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FASTEST

Fast-track hybrid testing platform for the development of battery systems

Deliverable D3.2: Reduced-order model development and validation

Laura Oca Perez

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Name	Organization	Date
Akhtar Zeb	VTT	27.05.2026
Bruno Rodrigues	ABEE	29.05.2026
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Project Abstract

Current methods to evaluate Li-ion batteries safety, performance, reliability and lifetime represent a remarkable resource consumption for the overall battery R&D process. The time or number of tests required, the expensive equipment and a generalised trial-error approach are determining factors, together with a lack of understanding of the complex multiscale and multi-physics phenomena in the battery system. Besides, testing facilities are operated locally, meaning that data management is handled directly in the facility, and that experimentation is done on one test bench.

The FASTEST project aims to develop and validate a fast-track testing platform able to deliver a strategy based on Design of Experiments (DoE) and robust testing results, combining multi-scale and multi-physics virtual and physical testing. This will enable an accelerated battery system R&D and more reliable, safer, and long-lasting battery system designs. The project's prototype of a fast-track hybrid testing platform aims for a new holistic and interconnected approach. From a global test facility perspective, additional services like smart DoE algorithms, virtualised benches, and Digital Twin (DT) data are incorporated into the daily facility operation to reach a new level of efficiency.

During the project, FASTEST consortium aims to develop up to TRL 6 the platform and its components: the optimal DoE strategies according to three different use cases (automotive, stationary, and off-road); two different cell chemistries, 3b and 4 solid-state (oxide polymer electrolyte); the development of a complete set of physic-based and data driven models able to substitute physical characterisation experiments; and the overarching DT architecture managing the information flows, and the TRL6 proven and integrated prototype of the hybrid testing platform.

LIST OF ABBREVIATIONS, ACRONYMS AND DEFINITIONS

Acronym	Name
BMS	Battery Management System
BTMS	Battery Thermal Management System
CFD	Computational Fluid Dynamics
DoD	Depth of Discharge
DoE	Design of Experiments
DT	Digital Twin
EC	Ethylene Carbonate
EIS	Electrochemical Impedance Spectroscopy
FEA	Finite Element Analysis
FIB	Focused Ion Beam
HPPC	Hybrid Pulse Power Characterisation
IR-drop	Instantaneous Voltage Drop
LFP	Lithium Iron Phosphate ($LiFePO_4$)
MOR	Model Order Reduction
MSMD	Multi-Scale, Multi-Domain
P2D	Pseudo-Two-Dimensional Model
PBM	Physics-Based Models
SEM	Scanning Electron Microscopy

SEI	Solid Electrolyte Interphase
SOC	State of Charge
SOH	State of Health
SPM	Single Particle Model
SPMe	Extended Single Particle Model
SSB	Solid-State Battery
TEM	Transmission Electron Microscopy

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1. EXECUTIVE SUMMARY

This deliverable presents the development, implementation, and validation of reduced-order models for lithium-ion (Gen3b) and solid-state (Gen4) battery technologies within the FASTEST project framework. The work focuses on enabling a computationally efficient yet physically consistent modelling approach that spans from cell to module and pack levels, supporting the development of the project's fast-track hybrid testing platform.

The modelling strategy builds upon the physics-based models defined in Deliverable D3.1, applying model order reduction (MOR) techniques to significantly reduce computational cost while preserving predictive capability. A systematic selection of MOR methods has been performed based on a set of key performance indicators (KPIs), including computational time, accuracy, adaptability, and the ability to dynamically update model parameters. These criteria ensure that the resulting models are suitable for multi-scale and multi-physics simulations while remaining compatible with the requirements of the FASTEST platform.

At cell level, the modelling framework combines electrochemical and thermal approaches. The electrochemical behaviour is represented using a reduced-order physics-based model derived from the Single Particle Model with electrolyte (SPMe), implemented with Orthogonal Collocation techniques to improve efficiency. In parallel, a pseudo-3D thermal model is developed, enabling the prediction of temperature distributions with limited computational burden. The coupling between electrochemical and thermal domains allows capturing the interaction between operating conditions and heat generation.

The proposed models have been validated against experimental data for both battery technologies. Results demonstrate good agreement in terms of voltage response and temperature evolution under representative operating conditions, including transient cycling and pseudo-steady-state tests. This confirms the ability of the models to accurately reproduce the main electro-thermal dynamics at cell level.

Building on these results, the modelling approach is extended to module and pack levels. At module scale, the methodology incorporates the structural components and thermal interfaces, capturing the main heat transfer paths while maintaining a reduced-order formulation. Different configurations are defined, including both experimental test setups and virtual full-scale battery packs, enabling the evaluation of realistic operating scenarios.

The scaling from module to pack level is achieved through simplified but physically consistent strategies, ensuring alignment between electrical and thermal representations. Validation at these higher levels shows a satisfactory agreement with experimental data, despite the increasing uncertainty associated with system-level interactions, such as airflow distribution and assembly tolerances.

Overall, the developed modelling framework provides a robust and flexible tool for electro-thermal analysis across multiple scales. Its reduced computational requirements make it especially suitable for integration within the FASTEST hybrid testing platform, where fast simulation capabilities are essential. In this context, the models contribute directly to the definition of advanced Design of Experiments (DoE) strategies and to the digitalisation of battery testing processes.

The outcomes of this work represent a key step towards the project's objective of accelerating battery system development, reducing experimental effort, and enabling more efficient, reliable, and scalable testing methodologies.

2. OBJECTIVES

The main objective of this deliverable is to develop and validate a set of reduced-order electro-thermal models capable of accurately representing the behaviour of battery systems across different scales, from cell to module and pack level, while significantly reducing computational cost. These models are designed to support the overall objectives of the FASTEST project, particularly the acceleration and optimisation of battery testing activities through digitalisation.

A key aspect of this work is the application of model order reduction (MOR) techniques to transform detailed physics-based models into computationally efficient formulations. The selection of the most suitable MOR approaches has been guided by a set of Key Performance Indicators (KPIs), defined to ensure that the resulting models meet the project requirements. These KPIs include computational time, accuracy with respect to high-fidelity models, adaptability to include additional physical phenomena such as thermal effects and ageing, and the capability to update model parameters dynamically.

Beyond model development, a central objective is to ensure that the resulting tools are robust and applicable at multiple levels of integration. This includes their validation against experimental data and their extension from cell-level descriptions to module and pack-level configurations, where additional physical interactions and system-level effects must be considered.

The developed models play a key role within the broader FASTEST project ecosystem. In particular, they provide a direct input to Work Package 2 (WP2), where they are used to support the definition and optimisation of Design of Experiments (DoE). Thanks to their reduced computational cost and sufficient accuracy, the models enable rapid exploration of operating conditions and parameter spaces, facilitating the identification of optimal testing strategies and reducing the need for extensive physical experimentation.

Furthermore, the models constitute a fundamental building block for the final integration of the FASTEST hybrid testing platform. Their capability to operate efficiently in a multi-scale and multi-physics context makes them suitable for real-time or near-real-time applications, where virtual and experimental testing are combined. In this sense, the models contribute directly to the development of the platform’s Digital Twin framework and to its overall objective of achieving a fast, reliable, and scalable battery testing methodology.

