ENERGY STORAGE SYSTEMS

SAFETY & RELIABILITY FORUM

Big data for the diagnosis and prognosis of deployed energy storage systems

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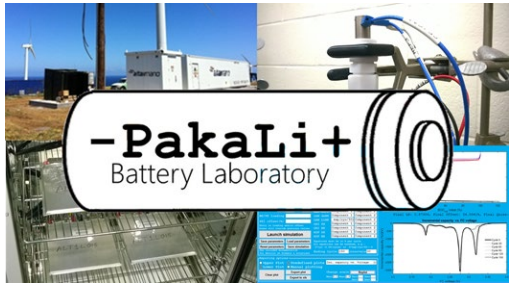

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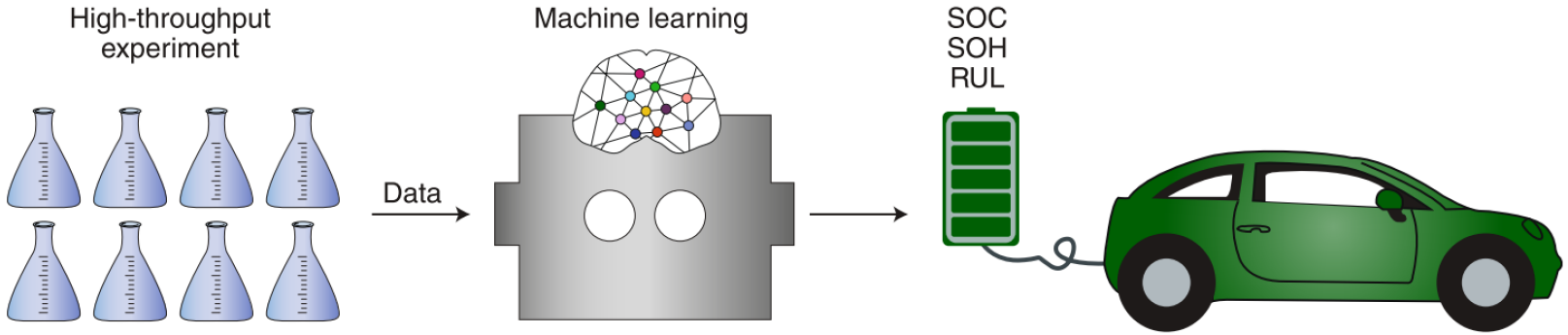
Big Data for Li-Ion Diagnosis and Prognosis

Artificial Intelligence

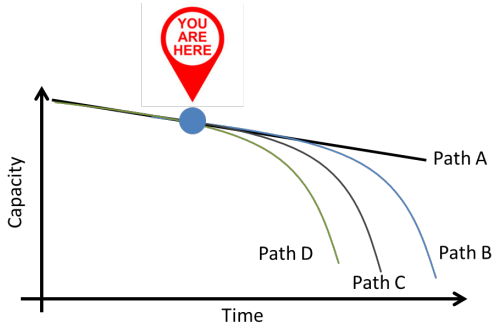
Objective/Significance



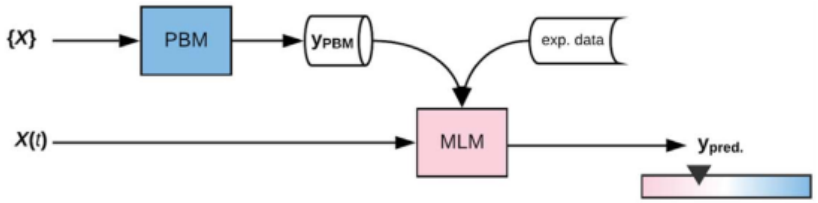
Man-Fai Ng et al., Nature Machine Intelligence, 2(3) p. 161-170 (2020)

Experimental data is costly and time consuming,
Most studies only test a couple batteries,
Biggest dataset: 124 batteries with only charge varying

Problematic because of path dependence.



Current state of the art is far from the big data needed to make AI work



Solution: Transfer Learning
Create synthetic training datasets

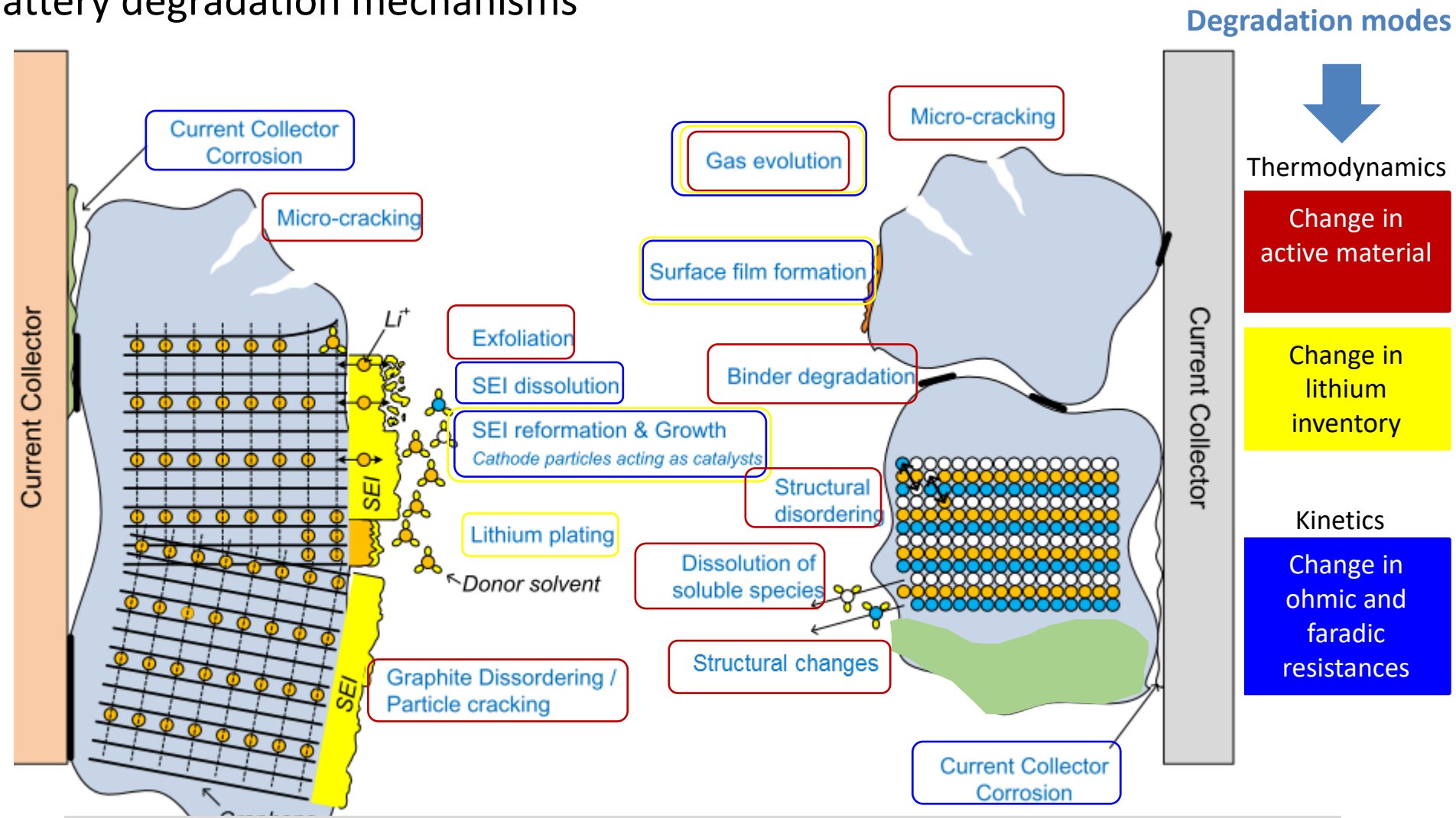
Aylol et al., Journal of The Electrochemical Society, 2021 168 030525

