the cell. As a result, applying baseline parameterization models derived from fresh cells to regenerated units introduces severe voltage prediction errors and miscalculated SOC estimates. Although the existing literature emphasizes the necessity of SOC-dependent parameterization [11–15], systematic empirical models that capture the parameter shifts specific to regenerated lithium-ion chemistries remain scarce. Specifically, the divergence in time constants ($\tau_i = R_iC_i$) and charge-transfer resistances between pristine and regenerated states is often oversimplified, neglecting the altered relaxation behaviors observed during rapid charge–discharge transients [16–19].

This study combines the identification of EECM elements from measurements of a regenerated VW e-Golf cell with the development of a global EECM implemented in the PLECS environment. The model includes Voc–SOC dependencies and SOC-dependent polynomial relationships that govern individual model components, enabling coverage of the measured responses without substantial overfitting. The third-order form of the polynomials is employed to capture the observed dynamics while remaining computationally tractable. The approach aligns with current trends in the literature that advocate a hybrid physics-based and data-driven modeling framework complemented by empirical verification against experimental data [20–23]. In critical SOC regions, particularly 0–10% and during relaxation, SOC-based polynomials improve the agreement between simulated and measured trajectories and enhance the reliability of cell capacity estimations.

The unique contributions of this research approach represent a major step forward for the second-life battery industry. While standard modeling approaches are typically optimized for first-life cells, this paper introduces a specialized framework designed to handle the unique physical and electrochemical realities of regenerated batteries. Most conventional equivalent circuit models struggle to provide reliable predictions in extreme low-charge states, often excluding or failing to parameterize the deep-discharge region. The study proves that the applied electrochemical pulsed-charging protocol restores nominal cell capacity in a way that physically expands the valid, predictable range of the EECM elements all the way down to the critical 0–10% SOC region. This allows for highly reliable cell capacity estimations and transient tracking even when the cell is nearly depleted.

2. Regeneration of the Battery Utilizing Pulsed Charging

Pulse charging involves the use of charge current pulses, which have a carefully controlled duty cycle, frequency, and peak amplitude to charge the LiPo battery. Figure 1 shows a pictorial representation of the waveforms of a pulse charger under operation. These carefully controlled charge current pulses ensure that the lithium ions that are electrochemically produced during each pulse from the cathode migrate to the anode and successfully intercalate before the next group of ions arrive at that electrode. This prevents

the accumulation of Li^+ ions on the surface of the electrode and hence mitigates dendrite formation, which is detrimental to the battery cycle life and inherently can be a safety risk [1,2].

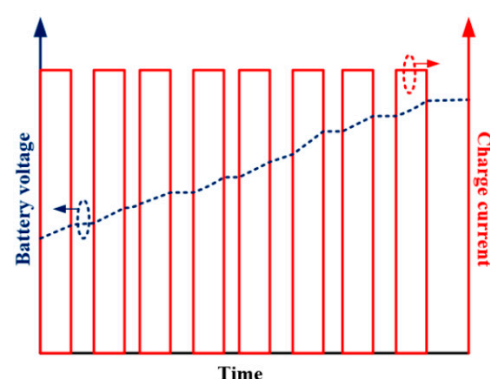


Figure 1. Illustration of the pulsed battery charging waveforms.

Charging Cycle Used for Battery Regeneration

The regeneration charging algorithm that was used (Figure 2) for the cell regeneration is divided into 30 charging cycles and 30 cycles of pause mutually alternating, whereby one cycle is lasting 1 s (Subsequence 1). After it, the 5 min of regeneration is applied on the battery (Subsequence 2). One sequence of the regeneration algorithm, valid for deep discharge, lasted 126 min.

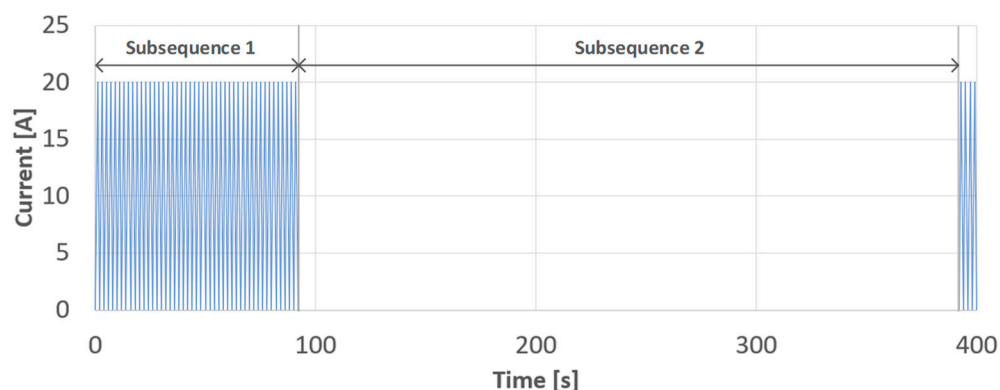


Figure 2. Time waveform of one part of the charging cycle used for battery regeneration.

The charging current impulse had an amplitude of 20 A, which refers to 1/3 of the capacity of the cell. The amplitude of the charging voltage was 3.65 V. For a given battery, the application of six sequences was realized to achieve the required OCV on the device, while a 16 h resting period was applied between individual sequences [20]. The flowchart of this algorithm is shown on Figure 3, while it was implemented within the test bench set-up described within [19].

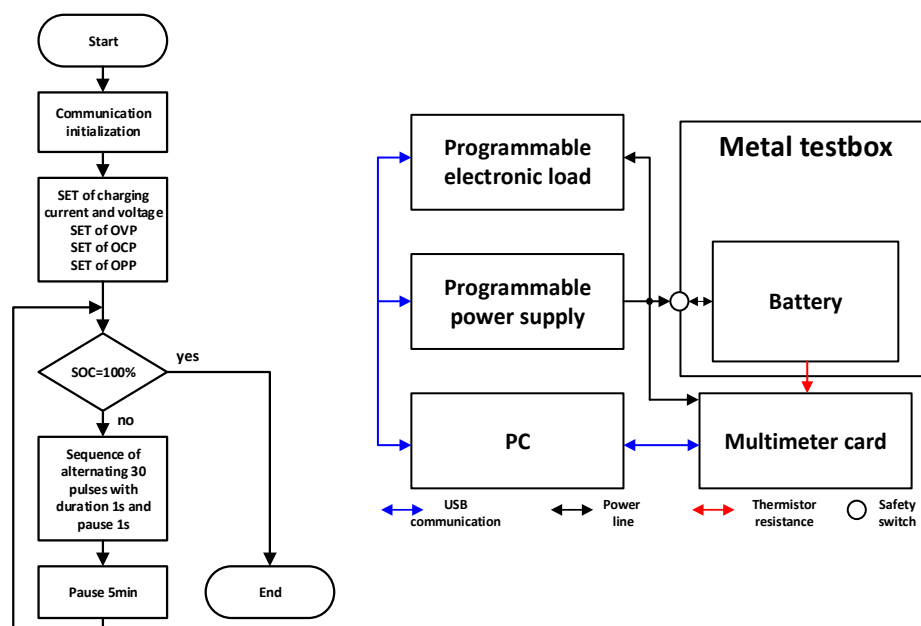


Figure 3. Flowchart of regeneration charging algorithm (left) and block diagram of laboratory mock-up used (right).