In summary, this deliverable aims not only to develop accurate and efficient models, but also to ensure their practical usability within the project’s workflow, supporting both advanced DoE strategies and the final system-level integration of the hybrid testing platform.

3. INTRODUCTION

The traditional R&D process for evaluating battery performance and lifetime relies heavily on resource-intensive, trial-and-error physical testing. To overcome these bottlenecks and accelerate deployment, the design of next-generation battery systems requires accurate, computationally efficient models. Cell performance modeling is essential for optimal system sizing and management, while robust aging models are critical for prognosticating long-term battery behavior.

However, battery modeling presents a critical challenge due to its inherent multiscale and multi-physics nature. A single cell operating in isolation under near-perfect cooling conditions behaves vastly differently than it would within a complex module or pack, where it is often compromised by pronounced thermal gradients. Consequently, an effective modeling framework must simultaneously capture the fast dynamics of electrochemical performance at the cell level and the slow dynamics of thermal evolution and degradation at the system level.

To address these complexities, the FASTEST project aims to develop a holistic, efficient multiscale modeling framework. By replacing generalized trial-and-error approaches with accurate physics-based and data-driven models, this framework will serve as a cornerstone of the project's overarching fast-track hybrid testing platform, paving the way for more reliable, safer, and long-lasting battery system designs.

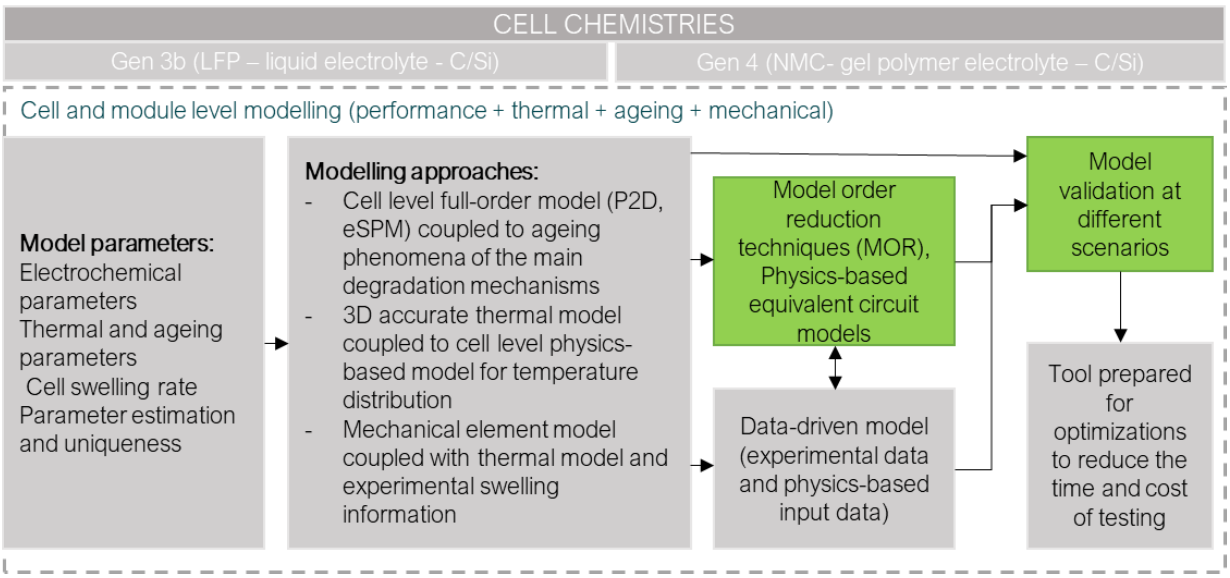


Figure 1. Summary of the modeling approach.

4. CELL LEVEL MODELLING

To achieve the holistic, multiscale framework envisioned in the FASTEST project, high-fidelity pack-level simulations must be built upon highly accurate cell-level descriptions. Physics-based models (PBMs) are instrumental at this scale, offering deep mechanistic insights into internal electrochemical processes and degradation mechanisms. Crucially, resolving these internal states is required to develop robust, predictive aging models. Nevertheless, the inherent computational burden of PBMs poses a challenge for efficient system-level integration. Therefore, MOR techniques are heavily leveraged to transform these detailed physical representations into computationally tractable models suitable for the project's fast-track testing platform. The following section outlines the various cell-level modeling and MOR strategies developed and applied in this context.

4.1 KPI for MOR selection

While numerous MOR methods can be employed to reduce the computational cost of physics-based models, their performance and applicability vary significantly. Consequently, robust criteria must be established to select the most suitable techniques for the project's specific requirements. To this end, Key Performance Indicators (KPIs) were defined to systematically evaluate and classify the available methods, as summarized in Table 1. During this evaluation, particular emphasis was placed on the analytical versus numerical nature of the MOR technique and its overall adaptability. This focus is driven by the project's requirement to dynamically update model parameters as a function of temperature and aging, thereby necessitating a seamless coupling of thermal and degradation models to the ROM.

Table 1. Key performance indicators used to select the employed reduced-order models.

KPI	Description
Computational time	How long do ROM simulations take?
Analytical or numerical method	Can the parameters of the model be changed once the ROM is built?
Accuracy	How accurate is the ROM compared to the FOM?
Adaptability	How difficult is it to add aging or thermal models to the ROM?

4.2 Physics-based model

Following the systematic evaluation of available MOR techniques against the project's criteria, the Orthogonal Collocation (OC) method was identified as the optimal approach for the core PBMs. Standard spatial discretization techniques, namely the Finite Element Method (FEM), Finite Difference Method (FDM), and Finite Volume Method (FVM), typically require highly refined meshes that lead to excessive computational execution times. In contrast, the OC method delivers highly accurate approximations of the internal electrochemical states at a fraction of the computational cost.

Beyond computational efficiency, the inherent analytical nature of the OC method directly addresses the project's critical need for model adaptability. By preserving a continuous mathematical representation of the cell's internal dynamics, this approach allows parameters to be updated dynamically during simulation. Consequently, it significantly simplifies the coupling of the underlying electrochemical equations with external degradation mechanisms, making the addition of robust aging models both straightforward and highly efficient.

To implement the underlying electrochemical physics, the Single Particle Model with electrolyte (SPMe) was adopted in place of the more complex Pseudo-Two-Dimensional (P2D) model. Although the P2D model provides an exhaustive spatial resolution of internal states, its computational demands are often prohibitive for multi-scale, system-level applications. The SPMe strikes an optimal balance for the FASTEST project: it significantly reduces the computational footprint by simplifying the solid-phase diffusion, yet it retains the essential electrolyte concentration and potential dynamics necessary for reliable performance prediction. Coupled with the OC method, the SPMe delivers an excellent compromise, achieving computational speeds far superior to the P2D model without sacrificing the necessary predictive accuracy [1] [2] [3].

4.3 Physics-based equivalent circuit model

The objective of this subtask was to develop physics-based equivalent circuit models (ECMs) at the cell level to bridge the gap between physics-based models and equivalent-circuit models by using circuit representations that have a clear physical meaning for each element. However, the initial aim was to scale the model from cell to module level. Due to computational limitations and insufficient model accuracy, the focus was kept at the cell level.

In this framework, every electrical component represents a specific physical process within the battery, ensuring that your ECM is not just a curve-fitting tool but a reflection of the cell's internal electrochemistry [4].