Dubarry M. et al., Journal of Power Sources 479 (2020) 228806

Big Data for Li-Ion Diagnosis and Prognosis

Li-ion batteries are complex systems

Lithium-ion battery degradation mechanisms



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

M. Dubarry, C. Truchot and B.Y. Liaw, *J.Power Sources*, **219** (2012) 204-216

Big Data for Li-Ion Diagnosis and Prognosis

Building a Digital Twin: Mechanistic modeling

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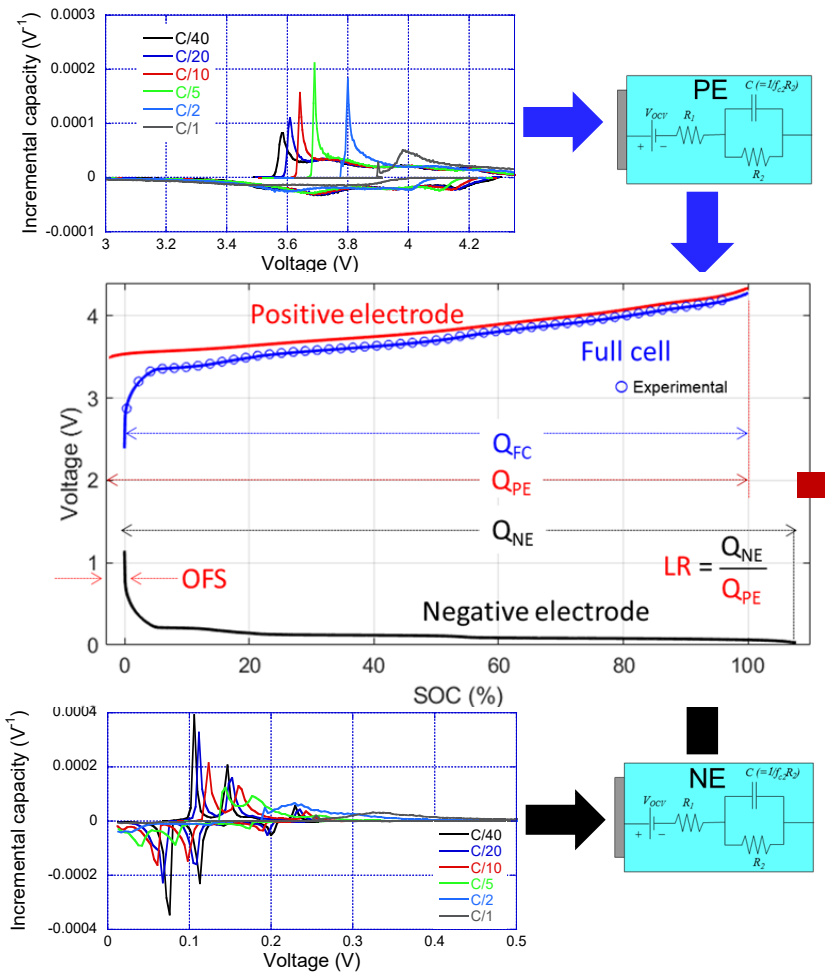
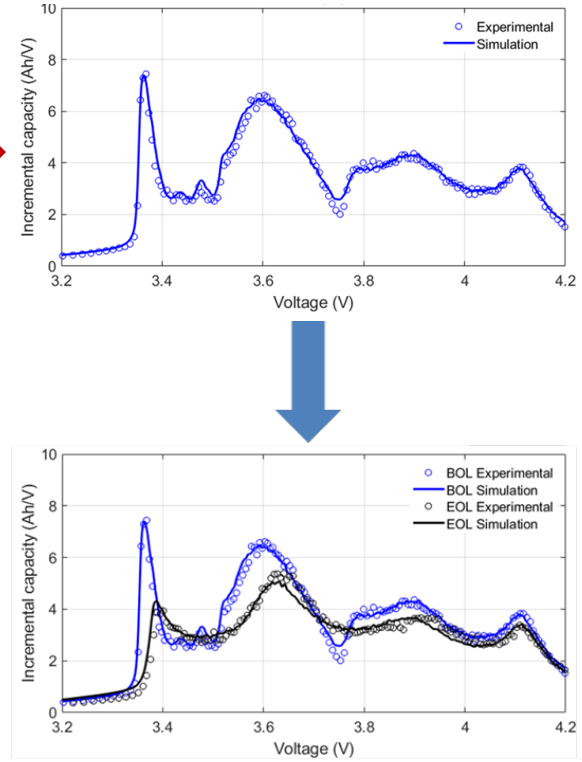
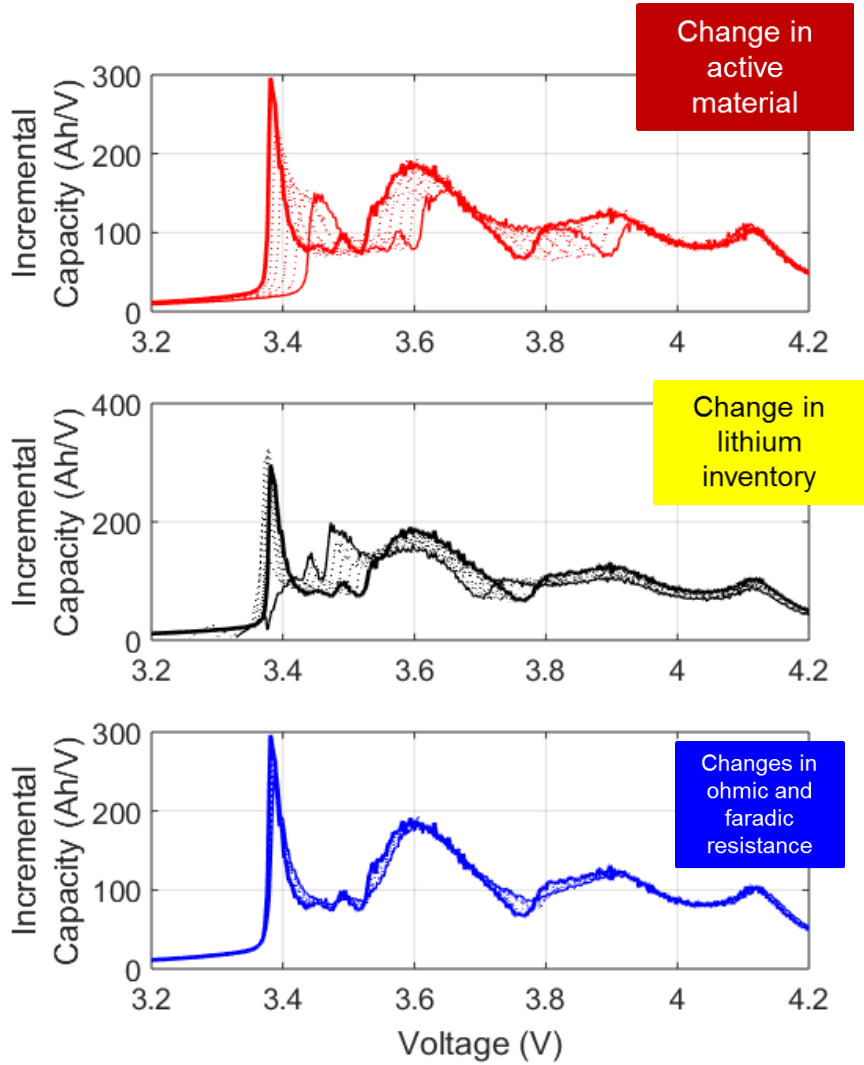
General Principles





