Battery Ageing • Battery Models • Battery Diagnostics • Battery Pack Design • Electromobility • Stationary Energy Storage • Energy System Analysis

Fast Charging of Lithium-ion Batteries with Monitoring and Controlling the Internal Physical States

7th Energy Storage Systems Workshop

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Center for Ageing, Reliability and Lifetime Prediction of Electrochemical and Power Electronic Systems (CARL)

CARL Center for Ageing, Reliability and Lifetime Prediction of Electrochemical and Power Electronic Systems | RWTH AACHEN UNIVERSITY

Super fast-charging station for highways

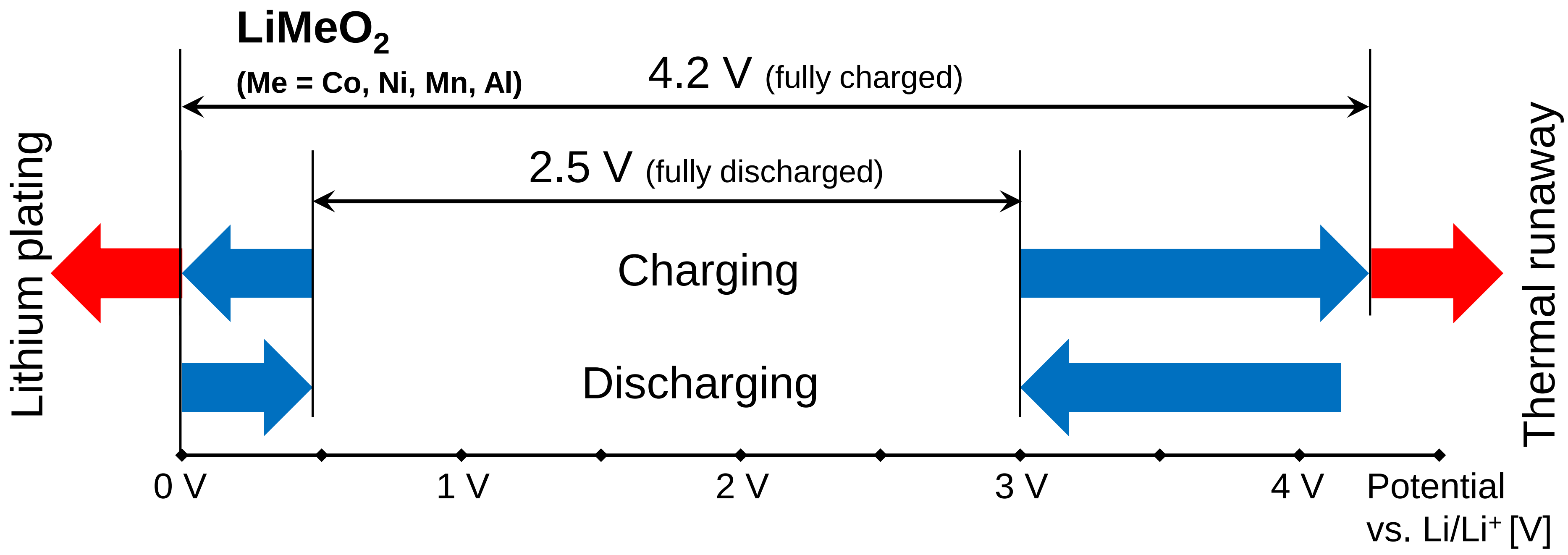
Picture: EnBW

Fast charging station for passenger cars –
300 kW charging for 15 to 20 min

Picture: DesignWerk

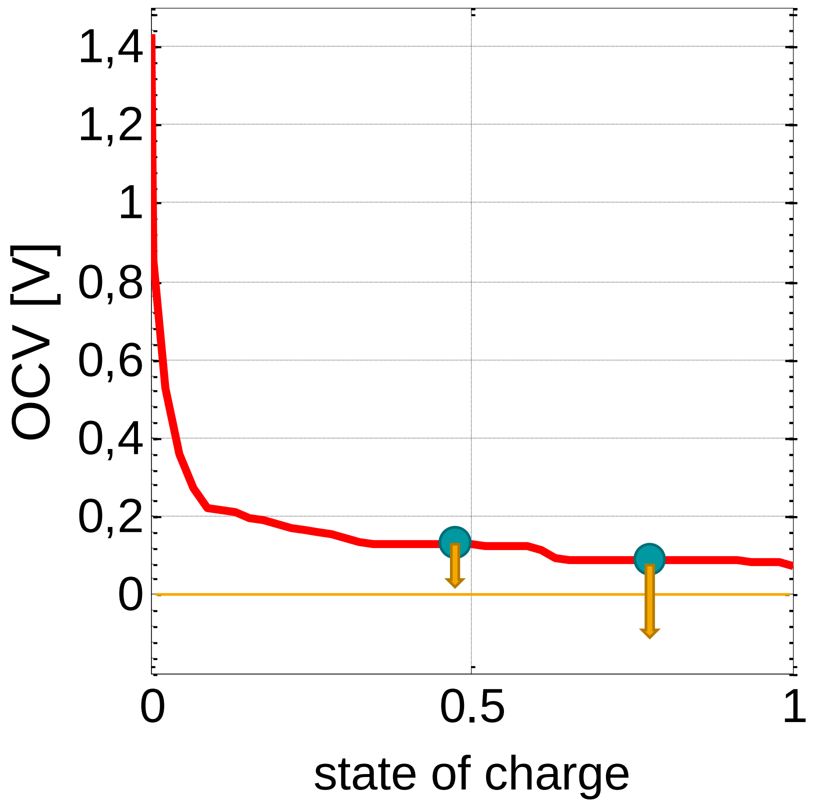
Fast charging station for trucks –
1 MW charging for about 45 min

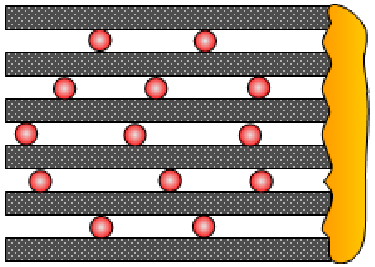
Charging of Lithium-Ion Batteries is limited by the negative Electrode Potential