Bridging the Gap: Physical Meaning of Circuit Elements
Following the modelling methodologies developed for LFP (Gen 3b) and Solid-State Batteries (SSB), physical origins are systematically assigned to each circuit element, as illustrated by the transmission line representation presented in Table 2 and Figure 2.

Table 2: The transmission line representation.

Circuit Element	Physical Process Represented	Governing Physics/Equation
Resistor (Rs)	Electronic conduction in the solid matrix.	Ohm's Law.
Resistor (Rl)	Mass transport/ion conduction in the electrolyte.	Concentrated electrolyte theory.
Resistor (Rct)	Charge transfer at the particle surface.	Butler-Volmer equation.
Voltage Source (U)	Thermodynamic equilibrium potential.	Nernst equation/Open Circuit Potential.
Resistor (Rdiff,s)	Solid-phase diffusion within active particles.	Fick's Second Law.

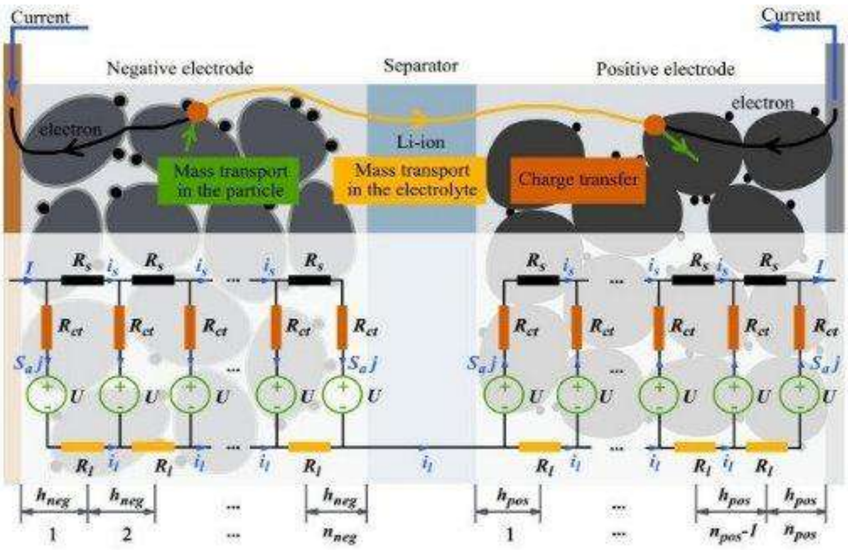


Figure 2: The representation of the transmission line structure.

This approach bridges first-principles electrochemical modelling and equivalent-circuit models (ECMs) by representing each porous electrode as a ladder of circuit elements that mirror physical processes (solid-phase and ionic resistances, charge-transfer resistances, and open-circuit voltage sources). All circuit parameters are derived from fundamental cell properties (material conductivities, reaction kinetics, diffusion coefficients, etc.), ensuring that every element retains a clear physical meaning and that no empirical adjusting is needed. This yields a hybrid physics-based ECM that offers improved transparency, accuracy, and computational efficiency compared to both full PDE models and traditional lumped ECMs.

Using a single unified framework, we instantiated the transmission-line P2D model for two distinct battery chemistries: an LFP ($LiFePO_4$) liquid-electrolyte cell and a solid-state battery (SSB) (NMC). The same core model structure was applied to both chemistries, with adjustments only in parameters and specific components to reflect their differences. For the LFP cell, the model incorporates the characteristic flat open-circuit voltage plateau of the LFP cathode and conventional porous electrode behaviour in a liquid electrolyte. For the SSB, we utilize the same transmission-line network but replace liquid electrolyte segments with solid electrolyte ionic resistances and include a high-resistance lithium metal anode interface. This minimal chemistry-specific tuning underscores the approach's generality and reproducibility: it maintains a consistent physics-based architecture across chemistries while accommodating their unique features.

Simulated discharge voltage profiles for both LFP and SSB cells show strong agreement with experimental data, confirming the model's accuracy across chemistries as shown in Figure 3. The LFP model captures the flat voltage plateau and sharp end-of-discharge drop typical of $LiFePO_4$ electrodes, closely matching measured voltage curves over time. Error metrics for the LFP cell (e.g., on the order of ~0.05–0.1 V RMSE, ~1–3% relative error) indicate excellent predictive performance. For the SSB, the model reproduces its higher initial IR-drop and gradually sloping voltage profile, reflecting the solid electrolyte's moderate ionic conductivity and prominent interfacial polarization at the lithium metal anode. The alignment with experiments indicates that the model correctly represents both the fast kinetics and ohmic limitations characteristic of these newer all-solid cells.

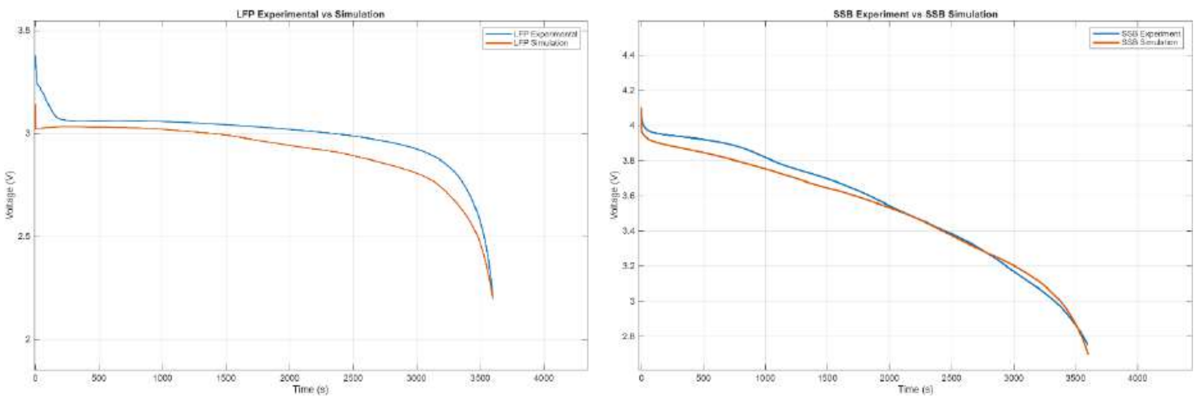


Figure 3: Simulated discharge voltage profiles for both LFP and SSB cells show strong agreement with experimental data.

4.4 Model validation and accomplishment of FASTEST technical objectives

These results demonstrate that the transmission-line P2D ECM provides a robust, cross-chemistry modelling platform. The side-by-side validation for LFP and SSB cells highlights how a unified physics-based circuit model can seamlessly adapt to differing battery behaviours from liquid-electrolyte systems with diffusion-limited flat plateaus to solid-state systems with transport and interface-limited voltage sag by adjusting only physically meaningful parameters. However, the simulated results show some deviations when compared with Model 1, indicating limitations in the current formulation.

Regarding the orthogonal collocation ROM, it can be observed in Figure 4 that the model accurately describes the voltage profile shown in the experiments. The model achieved a relative RMSE of 0.9% for the LFP cell and of 0.6% for the generation 4 solid-state battery, both below the objective 1.5% error.

