Project Review - Fast-Charging Optimization Using GA and PSO on a Single Particle Battery Model

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January 2, 2026

1 Overview of the Single Particle Model (SPM)

The Single Particle Model (SPM) is a physics-based electrochemical model commonly used to describe the behavior of lithium-ion battery cells with significantly reduced computational complexity compared to full Doyle–Fuller–Newman (DFN) models. In the SPM, each electrode is represented by a single, representative spherical particle, within which lithium diffusion is modeled explicitly, while spatial variations across the electrode thickness are neglected.

This simplification allows the SPM to capture key electrochemical and thermal dynamics relevant for charging studies, fast-charging optimization, and control-oriented analysis, while remaining computationally tractable for iterative simulation and optimization.

2 Key Modeling Assumptions

The Simscape Battery Single Particle Model relies on the following core assumptions:

- Each electrode (anode and cathode) is represented by a single spherical particle.
- Lithium diffusion is modeled only in the radial direction within each particle.
- Electrolyte concentration is spatially averaged across the cell thickness.
- Charge transport in solid and electrolyte phases is lumped into effective ohmic overpotentials.
- Temperature is modeled as a lumped thermal mass with uniform cell temperature.
- Side reactions (e.g., SEI growth, lithium plating) are not explicitly modeled.

These assumptions make the SPM particularly suitable for control and optimization studies where repeated simulations are required.

3 Electrochemical State Variables

The primary state variables in the SPM are:

- State of Charge (SOC)
- Lithium concentration within anode and cathode particles
- Average electrolyte concentration
- Cell temperature

SOC is directly related to the normalized average stoichiometry of the anode active material.

4 Lithium Diffusion in Active Material

Lithium diffusion within each electrode particle is governed by Fick's second law in spherical coordinates:

$$\frac{\partial c_s}{\partial t} = D_s \left(\frac{1}{r^2} \frac{\partial}{\partial r} \left(r^2 \frac{\partial c_s}{\partial r} \right) \right) \tag{1}$$

where:

- c_s is the solid-phase lithium concentration
- D_s is the diffusion coefficient of the active material
- r is the radial coordinate within the particle

The surface concentration obtained from this diffusion model directly influences reaction kinetics and terminal voltage.

5 Reaction Kinetics

Electrochemical reactions at the electrode–electrolyte interface are modeled using the Butler–Volmer equation:

$$I = I_0 \left[\exp\left(\frac{\alpha_a F \eta}{RT} \right) - \exp\left(-\frac{\alpha_c F \eta}{RT} \right) \right] \tag{2}$$

where:

- I is the applied current
- I_0 is the exchange current density
- η is the charge transfer overpotential
- F is Faraday's constant
- R is the universal gas constant
- T is the cell temperature

This formulation captures the nonlinear dependence of overpotential on current and temperature.

6 Open-Circuit Voltage (OCV)

The open-circuit voltage of the cell is calculated as the difference between cathode and anode equilibrium potentials:

$$V_{OC} = U_{cathode}(\theta_c) - U_{anode}(\theta_a) \tag{3}$$

where $U_{cathode}$ and U_{anode} are obtained from experimentally derived lookup tables as functions of electrode stoichiometry.

7 Terminal Voltage Expression

The terminal voltage predicted by the SPM is given by:

$$V = V_{OC} + \eta_{ct} + \eta_{mt} + I R_{ohmic} \tag{4}$$

where:

- η_{ct} is the charge-transfer overpotential
- η_{mt} is the mass-transport overpotential
- R_{ohmic} represents lumped resistive effects

This formulation explains the instantaneous voltage response observed when the charging current is changed.

8 Thermal Model

Thermal behavior is modeled using a lumped thermal mass:

$$C_{th} \frac{dT}{dt} = Q_{gen} - Q_{loss} \tag{5}$$

where:

- C_{th} is the battery thermal mass
- Q_{gen} is the internally generated heat (primarily ohmic and reaction losses)
- Q_{loss} represents heat dissipation to the environment

Heat generation is computed as:

$$Q_{gen} = I(V - V_{OC}) \tag{6}$$

This thermal formulation captures the slow temperature dynamics observed during charging.

