# Machine Learning-Based Identification of P2D Battery Model Parameters

Daniel Jakobsson

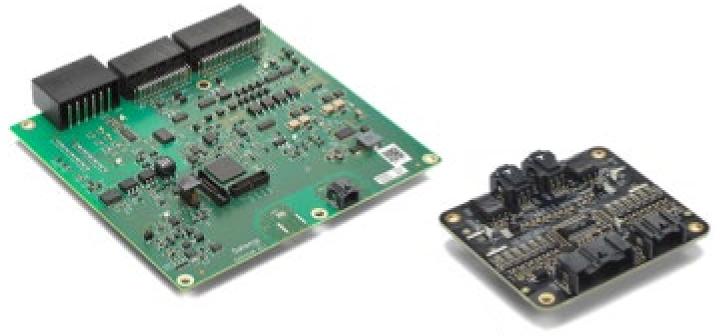
Supervisor: Torsten Wik

Department of Electrical Engineering
Automatic Control research unit

2026-08-18

# What should a BMS do?

- Guarantee safety
- Maximize performance
  - Energy
  - Power
- Minimize premature aging
  - Capacity loss
  - Available power

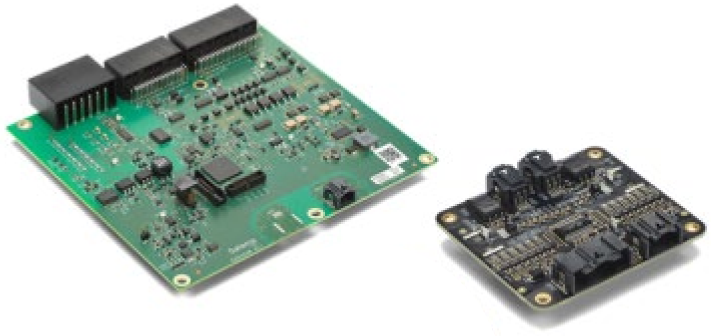


Lithiumbalance.com

# Traditional BMS

Max/min constraint on simple measures/estimates:

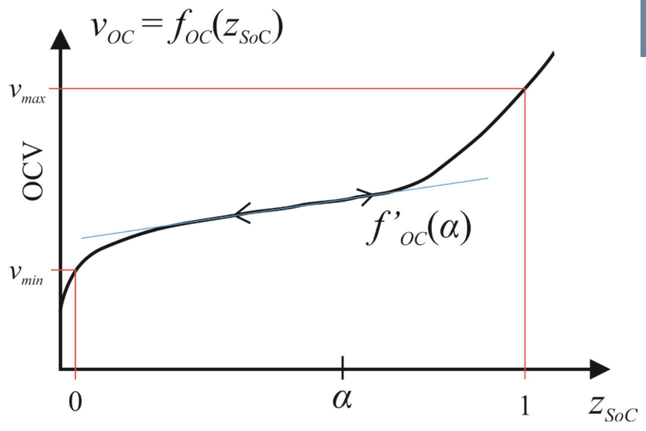
- Voltage
- Current
- Temperature

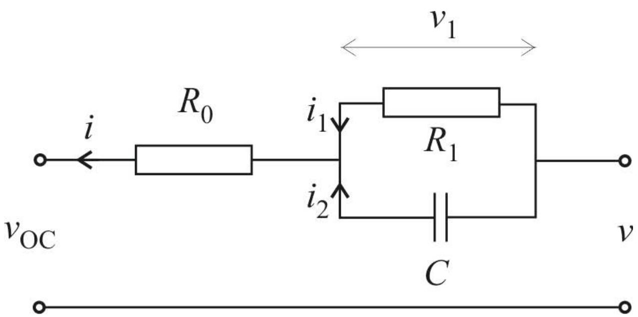


Lithiumbalance.com

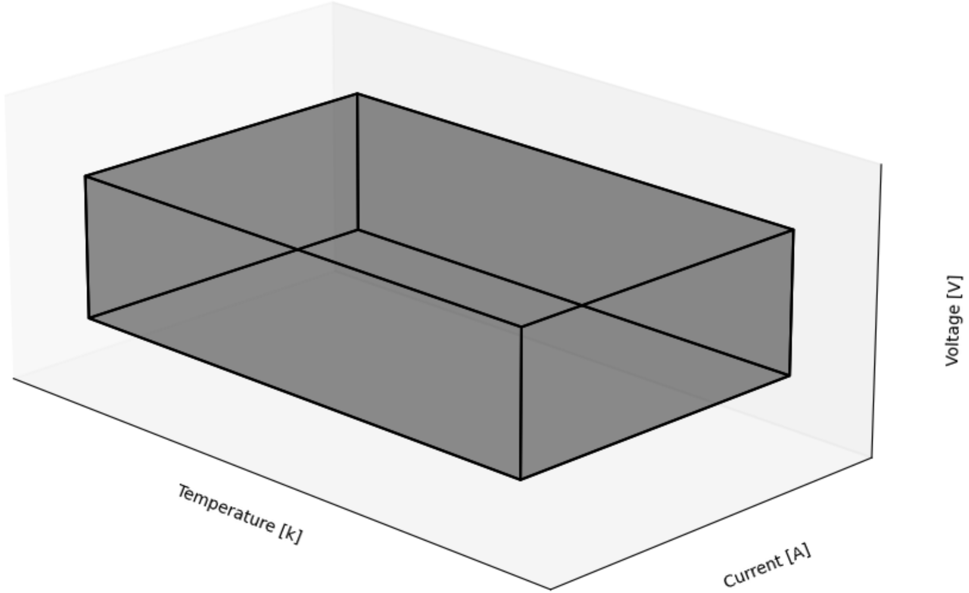
# Traditional BMS

- ECM based Thevenin circuit
  - OCV voltage source
- Locally linear dynamics
  - ➢Prediction errors
- No internal state representation
  - ➢Limited diagnostic
  - ➢No estimation of non measurables
- Poor “safe region” fit
  - ➢Worse performance
  - ➢Accelerated aging