Vary matching parameters to emulate degradation



Dubarry M. et al. Journal of Power Sources 219 (2012) 204-216

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Simulate any possible degradation

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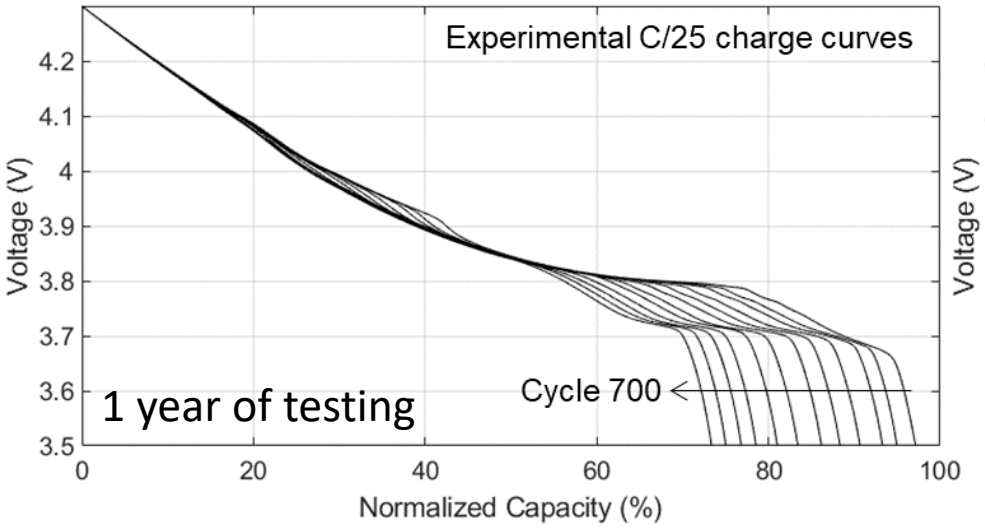
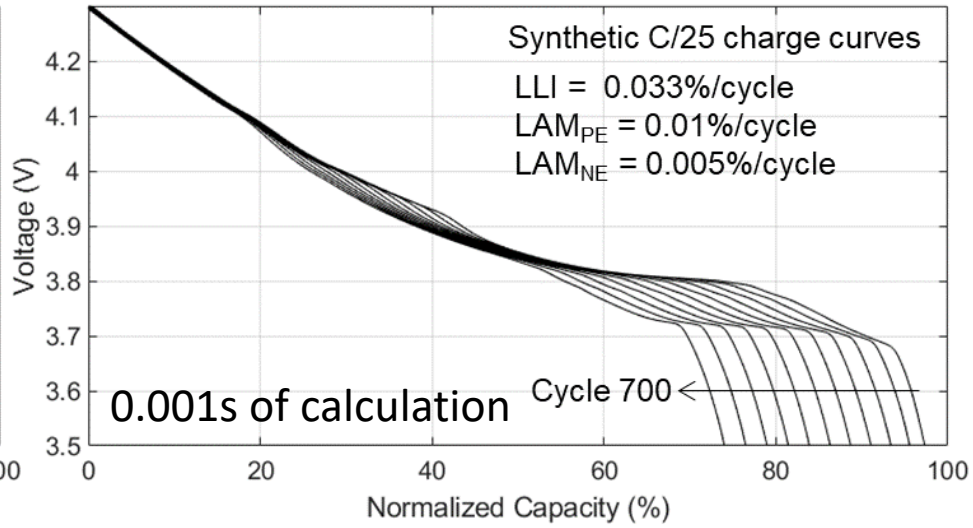
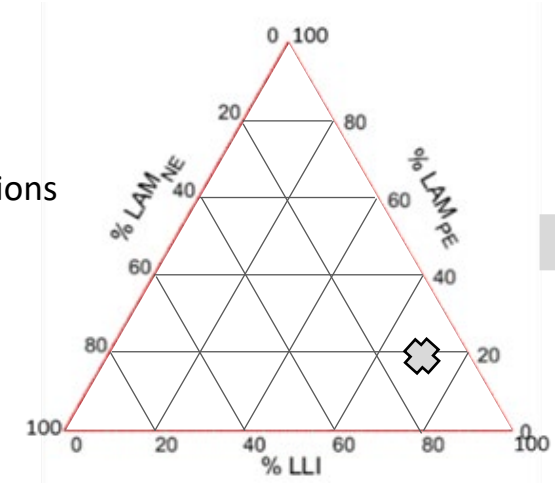
Emulation of battery electrochemical response