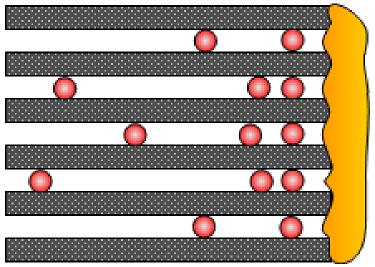


Why Lithium Plating happens

Depending on local anode potential

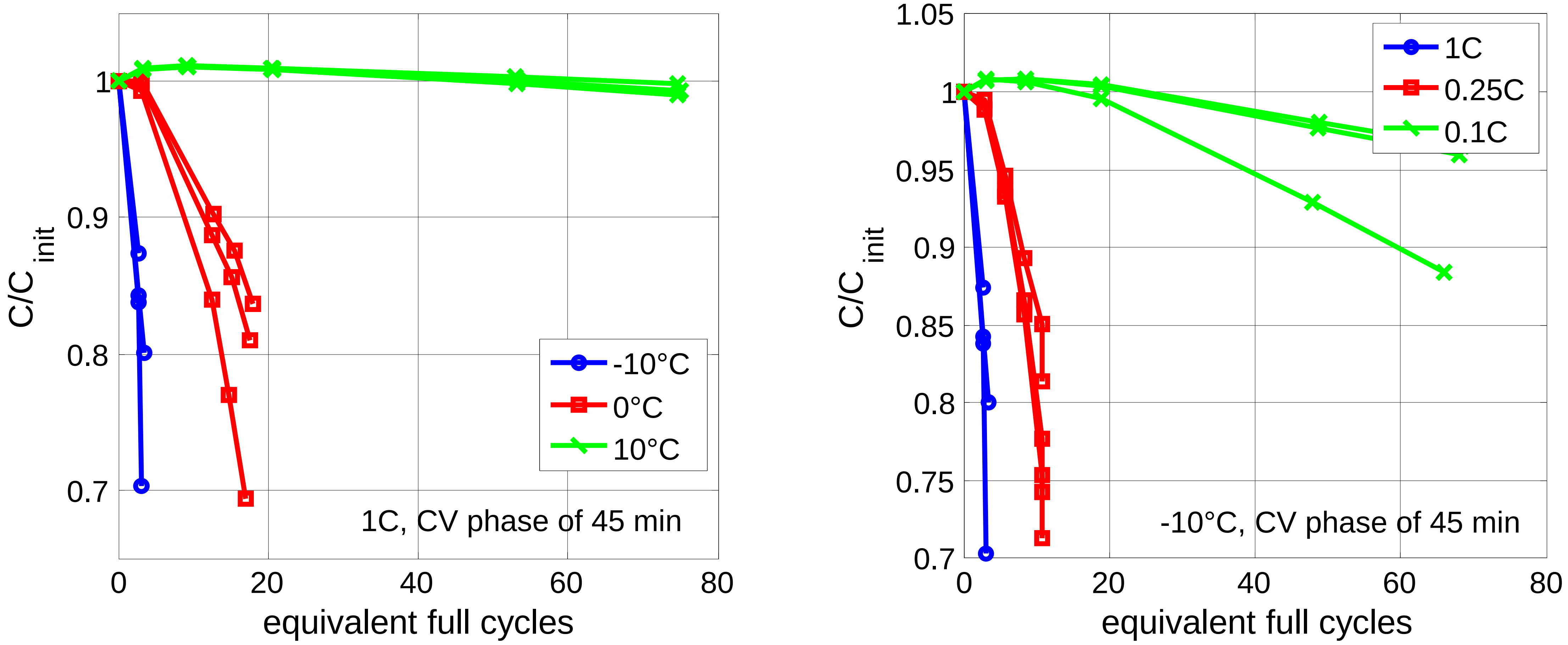






➔ Cells behave very differently

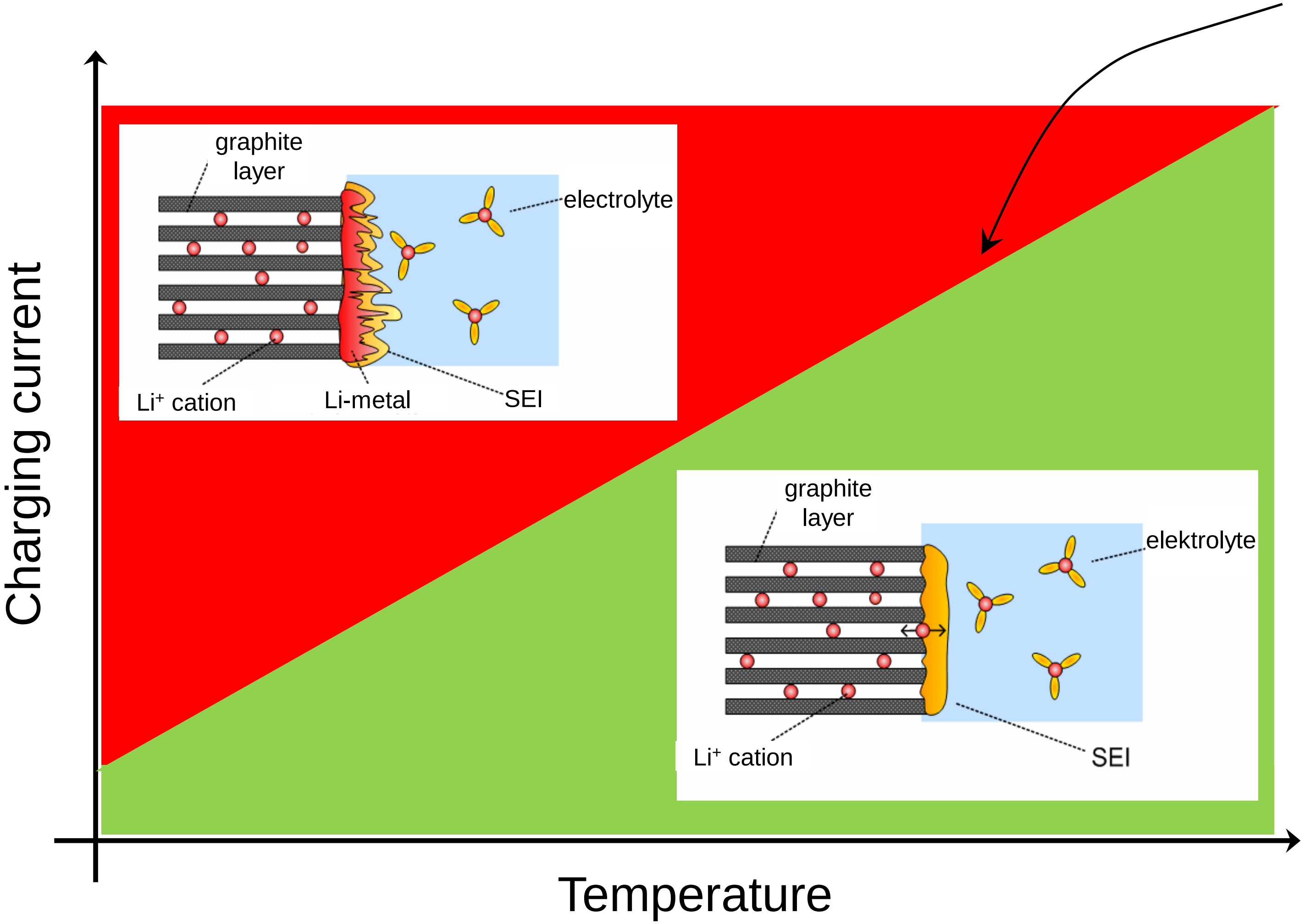
Ageing caused by Plating of a Kokam 40 Ah Cell at different Temperatures and Current Rates



Lithium Plating: Caused by excessive Currents at a given Temperature

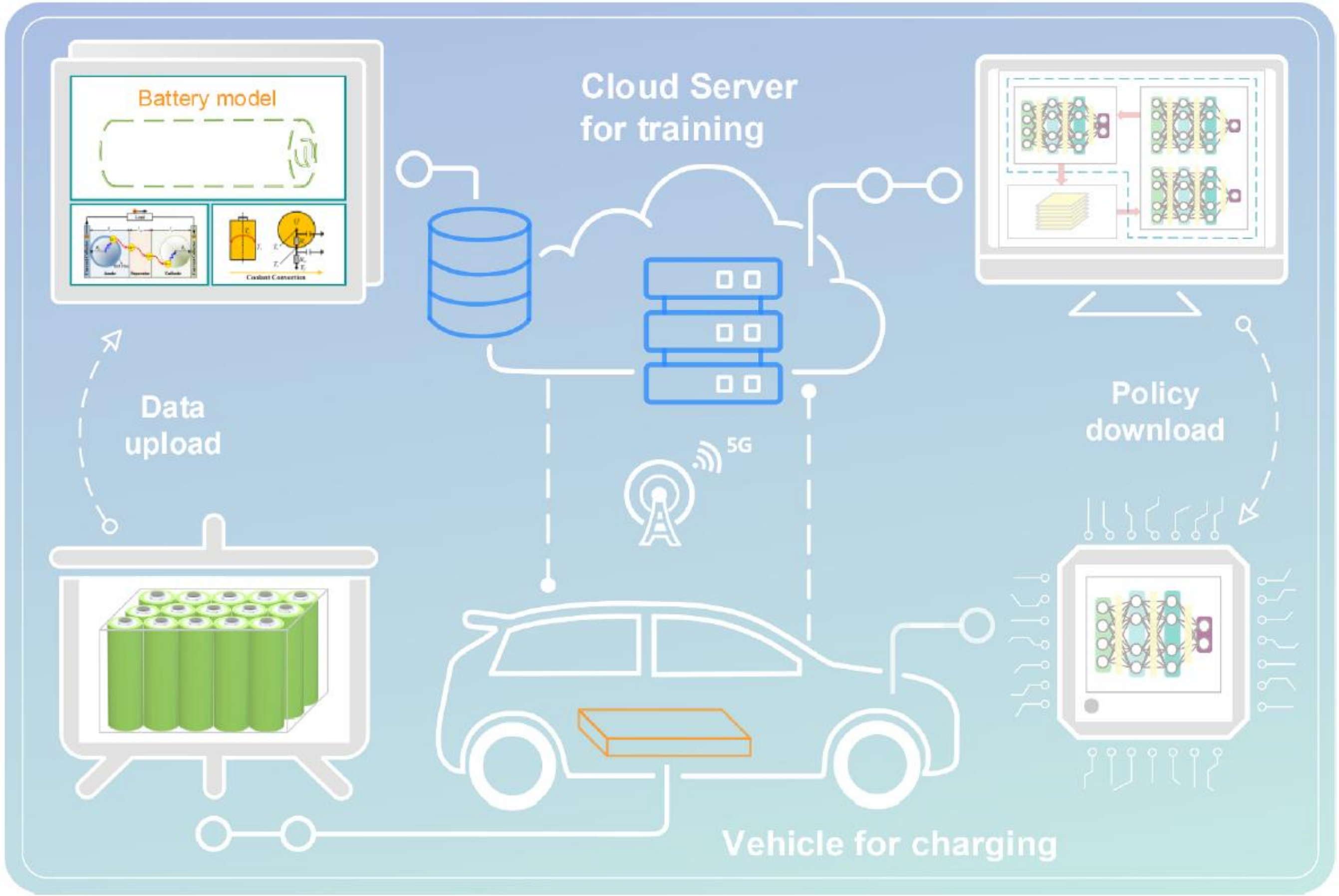
Non-linear function depending on

- Battery type
- Ageing
- State of charge



Solution approach

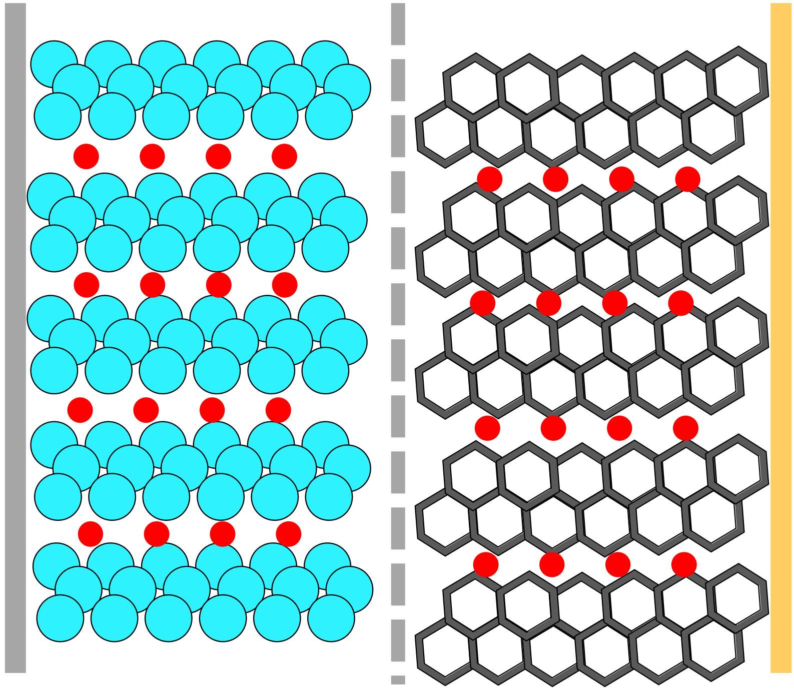
- Model for the prediction of plating
- Model implementation and reduction
- Online state estimation
- Parameter identification
- Controlling charging current