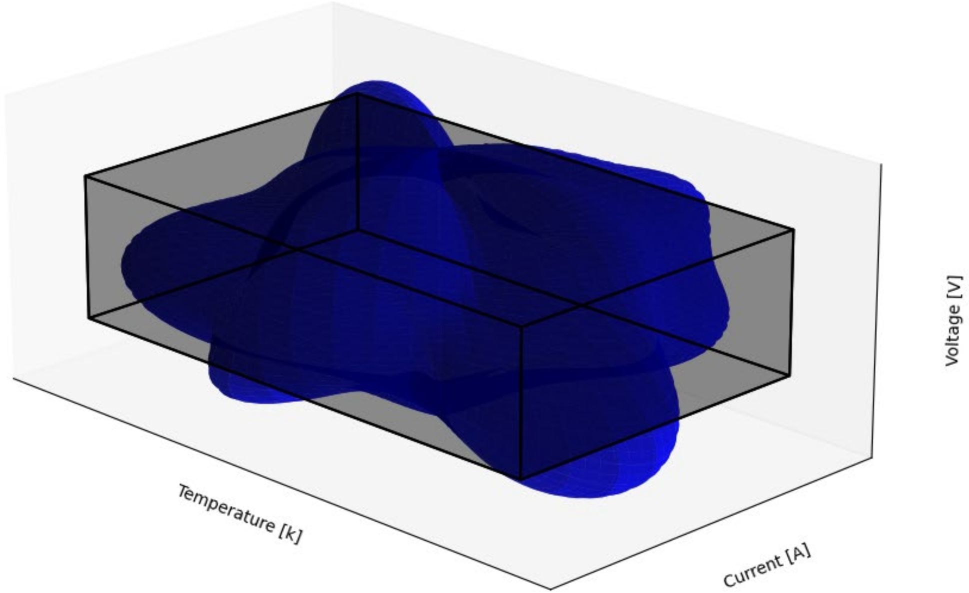


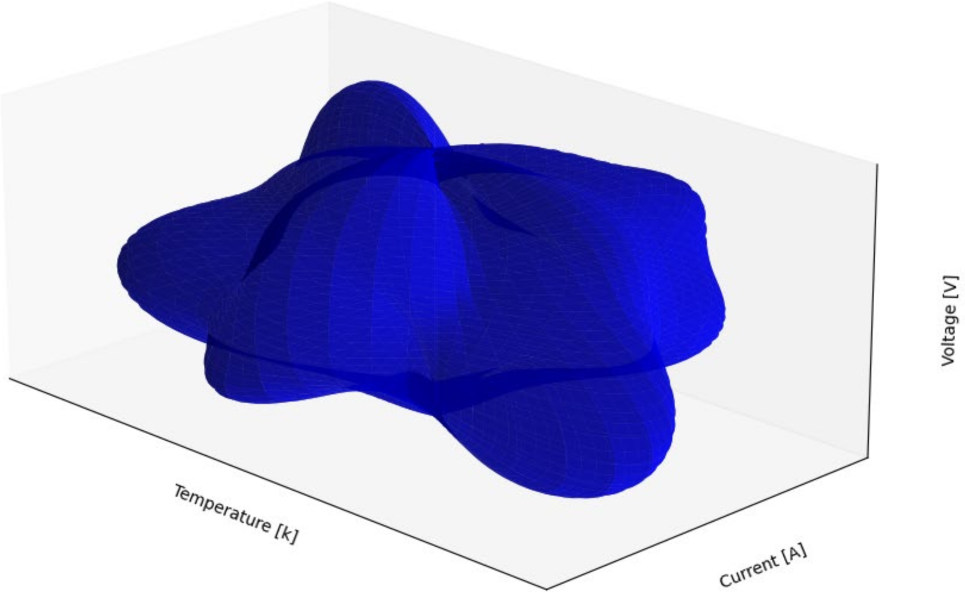
# ECM based BMS



# ECM & Physics based BMS



# Physics based BMS



# Physics based BMS

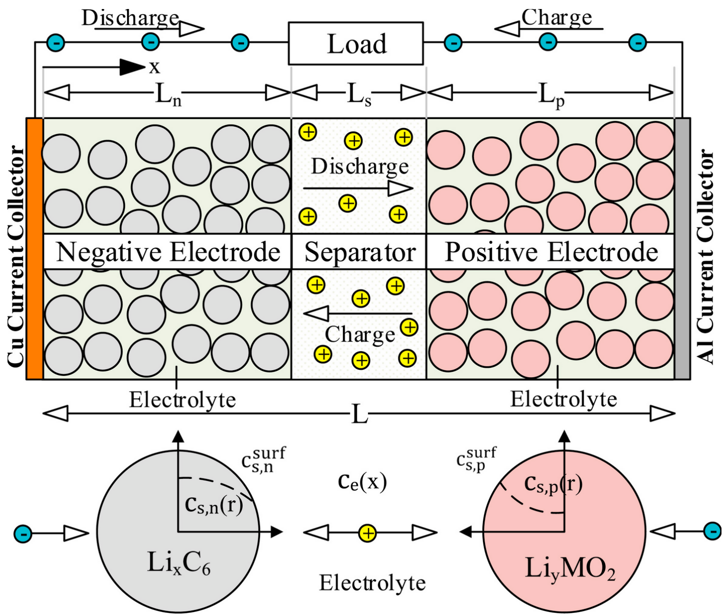
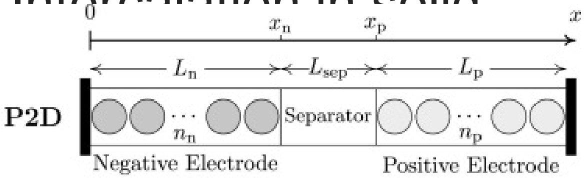



Figure by Jokar et al. (2016), Journal of Power Sources, 327:44-55.