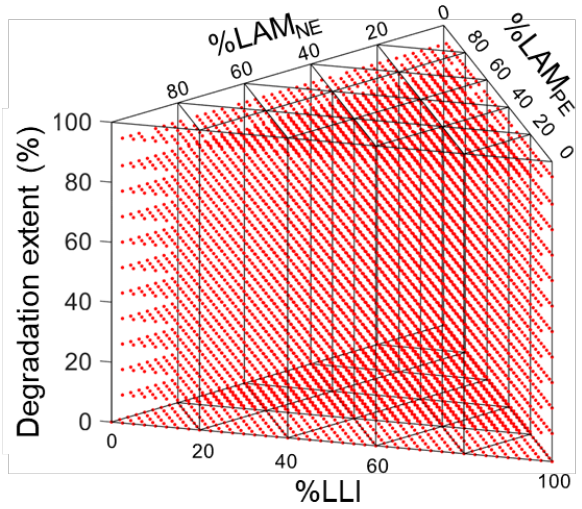




Aging reconstructed from simple equations

All possible degradations in ternary diagram:





Infinite training data for diagnosis AI algorithms

Mendeley Data, 2020; Vol. 2021, 10.17632/6s6ph9n8zg.3
Mendeley Data, 2020; Vol. 2021, 10.17632/bs2j56pn7y.3
Mendeley Data, 2021, 10.17632/2h8cpszy26.1
Mendeley Data, 2021, 10.17632/pb5xpv8z5r.1

HNEI Hawai'i Natural Energy Institute University of Hawai'i at Mānoa

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.

Big Data for Li-Ion Diagnosis and Prognosis
Take Home Message

Proof-of-concept methodology to generate **big data training datasets**

Universal tool for creation of data indistinguishable from real one

Broad applicability: cell chemistries, designs, and operating modes

Methodology could be **applied to different conditions** such as rate and temperature

Can handle **lithium plating with adjustable reversibility**

Ideal to **test validity** of different approaches for diagnosis or prognosis

The approach **does not remove the need for experimental testing**

It is still essential, and the only way, to decipher which conditions cater to specific degradation.

More details: Dubarry M. et al., Journal of Power Sources 479 (2020) 228806
Dubarry M. et al., Energies, 2021, 14(9), 2371

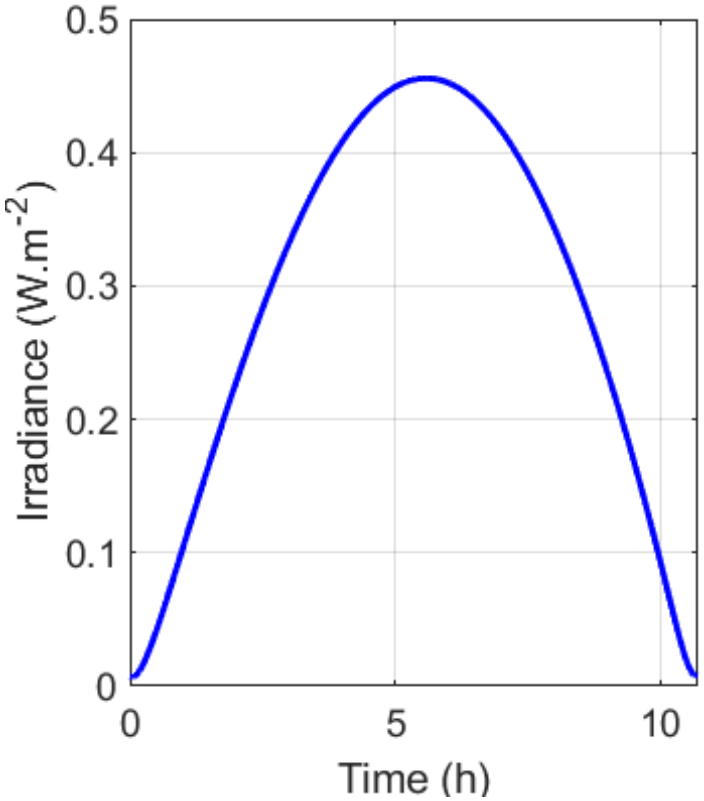
Data-Driven Diagnosis for PV Connected Batteries