Physical-chemical battery model

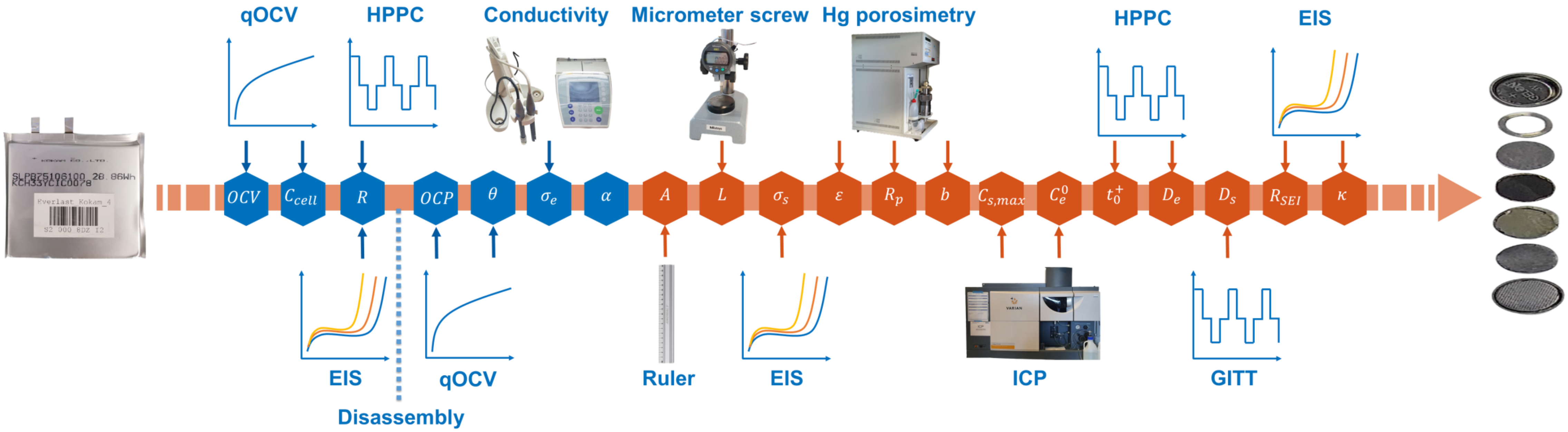
- Bottom-up approach
  - Physical processes → Cell voltage

- States and parameters have physical meaning
- Plating predictable via internal states
  - Plating Overpotential $\eta_{plating} < 0$ V



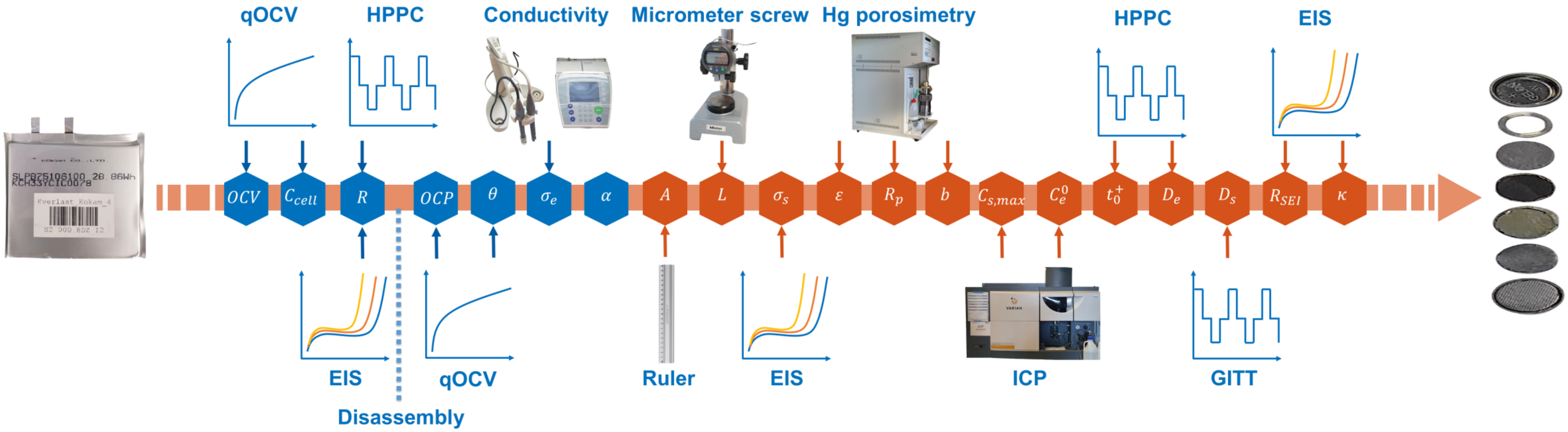
F. Ringbeck, Dissertation, ISEA, RWTH Aachen **2021**

State-of-the-art experimental parameter measurements



Li W, et al., Energy Storage Materials, **2021** (44): 557-570.

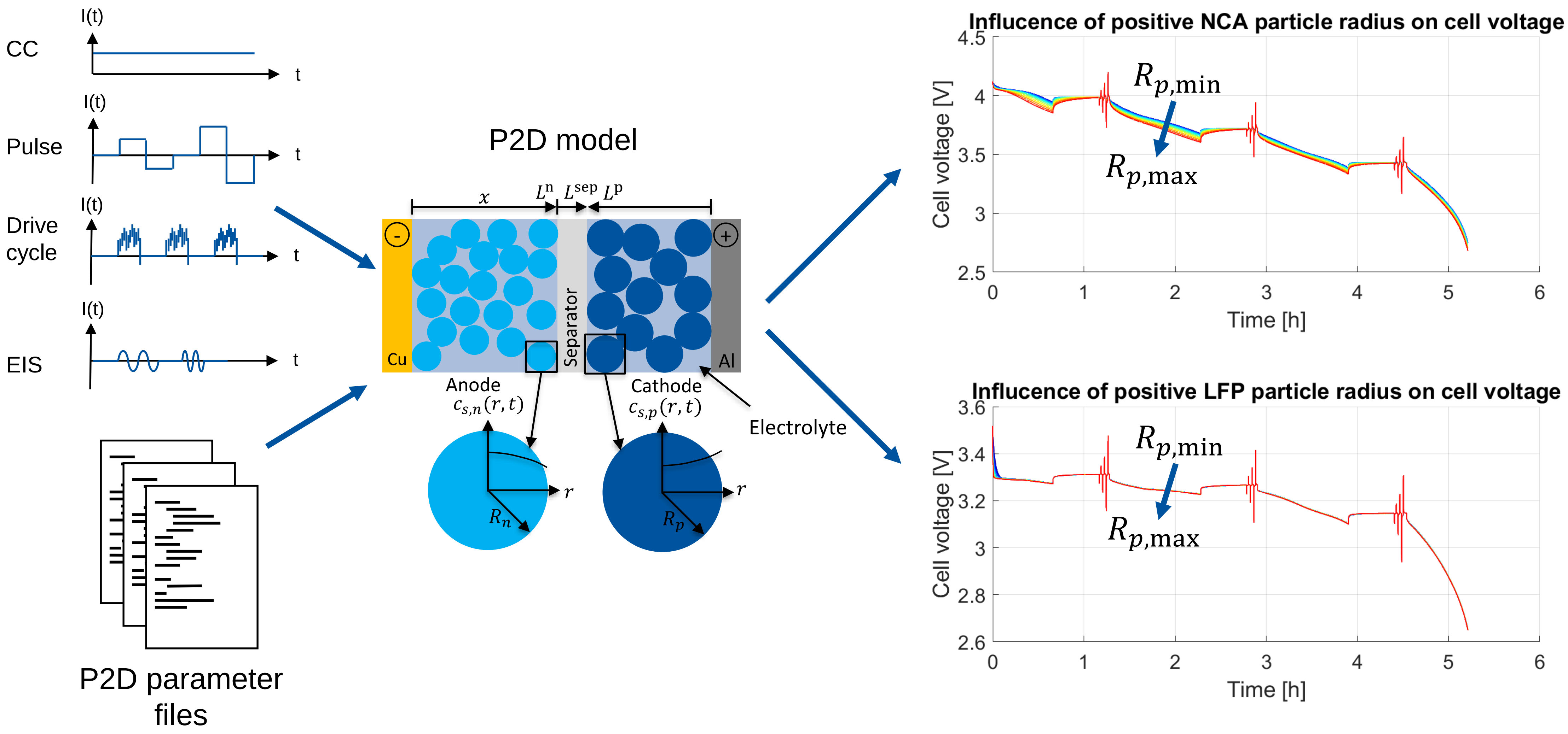
State-of-the-art experimental parameter measurements



Time + Cost + Accuracy → Data + AI

Li W, et al., Energy Storage Materials, **2022** (44): 557-570.

Sensitivity Analysis of Electrochemical Battery Models



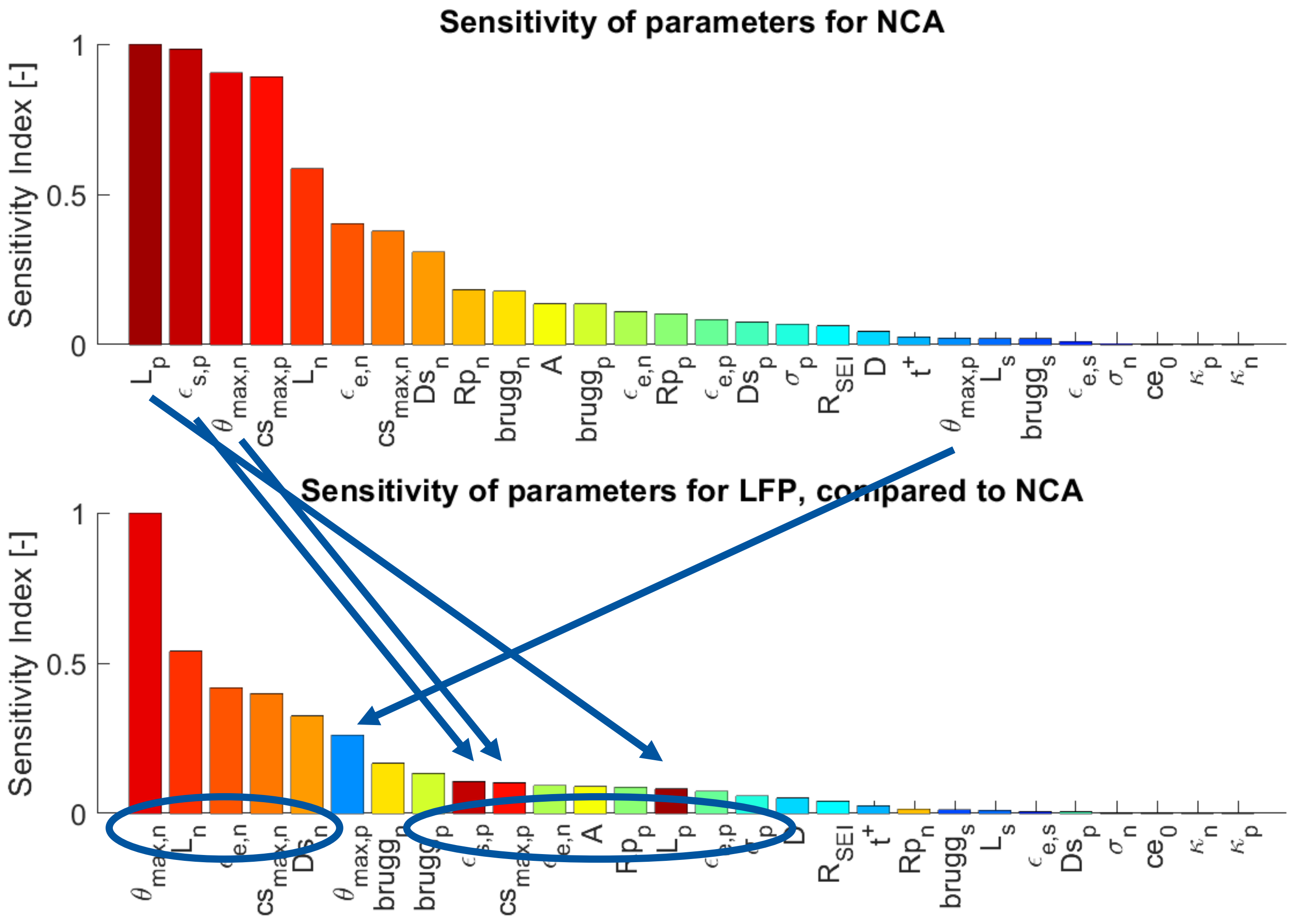
Luder D, et al., Advanced Battery Power Conference, Münster, Germany, 2022

