

Mechanistic Li-Ion Battery Modeling, What's Next?

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Mechanistic Li-Ion Battery Modeling, What's Next?

Objectives and motivations

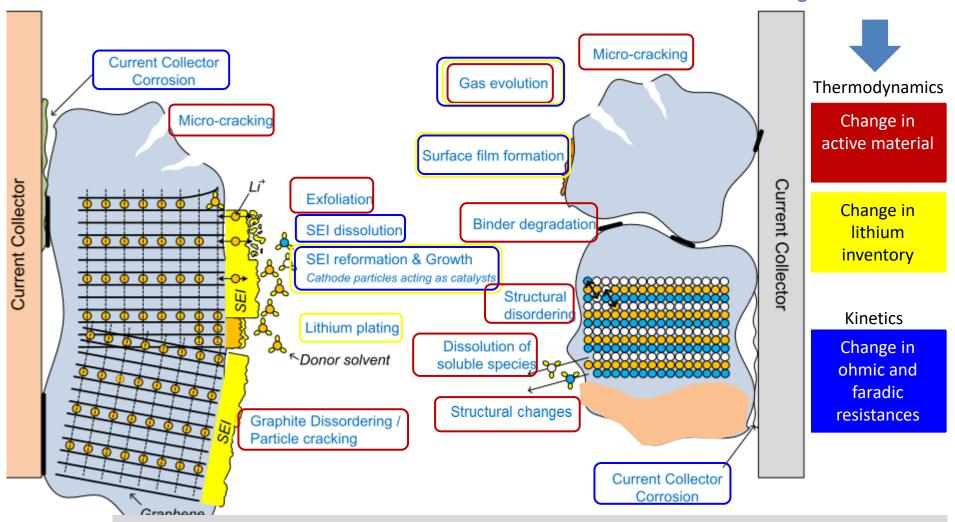
- Early development in mid 2000s by Bloom *et al.* and Honkura *et al.* along with differential voltage analysis.
- Conceptually based on early traditional physics-based modeling studies Less calculation-intensive while still providing material insights
- Detailed frameworks available since 2012 (Smith *et al.*, Dubarry *et al.*) Ease diagnosis of commercial Li-ion batteries Enable prognosis
- Approach well validated for low rate constant current data
- Degradation modes quantification
- Plating identification
- Knee forecasting
- But some limitations remains
- Faster rates, blends, inhomogeneities, non-constant current cycles...

This work proposes possible directions to improve the framework



The complexity of battery diagnosis Multiple mechanisms to consider

Lithium ion battery degradation mechanisms



Degradation modes refer to the impact of a mechanism rather than its root cause.

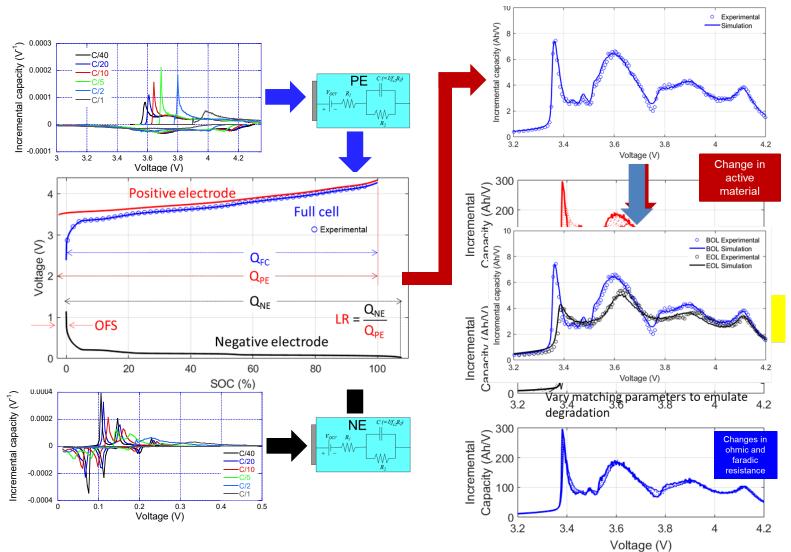


Degradation modes

General Principles



Loss of lithium inventory (LLI) & Loss of Active Material (LAM)