9 Simulation Setup and Model Architecture

9.1 Overall Simulation Structure

Figure 1 illustrates the complete Simulink–Simscape simulation setup used in this study. The model integrates a physics-based Single Particle Model (SPM) of a lithium-ion cell with a lumped thermal network, a supervisory charging controller, and a Coulomb-counting-based state-of-charge (SOC) estimator. This modular architecture allows independent development and debugging of electrochemical, thermal, and control subsystems, while enabling systematic evaluation of different charging strategies.

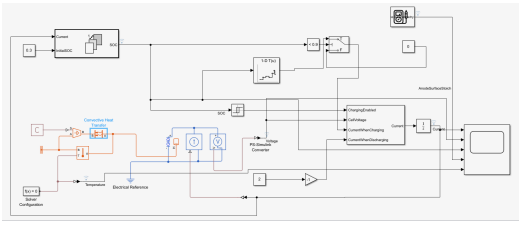

Figure 1: Simulink–Simscape simulation setup for the Single Particle Model based fast-charging study.

9.2 Thermal Circuit Representation

The thermal behavior of the battery cell is modeled using a lumped-parameter thermal circuit. The SPM block exposes a thermal port representing the average cell temperature, which is connected to a thermal mass element and a convective heat transfer element. This configuration captures the dominant heat storage and heat rejection mechanisms at the cell level.

The governing thermal equation implemented by the Simscape network is

$$C_{th}\frac{dT}{dt} = Q_{gen} - hA(T - T_{amb}) \qquad (7)$$

where C_{th} is the effective thermal mass of the cell, Q_{gen} is the internally generated heat due to electrochemical losses, hA is the effective convective heat transfer coefficient, and T_{amb} is the ambient temperature. The model assumes a spatially uniform temperature within the cell, which is appropriate for system-level charging and control studies.

9.3 Charging Control Logic (CC–CV Framework)

A supervisory Constant-Current–Constant-Voltage (CC–CV) charging framework is implemented to regulate the battery current during charging. In the initial phase, the controller enforces a constant charging current to rapidly increase the state of charge. As the battery approaches predefined SOC or voltage limits, the controller reduces or reverses the applied current to prevent overcharging and ensure safe operation.

The controller structure allows both charging and discharging currents to be explicitly commanded. Logical switching based on SOC thresholds enables automatic termination or reversal of charging once the target SOC is reached. This behavior was observed during debugging and explains the non-monotonic SOC trajectories beyond the charging cutoff.

9.4 Piecewise Current Definition Using Lookup Tables

To enable flexible fast-charging strategies, a one-dimensional lookup table is used to define piecewise-constant charging currents as a function of SOC. The current profile is defined as

$$I(SOC) = \begin{cases} I_1, & SOC < SOC_{break} \\ I_2, & SOC \geq SOC_{break} \end{cases} \qquad (8)$$

where I_1 and I_2 are constant current levels and SOC_{break} is the switching threshold. This formulation enables multi-stage constant-current charging while remaining simple enough for simulation-based optimization. In the present work, the lookup table structure is fixed, and the current magnitudes and switching point are treated as tunable parameters for later evaluation.

9.5 State-of-Charge Estimation via Coulomb Counting

The state of charge is estimated using a Coulomb counting method, which integrates the applied current over time relative to the nominal cell capacity. The SOC evolution is given by

$$SOC(t) = SOC(t_0) + \frac{1}{Q_{nom}} \int_{t_0}^{t} I(\tau)\, d\tau \quad (9)$$

where $SOC(t_0)$ is the initial SOC, Q_{nom} is the nominal cell capacity, and $I(t)$ is the terminal current (positive for charging). Coulomb counting provides a computationally efficient and transparent SOC estimate that is well-suited for simulation and optimization studies, where the applied current and initial conditions are known accurately.

10 SPM Parameterization and Data Sources

The electrochemical and thermal parameters used in the Single Particle Model were adopted from the parameter set introduced by Chen et al. (2020) and made available through the PyBaMM open-source battery modeling framework. This parameterization represents a graphite–NMC lithium-ion cell and has been widely used and validated in the literature for reduced-order electrochemical modeling.