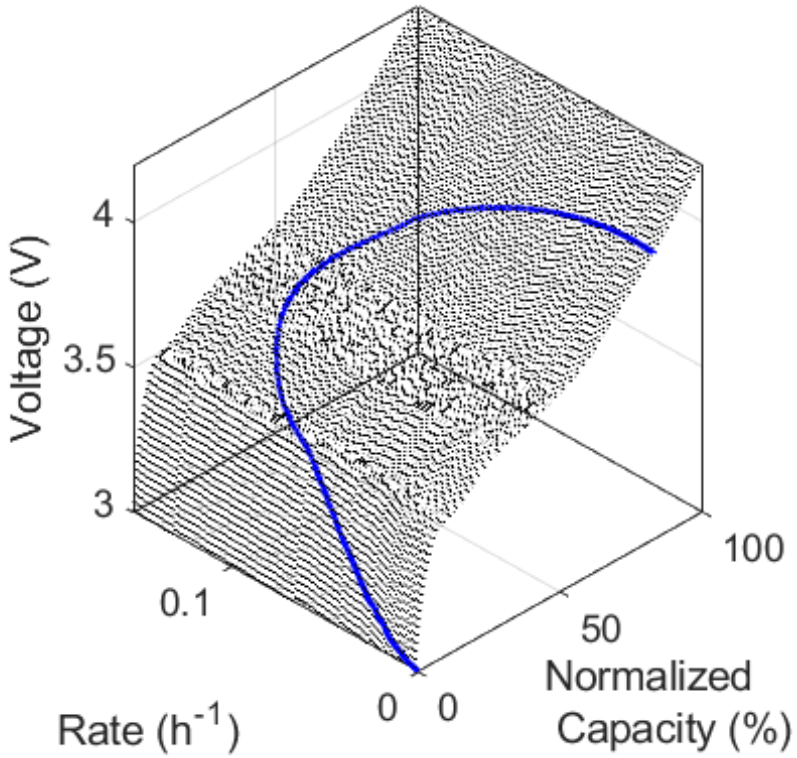
Current Synthetic dataset approach for constant current data only

- Not representative of deployed data (unless lengthy maintenance cycles)

Mechanistic model can be applied outside of constant current data

- Could use auspicious conditions for deployed systems
- Emulation of clear sky irradiance: predictable power output



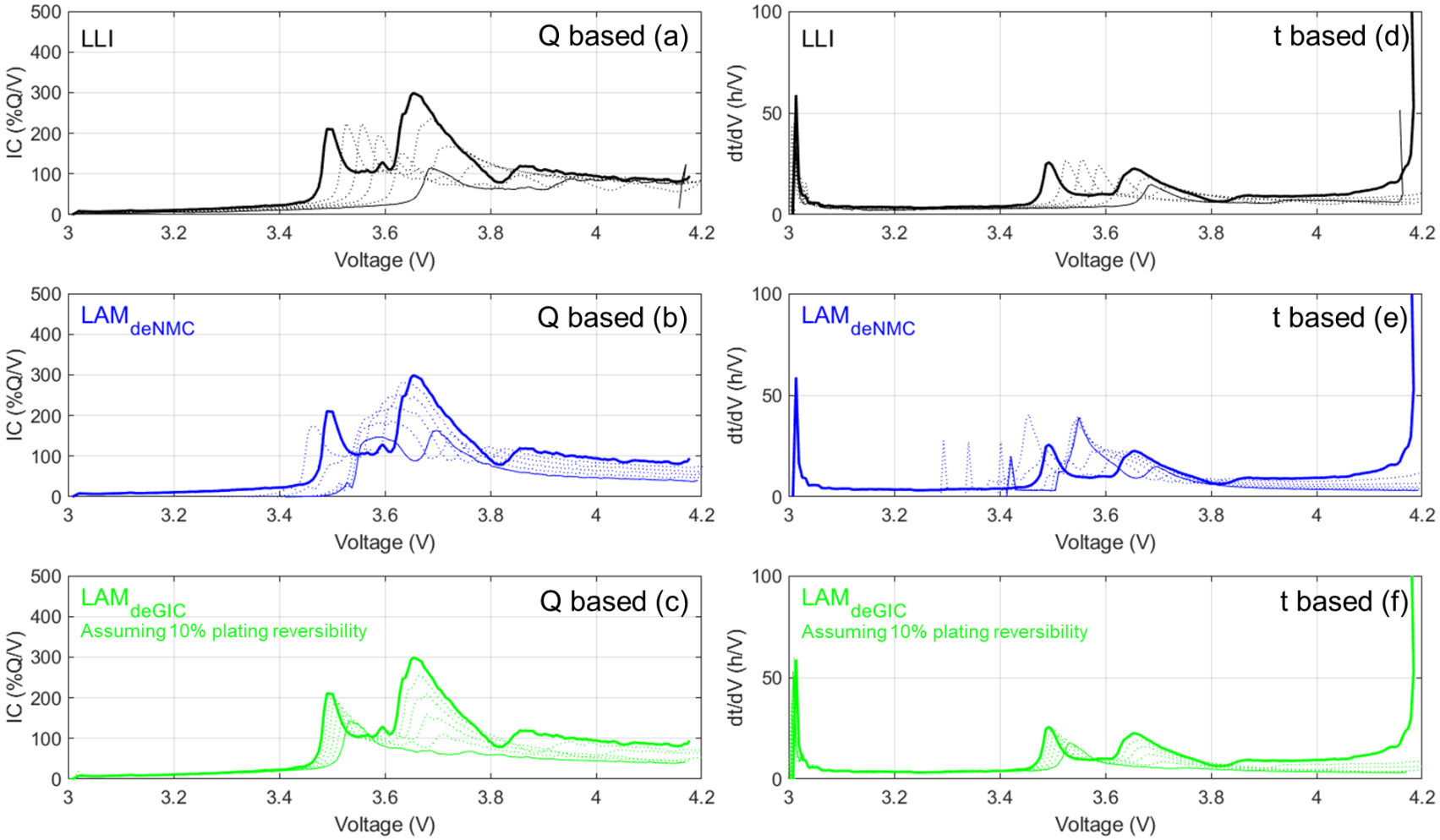


Dubarry M. and D. Beck, Accounts of Material Research, 10.1021/accountsmr.2c00082