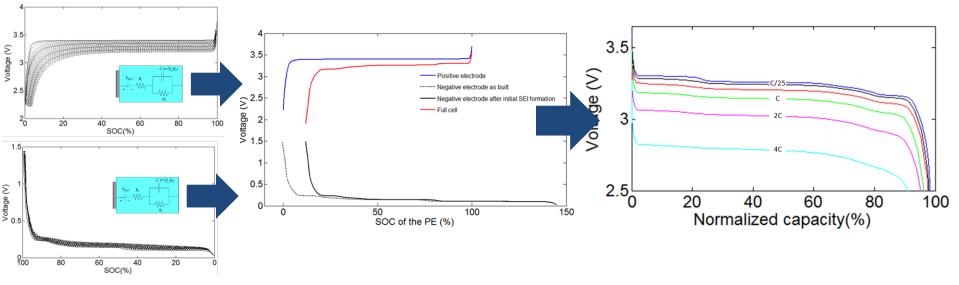


General Principles

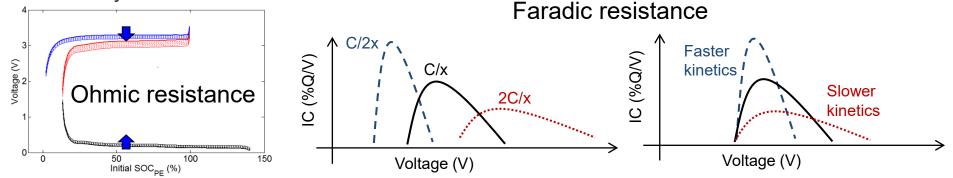


Emulating resistive and kinetic changes: Emulate effect of current From Half cell data at different rates

Use ECM to calculate voltage response at every possible rate



Enable adjustments of resistance and kinetics



General Principles

Change in ohmic and faradic resistances

Kinetics 400 Incr. Capacity / Ah V⁻¹ 300 C/35 log RDF_{PE} 0 200 -1 100 -2 C/35 C/5 -3 0 1 20 T/°C log IRDF_{NE} 0.5 40 4.2 3.6 *U* / V 3.8 3.4 3.2 300 0 Incr. Capacity / Ah V⁻¹ C/5 200 -0.5 10 100 8 log ORI / % 6 0 4 × 20 2 T/°C × 40 0 └ 3.1 4 3.8 3.2 3.3 3.4 3.5 3.6 3.6 3.4 3.2 U/V×10⁻³ $1/T/K^{-1}$



General Principles

Blending

Initial approach

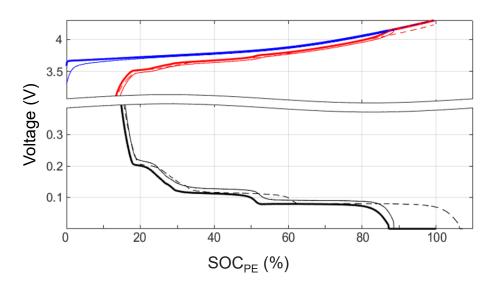
Not taking current distribution in consideration

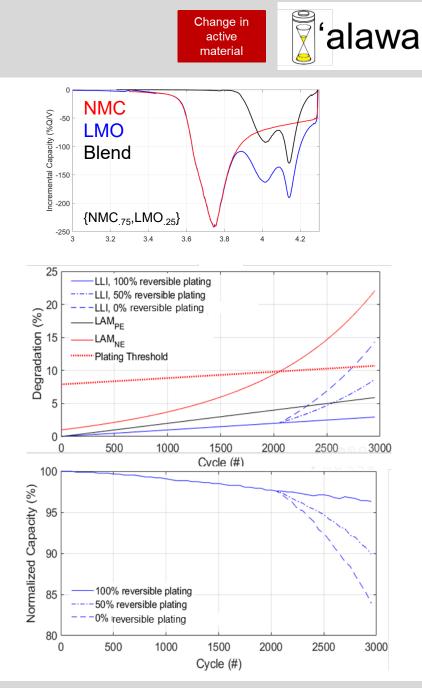
Lithium Plating

Add Li metal as active material when needed

Allow Knee simulation and prediction

LAM, Rate capability, or resistance based







Dubarry M. et al., Journal of Power Sources 479 (2020) 228806 Dubarry M. and D. Beck, Accounts of Material Research, 10.1021/accountsmr.2c00082

