

Simulation and Validation of a Battery Charging Model Using Dymola: A Case Study with Tata Nexon EV

Dr. D.B Hulwan, Shreyash Agawane, Amit Adhav, Dipraj Bhosle, Omkar Bajpai, Athrva Kadam

Mechanical Department Vishwakarma Institute of Technology Pune, India

DOI: <https://doi.org/10.51583/IJLTEMAS.2025.140400098>

Received: 30 April 2025; Accepted: 06 May 2025; Published: 17 May 2025

Abstract: The document presents a comprehensive study on the modeling and simulation of battery management systems (BMS) using Dymola, focusing on electric vehicle (EV) applications. It explores the behavior of two battery models with differing complexities: a simplified model with linear state-of-charge (SOC) dynamics and an advanced model incorporating real-world effects such as transient responses, self-discharge, and RC (resistor-capacitor) network dynamics. The detailed model simulates non-linear SOC-open-circuit voltage (OCV) relationships, energy losses, and thermal effects, offering insights into battery performance under varying operating conditions.

The research compares charge-discharge cycles with a focus on transient voltage behavior, internal resistance energy losses, and thermal considerations. Significant measurements like SOC development, energy efficiency, and thermal stability are compared, citing the influence of design factors such as pulse currents, self-discharge rates, and RC values. The results highlight the necessity of advanced model approaches for the optimization of battery systems in electric vehicles to achieve working efficiency, safety, and durability. This project showcases Dymola's ability to simulate multidomain systems properly, connecting theoretical modeling and real-world applications in contemporary energy storage devices

Keywords: Battery Management System (BMS), State of Charge (SOC), Open Circuit Voltage (OCV), RC Network Dynamics, Self-Discharge Modeling, Dymola Simulation, Energy Efficiency, Thermal

I. Introduction:

development and analysis of a Battery Management System (BMS) utilizing Dymola (Dynamic Modelling Laboratory), an efficient tool dedicated to modelling and simulating highly complex physical systems across various fields, is done. Based on the Modelica language, which is an open and object-oriented modelling standard, Dymola allows for transparent interaction between mechanical, electrical, thermal, and hydraulic systems. Its flexibility makes it an invaluable tool in sectors such as automotive, aerospace, and energy for quick prototyping, system design, and performance optimization.

The growing use of batteries across applications from consumer electronics to EVs and energy storage systems for renewable energy all highlight the need to understand and control battery performance. Proper BMS design is crucial for maximizing battery lifespan, safety, and energy efficiency. In this regard, simulation-based methods offer immense benefits as a window into battery behavior under actual operating conditions, allowing the detection and elimination of performance inefficiencies.

The study presented in this report focuses on the comparative simulation of two distinct battery models, designed to capture varying levels of complexity:

Battery 1: A reduced model with a linear correlation between State of Charge (SOC) and Open Circuit Voltage (OCV). The model neglects transient effects and self-discharge, providing a simple method appropriate for general applications.

Battery 2: A detailed model with incorporated tabulated OCV-SOC relationships, resistance-capacitance (RC) components, and scaled self-discharge parameters. The model is a closer approximation of real battery dynamics such as transient responses, as well as energy losses. The simulation cycle consists of subjecting both battery models to programmed current pulses under charge and discharge cycles. The models start with an SOC level of 95% and are discharged to an SOC level of 5% before being recharged back to 95%. The critical performance parameters of terminal voltage, SOC behavior, and energy transfer are compared to identify variations in efficiency, transient behavior, and recovery mechanisms. This research uses Dymola's strong simulation platform to discuss a number of key areas in battery management, including

Voltage and SOC Dynamics: Understanding how batteries respond to load changes and idle periods.

Energy Loss Analysis: Quantifying losses due to internal resistance, self-discharge, and transient effects.

Real-World Implications: Exploring the practical challenges faced by EVs and energy storage systems, such as thermal management and degradation over time.