3. Comparative Analysis of Characteristic Curves for Identification of the EECM for Unregenerated and Regenerated Cell

This section presents the experimental measurement datasets utilized for the parameter identification of the Electrochemical Equivalent Circuit Model (EECM) elements corresponding to the regenerated Volkswagen (VW) e-Golf battery cell. To facilitate a comparative analysis and quantify the efficacy of the applied regeneration algorithm, the operational characteristics of the baseline (unregenerated) cell are concurrently evaluated.

The primary electrical and thermodynamic characteristics of the unregenerated baseline cell are illustrated in Figure 4, while the corresponding post-regeneration discharge curve is depicted in Figure 5. A systematic cross-examination of these characteristic curves provides a benchmark to assess the performance, parametric shifts, and functional impact induced by the proposed regeneration methodology.

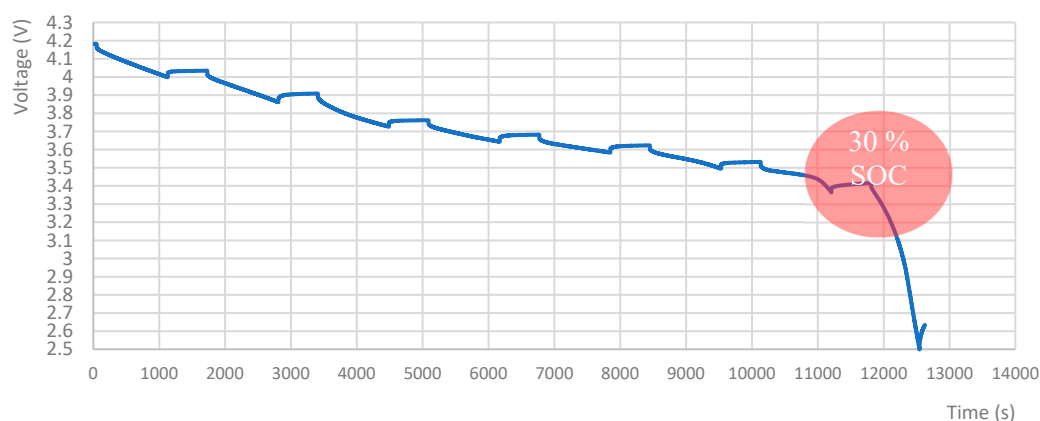


Figure 4. Discharge curve of unregenerated cell for EECM component identification.

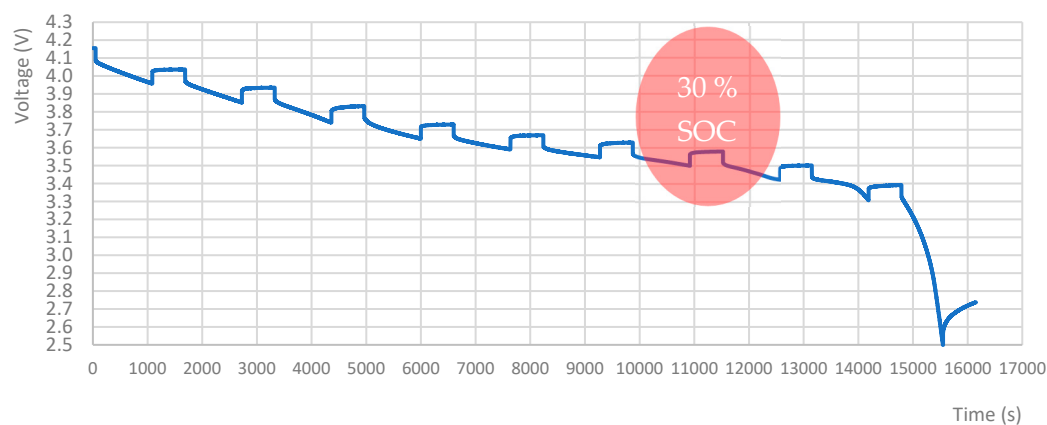


Figure 5. Discharge curve of regenerated cell for EECM component identification.

A comparative analysis of the characteristic curves presented in Figures 4 and 5 reveals a significant divergence in the transient voltage response during the cell relaxation periods. This morphological shift in the relaxation profiles is primarily attributed to the parametric variation in the Equivalent Circuit Model (ECM) elements, directly induced by the electrochemical restoration of the battery cell. Furthermore, evaluating the complete charging profile sequences demonstrates pronounced variance in the cell's internal resistance profile—characterized as the voltage stiffness—specifically in the region of the 30% State of Charge (SOC). These empirical findings demonstrate that the deployment of the proposed regeneration algorithm effectively facilitated the recovery of the cell's nominal capacity. A global EECM model composed of a series resistance R_s and two RC branches (R_1-C_1 and R_2-C_2) in parallel, with an Open-Circuit Voltage OCV that is a function of SOC, has been identified for both the unregenerated and regenerated cell. All RC parameters and OCV are expressed as SOC-dependent polynomials (third-order) to reflect regeneration-induced changes in the cell behavior. The process of the identification and design of the main components of the electrical equivalent model of the tested battery was performed according to methodologies described within [19,20].

A high-resolution comparative evaluation of the voltage profiles during the relaxation phase of the EECM parameter identification process is illustrated in Figures 6 and 7. These figures elucidate the micro-level transient dynamics and voltage recovery behavior, providing the empirical foundation required to quantify the precise parametric shifts between the unregenerated and regenerated states.