General Principles

Blending – What's next Need for a paralleling model Take current distribution into Consideration

Uses simulation at different rates

800 800 800 Incremental Capacity (%SOC/V) Separate Mostly Partially Overlapping response overlapping 600 600 response response LFP LMO LMO 400 400 NMC NCA NMC 200 200 3.4 3.6 4.2 3.4 3.6 3.8 4.2 3.4 3.6 4.2 3.8 4 4 3.8 4 Voltage (V) Voltage (V) Voltage (V) 0.1 0.1 0.1 0.08 0.08 0.08 LFP LMO NCA NMC LMO NMC Rate (h⁻¹) 90'0 0.06 0.06 0.04 0.04 0.02 0.02 0.02 0 0 20 40 60 80 100 0 20 40 60 80 100 0 20 40 60 80 SOC (%) SOC (%) SOC (%) (d) (e) 4 4 Voltage (V) 3.5 3.5 3 3 2.5 1002.5 20 40 60 80 0 0 20 60 40 80 100 SOC (%) SOC (%)

Change in

active

material

alawa

100

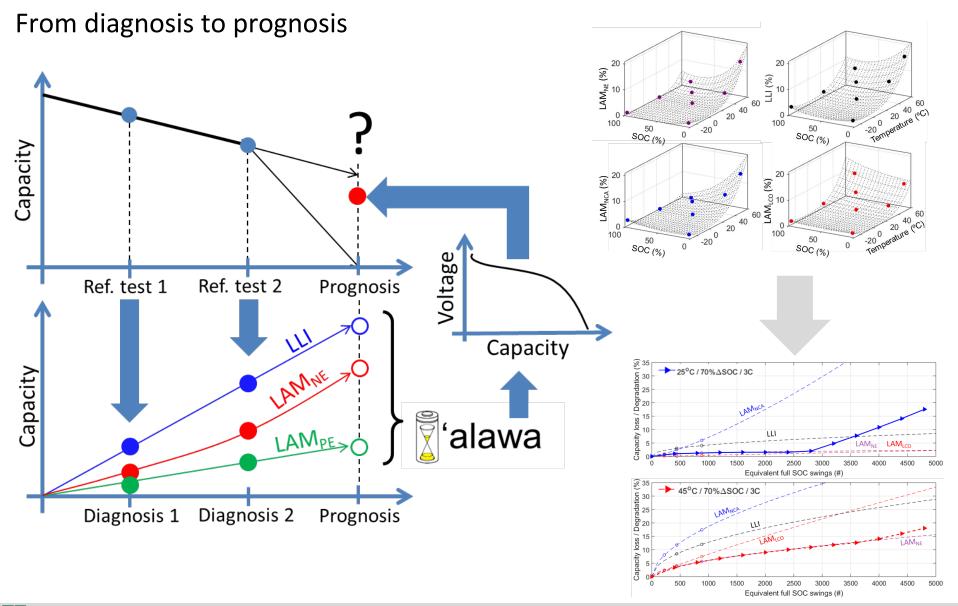
Voltage fade Phase transformation Solid Solution



Heubner, C.; Liebmann, T.; Schneider, M.; Michaelis, A. Electrochim. Acta 2018, 269, 745-760, doi:10.1016/j.electacta.2018.02.165c Dubarry M. and D. Beck, Accounts of Material Research, 10.1021/accountsmr.2c00082

General Principles







Journal of The Electrochemical Society, 166 (10) A1991-A2001 (2019)