Multi-chemistry parameter sensitivity analysis

- Perform Sensitivity Analysis
- Observe influence of
  - battery chemistries,
  - high power / high energy batteries

  on battery voltage, capacity, overpotential, impedance
- Investigate cathode / anode limitations

- Comparing NCA and LFP as cathode material:
  - LFP: capacity dependent parameters have smaller influence on cell voltage due to flat OCV



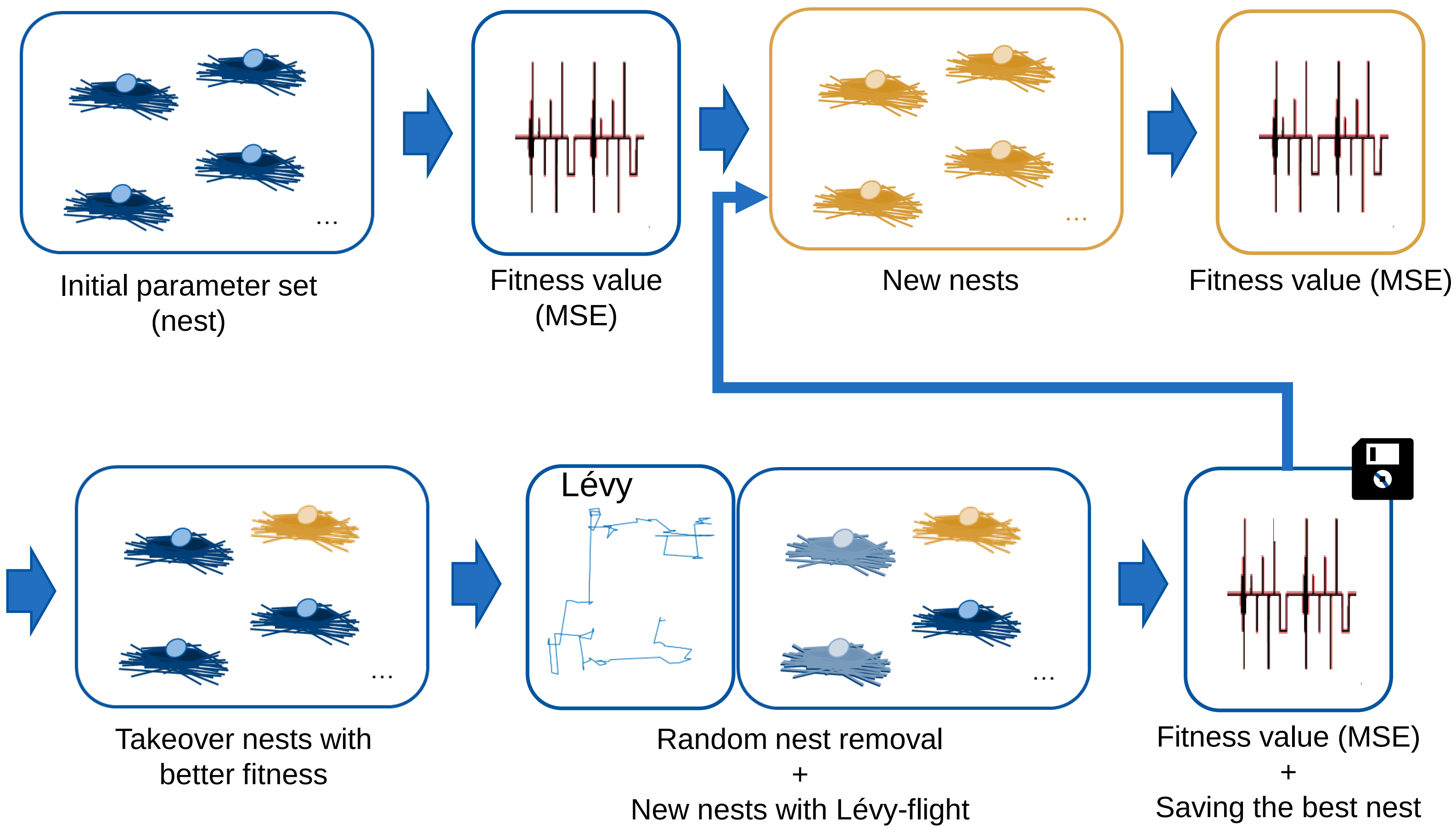
Parameters for anode

Parameters for cathode

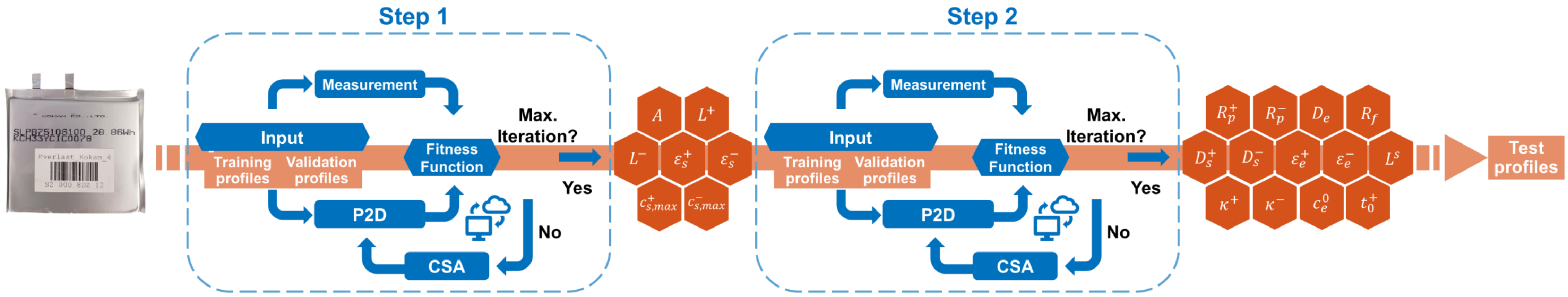
Luder D, et al., **2022**, in preparation

Metaheuristic algorithms

- Global optimization problem
  - Genetic algorithm
  - Particle swarm optimization algorithm
  - Cuckoo search algorithm (CSA)



Multi-objective multi-step data-driven identification



- Multi-objective identification
  - Minimization of the voltage errors between simulation and measurement
  - Minimization of the relative capacity errors between the electrodes

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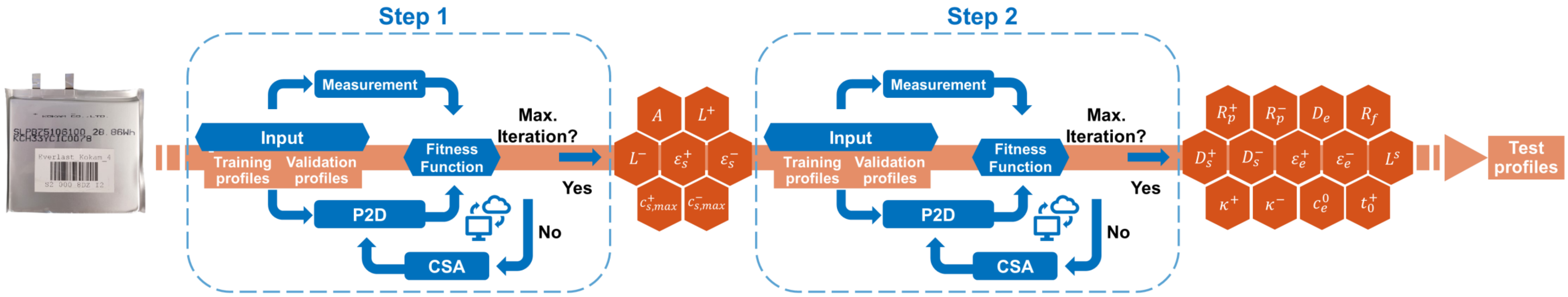
Multi-objective multi-step data-driven identification

