

# Physics-informed Modeling Framework for AI-based Battery Pack Design, Operation and Diagnostics Optimization

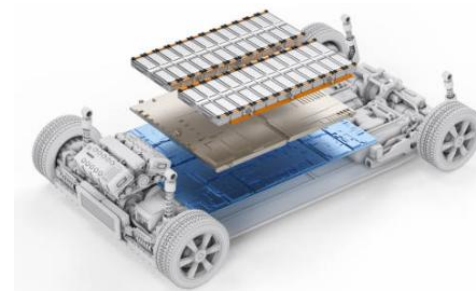
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## Motivation and Introduction

- Pack-level optimization necessitates the coupling of **electrical, electrochemical, and thermal** dynamics.
- High number of variables and cross-interactions** complicates systematic analysis.
- We provide a precise and flexible **physics-informed** simulation framework to enable **AI-assisted optimization** on pack-level.



## Main findings

- Explicit pack topology and cooling** modeled under fully configurable boundary conditions.
- DFN-level internal states at ECM-level speed** via adaptive discretization (SPMe → DFN).
- Validated** against measurements on physical cells using Virtual Parallel Connection (RMSE( $I$ ) < 1%).
- Enables optimization of **system design, operation and diagnostics** based on BMS-observable and cell-level hidden states.

## Inputs

<b>Topology</b> <ul style="list-style-type: none"> <li>msnp</li> <li>contacting network</li> <li>terminal position</li> </ul>	<b>Heterogeneities</b> <ul style="list-style-type: none"> <li>Intrinsic: <math>\Delta C_i, \Delta R_i, \Delta SoHi</math></li> <li>Extrinsic: <math>\Delta R_p, \Delta R_{int}, \Delta T, \Delta Q_{cool}</math></li> </ul>	<b>Physicochemical cell parameter set</b> <ul style="list-style-type: none"> <li>NCA   Si-Gr</li> <li><math>C_N = 4.5</math> Ah</li> <li><math>I_{ch,max} = 3C</math></li> <li><math>I_{dch,max} = 10C</math></li> </ul>	<b>Fidelity vs. Complexity on single-cell level</b> <ul style="list-style-type: none"> <li>Adaptive discretization in through plane: 1...N</li> <li>Adaptive discretization in solid domain: 3...N</li> </ul>
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## Outputs

<b>System-level states (BMS-observable)</b> <ul style="list-style-type: none"> <li><math>U_{sys}</math></li> <li><math>U_{module}</math></li> <li><math>I_{sys}</math></li> <li><math>T_{sensor}</math></li> </ul>	<b>Cell-level states (hidden)</b> <ul style="list-style-type: none"> <li><math>SoC_{cell}</math></li> <li><math>\eta_{anode}</math></li> <li><math>C_s</math></li> <li><math>c_l</math></li> <li><math>T_{cell,0D}</math></li> <li><math>Q_{gen}</math></li> </ul>
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## Multi-Cell Transmission Line Model

**Electro-thermal multi-cell model**

**Thermal**

(a) Cell-individual thermal boundary conditions

(b) Cell-individual thermal boundary conditions + cell-to-cell heat exchange

(c) Cell-individual thermal boundary conditions + cell-to-cell heat exchange + explicit integration of passive elements

Adaptive complexity

**Physicochemical single-cell model [1]**

Electrical Submodel

Electrolyte Diffusion Submodel

Solid Diffusion Submodel

Negative Electrode | Separator | Positive Electrode

Number of Elements: N (DFN), 1 (SPMe)

Particle Dimension

Lumped thermal cell model

**Validation against measurements on physical cells**

- Exp. Measurement via Virtual Parallel Connection (VPC) [2,3] on Molicel INR21700-P45b.
- 0.5C CCCV-Charge from 0 to 100% SOC

$\Delta I_{max} = 39.8 / 74.3 / 110.4$  mA

RMSE = 0.383 / 0.502 / 0.723%

## System Design

**Inhomogeneity analysis for given pack configuration**

- Quantify the impact of manufacturing and aging spread under topology and thermal constraints.
- Derive allowable tolerances and sensor placement.

Pack configuration (topology and cooling) 20 °C

Load: CCCV (3C), SOC 10-80%

Introduction of cell-to-cell and path resistance variances

Predicted pack response

## Fast Charging

**Anode-potential aware fast charging (single-cell)**

- Minimize charge time subject to  $\eta_{anode} \geq 10$  mV
- CC → CAP → CV (CAP: constant anode pot.)

Load: CC (6C) → CAP → CV 1s1p 22.5 °C SOC 10-80%

**Application at pack level under thermal and cell-to-cell inhomogeneity**

Identify limiting cell and its plating risk

Predicted pack response

## Differential Voltage Analysis

**Peak analysis over cell aging (single-cell)**

- Introduce Loss of Lithium Inventory (LLI): 6%, 10%, 14%
- Induces half-cell balancing shift
- Directly observable in single-cell DVA

Load: CC (0.05C) 1s1p SOC 0-100% 22.5 °C

**Application at pack level under SOH inhomogeneity**

Observation of voltage signal of the parallel configuration  $U_p$

Predicted pack response



Input for AI-assisted Optimization: pack design • operation • diagnostics

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