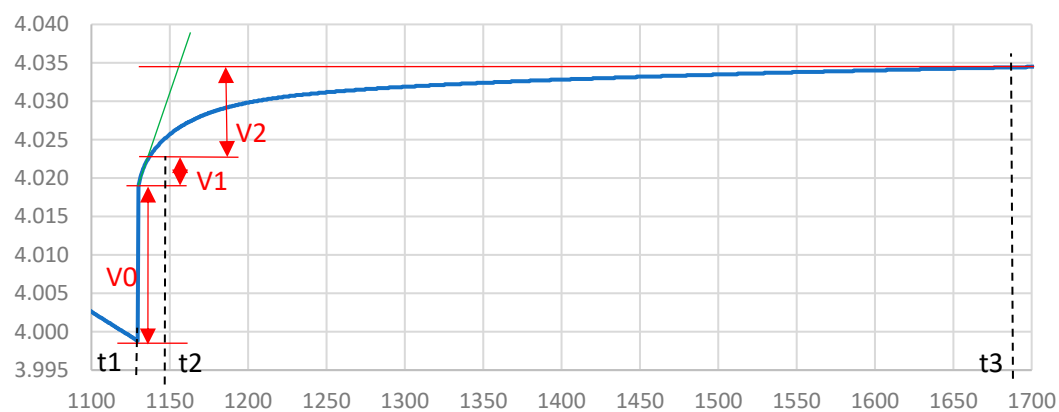


Figure 6. Details of the voltage regeneration during the relaxation phase for an unregenerated cell (details for 90% of SOC).

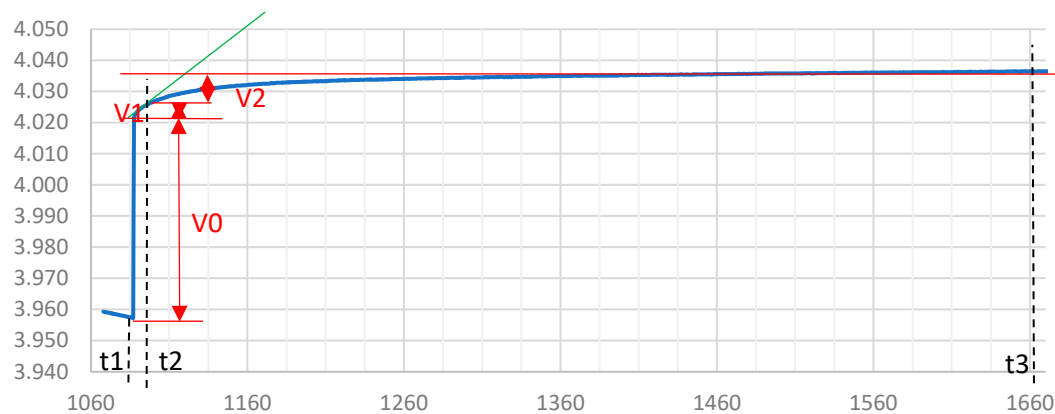


Figure 7. Details of the voltage regeneration during the relaxation phase for a regenerated cell (details for 90% of SOC).

Based on the empirical findings and the comparative evaluation of the characteristic curves, it can be concluded that the electrochemical regeneration of the cell expanded the parametric dependency of the ECCM elements down to the 0–10% State of Charge (SOC) region (Figure 5). This phenomenon serves as preliminary evidence that the deployment of the regeneration algorithm achieved the primary objective of enhancing the cell's nominal capacity. The quantitative comparison of key metrics has been previously investigated and published within [24] and [25].

However, it is necessary to establish that the exact operational envelope, safe boundary conditions, and long-term stability limits of the regenerated cell require further systemic validation. These aspects will be explicitly addressed and detailed in subsequent phases of this research.

ECCM Simulation Model Design

Utilizing the experimental datasets derived from the parameter identification process, the individual ECCM components were successfully quantified as a function of the cell's State of Charge (SOC). A comprehensive synthesis of these extracted parameters is compiled in Table 1, which delineates the discrete values of the resistive–capacitive ($R - C$) network components across an operational SOC range of 10% to 90%, referencing the transient data illustrated in Figure 7. Furthermore, the Open-Circuit Voltage (OCV) characteristic curve parameters, mapped within the 100% to 10% SOC spectrum, are systematically cataloged in Table 2.

Table 1. Values of ECCM RC elements of regenerated cell.

SOC	R_s (Ω)	R_1 (Ω)	R_2 (Ω)	C_1 (F)	C_2 (F)
90%	0.0077	0.0006	0.0012	21,580	464,800
80%	0.0078	0.0008	0.0014	15,414	403,241
70%	0.0076	0.0006	0.0029	19,920	204,733
60%	0.0076	0.0005	0.0014	19,153	411,512
50%	0.0076	0.0004	0.0017	20,750	354,416
40%	0.0076	0.0004	0.0018	20,750	328,657
30%	0.0076	0.0004	0.0017	21,342	336,643
20%	0.0076	0.0004	0.0014	24,900	408,083
10%	0.0076	0.0004	0.0022	22,636	263,060

Table 2. Values of EECM OCV of regenerated cell.

SOC	100%	90%	80%	70%	60%	50%	40%	30%	20%	10%
Voc (V)	4175	4070	3967	3867	3759	3693	3643	3605	3529	3443

Following the parameter extraction, a non-linear polynomial regression analysis was conducted on the empirical datasets compiled in Tables 1 and 2. This mathematical fitting procedure established the continuous functional dependencies for the resistive–capacitive ($R - C$) network components (Figures 8 and 9) and the Open-Circuit Voltage (OCV) characteristics (Figure 10) as a function of the State of Charge (SOC). From these graphical trends, analytical governing equations—designated as Equations (2)–(7)—were derived to formulate the core behavior of the Electrochemical Equivalent Circuit Model (EECM) for the regenerated Volkswagen (VW) e-Golf battery cell. To ensure numerical efficiency, the individual constituent equations were constrained to a maximum of a third-order polynomial, formalized as follows:

$$f(SOC) = a_3 \cdot SOC^3 + a_2 \cdot SOC^2 + a_1 \cdot SOC + a_0 \quad (1)$$

where a_3, a_2, a_1 , and a_0 represent the regression coefficients unique to each model parameter. Restricting the mathematical formulation to third-order polynomials provides a critical balance: it guarantees a high goodness-of-fit to the experimental data while maintaining a negligible computational burden.