## Pseudo two dimensional (P2D)

- Electrolyte dynamics
  - Diffusion & ion migration
- Intercalation in solid




- stoichiometry

Figure by Ai & Liu, Journal of Energy Storage, 67, 107512 (2023).
DOI: 10.1016/j.est.2023.107512.

- $OCV(SoC) \xrightarrow{P2D} OCP_p(y) - OCP_N(x)$
- Extendable with aging models
  - SEI growth, Li-plating, Particle cracking etc…

# Physics based BMS

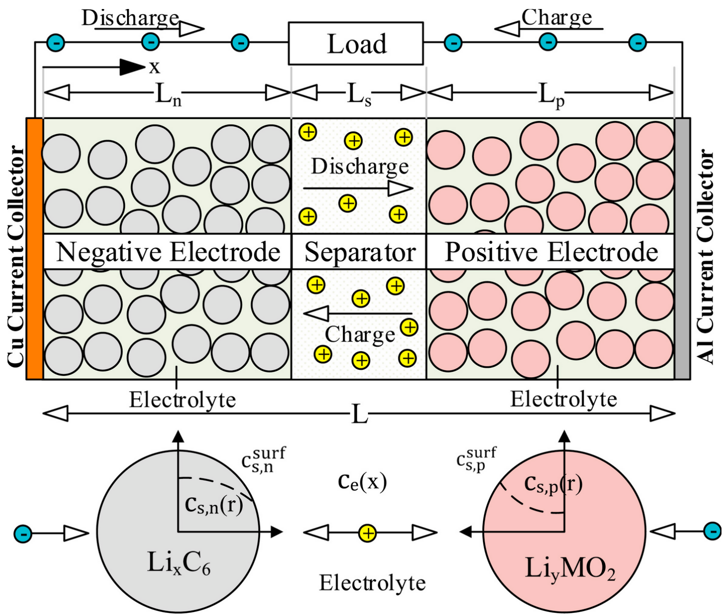



Figure by Jokar et al. (2016), Journal of Power Sources, 327:44-55.

## Pseudo two dimensional (P2D)

- Stiff PDAE
  - ➤ Slow and computationally heavy
  - ✓ Can be reduced for BMS implementation
- Large number of parameters $\theta(t_0)$
  - ➤ Lab-identifiable
  - ➤ Subset is time dependent

$$\theta_a(t_0) \neq \theta_a(t_x)$$

  - ❖ Method needed for updating $\theta_a$

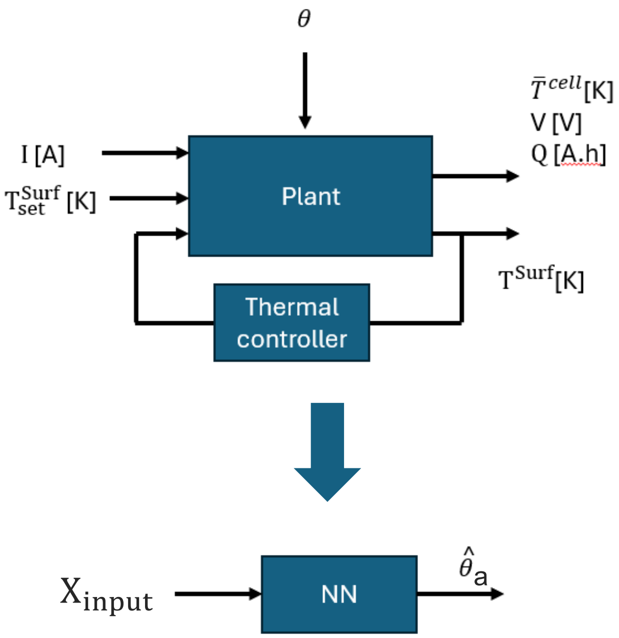
# Reparameterization of P2D

**Requirements:**

- Assume $\theta(t_0)$ for the battery type
- Limited data availability (regressor)
- Minimal interference with user

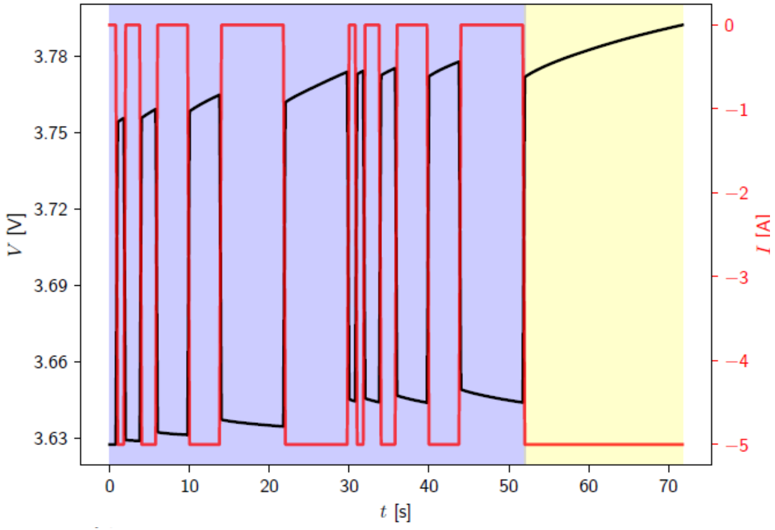
**Method:**

- Pulsed current + regular charging protocol
- Neural Network (NN) of $\hat{\theta}_a$