Data-Driven Diagnosis for PV Connected Batteries

Capacity vs. Time

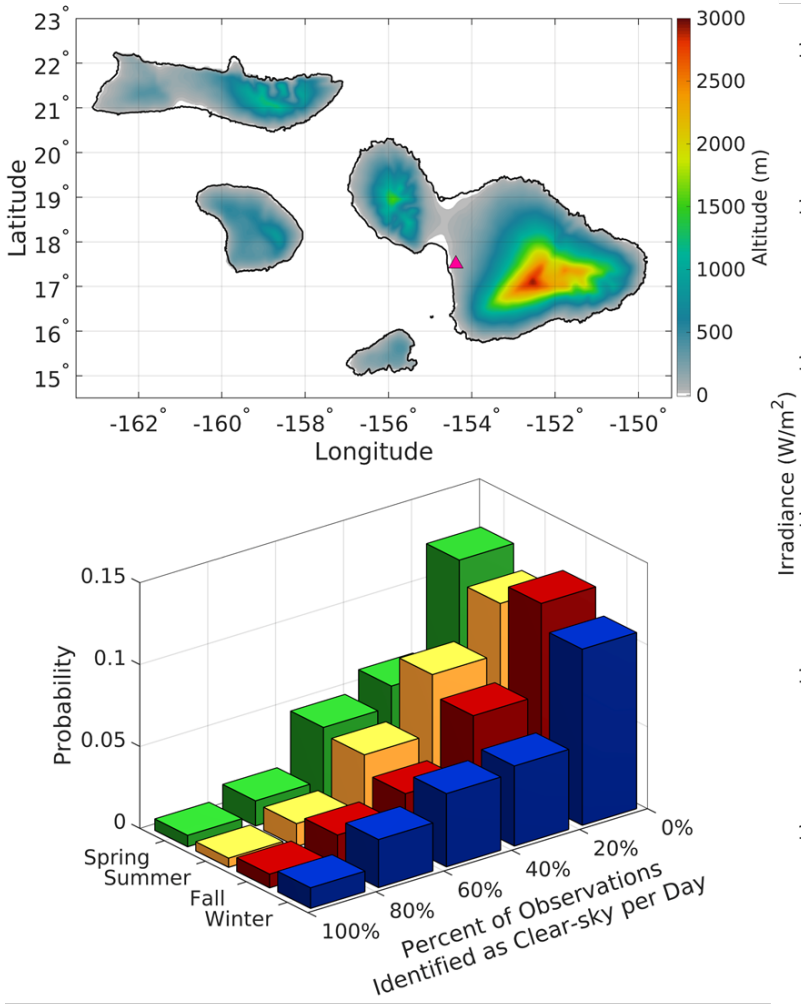
Uncorrelated because not constant current

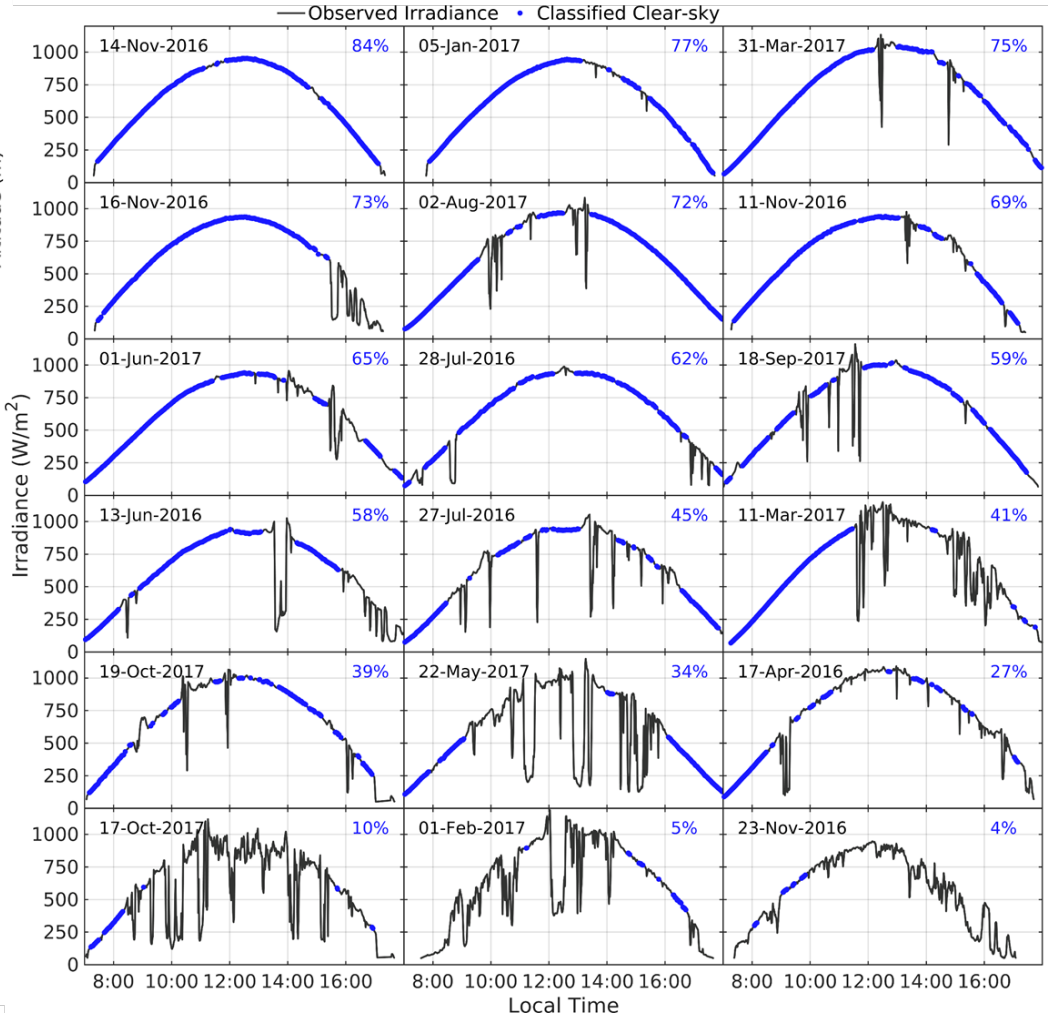


Dubarry M., Costa N., & Matthews D., Nature Communications, In press
Preprint available 10.21203/rs.3.rs-2058155/v1