$$R_s(SOC) = 4 \times 10^{-6} \cdot SOC^2 - 6 \times 10^{-5} \cdot SOC + 0.0078 \quad (2)$$

$$R_1(SOC) = 5 \times 10^{-6} \cdot SOC^2 - 9 \times 10^{-5} \cdot SOC + 0.0008 \quad (3)$$

$$R_2(SOC) = 2 \times 10^{-5} \cdot SOC^3 - 0.0003 \cdot SOC^2 + 0.0015 \cdot SOC - 4 \times 10^{-5} \quad (4)$$

$$C_1(SOC) = 82,070 \cdot SOC^3 - 111,220 \cdot SOC^2 + 33,993 \cdot SOC + 20,500 \quad (5)$$

$$C_2(SOC) = 2 \times 10^6 \cdot SOC^3 - 3 \times 10^6 \cdot SOC^2 + 1 \times 10^6 \cdot SOC + 198,981 \quad (6)$$

- R_s represents the ohmic (series) internal resistance of the cell (Ω).
- R_1 and R_2 denote the polarization resistances associated with the respective short-term and long-term transient RC branches (Ω).
- C_1 and C_2 denote the polarization capacitances (expressed in Farads, F) corresponding to the short-term and long-term electrochemical relaxation processes, respectively.
- SOC represents the cell's State of Charge, utilized as a normalized or scaled input variable according to the simulation environment configuration.

The equilibrium potential of the battery cell, which forms the baseline for the electrical model, is established by the Open-Circuit Voltage (OCV). Based on the regression analysis of the empirical dataset, the continuous second-order polynomial function mapping the OCV relationship across the State of Charge (SOC) spectrum is defined as follows:

$$OCV(SOC) = 0.3768 \cdot SOC^2 + 0.3687 \cdot SOC + 3.4276 \quad (7)$$

where:

- OCV represents the Open-Circuit Voltage of the cell expressed in Volts (V).

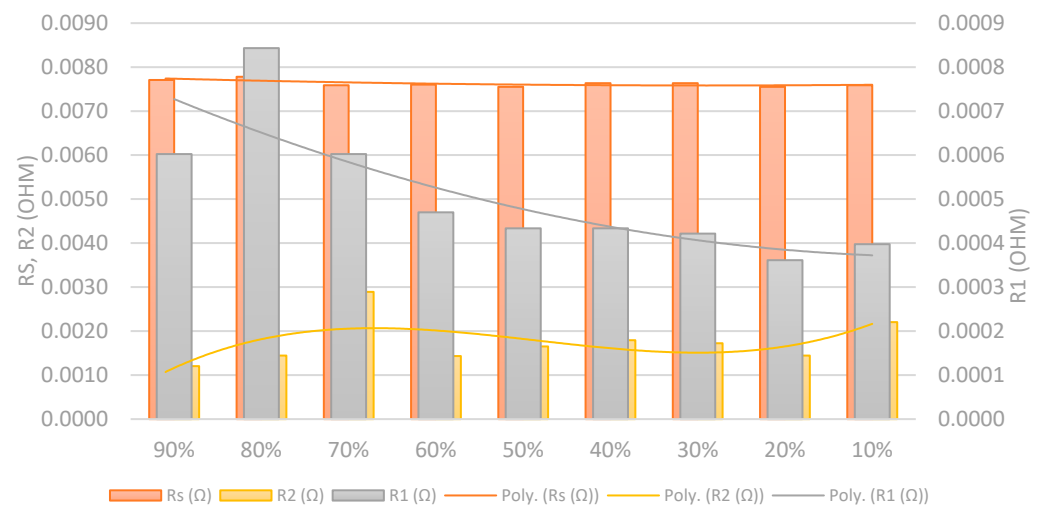


Figure 8. Graphical dependence of the resistance elements of EECM as a function of the State of Charge (SOC) for the regenerated battery cell.

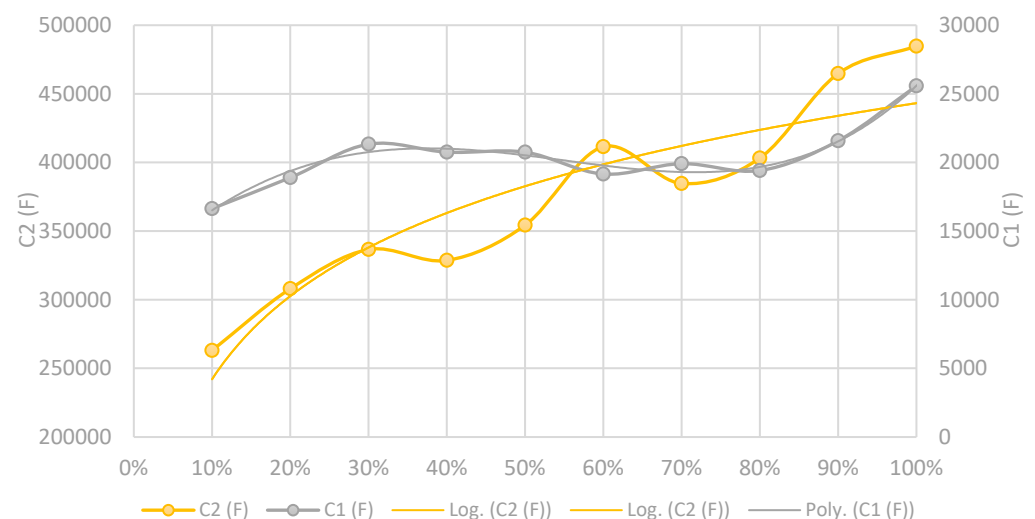


Figure 9. Graphical dependence of the capacitive elements of EECM as a function of the State of Charge (SOC) for the regenerated battery cell.

By integrating the derived polynomial expressions for both the resistive–capacitive network components and the Open-Circuit Voltage characteristics, the comprehensive simulation model was successfully established. The resulting electrical schematic and block configuration of the implemented EECM for the regenerated battery cell are depicted in Figure 11.