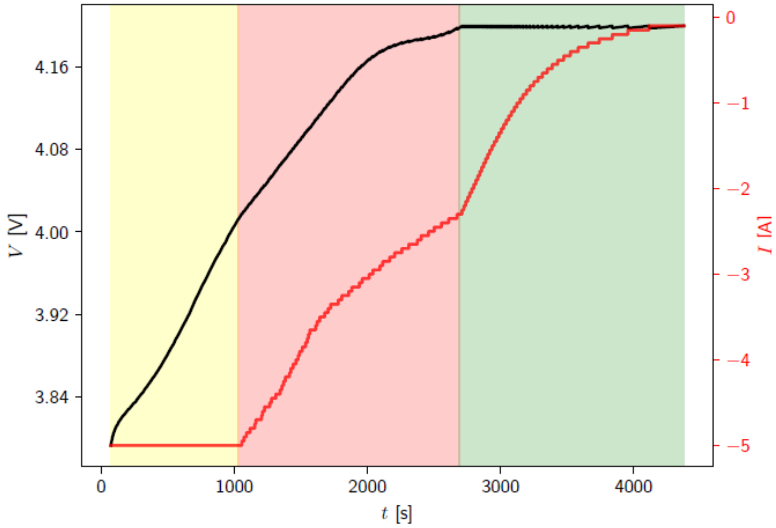


# Identification current

Pulsed current Constant current Constant internal potential Constant voltage




t< 72s




t> 72s

# Identification current

- Pulsed current
  - Excite system
- Constant current
  - Typically used in todays charging method
- Constant internal potential
  - Accessible from P2D model
  - Limit Li-plating
- Constant voltage
  - Typically used today
  - Limit cathode degradation for NMC811
  - Electrolyte breakdown

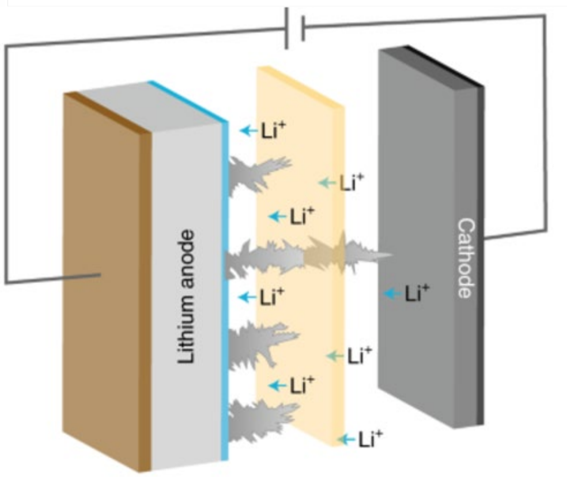
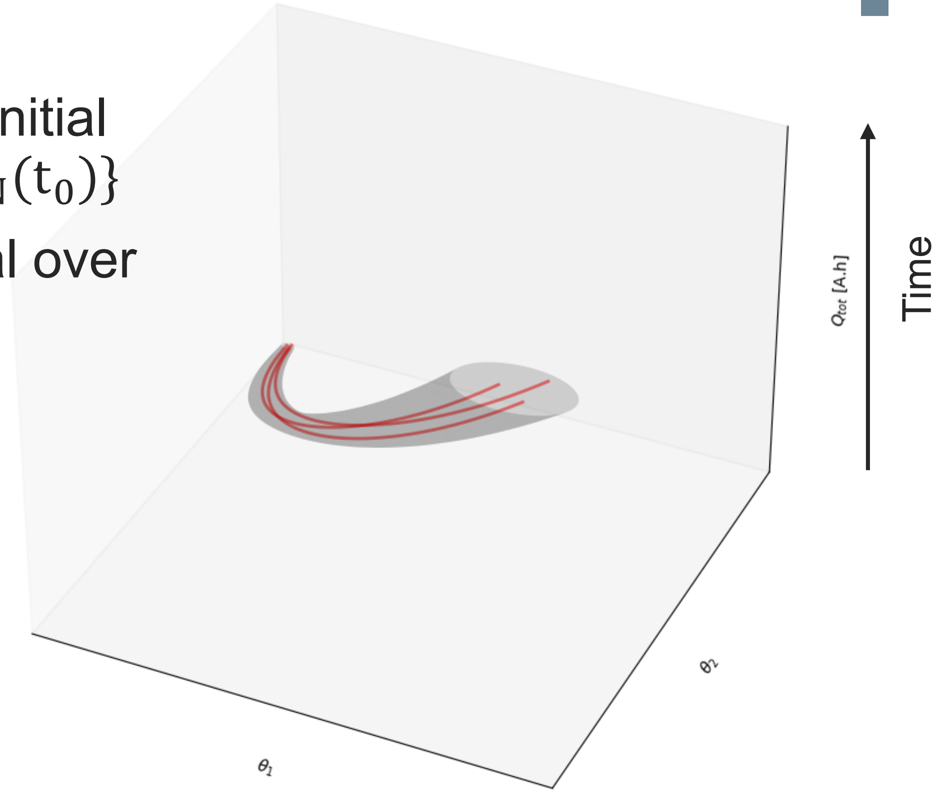



Figure by Imperial blog post: https://blogs.imperial.ac.uk/materials/2024/03/18/phd-spotlight-transforming-battery-technologies/