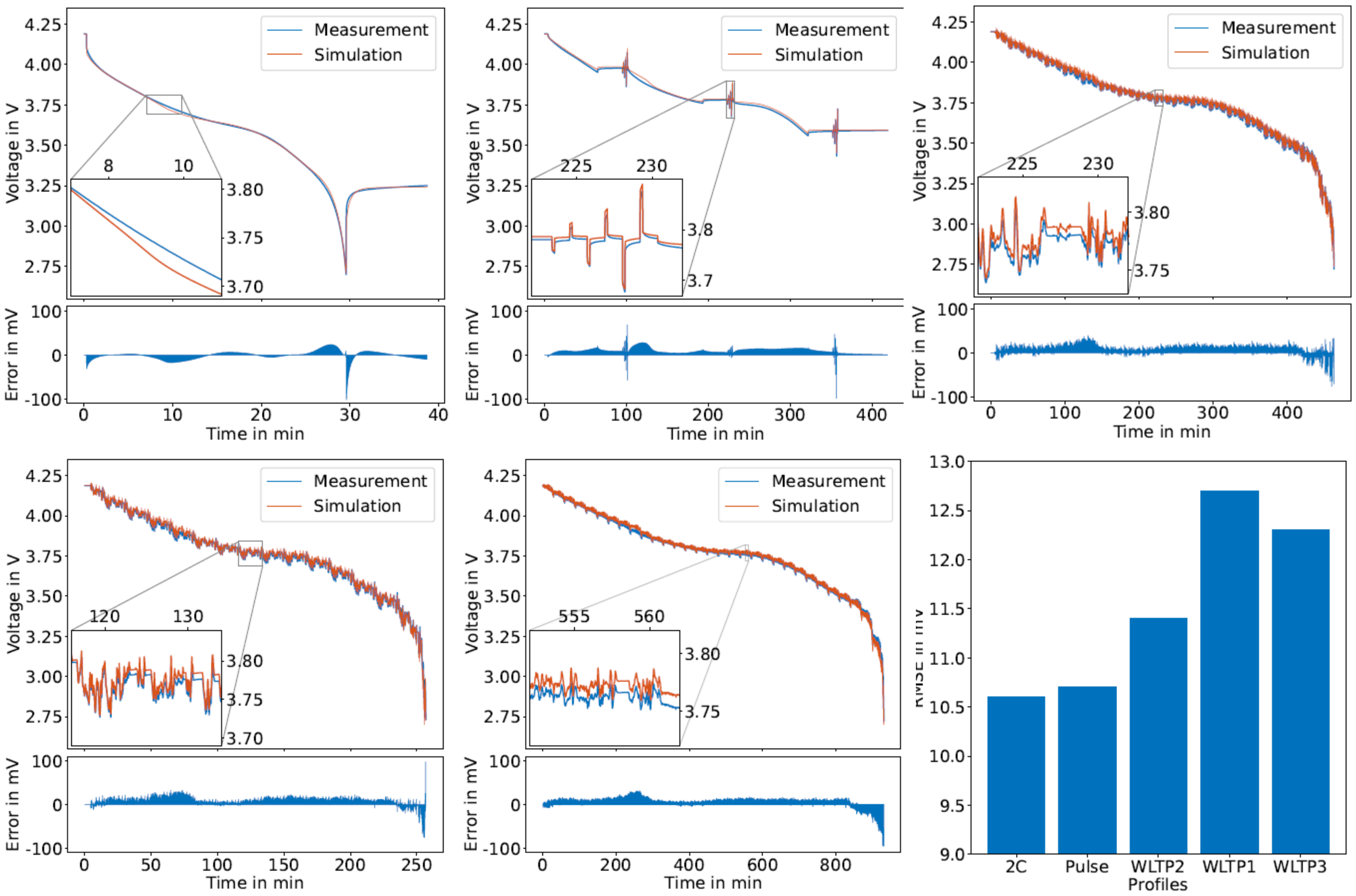


- Multi-objective identification
  - Minimization of the voltage errors between simulation and measurement
  - Minimization of the relative capacity errors between the electrodes
- Multi-step identification considering sensitivity difference
  - High-sensitivity parameters unchanged in the second step
- Machine learning-inspired identification process
  - Data grouping and training to overcome overfitting

Li W, et al., Energy Storage Materials, **2022** (44): 557-570.

Results: Experimental validation

- Training & Validation
- Test



Li W, et al., Energy Storage Materials, **2022** (44): 557-570.

Results: Experimental vs. Data-driven

- Lower RMSE under constant-current discharging

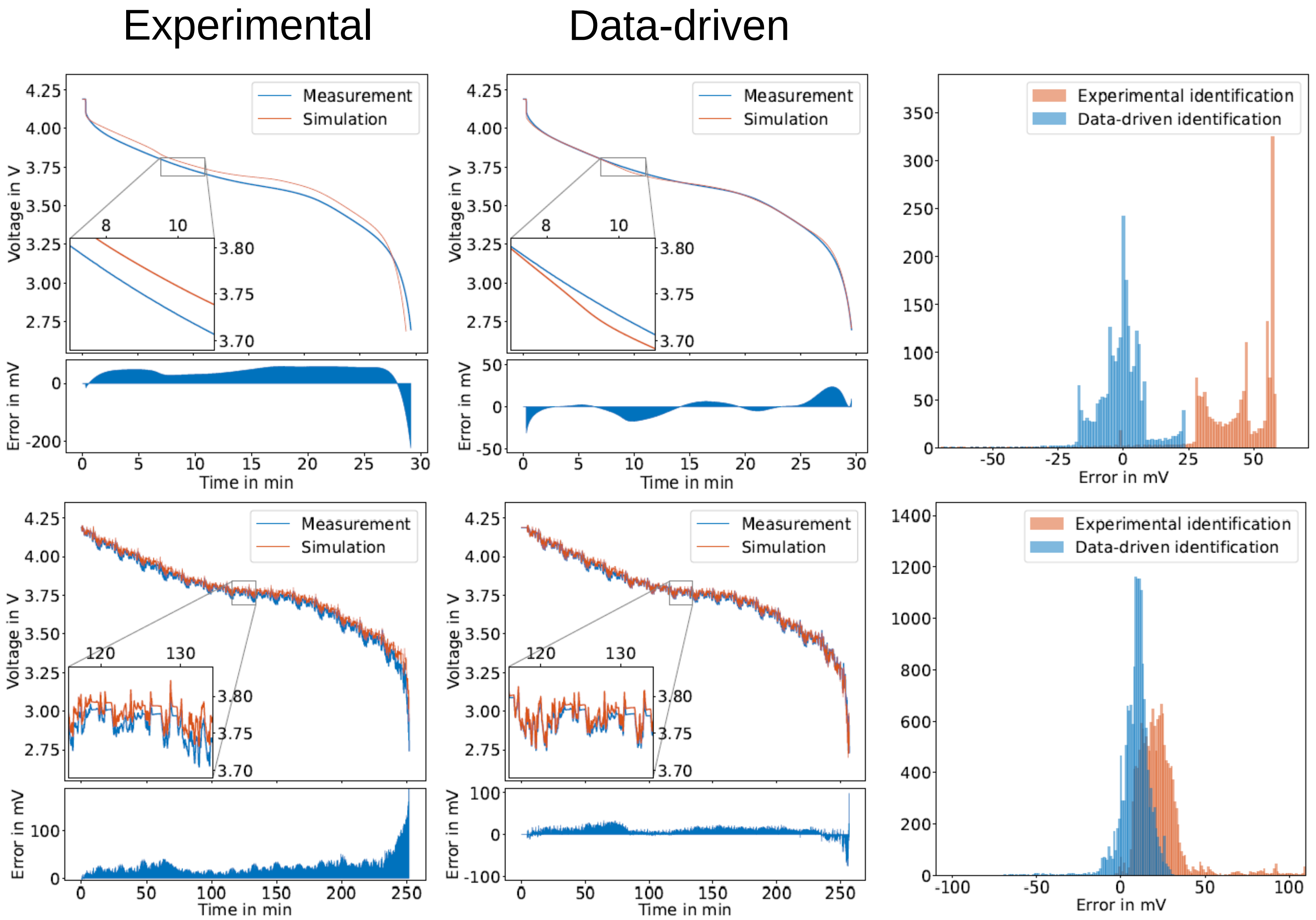
18.0%

- Lower RMSE under driving cycles

67.1%

- Lower electrode capacity errors

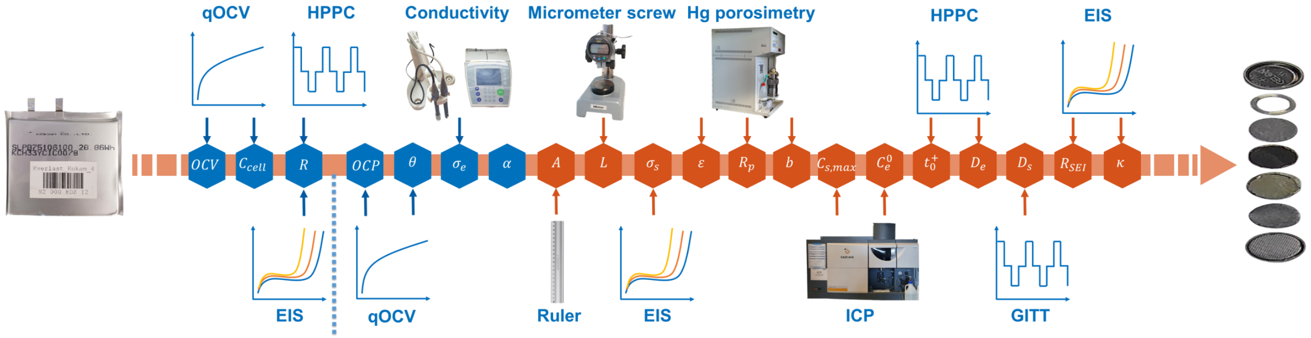
4.6%



Li W, et al., Energy Storage Materials, **2022** (44): 557-570.