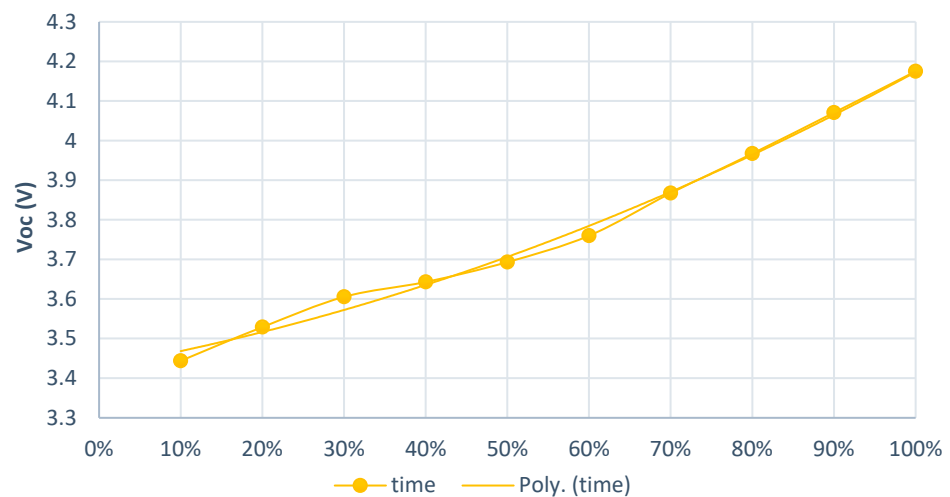


Figure 10. Graphical dependence of the open voltage circuit element of EECM as a function of the State of Charge (SOC) for the regenerated battery cell.

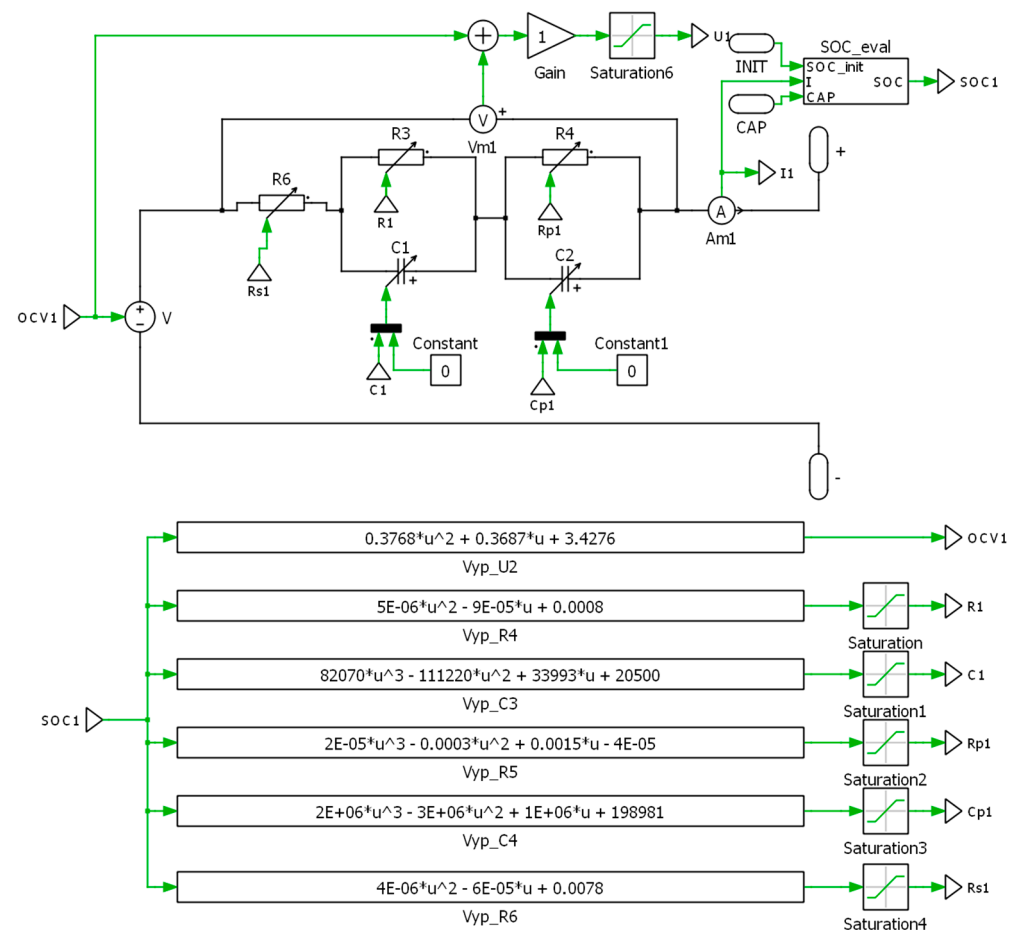


Figure 11. Electrical schematic and structural configuration of the developed simulation model for the regenerated battery cell.

At this point, it must be declared that the same approach is done for the unregenerated cell EECM elements determination and simulation model design.

4. Simulation-Based Verification of the Regenerated Battery Cell

To validate the accuracy and fidelity of the derived mathematical model, a simulation-based verification process was executed. The developed EECM, parameterized by equations (2)–(7), was subjected to dynamic load profiles to evaluate its predictive performance against empirical datasets obtained from the regenerated Volkswagen (VW) e-Golf battery cell.

A high-resolution comparison between the empirical discharge profile derived from laboratory measurements and the uncalibrated response of the simulation model (Figure 12) reveals two distinct operational regimes:

- Mid-to-High SOC Spectrum ($15\% \leq SOC \leq 100\%$): The equivalent circuit model (ECM) exhibits high fidelity and closely tracks the experimental baseline. The regression polynomials successfully replicate the pseudo-linear thermodynamic discharge behavior of the cell within this optimal range.
- Low SOC Boundary ($SOC < 15\%$): A pronounced divergence manifests as the cell approaches deep discharge. While the empirical boundary potential drops steeply to a cutoff voltage of 3.3 V, the pre-optimization simulation model terminates prematurely at a baseline of 3.4 V.

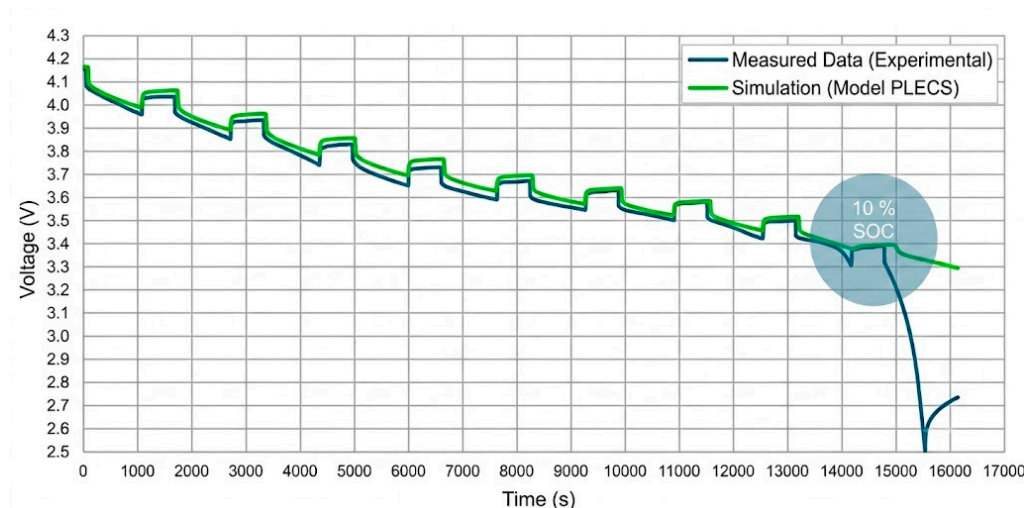


Figure 12. Comparison between the empirical discharge profile derived from laboratory measurements and the uncalibrated response of the simulation model.