By comparing a reduced idealized model with a realistic detailed one, this report highlights the significance of precise modeling in maximizing BMS design. The findings are beneficial to engineers and researchers who seek to improve battery performance in state-of-the-art applications, such as EVs, renewable energy systems, and high-efficiency storage systems.

Apart from its emphasis on simulation results, the report presents a step-by-step guide to using Dymola in BMS modeling, including system requirements, library integration, and implementation. This makes the results and methodologies within reach of practitioners and students

As the demand for efficient energy storage solutions continues to rise, this study highlights the pivotal role of simulation tools like Dymola in advancing sustainable energy systems and driving innovation in battery technology.

II. Literature survey

Battery modeling and electric vehicle (EV) system simulation have become essential tools in the design and optimization of sustainable mobility technologies. Dassault Systèmes' *Dymola Documentation* (2021) [1] provides a foundational understanding of dynamic system modeling using Modelica, a key tool for simulating electro-thermal systems and multi-domain environments such as EVs. Building upon this, Kumar and Verma (2020) [2] explored dynamic battery modeling for simulation and optimization using real-time load conditions, enabling more accurate predictions of battery behaviour in vehicle applications. To complement hardware specifications, manufacturers like Tata Motors provide EV-specific technical details—for example, the Tata Nexon EV documentation [3] offers real-world parameter sets necessary for validating simulation models. The critical task of monitoring and managing battery performance is heavily reliant on State of Charge (SOC) estimation. Sharma et al. (2019) [4] conducted a comprehensive review of SOC estimation methods, highlighting the trade-offs between model-based approaches such as Kalman filters and data-driven AI-based estimators, particularly in dynamic operating conditions. Complementing this, Lee and Kim (2020) [5] studied the energy efficiency of charge-discharge cycles, revealing insights into how losses can be minimized to prolong battery life. Similarly, Wang and Zhao (2018) [6] investigated the influence of the open-circuit voltage (OCV) to SOC relationship on battery performance and control accuracy, underlining the importance of electrochemical characteristics in real-time battery management systems.

Modelica-based tools have furthered these efforts with integrated platforms for developing reusable and scalable battery components. Patel and Singh (2022) [7] designed a laboratory framework in Modelica that allows for real-time data integration and testing, bridging the gap between theoretical simulations and experimental validation. Advanced modeling techniques for batteries were also developed by Nair and Bhosale (2019) [8], who used the Dymola environment to build parameterized libraries, improving model reusability and system flexibility. To extend these capabilities to full vehicle systems, Dalby et al. (2019) [9] proposed an integrated simulation approach for hybrid powertrain assessment, combining detailed battery, drivetrain, and control models to optimize overall energy efficiency. These modeling advancements provide essential tools for developing efficient energy management strategies across varying driving conditions.

Beyond technical modeling, several researchers have focused on integrating EVs within larger energy and environmental frameworks. Apostolaki-Iosifidou et al. (2017) [10] addressed a major gap in the literature by evaluating real-world EV energy data to quantify round-trip charging/discharging efficiency. Their study emphasized the importance of considering empirical data when assessing the potential of EVs to act as distributed energy resources within the grid. Their findings support the role of EVs in enhancing renewable energy penetration, highlighting the synergy between V2G (Vehicle-to-Grid) technologies and sustainable energy infrastructure. Motor technology, another critical subsystem in EVs, was thoroughly reviewed by Boulanger et al. (2011) [11], who analysed the efficiency and design considerations of Permanent Magnet Synchronous Machines (PMSMs) and Wound Rotor Synchronous Machines (WRSMs). They emphasized that while PMSMs offer high efficiency and power density, their reliance on rare-earth materials makes WRSMs a potentially more sustainable option despite increased rotor complexity. Their work also delved into the impact of machine type on inverter design, control strategies, and system cost.