# Construction of training data

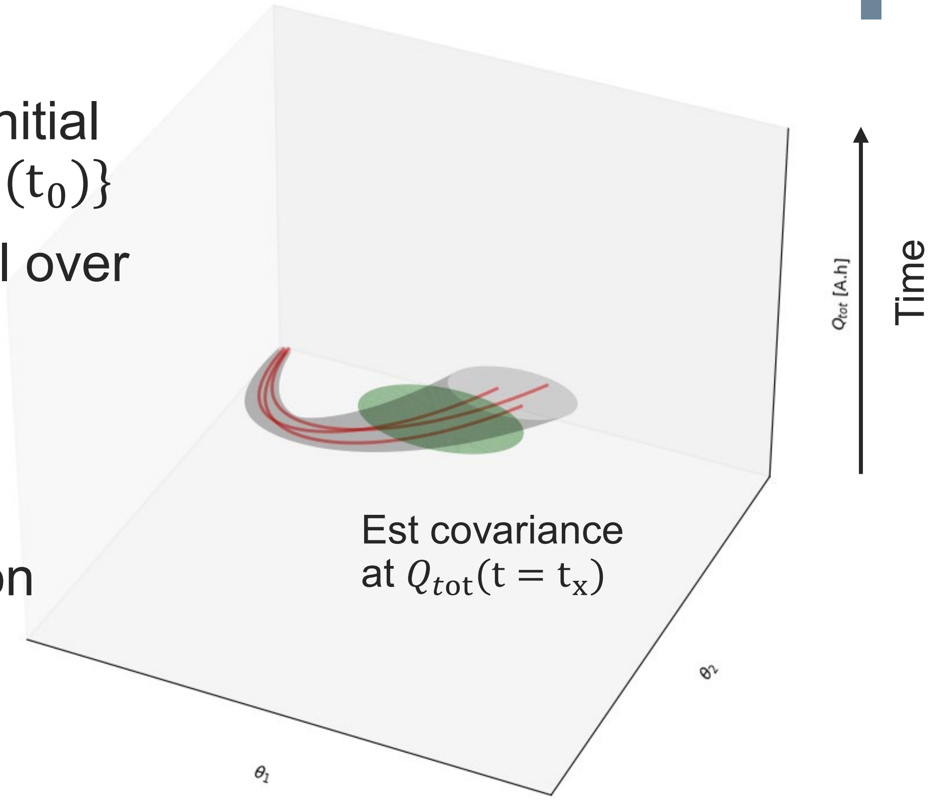
CHALMERS

1. Simulate N cells with different initial conditions $\{\theta_1(t_0), \theta_2(t_0), \ldots, \theta_N(t_0)\}$
2. Adding a 2nd degree polynomial over P2D particles for $\theta_a$
3. Construct an aging tube



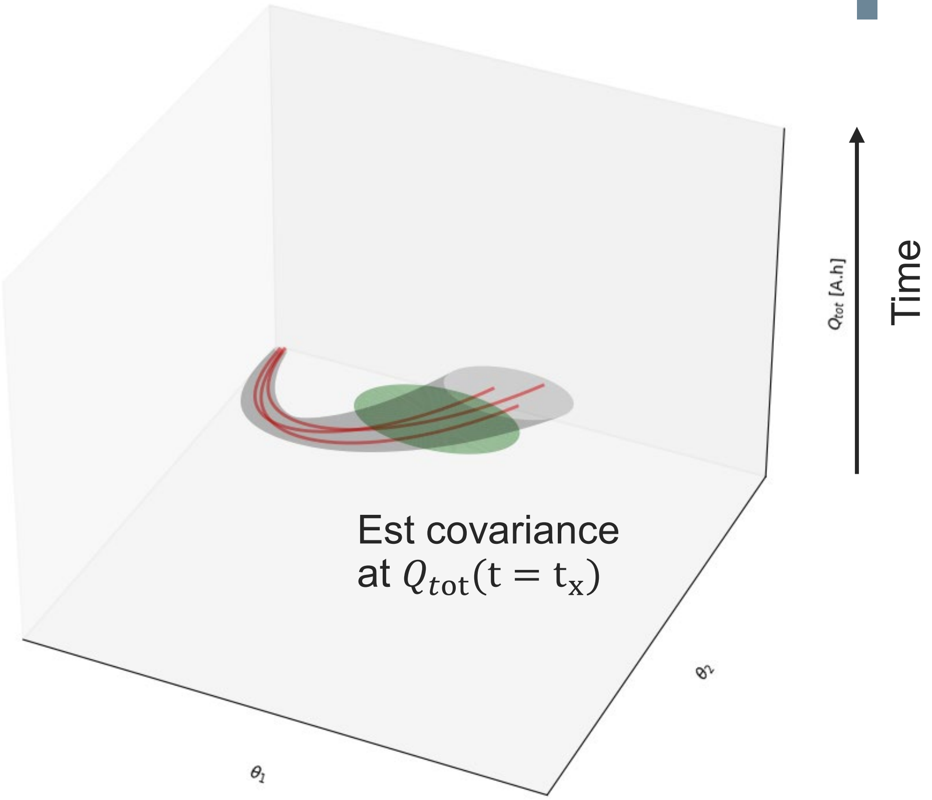
# Construction of training data

1. Simulate N cells with different initial conditions $\{\theta_1(\mathrm{t}_0), \theta_2(\mathrm{t}_0), \ldots, \theta_\mathrm{N}(\mathrm{t}_0)\}$
2. Adding a 2nd degree polynomial over P2D particles for $\theta_\mathrm{a}$
3. Construct an aging tube
4. Estimate covariance
5. Create $\theta$ combinations based on tube limits



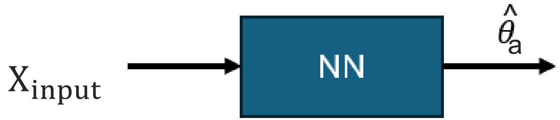
# Construction of training data

- $\theta$ combinations within our tube
- Efficient generation of training data for our NN estimator