Optimization of the Simulation Model for Enhanced Predictive Accuracy

To mitigate the localized tracking anomalies identified within the low State of Charge ($SOC < 15\%$) domain, a targeted optimization framework was deployed. The primary objective of this calibration procedure was to refine the parameter trajectories of the EECM—specifically the boundary limits of the non-linear resistance elements (R_s, R_1, R_2) and the Open-Circuit Voltage (OCV) coefficients—thereby maximizing global simulation fidelity without escalating computational complexity.

The optimization of the simulation model specifically targets the enhancement of parameter trajectories and electrochemical dependencies within the low State of Charge domain ($SOC < 10\%$). To achieve this, the optimization routine isolated the specific segment of the parameter identification algorithm corresponding to the 0% SOC boundary during the final relaxation phase (Figure 13).

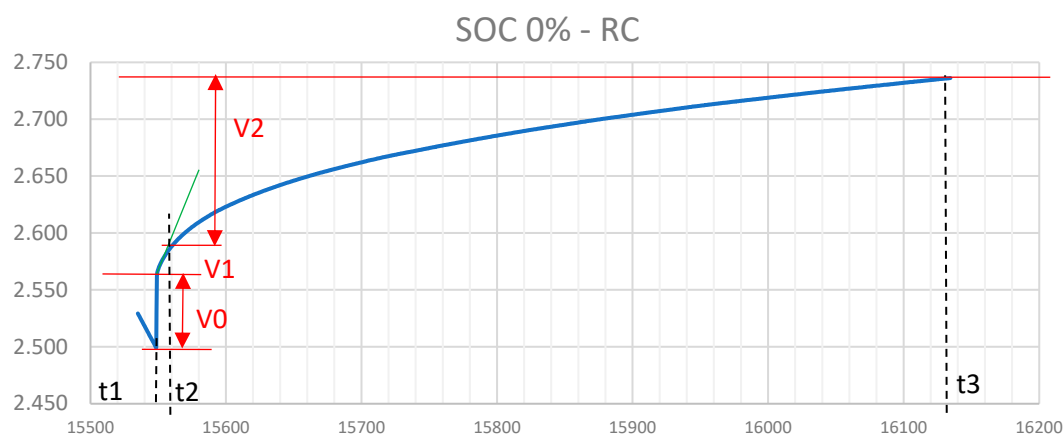


Figure 13. Transient voltage profile during the relaxation phase at the 0% SOC state for the regenerated battery cell.

Focusing the calibration on this terminal transient state is highly critical; at the end of the discharge cycle, the cell exhibits maximum concentration polarization and a prolonged voltage relaxation tail. By mathematically re-evaluating this specific boundary node, the transient dynamic response of the *RC* networks can be precisely adjusted to match the real-world recovery voltage of the cell, effectively resolving the prior tracking discrepancies without inducing overfitting in the mid-SOC regions.

By analyzing the transient voltage recovery profile (Figure 13) and applying the established parameter identification methodology for the Equivalent Circuit Model (ECM) *RC* networks [19,20], the discrete electrical parameters for this specific boundary state were successfully extracted. These calculated values, along with the corresponding steady-state Open-Circuit Voltage (*OCV*) for this terminal condition, are summarized in Table 3.

Table 3. Extracted *RC* parameter values of the Equivalent Circuit Model (ECM) for the 0% SOC relaxation phase.

0%	Value	Unit
Idisch	8.3	(A)
V0_0%	6.23×10^{-2}	(V)
V1_0%	2.60×10^{-2}	(V)
V2_0%	1.75×10^{-1}	(V)
Rs	7.51×10^{-3}	(Ω)
R1	3.13×10^{-3}	(Ω)
R2	2.11×10^{-2}	(Ω)
t2-t1	12	(s)
t3-t1	570	(s)
C1	3.83×10^{-3}	(F)
C2	2.70×10^{-4}	(F)
OCV	2675	(V)

The continuous operational trajectories of the Equivalent Circuit Model (ECM) parameters, recalibrated to incorporate the critical 0% State of Charge (SOC) boundary node, are graphically illustrated in Figures 14–16. Each figure explicitly details the corresponding mathematical approximation functions derived via non-linear regression analysis. These updated formulations were subsequently embedded within the simulation

model of the regenerated battery cell to accurately govern the dynamic behavior of the resistive and capacitive elements across the full operating spectrum.

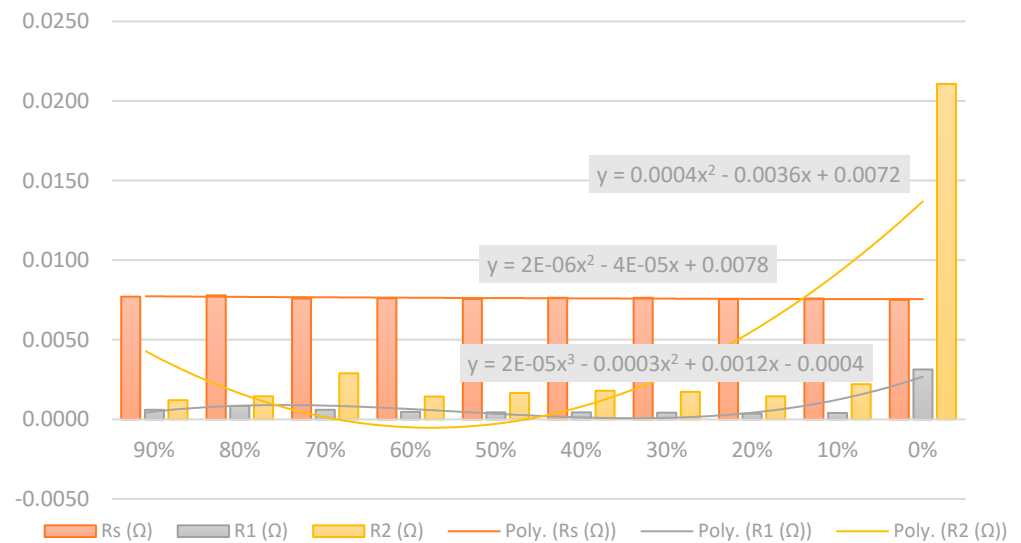


Figure 14. Graphical dependency of the ECM resistive parameter values as a function of SOC for the optimized simulation model of the regenerated battery cell.