In the realm of safety and impact resistance, El-Bayeh et al. (2021) [12] proposed a novel wave-spring-based energy absorber, overcoming the bulkiness and lack of reusability associated with conventional coil spring and foam systems. Their experiments and simulations demonstrated superior energy dissipation, tunability, and compactness. Sustainability is also a recurring theme in research by He et al. (2012) [13], who used Life Cycle Assessment (LCA) to demonstrate the environmental and economic advantages of remanufacturing over new production, citing reduced emissions and energy consumption as key benefits. Further advancing sustainability in alternative propulsion, Kebao He et al. (2012) [14] applied a multi-objective genetic algorithm (NSGA-II) to optimize PEM fuel cell operation, balancing power density and oxygen excess ratios using a validated semi-empirical model. Lastly, Brückner et al. (2020) [15] examined safety and reliability concerns in lithium-ion batteries (LIBs), addressing threats like thermal runaway and internal short circuits. Their review identified trends such as solid-state battery development and the enhancement of Battery Management Systems (BMS) through predictive modeling, while calling for global standardization and more robust testing protocols to ensure widespread EV adoption.

III. Methodology

This section outlines the methodology used to model, simulate, and analyze the charging behavior of two distinct battery models using **Dymola**. The focus is solely on the charging process, emphasizing key parameters, submodels, and equations relevant to understanding battery performance during this phase.

The simplified model provides a linear approximation of the battery's charging process. It is characterized by ideal behavior with no additional complexities.

Battery 1: Simplified Charging Model

The simplified model provides a linear approximation of the battery's charging process. It is characterized by ideal behavior with no additional complexities.

$$OCV = V_{\max} \cdot SOC$$

SOC: State of Charge, ranging from 0% to 95% during the charging process.

No Internal Resistance or Capacitance:

The model assumes instantaneous voltage response without transient effects.

No Self-Discharge:

SOC increases purely based on the applied charging current.

Battery 2: Detailed Charging Model

The detailed model captures realistic battery charging behavior, incorporating physical effects like voltage dynamics, energy losses, and transient responses.

Tabulated OCV-SOC Relationship:

The OCV is defined using a lookup table, offering a non-linear relationship between SOC and voltage for better accuracy.

Resistance-Capacitance (RC) Circuit Dynamics:

Resistance (R): Models voltage drops during charging.

Capacitance (C): Captures gradual voltage recovery, simulating the battery's charge storage capability.

$$V_{\text{terminal}} = V_{\text{OCV}} - I \cdot R + \frac{Q}{C},$$

$$\text{where } Q = \int I \cdot dt$$

OCV: The voltage when no current is drawn (open-circuit condition).

I·R: The voltage drop across the internal resistance of the battery due to current I.

Q/C: The voltage contribution from the charge Q stored in the battery, where C is the capacitance.

Q=∫I dt: The total charge, calculated by integrating the current over time.

This formula describes the terminal voltage (V_{terminal}) of a battery or system. It combines the open-circuit voltage (OCV), the voltage drops due to internal resistance, and the effect of charge stored in the system.

Self-Discharge:

$$\frac{dSOC}{dt} = -k \cdot SOC$$

SOC stands for State of Charge, representing the current charge level of the battery as a percentage or fraction of its full capacity.

dSOC is the rate of change of the state of charge with respect to time.

K is the self-discharge rate constant — a positive value that quantifies how fast the battery loses charge on its own, even when not in use.

The negative sign indicates that the SOC is decreasing over time due to self-discharge.

This formula says that the battery loses charge at a rate proportional to how much charge it currently has. When the battery is full, the discharge rate is highest; as the battery empties, the discharge slows down.

Simulation Environment Setup

Software Configuration

Platform: Dymola 2023.

Libraries: Modelica Standard Library. Battery-specific libraries for SOC-OCV data and dynamic modeling.