# Neural network

- $X_{\mathrm{input}}$ has timeseries and fixed data
- $X_{\mathrm{Time}}$:
  - Pulsed current part sampled at 0.25s
  - Current, Terminal voltage, and estimate SoC
- $X_{\mathrm{Fixed}}$:
  - Capacity estimated by BMS
  - Sampled current, terminal voltage, and SoC

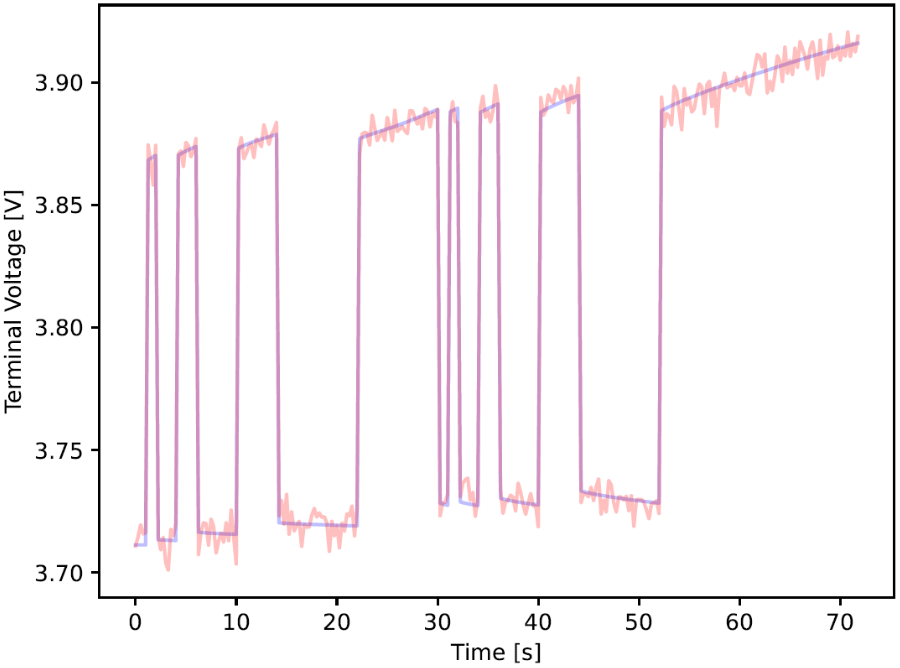



- $\hat{\theta}_{\mathrm{a}}$:
  - Negative electrode porosity
  - Negative/positive electrode active material
  - SEI layer on particle & crack
  - Total lithium ions in battery

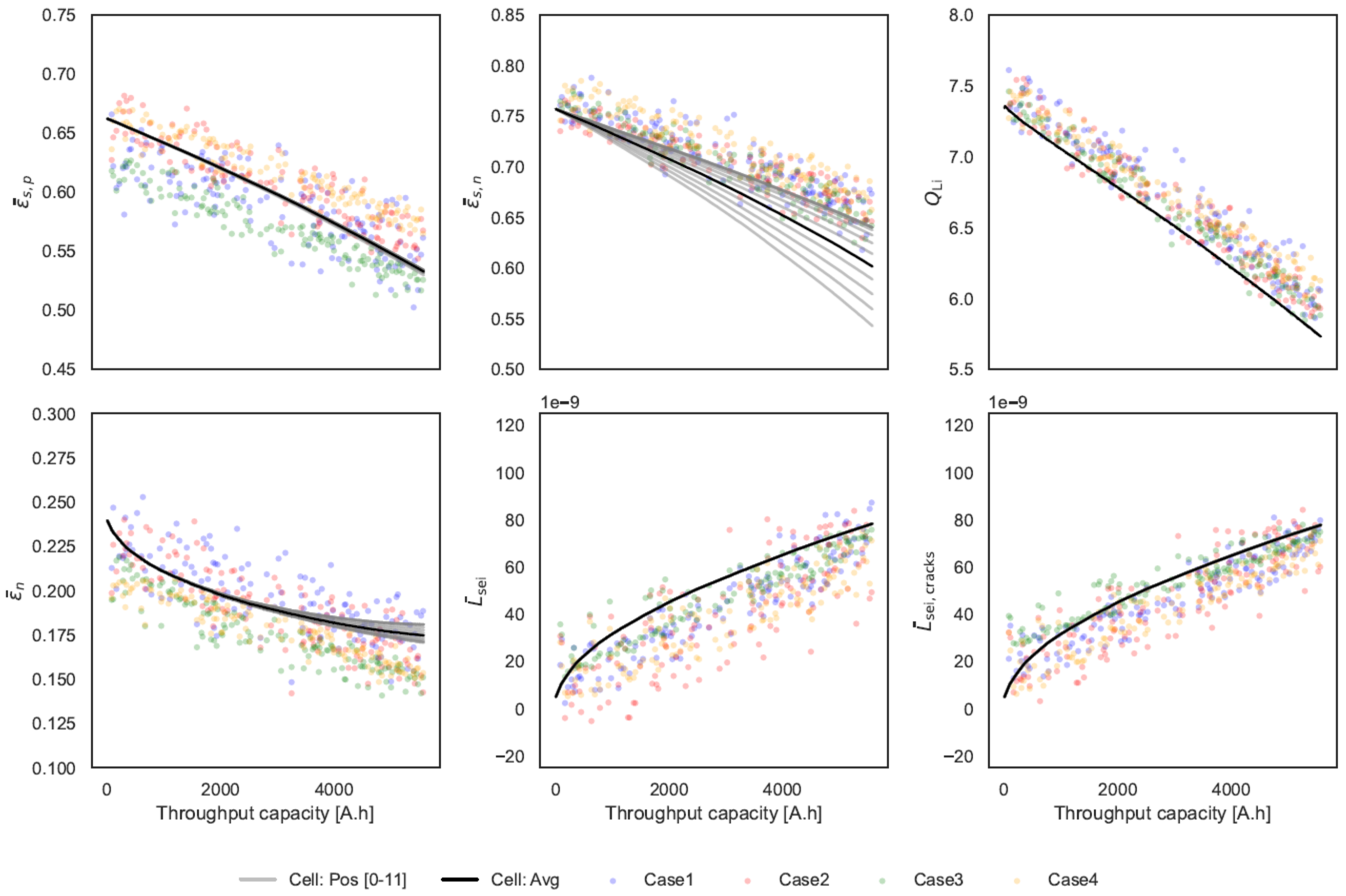
# Neural network

- Validation data:
  - gaussian/uniform offset sensor noise ($\mathrm{X_{input}}$)
- Training data:
  - $\mathrm{X_{input}}$
  - Perturbed $\theta(\mathrm{t_0})$