Data-Driven Diagnosis for PV Connected Batteries

Clear-sky assessment

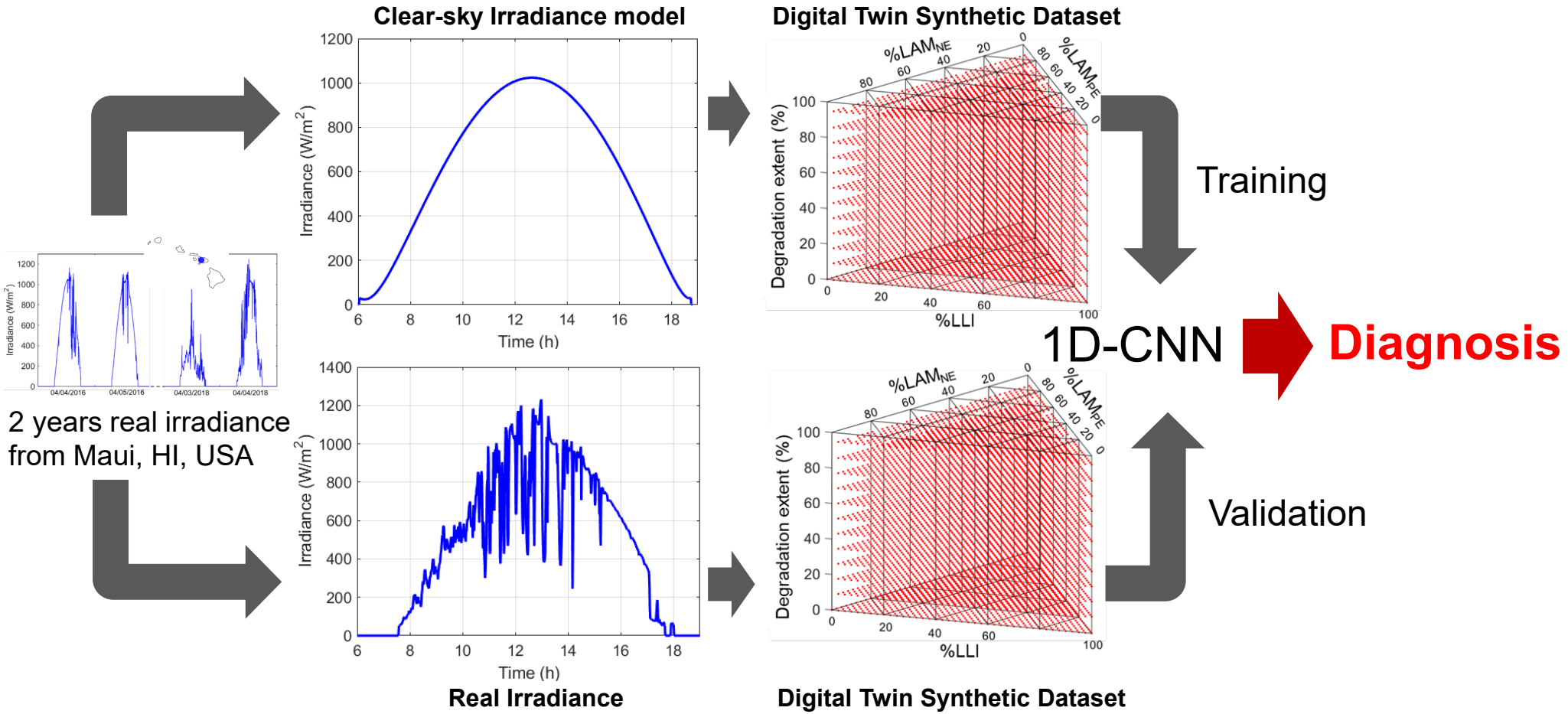




Dubarry M., Costa N., & Matthews D., Nature Communications, In press
Preprint available 10.21203/rs.3.rs-2058155/v1

Data-Driven Diagnosis for PV Connected Batteries

Mechanistic model can be applied outside of constant current data



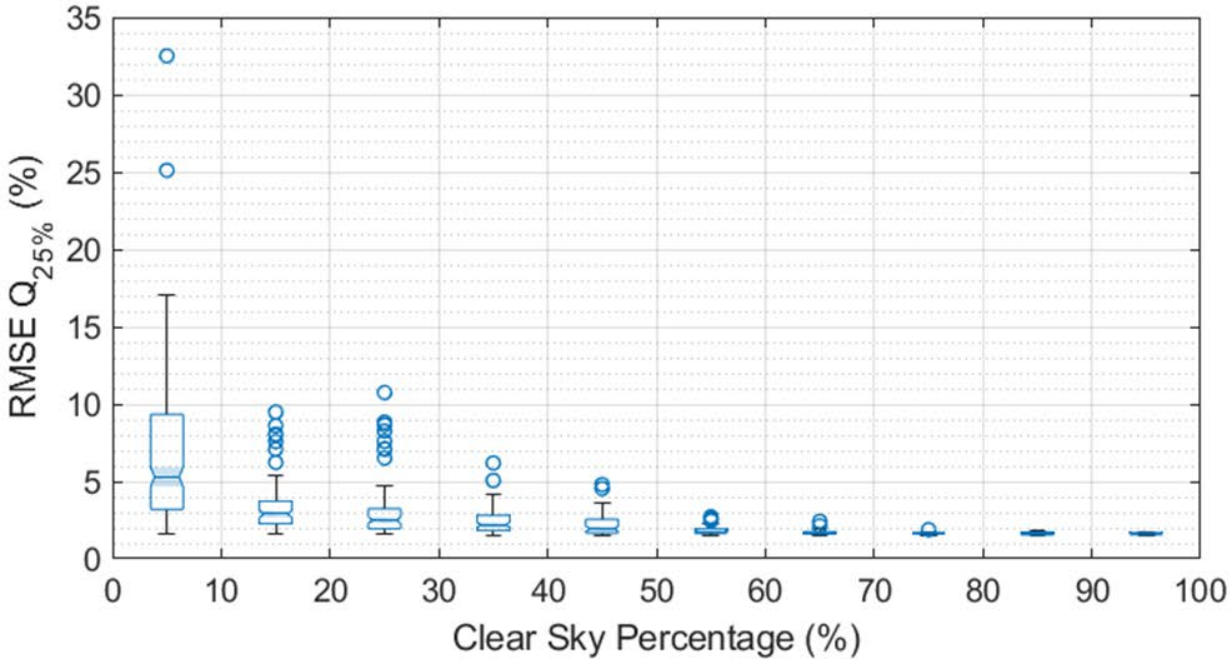
Dubarry M., Costa N., & Matthews D., Nature Communications, In press
Dubarry M., Yasin F., Costa N., & Matthews D., Batteries, In preparation