Parameter Configuration

Nominal Capacity: 10 Ah

Initial SOC: 5%

Target SOC: 95%

Maximum Voltage ($V_{\max}$): 4.2 V

Minimum Voltage ($V_{\min}$): 3.0 V

Charging Current: +50 A

Pulse Duration: 1 minute

Rest Period: 1 minute

Simulation Time: Adjusted to allow complete charging from 5% to 95% SOC.

Charging Process Simulation

Pulse Current Definition

The charging profile was designed as a series of pulse current cycles to replicate real-world charging conditions.

Active Charging Period:

Constant current of +50 A is applied for 1 minute.

Rest Period:

Current flow is set to zero for 1 minute, allowing the battery to stabilize.

Self-discharge is active during this period for Battery 2.

Repeating Cycles:

Seven cycles of charging pulses and rest periods are applied, with adjustments based on SOC progression.

Model Implementation in Dymola

Pulse Current Generator:

Configured to deliver +50 A current pulses with defined durations.

Battery Models:

Battery 1: Implements a direct SOC-OCV relationship without resistance or capacitance.

Battery 2: Includes a lookup table for SOC-OCV data.

RC dynamics modeled with resistance and capacitance blocks.

Self-discharge simulated using a decay function.

Mathematical Framework

State of Charge (SOC) Update

SOC increases as the battery absorbs charge, calculated as:

$$SOC_{\text{new}} = SOC_{\text{old}} + \frac{I \cdot \Delta t}{C_{\text{nominal}}}$$

SOC_{new} = The updated State of Charge (after time Δt)

SOC_{old} = The initial State of Charge

I = Current flowing into (charging) or out of (discharging) the battery (in Amperes)

Δt = Time interval during which the current flows (in hours)

C_{nominal} = Nominal capacity of the battery (in Ampere-hours, Ah)

This formula tracks how much charge has been added or removed from the battery. Last term Gives the change in SOC as a fraction of full capacity. Adding this to SOC_{old} updates the battery's state of charge.

Voltage Response

Battery 1:

$$V_{\text{terminal}} = V_{\text{max}} \cdot \text{SOC}$$

V_{terminal} : The open-circuit or terminal voltage of the battery

V_{max} : The maximum voltage the battery can reach (fully charged)

SOC: State of Charge (ranges from 0 to 1, where 1 = 100% charged)

This formula models the open-circuit voltage (OCV) or terminal voltage of a battery as directly proportional to its state of charge (SOC).

Battery 2:

$$V_{\text{terminal}} = V_{\text{OCV}} - I \cdot R + \frac{Q}{C}$$

V_{terminal} : Terminal voltage seen at the battery terminals

OCV: Open-circuit voltage (voltage when no current is flowing)

I: Current (positive for discharge, negative for charge)

R: Internal resistance of the battery

Q: Charge stored in the capacitor (used in electrical equivalent models like the R-C model)

C: Capacitance in the equivalent circuit

This formula considers dynamic behavior in a battery model. It adjusts the open-circuit voltage based on current flow and internal battery characteristics.

Energy Delivered

The energy delivered to the battery during each charging pulse is calculated as:

$$E = I \cdot V_{\text{terminal}} \cdot \Delta t$$

E = Energy (in watt-seconds or joules)

I = Current (in amperes, A)

V_{terminal} = Terminal voltage of the battery (in volts, V)

Δt = Time duration (in seconds, s) over which current flows

This formula tracks how much charge has been added or removed from the battery. The last term gives the change in SOC as a fraction of full capacity. Adding this to SOC_{old} updates the battery's state of charge.