| | |
|---|---|
| **Case 1:** no corruption | **Case 2:** 5% perturbation of $\theta(t_0)$ |
| **Case 3:** noise added to $X_{input}$ | **Case 4:** noise added to $X_{input}$ 5% perturbation of $\theta(t_0)$ |

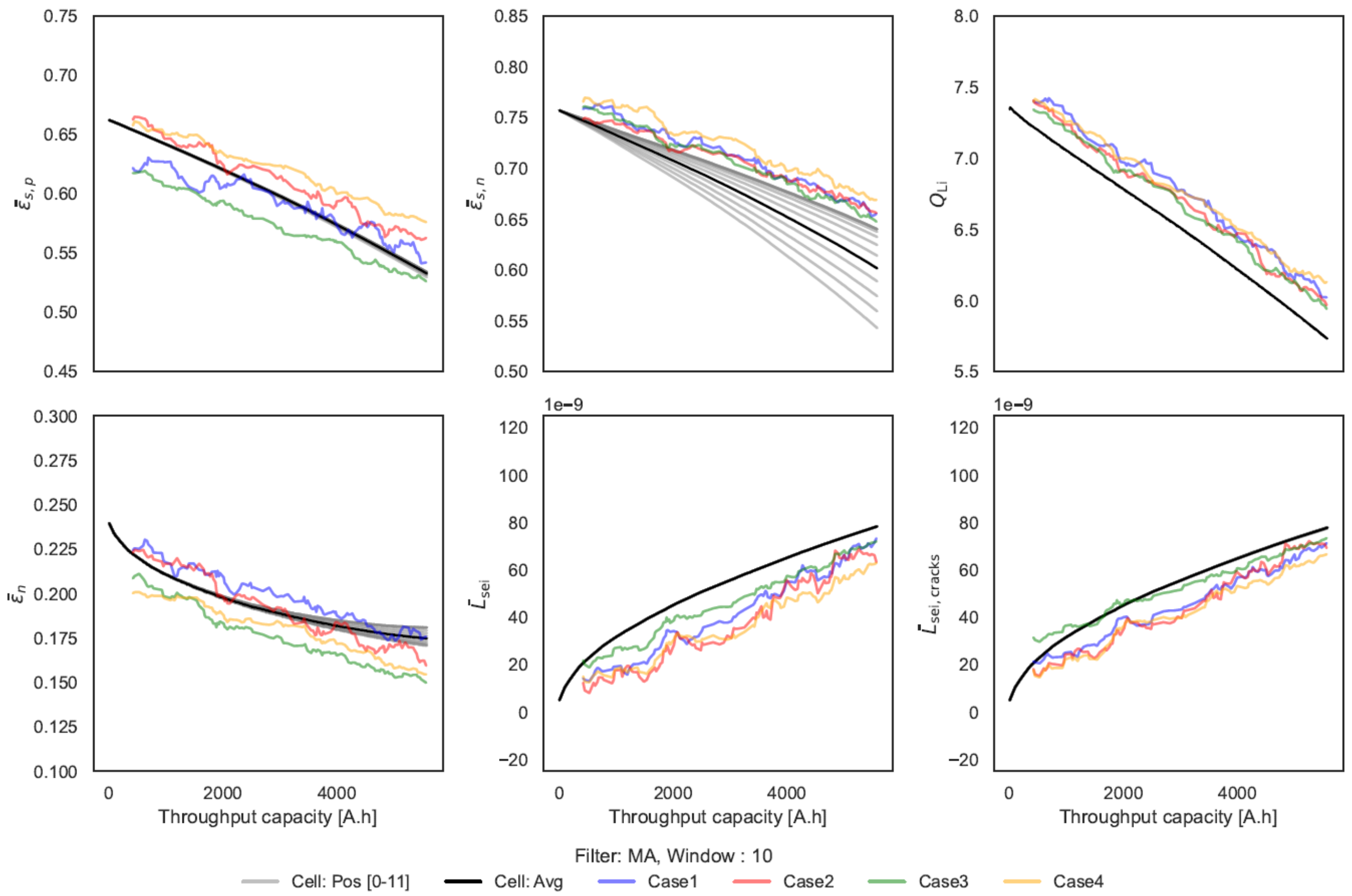


# Estimation performance: spot



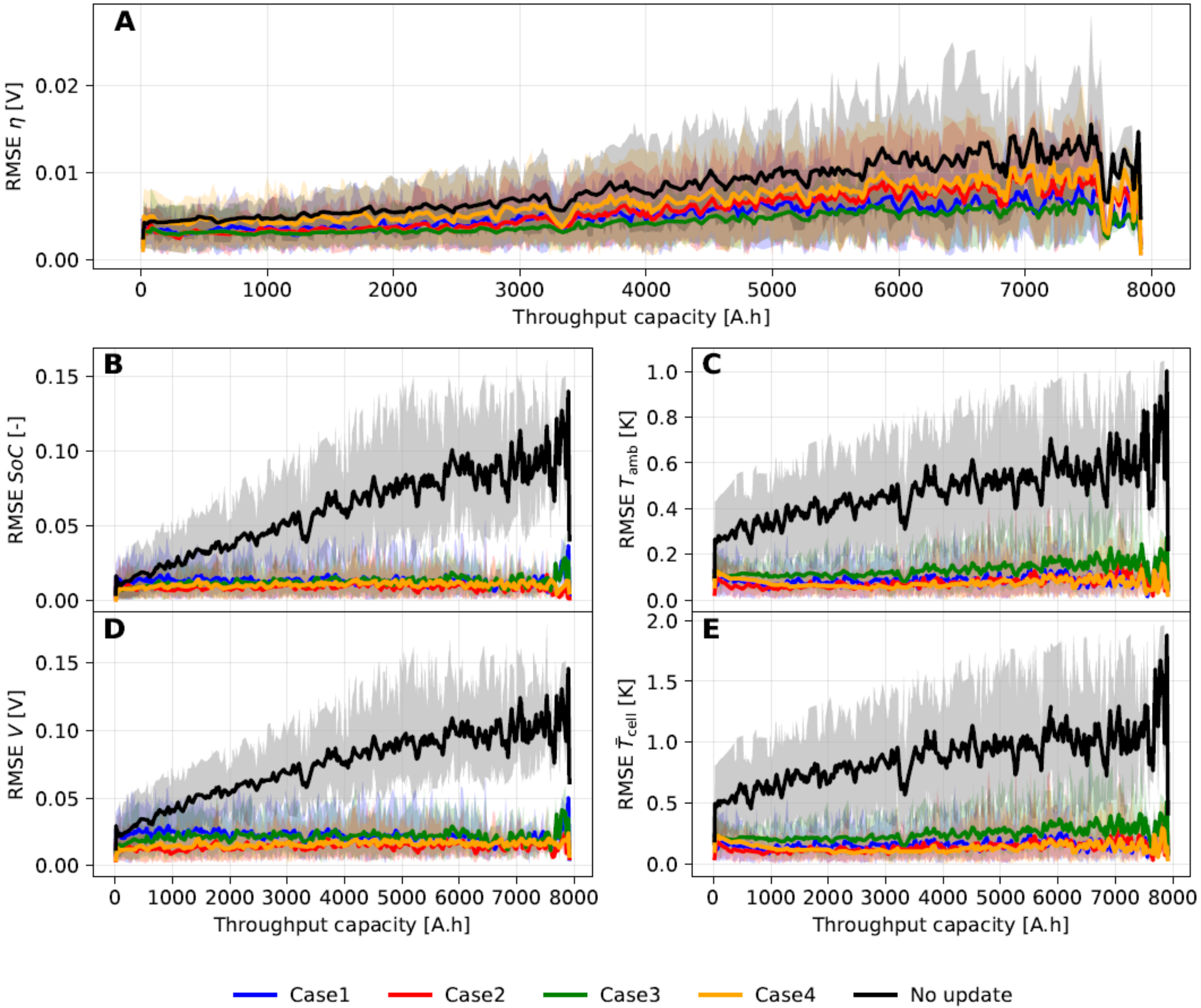
0.75
0.70
0.65
0.60
0.55
0.50
0.45
$\bar{\varepsilon}_{s,p}$
0.85
0.80
0.75
0.70
0.65
0.60
0.55
0.50
$\bar{\varepsilon}_{s,n}$
8.0
7.5
7.0
6.5
6.0
5.5
$Q_{\mathrm{Li}}$
0.300
0.275
0.250
0.225
0.200
0.175
0.150
0.125
0.100
$\bar{\varepsilon}_n$
1e−9
120
100
80
60
40
20
0
−20
$\bar{L}_{\mathrm{sei}}$
1e−9
120
100
80
60
40
20
0
−20
$\bar{L}_{\mathrm{sei,\,cracks}}$
0
2000
4000
Throughput capacity [A.h]
0
2000
4000
Throughput capacity [A.h]
0
2000
4000
Throughput capacity [A.h]
Cell: Pos [0-11]
Cell: Avg
Case1
Case2
Case3
Case4

# Estimation performance: ma filtered



0.75