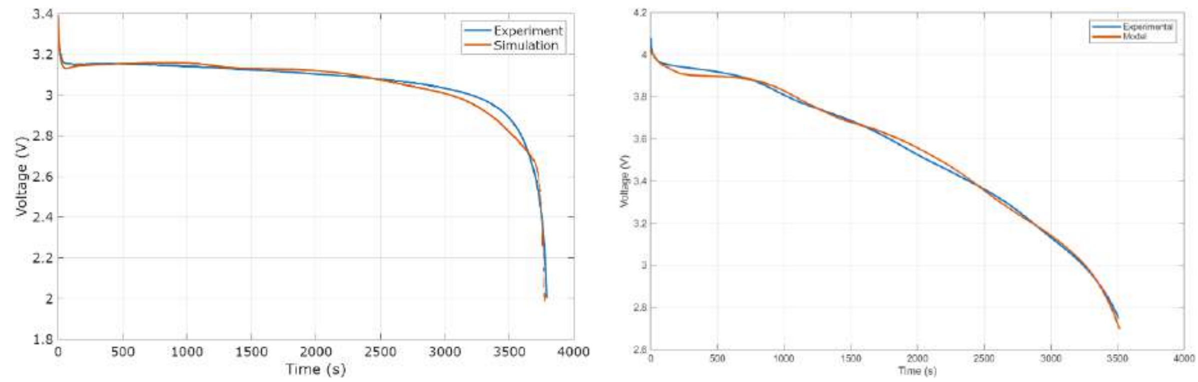


Figure 4. 1C constant-current discharge profiles for the ROMs validation: a) for the generation 3b cell and b) for the generation 4 cell.

4.5 Reduced-order 3D accurate thermal cell level model coupled with physics-based model

The thermal modelling framework developed in this work is based on a computationally efficient approach designed to enable the spatially resolved evaluation of temperature fields while maintaining a reduced computational cost. The methodology relies on a reduced-order formulation, in which the outputs from electrochemical models are used as inputs for the thermal problem, allowing the prediction of temperature distributions without the need for fully resolved three-dimensional numerical simulations. This approach is particularly well suited for scenarios requiring repeated simulations, such as parametric studies or system-level analyses, where computational efficiency is a key requirement [5].

The spatial resolution of the temperature field is achieved through a pseudo-three-dimensional (pseudo-3D) formulation, which combines the use of aggregated thermal parameters with a simplified discretization of the geometry. Instead of resolving the full 3D structure, the model employs a reduced representation in which the most relevant spatial directions are discretized, while less critical dimensions are treated using lumped or average properties. This strategy enables the capture of temperature gradients and localized effects, such as hot spots, while significantly reducing the number of degrees of freedom compared to high-fidelity numerical models. The use of grouped or effective thermal properties, including thermal conductivity and heat capacity, further contributes to reducing the overall model complexity while preserving the dominant heat transfer mechanisms within the cell [6].

Heat generation within the cell is computed by considering both irreversible and reversible contributions. The irreversible component accounts for resistive losses and electrochemical overpotentials and is estimated using a simplified Newton-type formulation based on the operating current and equivalent internal parameters derived from the electrochemical model. The reversible component represents the entropic heat associated with electrochemical reactions and is calculated using relevant thermodynamic coefficients when available. Both contributions are derived from electrochemical model outputs, ensuring consistency between the predicted electrical behavior and the resulting thermal response. This one-way coupling allows the thermal model to capture the dependence of heat generation on operating conditions, such as current load and state of charge, without introducing additional complexity in the solution strategy.

The temperature field is obtained by solving the transient heat balance equation using effective material properties that represent the overall behavior of the cell. This homogenized approach avoids the explicit modelling of internal layered structures while still capturing the dominant thermal dynamics. The resulting formulation allows for the evaluation of both steady-state and transient temperature distributions under varying operating conditions.

At the cell level, boundary conditions are defined to represent typical operation within a controlled climatic chamber environment. External surfaces are subjected to convective heat transfer conditions characterized by a heat transfer coefficient and an ambient temperature. Additional simplifications, such as symmetry assumptions or adiabatic boundaries, may be applied where appropriate to reduce computational requirements. These boundary conditions are selected to ensure alignment between the modelling framework and experimental validation setups, facilitating a consistent comparison between numerical predictions and measured data.

The following section presents the thermal results obtained for the two cells under study, together with the validation of the modelling approach through comparison with experimental data. The analysis begins with the Gen3b cell, which represents conventional lithium-ion technology. For validation purposes, two operating scenarios are considered.

First, a transient test is analysed. The transient experiment consists of three complete charge–discharge cycles. The charging process (negative current values) is performed in two stages, combining a constant current phase at a 1C rate followed by a constant voltage phase. Discharge (positive current values) is carried out at a 2C rate. The test is conducted under controlled environmental conditions, with a constant ambient temperature of 25 °C. The comparison between numerical predictions and experimental measurements shows a satisfactory agreement, with temperature deviations remaining below 1.5 °C throughout the entire test. These results demonstrate the capability of the proposed thermal model to accurately capture the transient thermal response of the cell under dynamic operating conditions - Figure 5.

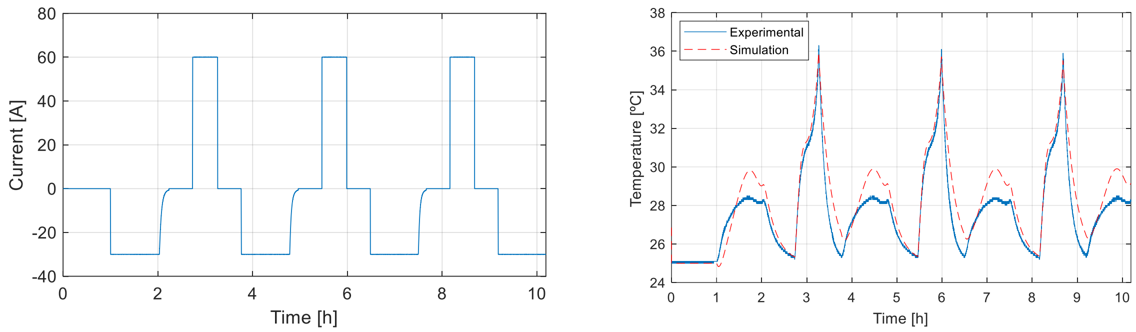


Figure 5. Transient thermal results for Gen3b cell: a) applied current with three cycles including full 1C-charge (CC-CV) and full 2C-discharge (CC); b) average cell temperature at ambient temperature of 25 ºC.

The analysis is extended to a pseudo-steady-state validation case, specifically designed to isolate the dominant heat generation mechanisms and minimize the influence of transient effects. In this test, the cell is first brought to an intermediate state of charge (SoC), which is then maintained throughout the experiment. Once this reference SoC is reached, a sequence of short charge–discharge micro-cycles is applied. Each micro-cycle consists of a high-rate current pulse, with charge and discharge phases of equal magnitude (2C), followed by a short relaxation period. The duration of these pulses is intentionally limited to a few seconds, and the sequence is repeated continuously until thermal stabilization is achieved.