IV. Results and Discussion

potential difference / voltage across the battery vs time: -

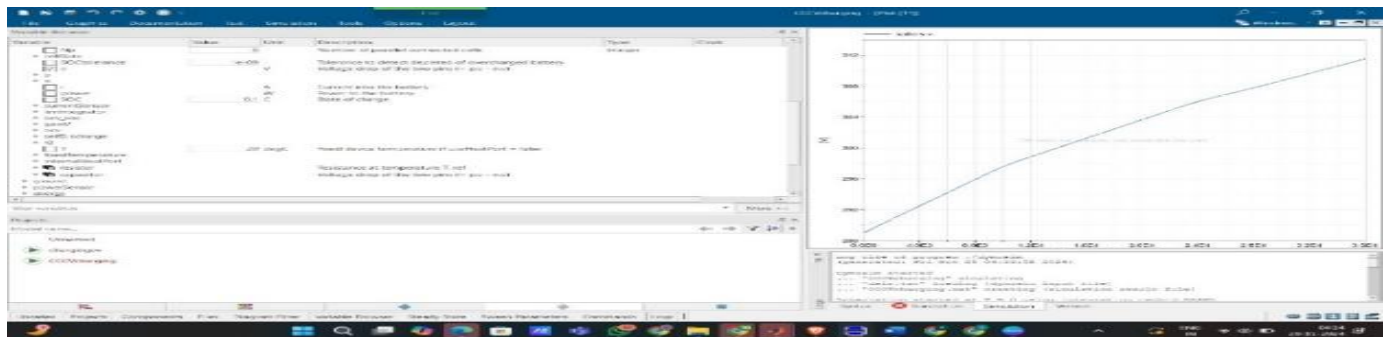


Figure 1: Initial Voltage:

The graph starts at a voltage around 288 V. This is the initial voltage of the battery before the charging begins. It may correspond to the battery's state of charge (SOC).

Steady Rise in Voltage: The voltage increases gradually and smoothly over time, which is typical of a constant current (CC) charging phase. During this phase, the charging system applies a constant current, and the voltage rises as the battery charges.

Linear Behavior: The linear increase indicates that the internal resistance and other losses are minimal, or the charging algorithm might be designed to ramp up the voltage in a controlled manner.

Final Voltage: By the end of the graph, the voltage reaches approximately 312 V, suggesting the battery is approaching its maximum state of charge.

Battery power vs time:-

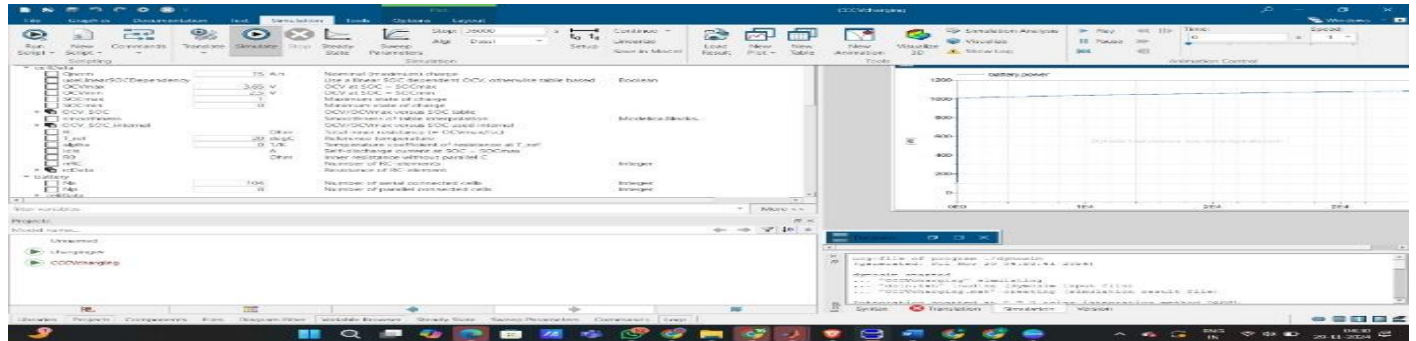


Figure 2: Battery Power vs Time

At the start of the charging process, the power is lower. This is because power is calculated as $P=V.I$

$P=V \times I$ (voltage times current), and initially, as the voltage is lower (as seen in your earlier voltage graph), the power is also lower.