Experiment: Samsung 35e (NCA / Graphite + Si)

- Opening the cells at different SOHs



- Data-driven identification framework

Total 28 parameters

Aging mechanisms analysis

Aging-related parameters

Sensitivity analysis

Aging-related Parameters with high sensitivity

Identification of aged cell

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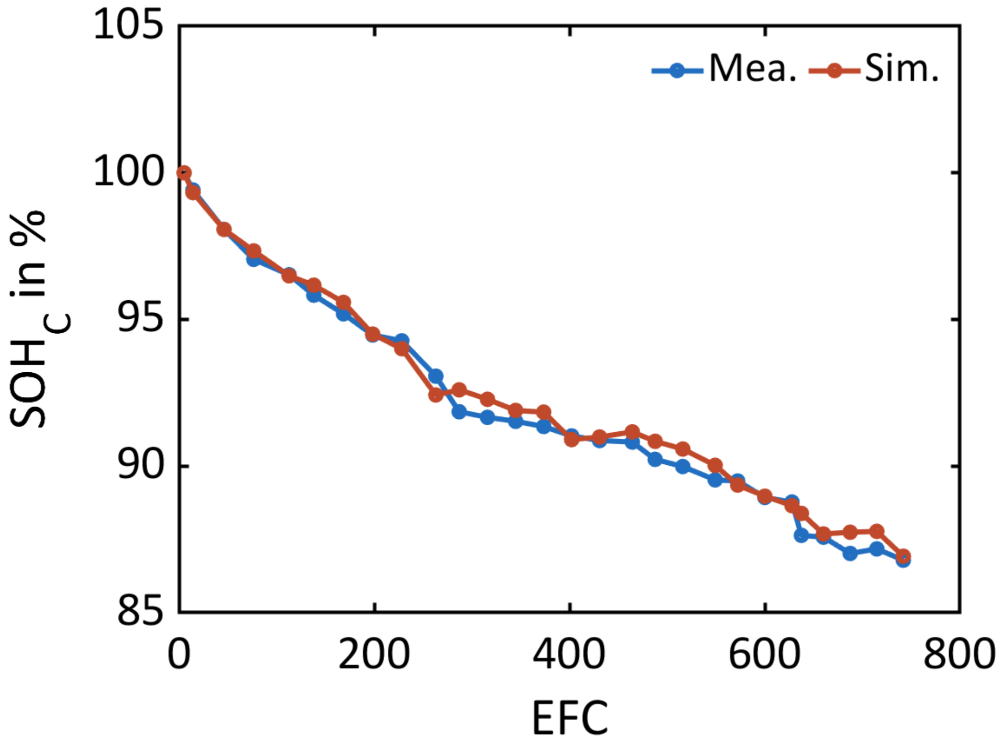
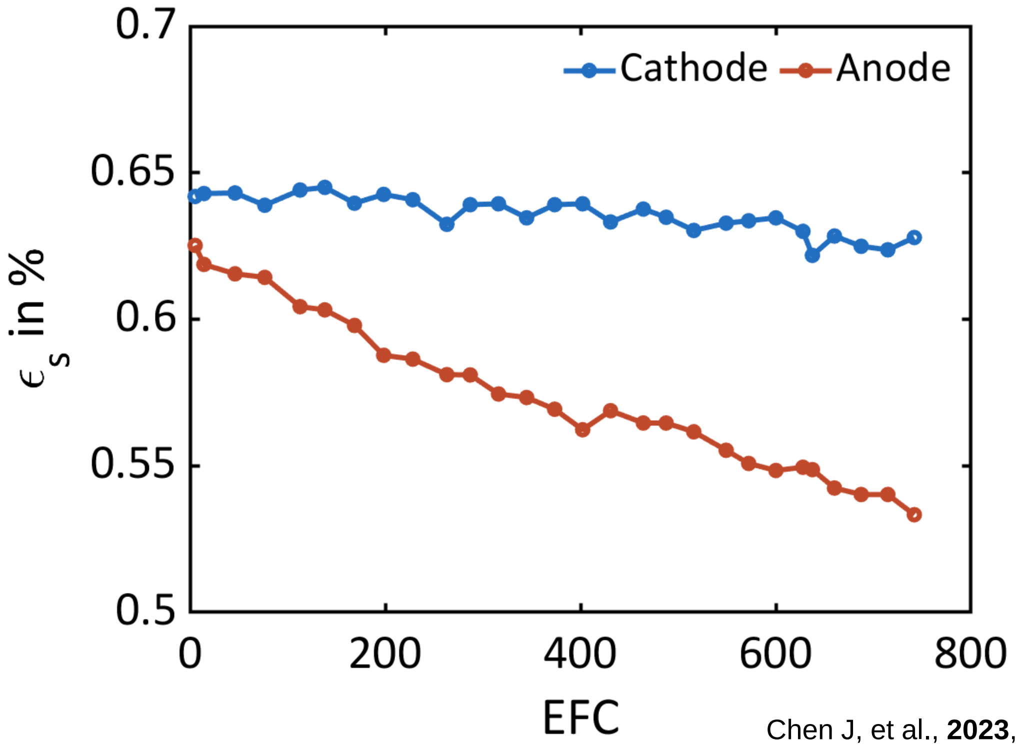
Results

- Capacity fade
  - $\mathrm{SOH}_C = \frac{C_{N,t}}{C_N}$
  - Capacity fade can be accurately estimated
- Volume fraction of the solid active material
  - $\boldsymbol{\varepsilon_s^-}$ decrease more rapidly than $\boldsymbol{\varepsilon_s^+}$ during aging

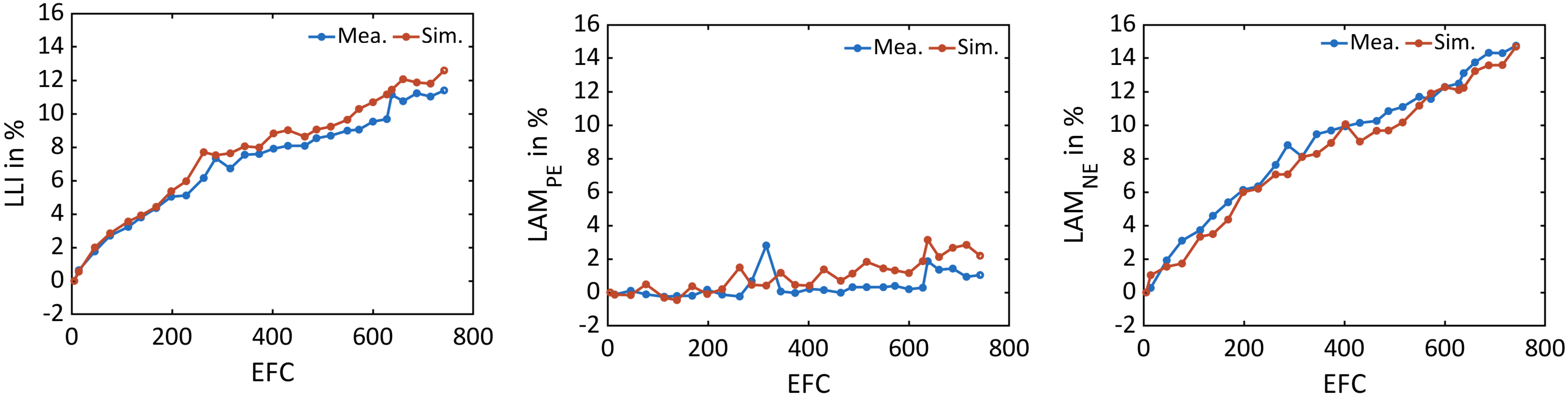




Chen J, et al., **2023**, in preparation

Results

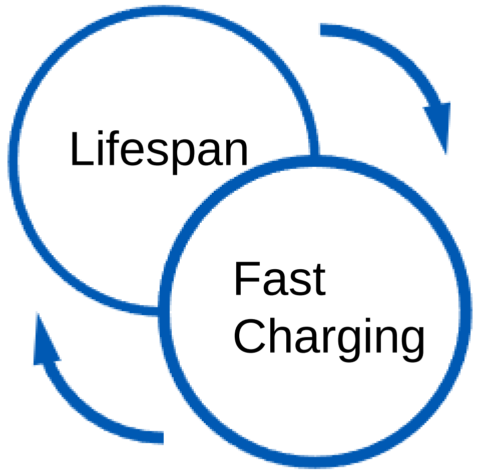
- Degradation modes
  - The degradation modes of the battery can be accurately estimated
  - LAMNE and LLI play a major role in the aging process of batteries

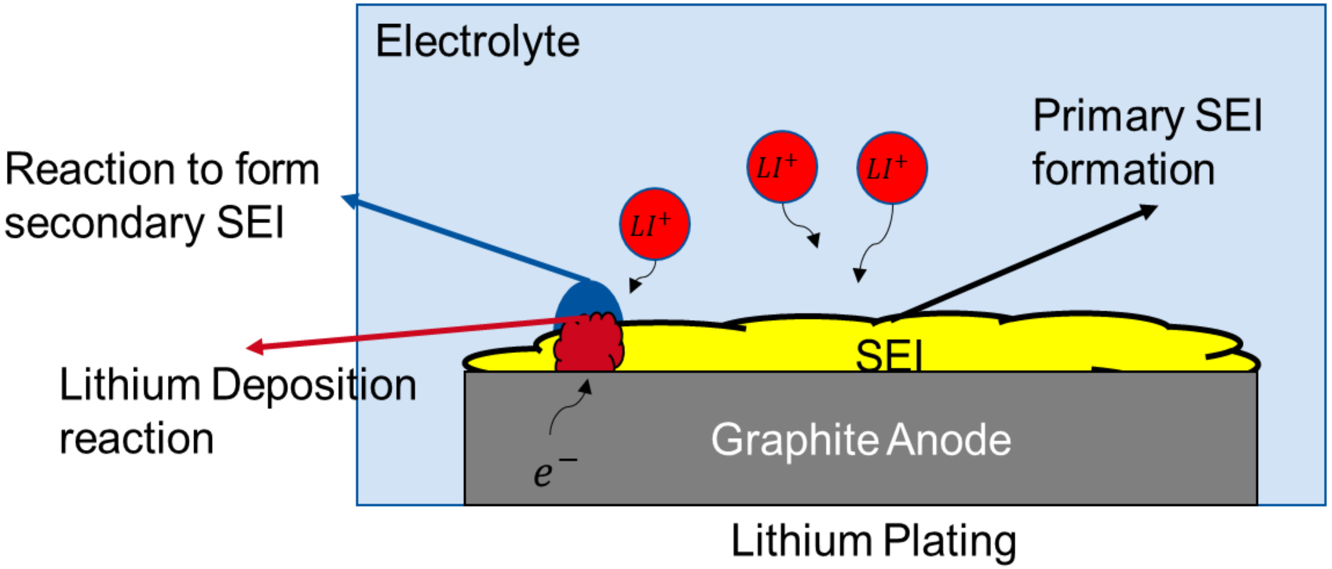


Chen J, et al., **2023**, in preparation

Fast Charging Trade-off

- Trade-off between fast charging and ageing
- Lithium plating





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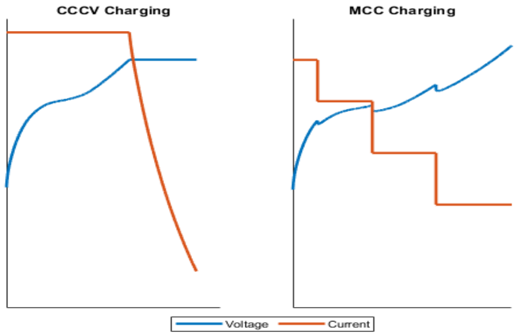
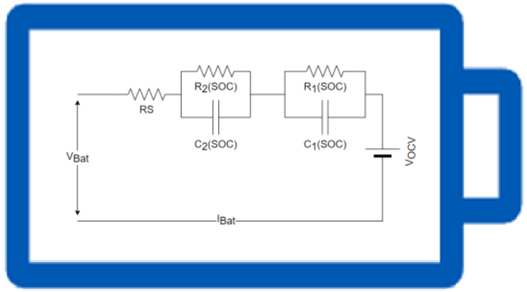
Charging Protocols