The rationale behind this testing protocol is twofold. On the one hand, the use of rapid and symmetric charge–discharge cycling effectively suppresses long-term transient effects associated with large SoC variations, allowing the system to converge towards a quasi-steady thermal regime. On the other hand, the reversible (entropic) heat generation component is largely cancelled out, as it exhibits opposite signs during charge and discharge phases. As a result, the net heat generation over a complete micro-cycle is dominated by irreversible contributions, primarily associated with resistive and polarization losses. This creates a particularly suitable framework for validating the thermal model, as it allows a more direct comparison between predicted and measured temperature distributions without the additional uncertainty associated with reversible heat effects.

Under these conditions, the SoC remains effectively constant, while the temperature progressively increases until a steady thermal state is reached, defined by the balance between internally generated heat and external heat dissipation. The experimental characterization of the thermal field is performed using five thermocouples distributed across the cell surface, providing a discrete representation of the temperature distribution. From these measurements, an approximate thermal contour can be reconstructed and used as a reference for validation purposes.

The numerical results are compared against this experimentally derived temperature distribution. The comparison shows that the model is able to reproduce both the average temperature level and its spatial distribution with good accuracy - Figure 6. First, the predicted mean temperature is in close agreement with the experimental observations, which confirms the capability of the model to capture the global thermal behaviour of the cell under controlled boundary conditions representative of a climatic chamber. Second, both numerical and experimental results exhibit limited spatial temperature variation across the surface, indicating a relatively homogeneous thermal field under the tested conditions.

A consistent feature observed in both datasets is the presence of a slightly cooler region in the vicinity of the tab connections. This behaviour can be explained by enhanced heat dissipation in these conditions, where the electrical connections effectively increase the available surface area for heat transfer and introduce additional conductive paths. The model successfully captures this effect, which further supports its ability to represent localized thermal phenomena despite the use of a reduced-order formulation.

Overall, the pseudo-steady-state test provides a robust validation scenario, as it isolates irreversible heat generation and removes strong transient influences, thereby enabling a clearer assessment of the thermal model performance in predicting both average temperatures and spatial gradients within the cell.

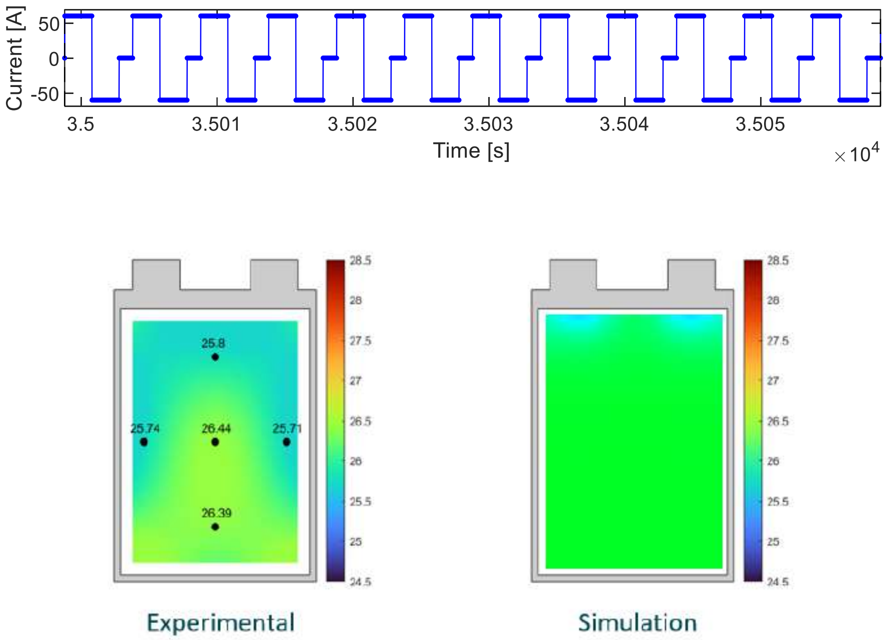


Figure 6. Pseudo-steady thermal tests for Gen3b cell: a) applied current including a phase with 2C charge for 2 seconds + 2C discharge for 2 seconds + rest for 1 second; b) experimental and numerical temperature contour.

The analysis is extended to the solid-state cell (Gen4). Based on the results obtained for the Gen3b cell, no significant temperature gradients are expected at the cell surface under comparable operating conditions. Consequently, pseudo-steady-state test results are not included for this case. This assumption is supported by dedicated thermal experiments performed with two thermocouples, which confirmed negligible temperature differences across the surface. Further details on these experimental results can be found in Deliverable 3.4. Therefore, the discussion focuses exclusively on the transient thermal response of the cell. For this purpose, a cycling profile consisting of five complete cycles is applied, including full 1C charge (CC–CV) and full 1C discharge (CC). The comparison between numerical and experimental results shows a generally good agreement throughout the test - Figure 7. The temperature evolution during the charge phases is accurately captured, with only minor discrepancies observed. Slight deviations appear towards the end of the discharge, particularly at very low states of charge (below approximately 5%). These differences can be attributed to the increased sensitivity of the heat generation calculation under such conditions, where small deviations in voltage or open-circuit voltage (OCV) estimation may lead to amplified errors in the predicted heat generation, and consequently in the temperature response. Overall, the model demonstrates a satisfactory predictive capability for the transient thermal behaviour of the solid-state cell.

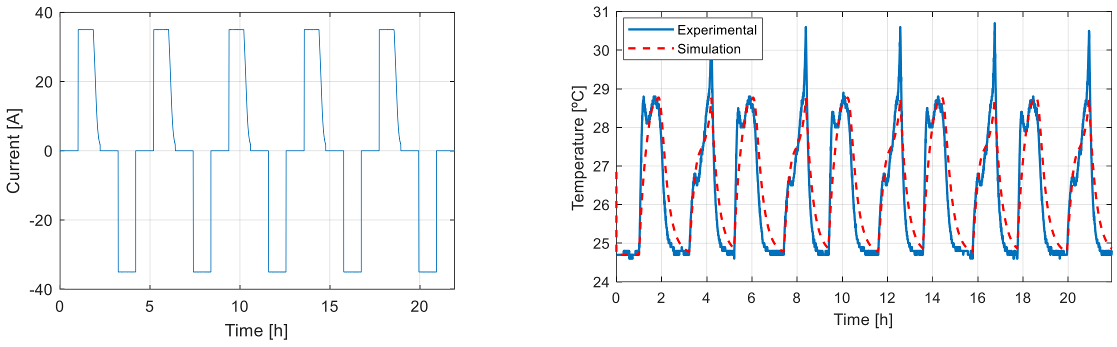


Figure 7. Transient thermal results for Gen4 cell: a) applied current with five cycles including full 1C-charge (CC-CV) and full 1C-discharge (CC); b) average cell temperature at ambient temperature of 24.8 ºC.

In summary, the proposed thermal modelling methodology combines a reduced-order pseudo-3D formulation with electrochemically driven heat generation, enabling an efficient yet physically consistent prediction of spatial temperature distributions at cell level. The approach has been applied and validated across two different technologies, namely a conventional lithium-ion cell (Gen3b) and a solid-state cell (Gen4), under representative operating conditions including both transient cycling and, where relevant, pseudo-steady-state profiles. The selected current profiles, ranging from dynamic multi-cycle operation to controlled high-frequency micro-cycling, have allowed a comprehensive assessment of the model under realistic scenarios. The comparison with experimental measurements demonstrates consistently good agreement, both in terms of average temperature evolution and spatial distribution, with only minor deviations observed under extreme operating conditions. Overall, the results confirm the robustness and predictive capability of the methodology, supporting its suitability as a reliable tool for thermal analysis in battery modelling applications.