The Chen2020 parameter set provides physically consistent values for electrode geometry, solid-phase diffusion coefficients, exchange current densities, open-circuit voltage functions, and lumped thermal properties. These parameters were selected to ensure that the Simscape SPM implementation reflects realistic lithium-ion cell behavior while remaining computationally efficient for repeated simulation and optimization.

By relying on a well-established and openly documented parameter set, the present work focuses on charging strategy formulation and system-level behavior rather than parameter identification or cell-specific tuning.

11 Practical Simplification of Charging Control Logic

Initial simulations employed a conventional Constant-Current–Constant-Voltage (CC–CV) charging controller. However, when coupled with the physics-based SPM and variable-step Simscape solvers, the CC–CV controller exhibited rapid current variations near the voltage and SOC transition regions. These fast switching events led to numerical stiffness, transient current spikes, and degraded simulation robustness.

To ensure stable and interpretable simulation results, the CC–CV controller was subsequently simplified for the present study. The voltage limit was set sufficiently high such that the controller effectively acted as a supervisory switch rather than an actively regulating CV loop. As a result, the charging process was dominated by constant-current operation with controlled termination based on SOC and voltage thresholds.

This simplification isolates the impact of current magnitude and SOC-based switching on charging performance while avoiding numerical artifacts introduced by aggressive voltage regulation. A more detailed investigation of tightly coupled CC–CV control dynamics is identified as an important topic for future work.

12 Open-Circuit Voltage Characterization

To determine an appropriate terminal voltage limit for charging, an open-circuit voltage (OCV) characterization was performed using the SPM model. A small-magnitude charging current of 0.05A was applied to the cell in order to minimize ohmic and kinetic overpotentials, thereby approximating near-equilibrium conditions.

12.1 OCV Test Results

Figure 2 shows the terminal voltage response of the cell during the low-current OCV characterization experiment. A sufficiently small charging current was applied to minimize ohmic and kinetic overpotentials, allowing the terminal voltage to closely track the equilibrium open-circuit voltage predicted by the SPM.

As the state of charge increased, the terminal voltage asymptotically approached a maximum value of approximately 3.346 V. This value was therefore selected as the nominal terminal voltage limit for subsequent charging optimization studies.

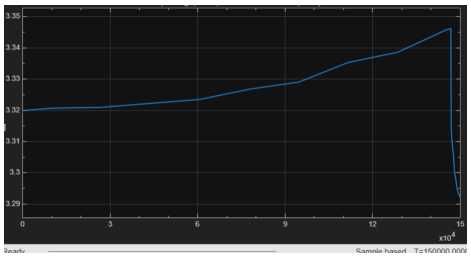

Figure 2: Open-circuit voltage characterization using a low-magnitude charging current.

13 Thermal Response Under Increasing Charging Current

Prior to multi-stage charging optimization, the thermal response of the battery cell was evaluated under a range of constant charging currents. This study was conducted to understand the relationship between charging current magnitude and peak cell temperature, and to assess whether thermal constraints are expected to become active within the investigated operating range.

Figure 3 illustrates the maximum cell temperature observed during charging as a function of the applied constant current. The results show an approximately linear increase in peak temperature with increasing current, consistent with the dominant contribution of ohmic and polarization losses in the SPM thermal formulation.

Within the examined current range, the maximum temperature remained below the imposed thermal limit of 313 K, indicating that voltage constraints are more restrictive than thermal constraints for the considered charging horizon. This observation motivates the focus on voltage-limited optimization in subsequent multi-stage charging studies.

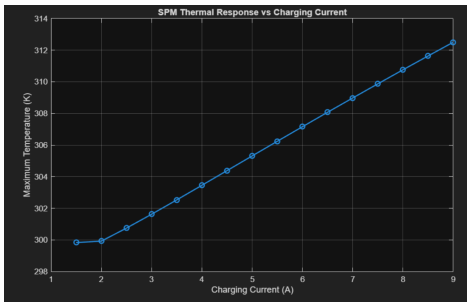

Figure 3: Maximum cell temperature as a function of constant charging current.