0.70
0.65
0.60
0.55
0.50
0.45
$\bar{\varepsilon}_{s,p}$
0.85
0.80
0.75
0.70
0.65
0.60
0.55
0.50
$\bar{\varepsilon}_{s,n}$
8.0
7.5
7.0
6.5
6.0
5.5
$Q_{\mathrm{Li}}$
0.300
0.275
0.250
0.225
0.200
0.175
0.150
0.125
0.100
$\bar{\varepsilon}_n$
1e−9
120
100
80
60
40
20
0
−20
$\bar{L}_{\mathrm{sei}}$
1e−9
120
100
80
60
40
20
0
−20
$\bar{L}_{\mathrm{sei,\,cracks}}$
0
2000
4000
Throughput capacity [A.h]
0
2000
4000
Throughput capacity [A.h]
0
2000
4000
Throughput capacity [A.h]
Filter: MA, Window : 10
Cell: Pos [0-11]
Cell: Avg
Case1
Case2
Case3
Case4

# Estimation performance: RMSE ma filtered


A
RMSE $\eta$ [V]
Throughput capacity [A.h]
B
RMSE $SoC$ [-]
C
RMSE $T_{\mathrm{amb}}$ [K]
D
RMSE $V$ [V]
E
RMSE $\bar{T}_{\mathrm{cell}}$ [K]
Throughput capacity [A.h]
Throughput capacity [A.h]
Case1
Case2
Case3
Case4
No update

CHALMERS
UNIVERSITY OF TECHNOLOGY

# Construction of training data