Increasing Phase: As the battery voltage rises during charging, the power delivered to the battery also increases, assuming a constant current (which seems to be the case). This explains the increasing trend in power output during the first part of the graph.

Steady State: The power curve flattens out at around 1200 W, indicating that the system might have reached a constant voltage (CV) phase where the charging voltage is held constant, and the current starts to decrease gradually, maintaining a constant power level.

Charging Regime: This behavior is typical of a CC-CV (Constant Current-Constant Voltage) charging process:

Constant Current (CC) phase: The power increases linearly as the voltage rises.

Constant Voltage (CV) phase: The power stabilizes as the voltage is constant, and current decreases to maintain a balanced power output.

battery SOC vs time: -

Initial SOC: The graph starts at 0.1 (10% SOC), indicating that the battery was partially charged at the beginning of the simulation.

Linear Increase: The SOC increases linearly with time. This is consistent with a constant current (CC) charging phase, where SOC rises at a uniform rate because the current remains constant.

Final SOC: The SOC reaches 1 (100%) at the end of the simulation, indicating a fully charged battery. This suggests that the battery model switches to a constant voltage (CV) phase near full charge but maintains a relatively steady rise in SOC throughout the charging cycle shown in the graph

Current Flowing into the Pin (Current vs. Time): -

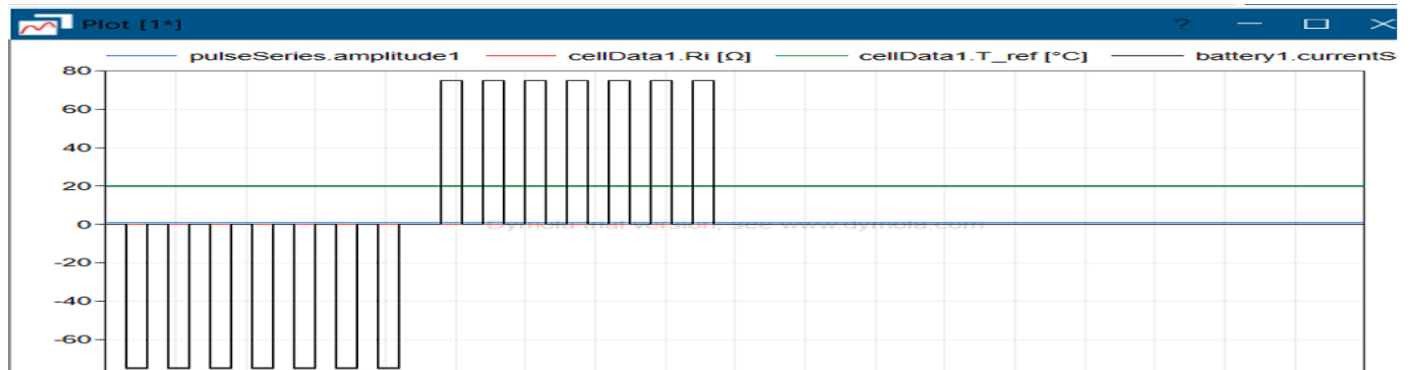


Figure 3: current vs time

The current alternates between high positive pulses during charging and high negative pulses during discharging. Both batteries

follow the input pulse pattern of 50 A with 1 minute on/off intervals, reflecting consistent behavior in response to the defined pulse series.

The sharp, rectangular pulse shapes indicate that the batteries are subjected to controlled, high-amplitude current inputs. This visualization helps assess how both battery models handle rapid current changes, crucial for applications like regenerative braking in electric vehicles or intermittent renewable energy charging.