14 Single-Current Charging Optimization Using Genetic Algorithm

As an initial step toward fast-charging optimization, the charging strategy was simplified to a single constant-current profile. In this formulation, the battery is charged using a fixed current magnitude from the initial SOC until a target SOC is reached. This reduced problem serves as a baseline case to validate the optimization framework before introducing multi-stage or SOC-dependent current profiles.

The objective of the optimization is to minimize the total charging time required to reach the target SOC, subject to thermal and voltage safety constraints. Specifically, the following limits were enforced:

- Maximum allowable cell temperature: $T_{\max} = 313\,\mathrm{K}$
- Maximum allowable terminal voltage: $V_{\max} = 3.346\,\mathrm{V}$

These constraints ensure safe operation while allowing the optimizer to explore the upper bounds of feasible charging current.

14.1 Genetic Algorithm Overview

A Genetic Algorithm (GA) was employed to solve the single-current optimization problem. Genetic algorithms are population-based, stochastic optimization methods inspired by the principles of natural selection and biological evolution. Unlike gradient-based methods, GAs do not require objective function smoothness or differentiability, making them well-suited for simulation-based optimization involving nonlinear dynamics, discontinuities, and black-box models.

The GA operates by evolving a population of candidate solutions over successive generations. Each candidate solution represents a possible value of the charging current. The algorithm evaluates the fitness of each candidate based on the objective function and iteratively improves the population through genetic operators such as selection, crossover, and mutation.

14.2 GA Implementation for Charging Optimization

In the present study, each individual in the GA population corresponds to a single decision variable: the constant charging current magnitude. For each candidate current, a full Simulink–Simscape simulation of the SPM-based battery model is executed. The resulting SOC, temperature, and terminal voltage trajectories are analyzed to compute the objective function.

The fitness function is defined as the charging time required to reach the target SOC, augmented with quadratic penalty terms if either the temperature or voltage constraints are violated. Solutions that fail to reach the target SOC within the simulation time horizon are heavily penalized to discourage infeasible candidates.

Through successive generations, the GA balances exploration of the search space with exploitation of promising solutions, converging toward a charging current that minimizes charging time while respecting both thermal and voltage limits.

14.3 Single-Current Optimization Results

Figure 4 illustrates the outcome of the genetic algorithm optimization for the single-current charging case. The optimal current is observed to lie near the constraint boundaries, indicating that the charging process is limited primarily by voltage and thermal considerations rather than SOC dynamics alone.

This result establishes a validated baseline for subsequent optimization studies involving multi-stage current profiles and SOC-dependent control strategies.

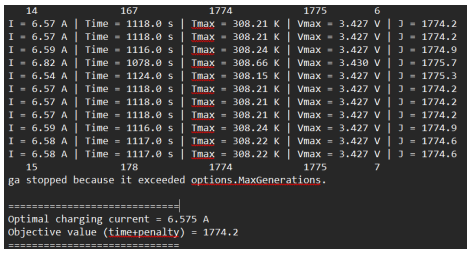

Figure 4: Genetic algorithm optimization result for single constant-current charging under temperature and voltage constraints.

15 Multi-Stage Charging Optimization Using Particle Swarm Optimization

Following the validation of the optimization framework using a single constant-current charging strategy, the study was extended to multi-stage charging profiles. In this formulation, the charging current is allowed to vary as a function of the state of charge, enabling faster charging while maintaining compliance with thermal and voltage constraints.

A two-stage constant-current strategy was adopted as the next level of complexity. The charging current is defined by three decision variables:

- Initial charging current I_1
- Secondary charging current I_2
- SOC switching point SOC_{break}

For $SOC < SOC_{break}$, the battery is charged at current I_1, while for $SOC \geq SOC_{break}$, the charging current is switched to I_2. This structure captures the essential behavior of practical fast-charging strategies while remaining computationally tractable.