5. MODULE AND PACK LEVEL MODELLING

This section presents an overview of the modelling approach followed at module and pack level, building upon the cell-level descriptions introduced previously. The objective is to extend the understanding of electro-thermal behaviour from individual cells to more representative system configurations, closer to real operating conditions.

At these higher levels of integration, additional factors become relevant, such as the interaction between components, heat distribution across the assembly, and the influence of the system layout. For this reason, simplified but physically meaningful modelling techniques are adopted in order to balance accuracy and computational efficiency.

The module is considered as the first level of integration where cells are electrically and thermally connected, along with auxiliary components required for operation and control. From there, different configurations are defined to represent battery packs of increasing complexity, including both experimental setups and full-scale virtual systems.

The approach aims to provide a consistent framework to analyse the performance of different technologies under comparable conditions. In addition, it enables the evaluation of key variables such as voltage response and temperature evolution at different scales.

Finally, the reliability of the models is assessed through comparison with experimental data, ensuring that the main trends and behaviours are adequately captured. This validation step is essential to support the use of the models for further analysis and system-level studies.

5.1 Reduced-order 3D accurate thermal module level model coupled with physics-based model

At the module scale, the models build upon the cell-level models described in the previous section. This section first presents the designs of the Gen3b and Gen4 modules. In both cases, the electrical architecture consists of a series connection of 16 cells, along with a junction box integrating key components such as the contactor, pre-charger, resistor, fuse, DC-DC converter, relays, and both BMS master and slave units. In addition, the module includes PowerLok terminals and DB9 connectors for CAN communication.

From a thermal perspective, both designs follow a similar approach. The module structure incorporates a mechanical absorber and thermal interface material (TIM) on each side of the active cell area to ensure proper mechanical compliance and effective thermal contact. Heat generated within the cells is transferred to a central heat sink, which distributes it towards both sides of the module. This heat is subsequently dissipated through lateral heat sinks located on either side of the assembly.

The entire system is enclosed within a housing where two fans are responsible for driving the airflow across the heat sinks, enhancing convective heat transfer. The fans used in the design have typical dimensions of 80 × 80 × 25 mm, with a maximum static pressure of 20.46 mmH_2O and a maximum airflow rate of 88.4 CFM - Figure 8.

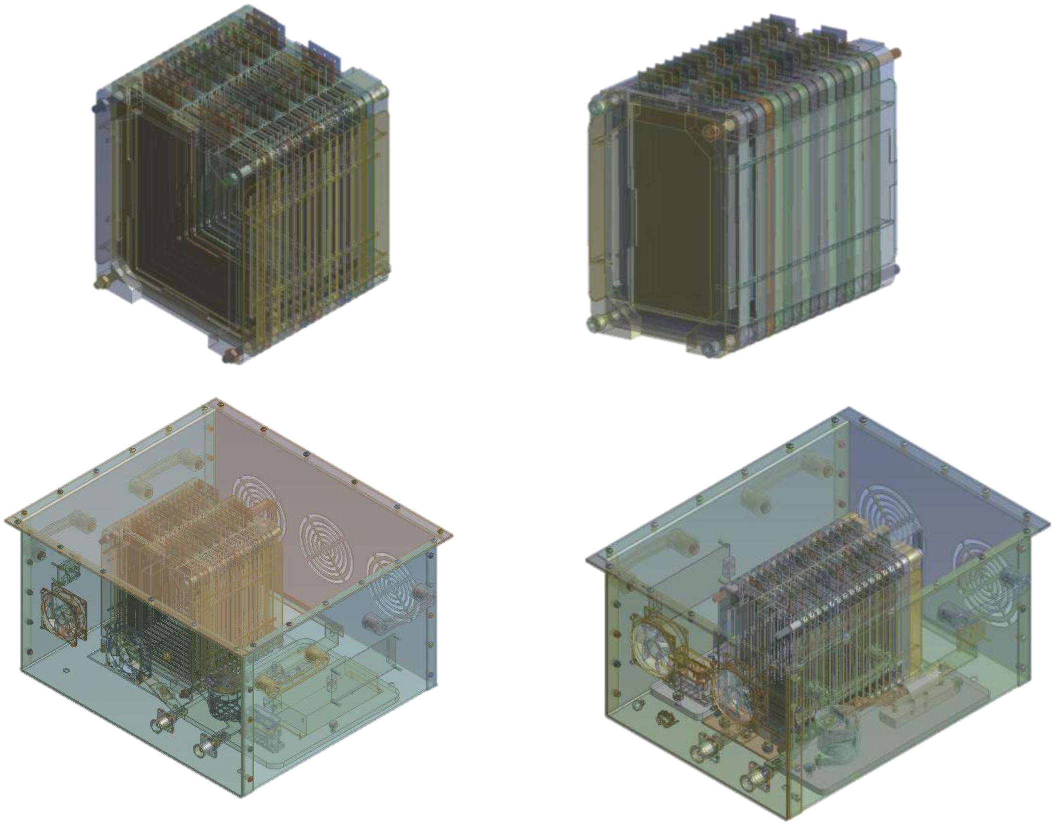


Figure 8. Design of the modules; a) Gen3; b) Gen4.

For the thermal modelling, the lumped-parameter approach applied at the cell scale has been extended to the module level, incorporating the geometry of the different structural components as well as their associated material properties. This approach enables capturing the main heat transfer paths within the assembly while maintaining a reduced computational cost. The thermophysical properties assigned to each component—such as density, thermal conductivity, and specific heat capacity—are defined based on their material composition and geometric representation. The following section provides a detailed description of the thermophysical properties considered for each individual element - Table 3.

Table 3. Thermophysical properties assigned to each component.

Component	Material	*k* (W/m·K)	*ρ* (kg/m³)	C_p (J/kg·K)
Heat-sink and heat-spreader	Aluminium	235	2700	900
Insulation layer	Calcium-magnesium silicate	0.125	200	1600
Thermal interface layer	Silicone	5	3300	1200
Cell holder	High temp resin	0,14	1040	1300

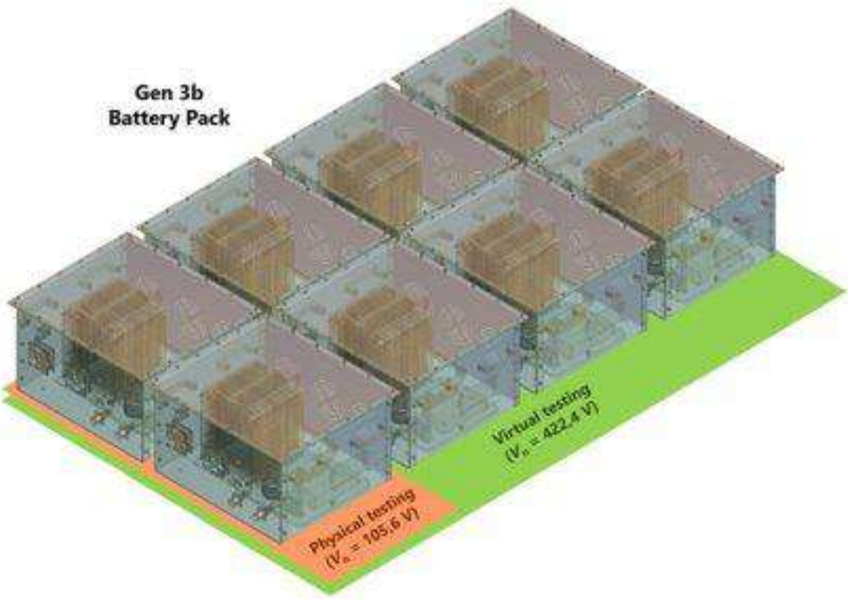
5.2 Scale-up of module level model to pack analysis

Based on the nominal voltages of each module (52.8 V for the Gen3b module and 58.4 V for the Gen4 module), scaling strategies have been defined to construct pack-level configurations. Two types of pack configurations have been considered: physical test packs and virtual packs for system-level assessment.