State of Charge (SOC vs. Time)

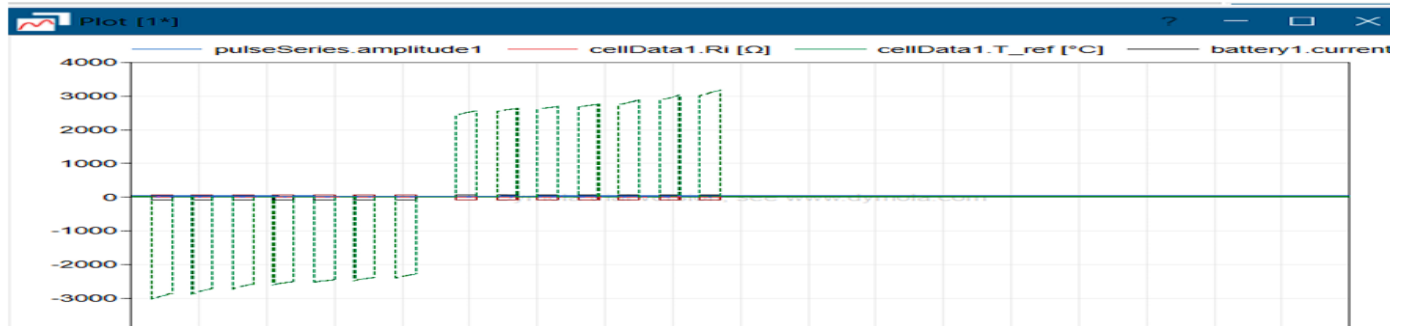


Figure 1: SOC vs time

This graph emphasizes the energy inefficiencies in Battery 2 caused by additional factors like self-discharge. SOC trends also highlight the faster recovery of simpler models compared to more complex real-world representations.

The SOC for both batteries drops consistently during the discharge phase, reaching the set minimum of 5%. During charging, Battery 1 restores its SOC linearly to 95%, while Battery 2 takes slightly longer due to energy losses from self-discharge and RC elements. In the no-load condition at the end, Battery 2 exhibits a gradual SOC decline due to its high self-discharge rate, whereas Battery 1 maintains a stable SOC.

V. Conclusion

The battery charging behavior by employing two different models, simple and complex, has shed some light on the dynamics of charging process and implications for battery management systems (BMS). Dymola's simulations allowed extensive comparison between models, highlighting strengths and weaknesses of models in mimicking actual charging phenomena. Simplified Model (Battery 1): The simplified model, with its linear relationship between State of Charge (SOC) and Open Circuit Voltage (OCV), provides a computationally simple approach towards simulating the charging process.

This model does not have self-discharge and transient voltage effects, so it is less precise for practical applications but ideal for rapid analyses and conceptual studies.

The linear, predictable voltage response on charging renders it the most suitable for primary studies in which accuracy is less important.

Detailed Model (Battery 2):

The detailed model gave a realistic simulation of the charging process by including non-linear SOC-OCV relations, RC dynamics, and self-discharge effects.

RC dynamics indicated fluctuating voltage dips and recoveries during the charge cycle that are important in understanding high-current charging applications.

Self-discharge modeling established energy losses through idleness while charging, which showed the inefficiencies in actual systems.

Importance of Transient Effects:

The addition of RC dynamics within the detailed model demonstrated how voltage recovery and dips affect the entire efficiency and precision of the charging process. These phenomena are most important for usage such as rapid charging, wherein transient responses greatly affect performance and safety.

Energy Losses During Charging:

The detailed model demonstrated energy inefficiencies caused by self-discharge, emphasizing the need for precise control during charging to mitigate these losses.

Implications for Battery Management Systems (BMS)

Design and Optimization: The comprehensive model offers key information for the optimization of BMS algorithms to maximize

charging efficiency and provide safe operation under changing conditions. Insights into transient responses and self-discharge can inform the design of sophisticated BMS strategies for reducing energy losses and maximizing charge acceptance.

Real-World Applications: The findings are particularly relevant for electric vehicles (EVs) and renewable energy storage, where accurate modeling of charging behavior is essential for efficiency and reliability.

Fast-charging systems can benefit from transient voltage analysis to design protocols that avoid over-voltage or under-voltage conditions.