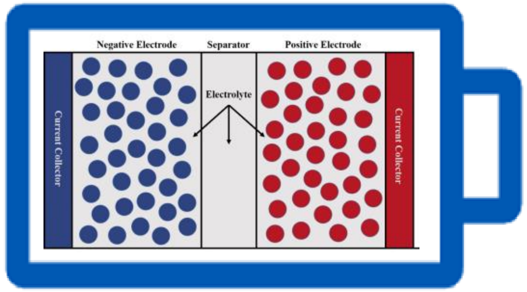
Existing Charging Protocols



- Passive Methods
  - Predefined current and voltage levels
  - Does not account for battery state

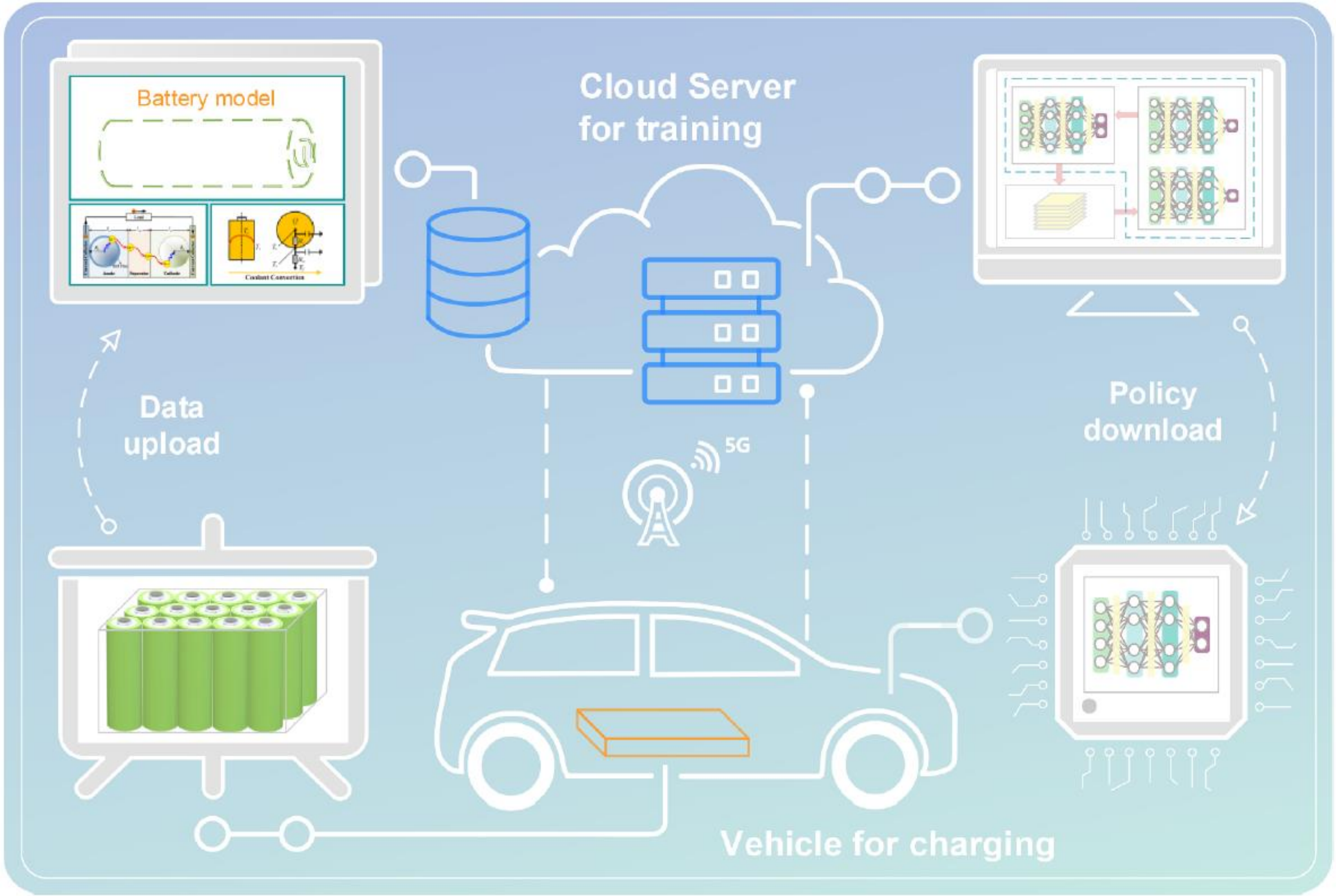


- Equivalent Circuit Models
  - Modelling of electrical characteristics
  - Does not model side reactions



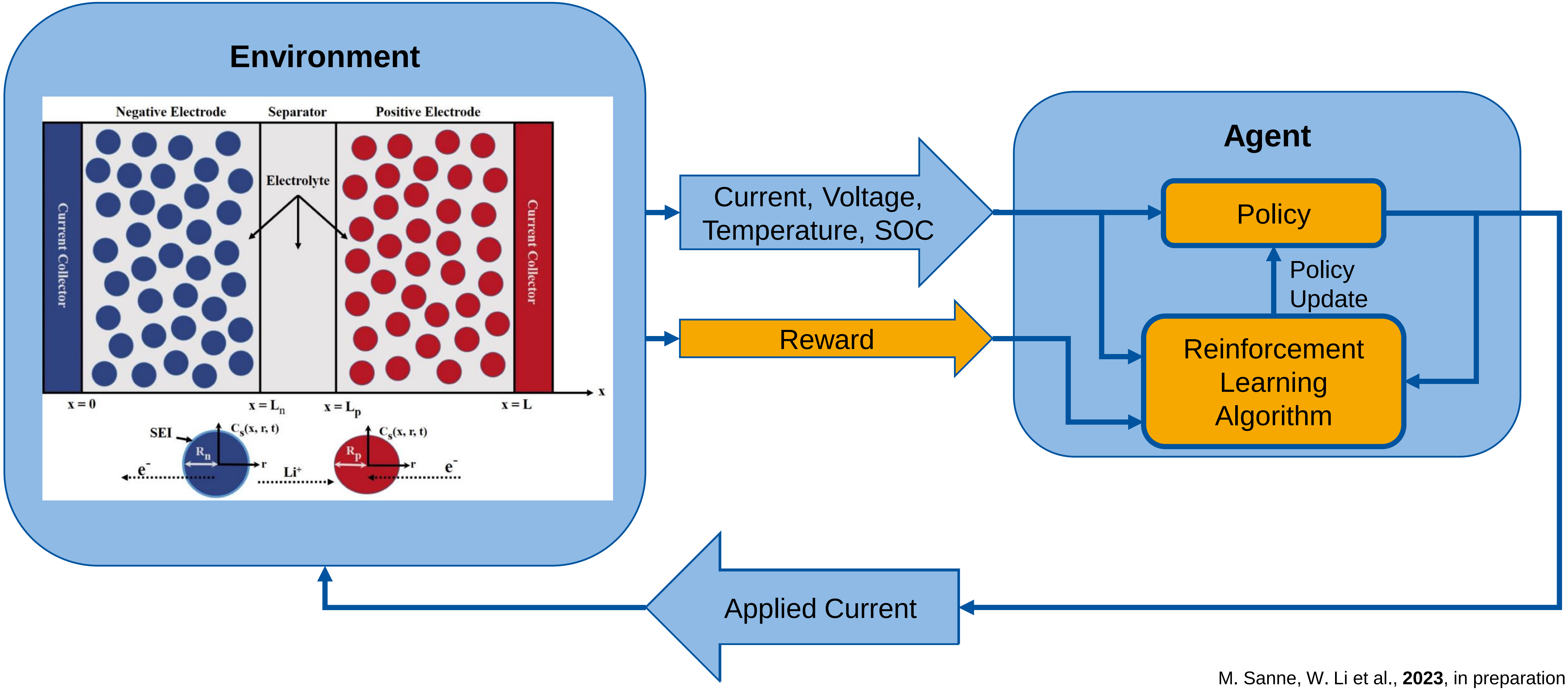
- Electrochemical Models
  - Modelling of internal cell state
  - High complexity needing model simplifications