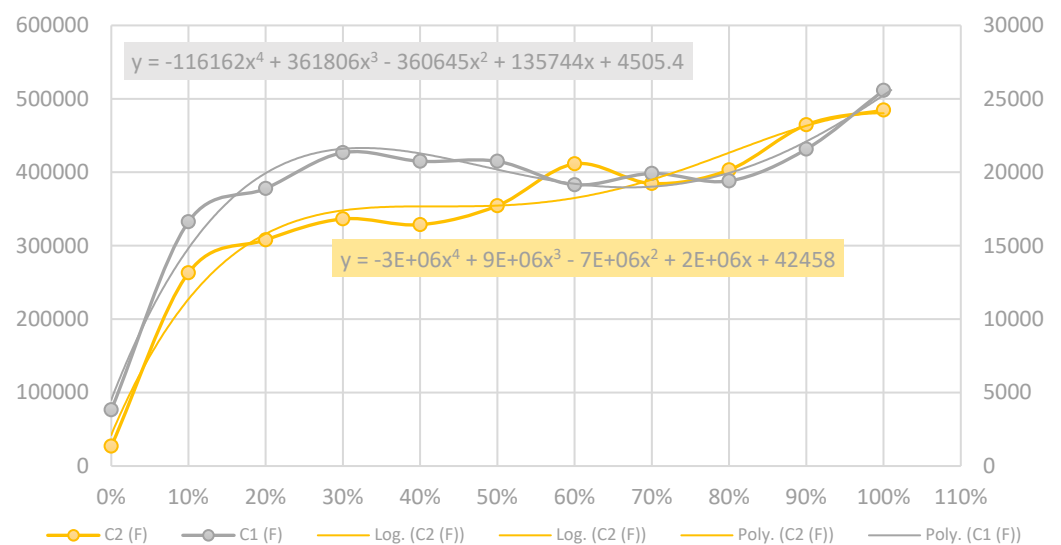


Figure 15. Graphical dependency of the ECM capacitive parameter values as a function of SOC for the optimized simulation model of the regenerated battery cell.

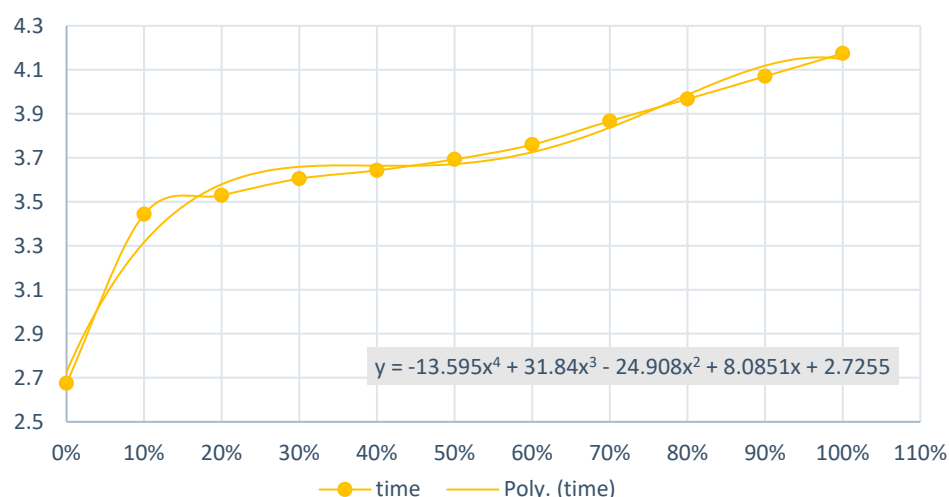


Figure 16. Graphical dependency of the Open-Circuit Voltage (OCV) parameter as a function of SOC for the optimized simulation model of the regenerated battery cell.

As indicated by the updated regression formulations, the newly implemented mathematical approximations utilize a higher polynomial order. This expansion was strictly necessary to accurately encompass the severe non-linearities introduced by the terminal relaxation phase at the 0% SOC boundary.

Crucially, from an embedded systems perspective, this structural refinement does not present a performance bottleneck. Because the formulation relies on algebraic polynomial equations rather than iterative transcendental functions or complex differential sub-models, the execution requires negligible floating-point operations. By relying strictly on explicit algebraic polynomial equations rather than computationally intensive partial differential equations or iterative numerical solvers, the proposed modeling framework maintains direct real-time compatibility. This mathematical design ensures that the transition from a third-order baseline to the optimized model yields a massive boost in low-SOC tracking accuracy with practically zero hardware execution penalty.

Following the integration of the higher-order approximation equations—which explicitly incorporate the terminal electrochemical dynamics of the 0% SOC boundary zone, the simulation analysis was executed to verify the updated cell characteristics. This validation procedure serves to evaluate the global tracking precision of the recalibrated model and confirm the elimination of the prior boundary deviations. The definitive output profiles and comparative curves obtained from this verification analysis are presented below (Figure 17).