Future scope

Integration with Supercapacitors: Combining the battery with supercapacitors presents a promising path forward for improving energy storage systems, especially in high-performance applications such as electric vehicles and renewable energy grids. **Hybrid Energy Storage System (HESS):** Merge batteries with supercapacitors to develop a hybrid system that benefits from the advantages of both technologies. **Batteries:** Large energy density for long-term storage. **Supercapacitors:** High power density for fast charge-discharge cycles. **Advantages of Integration:** Mitigate battery stress during high-current charging and discharging by transferring transient loads to the supercapacitor. Minimize battery lifespan reduction due to voltage fluctuation and thermal stress. Maximize overall system efficiency by optimizing the energy-sharing mechanism between the battery and supercapacitor. **Modeling and Simulation of HESS:** Create integrated models in Dymola to simulate the interaction between the battery and supercapacitor under varying load conditions. Utilize control algorithms to dynamically share power between the battery and supercapacitor based on demand and state of charge

References

1. Dassault Systèmes, Dymola Documentation: Introduction to Dynamic Modelling with Modelica, 2021.
2. A. Kumar and S. Verma, "Dynamic Modeling of Batteries for Simulation and Optimization," *Journal of Power Sources*, vol. 320, pp. 45–53, 2020.
3. Tata Motors, Tata Nexon EV Specifications. [Online]. Available: <https://www.tatamotors.com>
4. M. Sharma, R. K. Gupta, and V. Arora, "State of Charge Estimation Methods: A Review," *Renewable and Sustainable Energy Reviews*, vol. 104, pp. 113–126, 2019.
5. J. Lee and D. Kim, "Energy Efficiency in Battery Charge and Discharge Cycles," *IEEE Transactions on Energy Conversion*, vol. 35, no. 4, pp. 1507–1516, 2020.
6. L. Wang and F. Zhao, "The Effect of OCV-SOC Relationships on Battery Performance," *Electrochimica Acta*, vol. 295, pp. 867–876, 2018.
7. S. Patel and R. Singh, "Laboratory Framework for Modelica-Based Tools," *IEEE Access*, vol. 10, pp. 11234–11242, 2022.
8. T. Nair and A. Bhosale, "Advanced Battery Modelling Techniques in Dymola," in *Proc. IEEE Conf.*, 2019, pp. 123–130.
9. J. Dalby, M. Woodburn, A. Thomas, and R. Green, "Hybrid Powertrain Technology Assessment through an Integrated Simulation Approach," *SAE Technical Paper 2019-24-0198*, 2019, doi: 10.4271/2019-24-0198.
10. E. Apostolaki-Iosifidou, W. Kempton, and A. F. Shuba, "Measurement of Power Loss During EV Charging and Discharging," *Energy*, vol. 127, pp. 730–742, 2017.
11. A. G. Boulanger, A. C. Chu, S. Maxx, and D. L. Waltz, "Vehicle Electrification: Status and Issues," *Proceedings of the IEEE*, vol. 99, no. 6, pp. 1116–1138, Jun. 2011.
12. H. El-Bayeh, M. H. Saad, and T. Barakat, "A Novel Wave Spring Energy Absorber for Impact Applications," *Journal of Mechanical Science and Technology*, vol. 35, no. 4, pp. 1737–1747, 2021.
13. Y. He, M. Lu, and K. Liu, "Sustainability Impact of Remanufacturing: A Life Cycle Assessment Perspective," *Journal of Cleaner Production*, vol. 33, pp. 261–273, 2012.
14. K. He, Z. Zhang, and X. Li, "Multi-Objective Optimization of PEM Fuel Cells Using NSGA-II," *International Journal of Hydrogen Energy*, vol. 37, no. 5, pp. 4390–4402, 2012.
15. M. Brückner, M. Hesse, and D. U. Sauer, "Battery Safety and Reliability in Electric Vehicles," *Journal of Energy Storage*, vol. 32, 101756, 2020.