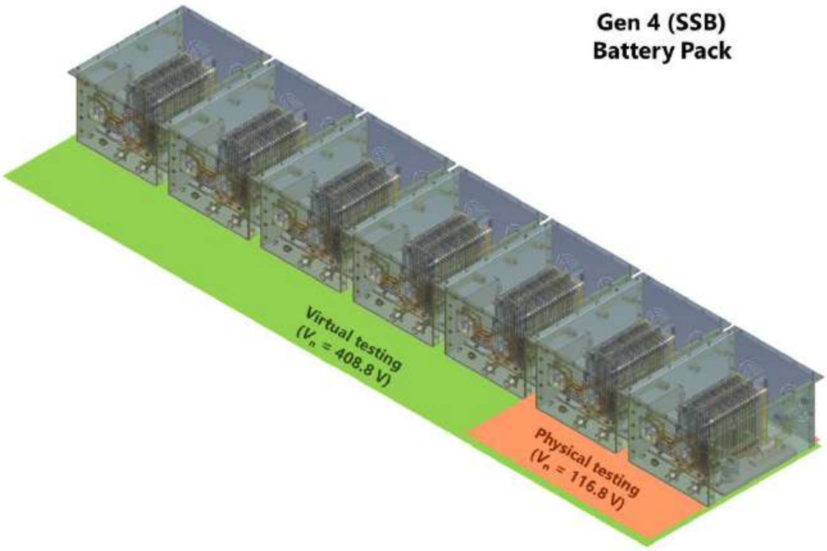
In both technologies, the experimental test packs are composed of two modules connected in series, providing a representative but manageable configuration for validation purposes. In contrast, the virtual pack configurations have been designed to meet a target system voltage of approximately 400 V, enabling the evaluation of full-scale operating conditions.

For the Gen3-based architecture, the target voltage is achieved by connecting eight modules in series, both electrically and thermally, ensuring consistency between the electrical topology and the thermal network representation. For the Gen4 (solid-state battery, SSB) configuration, seven modules connected in series are sufficient to reach a comparable voltage level due to the higher nominal voltage per module.

These configurations allow for a consistent comparison between technologies while preserving realistic operating conditions. The following figures illustrate the layout and configuration of both the physical test packs and the virtual full-scale packs for each cell technology - Figure 9.



a)



b)

Figure 9. Physical and virtual battery pack definitions; a) Gen3; b) Gen4.

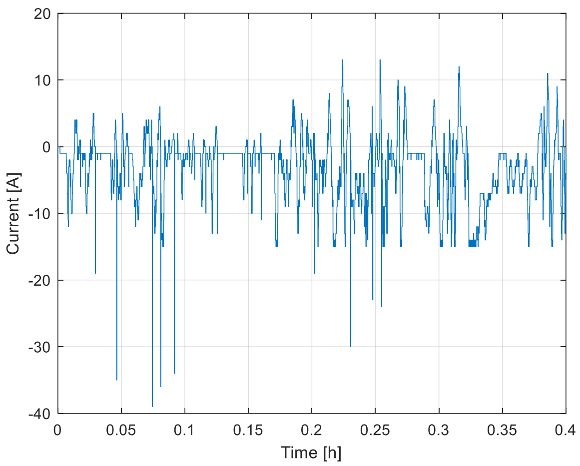
5.3 Model validation

In this final section, a validation of the model is performed at both module and pack scales. The analysis is first carried out for the Gen3b configuration at the "physical pack" level, consisting of two battery modules connected in series. As input, a dynamic current profile is applied, corresponding to a use case previously defined within Work Package 1. The simulation is initialized with a state of charge (SoC) of 30% and a uniform initial and ambient temperature of 25.5 °C.

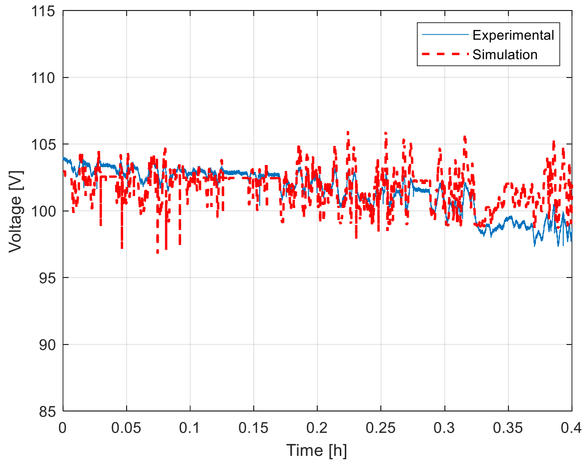
Given that modelling uncertainties significantly increase when scaling up from cell to pack level—due to factors such as thermal interactions, assembly tolerances, and airflow variability—the numerical-experimental correlation obtained for the voltage response can be considered satisfactory.

Regarding thermal behaviour, the comparison is strongly influenced by the limited resolution of the experimental temperature measurements, which were recorded as integer values only. This discretization introduces noise and restricts the direct assessment of transient temperature evolution. To address this limitation, the experimental data have been post-processed using an exponential fitting approach. This method provides a smoothed temperature curve that better represents the underlying thermal dynamics by filtering measurement quantization effects while preserving the global trend and time constant of the system.

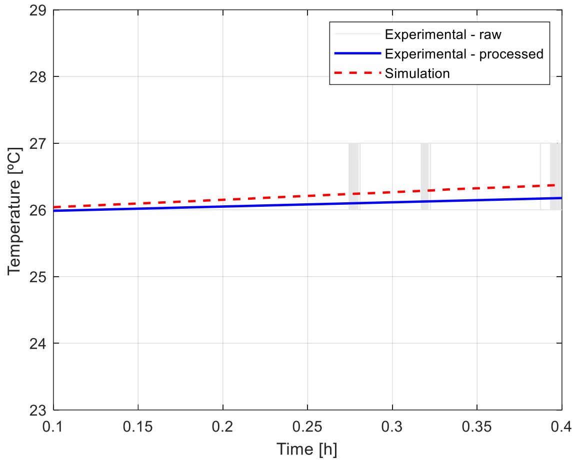
Despite these limitations, the comparison shows that the predicted temperature evolution is consistent with the experimental results in both magnitude and overall trend - Figure 10. Therefore, the thermal model at pack scale for the Gen3b cell technology is considered to be satisfactorily validated within the expected level of accuracy.



a)



b)



c)

Figure 10. Electro-thermal results for Gen3b physical battery pack; a) applied current profile; b) voltage; c) average temperature.