15.1 Particle Swarm Optimization Overview

To solve the multi-stage charging optimization problem, Particle Swarm Optimization (PSO) was employed. PSO is a population-based, stochastic optimization technique inspired by the collective behavior of social organisms such as bird flocks or fish schools. Unlike genetic algorithms, PSO does not rely on crossover or mutation operators; instead, candidate solutions evolve by sharing information about their best-known positions in the search space.

Each particle represents a potential solution vector and is characterized by both a position and a velocity. During each iteration, particles update their velocities based on three components: inertia, attraction toward the particle's own best-known position, and attraction toward the globally best-known position. This mechanism enables efficient exploration of the search space while maintaining rapid convergence toward promising regions.

15.2 Motivation for Transition from GA to PSO

While the genetic algorithm performed reliably for the single-variable optimization problem, extending the GA framework to multiple continuous decision variables resulted in slower convergence and increased computational cost due to repeated simulation evaluations. In contrast, PSO is particularly well-suited for low- to medium-dimensional continuous optimization problems and has been shown to converge more rapidly in simulation-based, black-box optimization settings.

Given the increased dimensionality of the two-stage charging problem and the high cost associated with each Simulink–Simscape simulation, PSO was selected as a more efficient optimization method. Its ability to balance exploration and exploitation with fewer hyperparameters made it advantageous for tuning current magnitudes and SOC switching points simultaneously.

15.3 PSO Formulation for Two-Stage Charging

In the present implementation, each particle in the swarm corresponds to a candidate charging strategy defined by the vector

$$\mathbf{x} = [I_1,\ I_2,\ SOC_{break}]\,. \tag{10}$$

For each particle position, a full simulation of the battery model is performed, and the charging time required to reach the target SOC is computed. Quadratic penalty terms are applied if either the maximum allowable temperature ($T_{\max} = 313\,\mathrm{K}$) or the maximum terminal voltage ($V_{\max} = 3.346\,\mathrm{V}$) is exceeded. Particles that fail to reach the target SOC within the simulation horizon are heavily penalized.

The PSO iteratively updates particle positions based on fitness evaluations, gradually converging toward an optimal multi-stage charging strategy that minimizes charging time while satisfying all imposed constraints.

15.4 Multi-Stage Optimization Results

The results of the particle swarm optimization for the two-stage charging strategy are summarized in Figure 5. The optimized current profile demonstrates improved charging performance relative to the single-current baseline while remaining within both thermal and voltage limits.

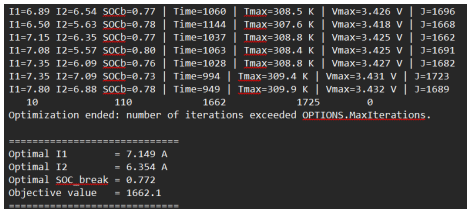

Figure 5: Particle swarm optimization result for two-stage constant-current charging.

These results confirm that introducing SOC-dependent current switching provides a meaningful improvement in charging efficiency and establishes a foundation for further exploration of more advanced charging strategies.

16 Conclusion

This project reviewed and implemented a simulation-based framework for fast-charging optimization of lithium-ion batteries using the Single Particle Model. By combining physics-based electrochemical modeling with heuristic optimization techniques, the study demonstrated a systematic approach to evaluating charging strategies under voltage and thermal constraints.

A progression from single constant-current charging to a two-stage SOC-dependent charging profile enabled validation of the optimization methodology while maintaining numerical stability and interpretability. Genetic Algorithm optimization provided a robust baseline solution for the single-variable problem, while Particle Swarm Optimization proved more efficient for the multi-parameter charging strategy. Across all investigated cases, terminal voltage emerged as the dominant limiting factor, with cell temperature remaining below the imposed safety threshold.

While the present work focuses on simplified control logic and lumped thermal behavior, the framework is fully reproducible and readily extensible. Future work will incorporate tighter CC–CV coupling, degradation-aware constraints such as lithium plating and SEI growth, and more advanced optimization and control techniques, including model predictive control. Overall, this project establishes a practical and extensible foundation for fast-charging studies using reduced-order battery models.