Machine learning-based fast charging



Z. Wei, W. Li, D. U. Sauer et al., **2023**, Energy Storage Materials 56 62-75

Offline Learning Environment



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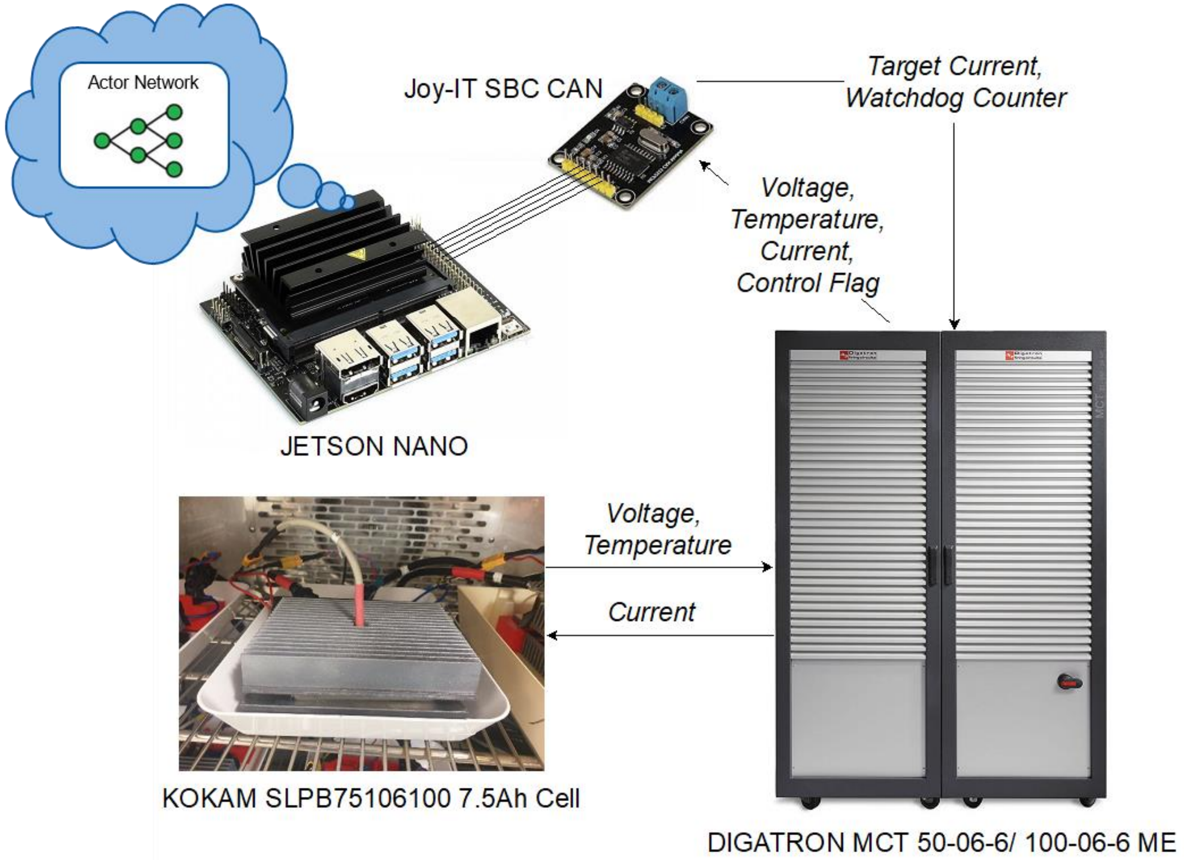
Testing Procedure - Experimental Setup

- Scenario
  - Charge from 10% SOC to 80% SOC
  - Temperature 0 °C
  - Active Cooling with Aluminium Cooling Plates
  - Charging Time ~ 54 minutes

- Benchmarks
  - Constant Current Constant Voltage (CCCV)
  - Multistage Constant Current (MCC)



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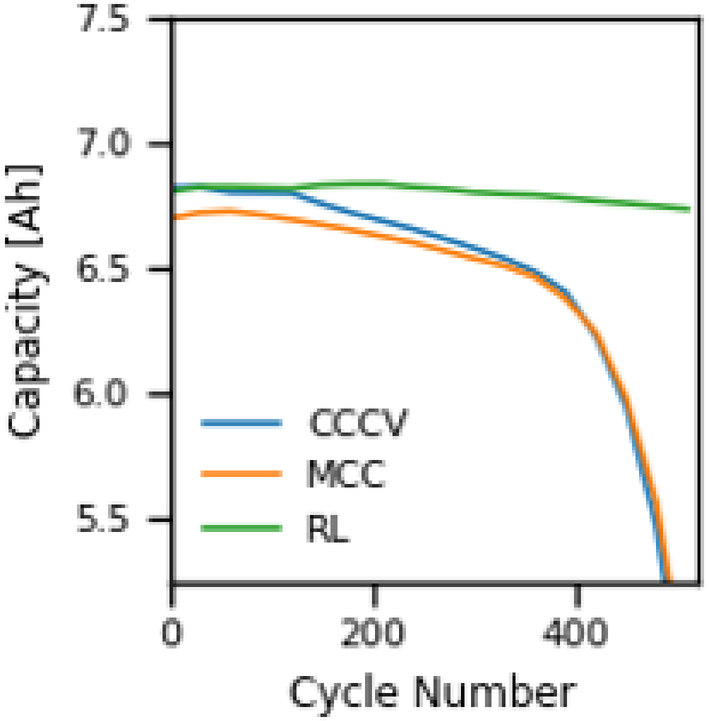
Benchmarks of model-based control with self-learning of model parameters

- Benchmarks
  - CCCV @ 0.787 C
  - MCC @ 1.25, 1.05, 0.85, 0.5 C

<u>Capacity</u> / Internal Resistance / Loss mechanisms



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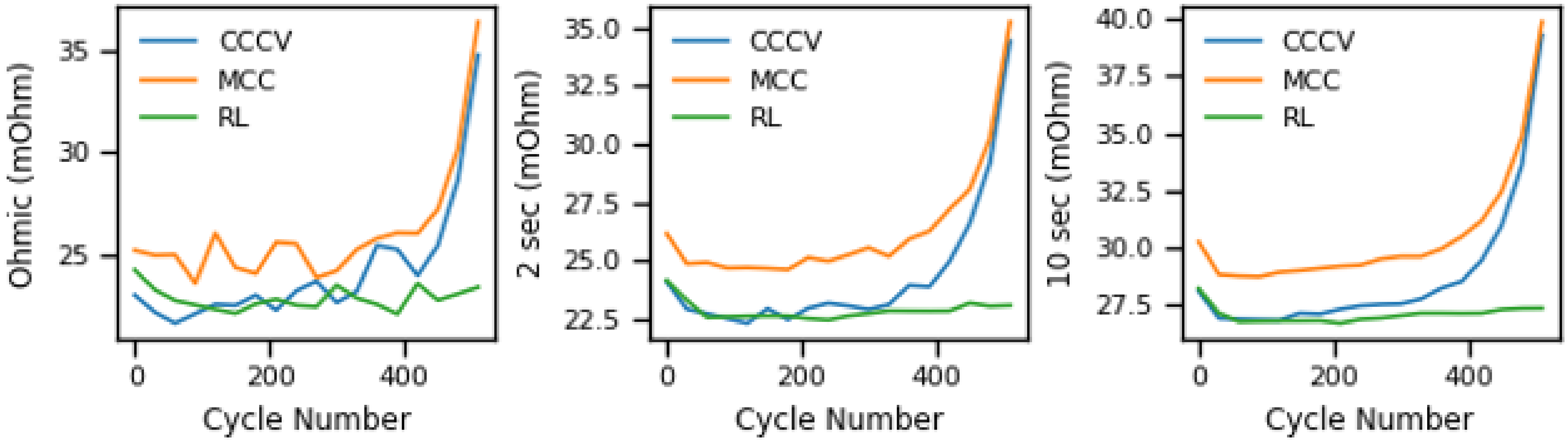

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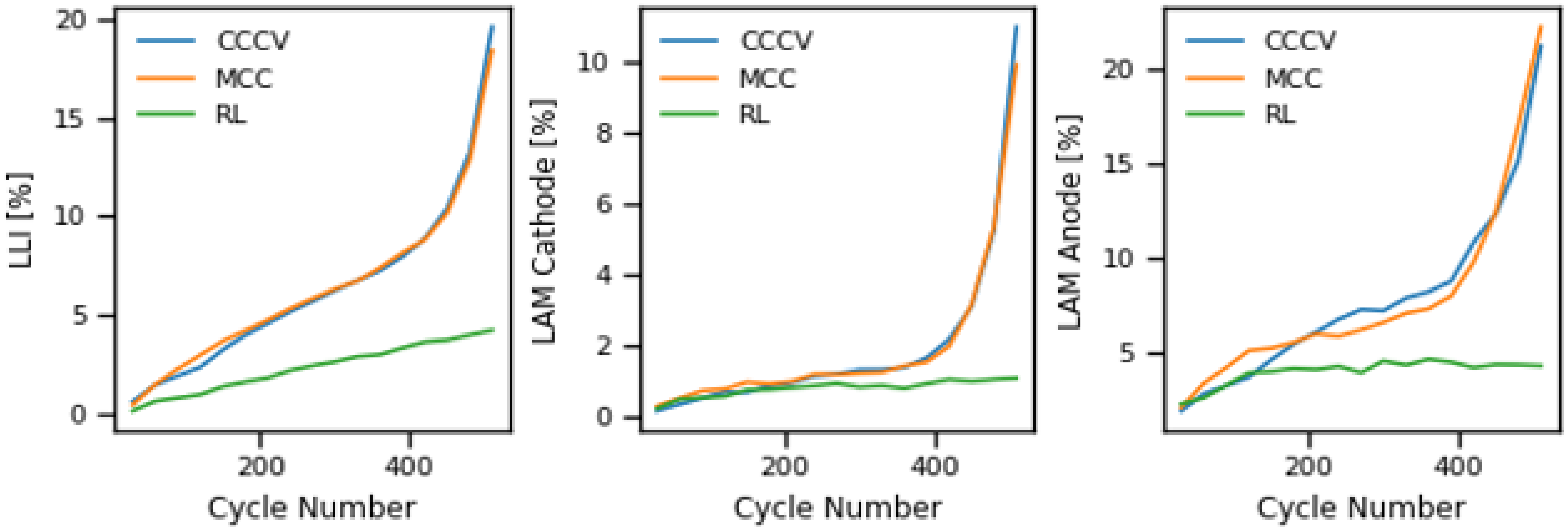

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Summary

- Fast charging is the most critical operation phase for the lifetime of batteries.
- Proper control of charging protocol is essential.
- Model-controlled charging can bring the shortest charging times without accelerated ageing.
- Machine-learning algorithms help to identify and to adapt the model parameters throughout the lifetime.
- Very good results for lifetime extension have been achieved.

Thank you
for your attention

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