Secondly, the Gen4 configuration is analysed at module scale. The applied input consists of a current profile combining a discharge phase at C/10 followed by a charging phase at C/2, allowing the evaluation of the model under both operating conditions. The test is initialized with a state of charge (SoC) of 35% and a uniform initial and ambient temperature of 24.8 °C.

As previously discussed, model uncertainties increase with system scale, although they are expected to remain lower at module level than at full pack level. Within this context, the numerical-experimental correlation of the voltage response can be considered reasonably satisfactory, capturing the main features of the measured behaviour.

From a thermal standpoint, the comparison is again constrained by the limited resolution of the experimental temperature measurements, which were recorded as integer values. This discretization reduces the fidelity of transient analysis, particularly in low-gradient regions. To mitigate this effect, a similar post-processing strategy to that applied in the Gen3b case is adopted, where the experimental data are complemented with a fitted curve to better represent the underlying thermal evolution.

Despite these limitations, the model is able to reproduce the temperature evolution with good agreement in both magnitude and trend. The consistency observed between numerical predictions and experimental data supports the validity of the modelling approach - Figure 11. Therefore, the Gen4 model is considered to be satisfactorily validated at module scale within the expected level of accuracy.

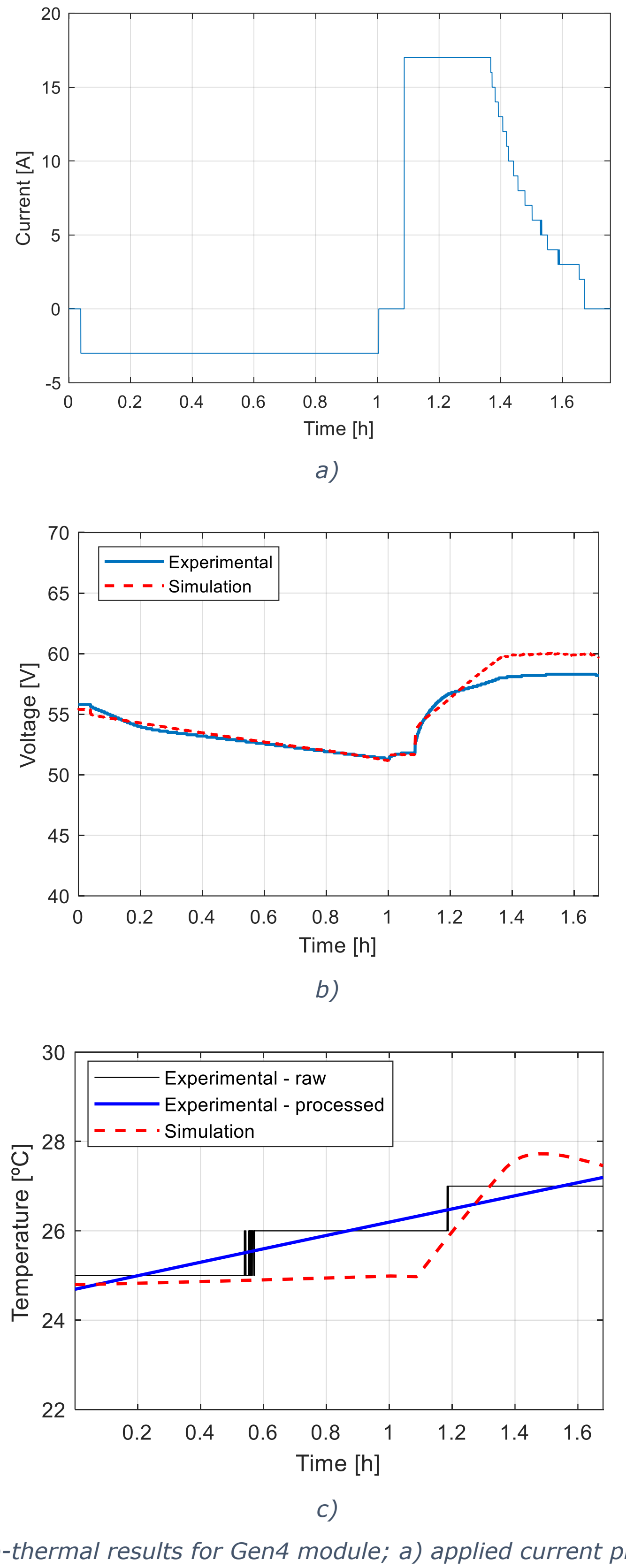


Figure 11. Electro-thermal results for Gen4 module; a) applied current profile; b) voltage; c) average temperature.

6. CONCLUSIONS

This deliverable has presented the development and validation of a comprehensive reduced-order modelling framework for battery systems, covering cell, module, and pack levels. The work addresses one of the main challenges in battery modelling: achieving a balance between physical accuracy and computational efficiency, particularly in the context of multi-scale and multi-physics simulations.

At cell level, the combination of physics-based electrochemical models with reduced-order thermal formulations has proven to be an effective strategy. The use of the Single Particle Model with electrolyte (SPMe), implemented through Orthogonal Collocation, provides a computationally efficient representation of the internal electrochemical processes while maintaining sufficient accuracy. The integration of a pseudo-3D thermal model enables the prediction of temperature distributions, capturing both global trends and local effects such as thermal gradients and hot spots.

The validation results demonstrate that the proposed modelling approach is able to reproduce the main electro-thermal behaviour of both conventional lithium-ion (Gen3b) and solid-state (Gen4) cells. Good agreement with experimental data has been achieved under different operating conditions, including transient cycling and pseudo-steady-state scenarios. The observed deviations remain within acceptable limits and are mainly associated with uncertainties in experimental measurements or extreme operating conditions.

The extension of the modelling framework to module and pack levels confirms its flexibility and scalability. By incorporating simplified representations of structural components and thermal interfaces, the models are able to capture the dominant heat transfer mechanisms within the system while preserving a reduced computational cost. The defined scaling strategies allow the construction of both experimental and virtual pack configurations, enabling the analysis of realistic operating conditions.

At these higher levels of integration, the comparison with experimental data shows a satisfactory agreement in terms of both voltage response and temperature evolution. Although uncertainties increase due to factors such as thermal interactions, airflow distribution, and assembly variability, the models successfully capture the overall system's behaviour and trends. This validates their suitability for system-level analysis and supports their use in further applications.

One of the main outcomes of this work is the demonstration that reduced-order models can provide a reliable alternative to high-fidelity simulations for many practical applications. Their reduced computational requirements make them especially valuable in contexts where a large number of simulations is required, such as parametric studies, optimisation tasks, or real-time applications.

In the context of the FASTEST project, the developed models represent a key enabling technology. They directly support the definition of efficient Design of

Experiments (DoE) [7] strategies and contribute to reducing the reliance on costly and time-consuming physical testing. Moreover, their integration into the hybrid testing platform paves the way for advanced digitalisation of battery testing processes, including the implementation of Digital Twin concepts.

Overall, the results obtained in this deliverable confirm the robustness, accuracy, and applicability of the proposed modelling framework. Future work will focus on further refining the models, extending their capabilities (e.g., including ageing effects), and integrating them more deeply into the FASTEST platform for full system-level operation.

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