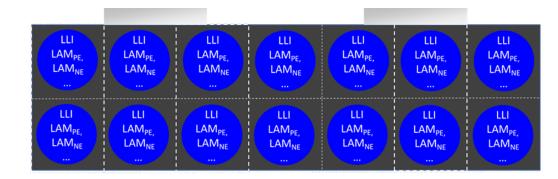
Prospective Features

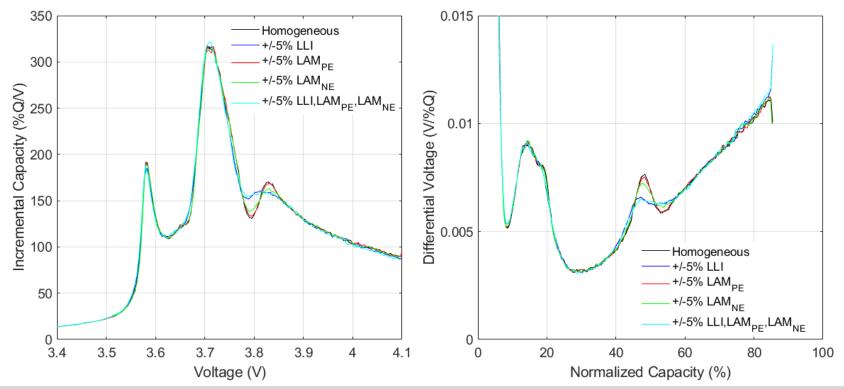
Inhomogeneities

Uses simulations at diff. rates

- Uses paralleling model
- For modules
- For large electrodes

Possible Li transfer between segments



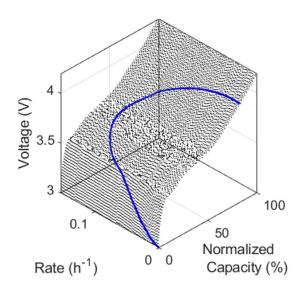




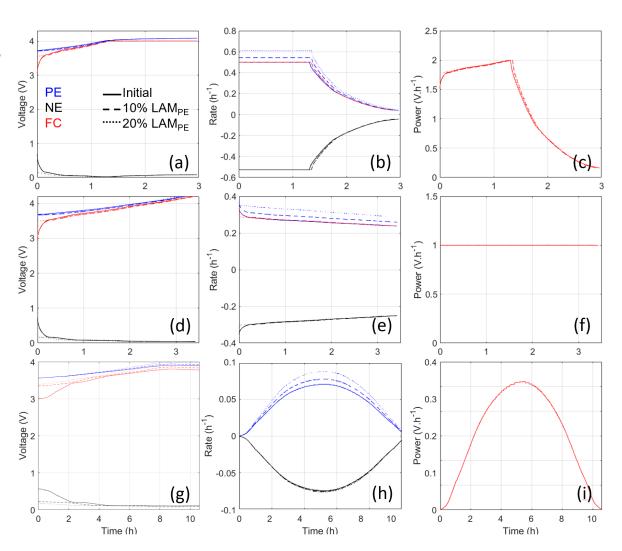


Prospective Features

Complex duty cycles Uses simulations at diff. rates Uses paralleling model



Poster A-2466 Data-Driven Direct Diagnosis of PV Connected Batteries





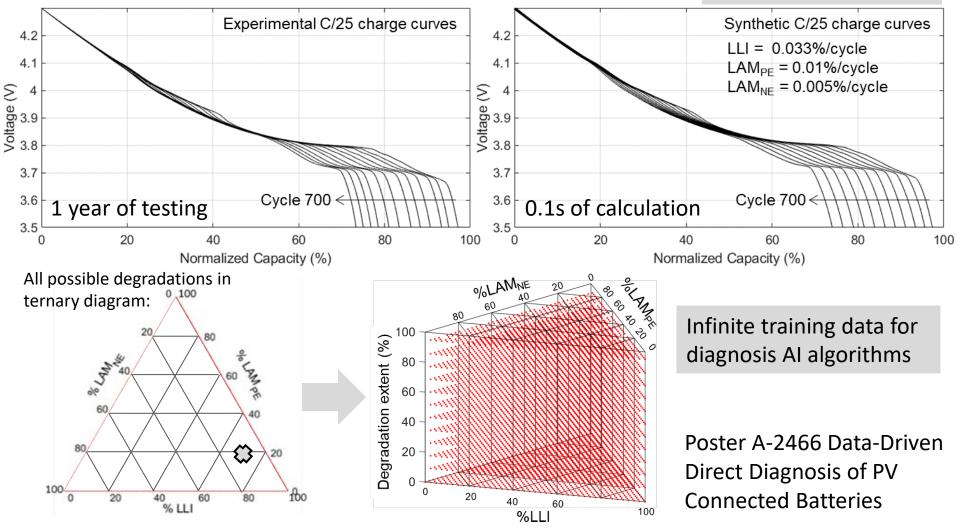


Big Data for Li-Ion Diagnosis and Prognosis Use the mechanistic modeling approach



Emulation of battery electrochemical response

Aging reconstructed from simple equations





Dubarry M. et al., Journal of Power Sources 479 (2020) 228806, Dubarry M. et al., Energies 2021, 14, 2371. https://doi.org/10.3390/en14092371 Dubarry, M., et al. (2017). "State of health battery estimator enabling degradation diagnosis: Model and algorithm description." Journal of Power Sources **360**: 59-69.

Li-ion batteries Digital Twins Mechanistic modeling



Summary

Validated

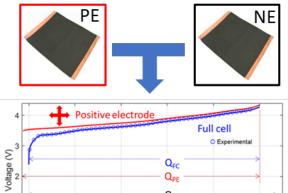
Degradation mode diagnosis LLI, LAMs, Kinetics Material based prognosis