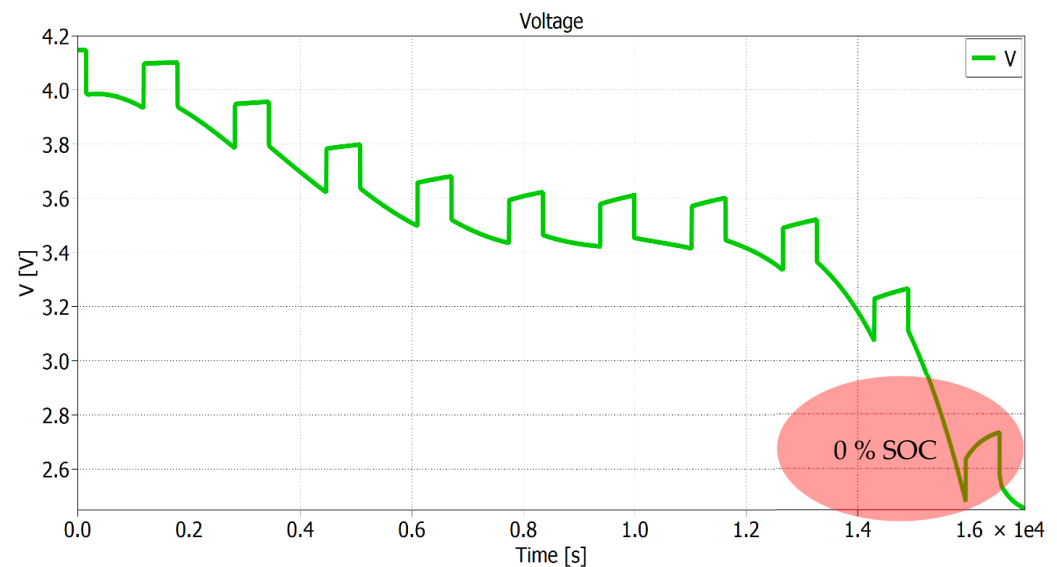


Figure 17. Discharge profile of the updated simulation model of the regenerated cell.

The achieved simulation results clearly demonstrate a substantial enhancement in predictive accuracy across the entire State of Charge (SOC) spectrum. Most notably, this calibration framework successfully eliminates the prior discrepancies within the critical low-capacity domain ($SOC \rightarrow 0\%$). When benchmarked against the original laboratory dataset previously illustrated in Figure 13, the optimized model seamlessly tracks the sharp asymptotic voltage drop at the end of discharge, thereby validating the efficacy of the targeted parameter extraction routine (Figure 18).

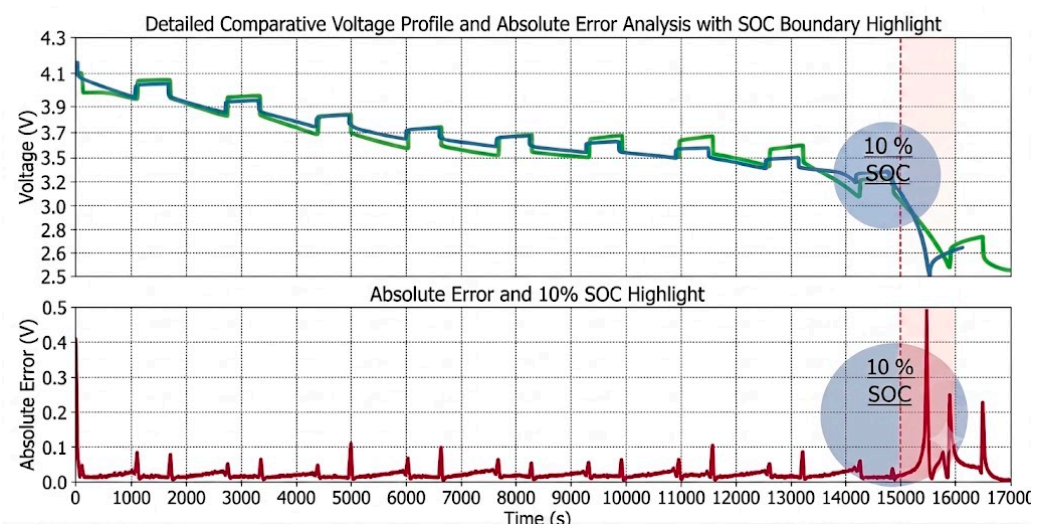


Figure 18. Discharge profile of the updated simulation model of the regenerated cell. Blue line—measured data. Green line—simulated data. Red line—absolute error between simulation and measurement.

To systematically assess the impacts of both the physical restoration process and the mathematical calibration, a high-resolution benchmark (Figure 18) was conducted among the following three distinct model architectures:

- **Degraded State Baseline Model:** The simulation model capturing the VW e-Golf battery cell prior to the regeneration process, representing the original, degraded state at the boundary of its operational lifespan (End-of-Life benchmark).

- Post-Regeneration Transient Model: The simulation model representing the restored VW e-Golf cell following the application of the pulse-charging regeneration protocol, configured with a predefined frequency and current impulse amplitude.
- Optimized Post-Regeneration Model: The final calibrated simulation model of the restored VW e-Golf cell, incorporating the targeted boundary-layer optimization framework to maximize global tracking fidelity.

5. Conclusions

This investigation successfully established, verified, and optimized a 2-RC Electrical Equivalent Circuit Model (EECM) implemented in the PLECS environment to capture the complex, non-linear electrochemical behavior of second-life regenerated traction battery cells (VW e-Golf). The application of a specialized pulsed-charging electro-reconditioning protocol fundamentally restored cell performance, extending the predictable parameterization spectrum down to the critical 0–10% State of Charge (SOC) region and altering transient relaxation behavior, as well as voltage stiffness, around 30% SOC. While an initial baseline parameterization utilizing third-order polynomials provided high tracking fidelity across mid-to-high SOC ranges ($SOC \geq 15\%$), it exhibited noticeable voltage prediction errors near deep discharge. To resolve this, a targeted boundary-layer optimization framework was executed, isolating the terminal 0% SOC relaxation phase ($I_{\text{disch}} = 8.3 \text{ A}$) to recalibrate the model's non-linear resistive (R_s, R_1, R_2) and capacitive (C_1, C_2) trajectories alongside the Open-Circuit Voltage (OCV) profile. Integrating these updated higher-order algebraic regression equations completely eliminated low-SOC tracking discrepancies and accurately mapped the sharp asymptotic voltage drop near the cutoff without inducing overfitting in upper operational regimes. Crucially, because the parameterization relies strictly on explicit algebraic polynomial evaluations rather than computationally intensive differential solvers, the optimized model maintains an exceptionally light floating-point burden, rendering it directly deployable for real-time Hardware-in-the-Loop (HIL) testing and embedded Battery Management System (BMS) architectures. Ultimately, this research provides a validated, high-fidelity modeling framework for regenerated lithium-ion cells, laying the essential groundwork for future studies to incorporate wide-range thermal cross-dependencies, assess long-term capacity fade during extended secondary cycling, and ensure operational safety in commercial second-life energy storage modules.

Author Contributions: Concaepthualization, methodology, software, validation, formal analysis, investigation, data curation, writing original draft, funding acquisition, M.F.; resources, M.D.; visualization, formal analysis, D.A. All authors have read and agreed to the published version of the manuscript.

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