With knee or not Plating, reversible or not

Electrochemical responses Constant current Simple blends Overdischarge Overcharge Big Data Low rates

Feature of Interest Tracking

Mechanistic Modeling Approach



0

capacity (Ah/V)

Incremental

2

0¹ 3.2

3.4

3.6

OFS Negative electrode Q_{FC} Q_{PE} Q_{NE} LR = Q_{NE} Dy Big BOL Experimental C = CO CO CO CO CO CO C = CO CO CO CO C = CO CO CO C = CO CO CO C = CO CO C = CO CO C = CO C

3.8

Voltage (V)

4.2

Under validation

Electrochemical responses Na-ion and other chemistries Advanced blends Voltage fade Inhomogeneous electrodes Large battery packs Dynamic duty cycles

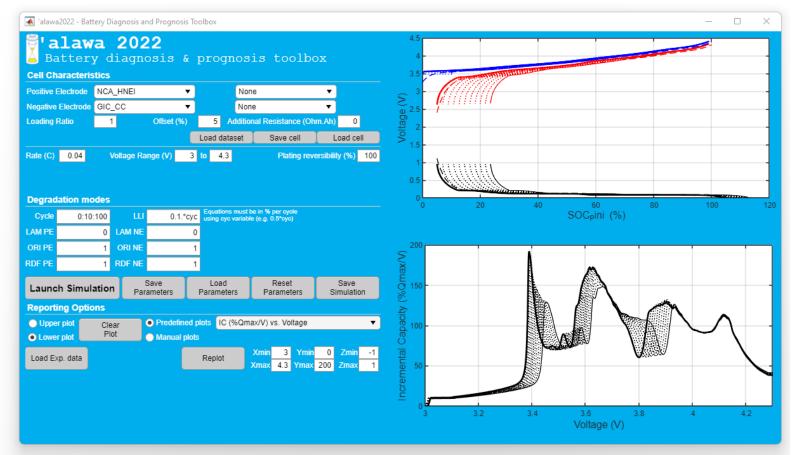
Big Data High rates Temperatures Blends Non-continuous duty cycles



Li-ion batteries Digital Twins Graphical user interface: the 'alawa toolbox



Simple, fast, powerful and accurate diagnosis and prognosis tool



Free licensing available for academic applications.

Back door access for synthetic cycles generation available with collaboration

Licensing available for industry users (GUI and backdoor)



https://www.soest.hawaii.edu/HNEI/alawa/

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Mahalo for your attention! Questions?



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