Data-Driven Diagnosis for PV Connected Batteries

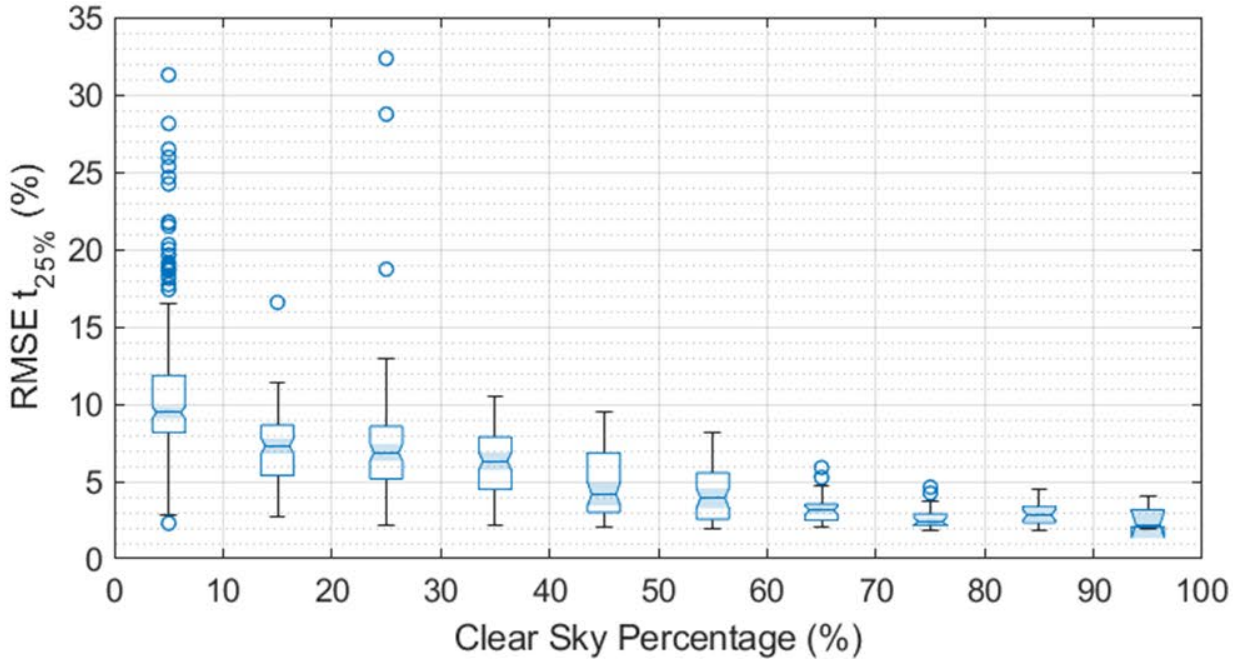
Diagnosability tested on 1 ML algorithms for 2 years of data

720 days, 10000 degradation paths, up to 25% degradation in 1% increments

Impact of cloud coverage



Plateaued above 50% clear sky



Plateaued above 70% clear sky

Dubarry M., Costa N., & Matthews D., Nature Communications, In press
Dubarry M., Yasin F., Costa N., & Matthews D., Batteries, In preparation

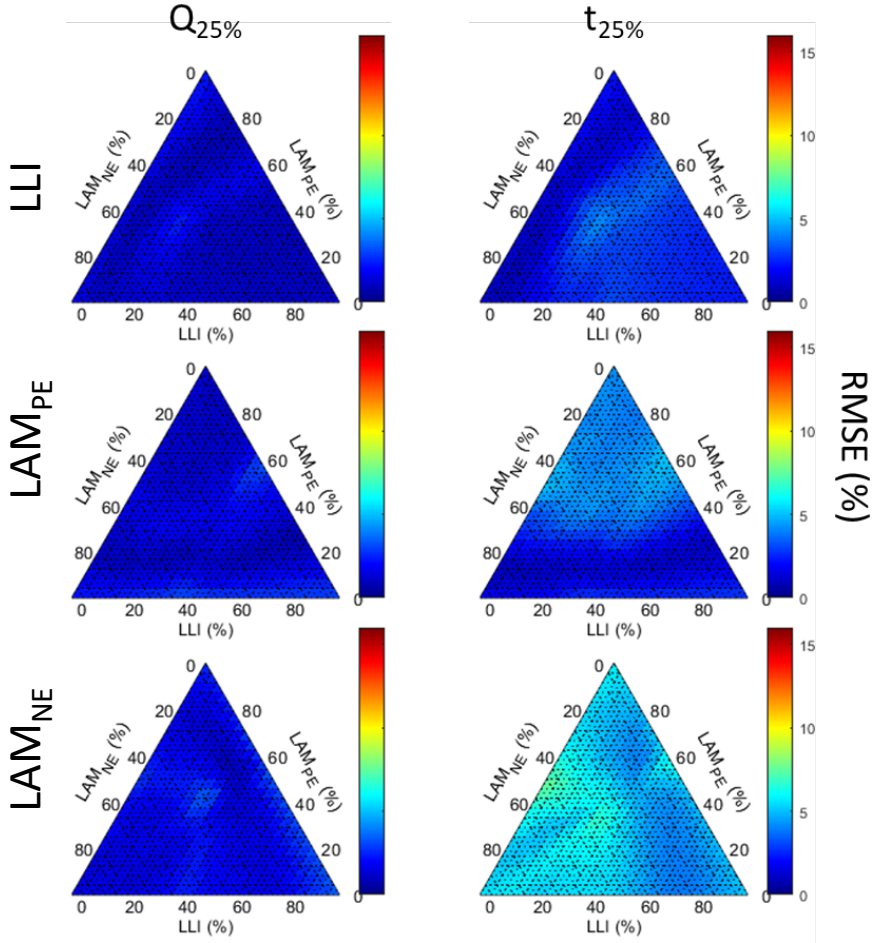
Big Data for Li-Ion Diagnosis and Prognosis

Data-Driven Diagnosis for PV Connected Batteries

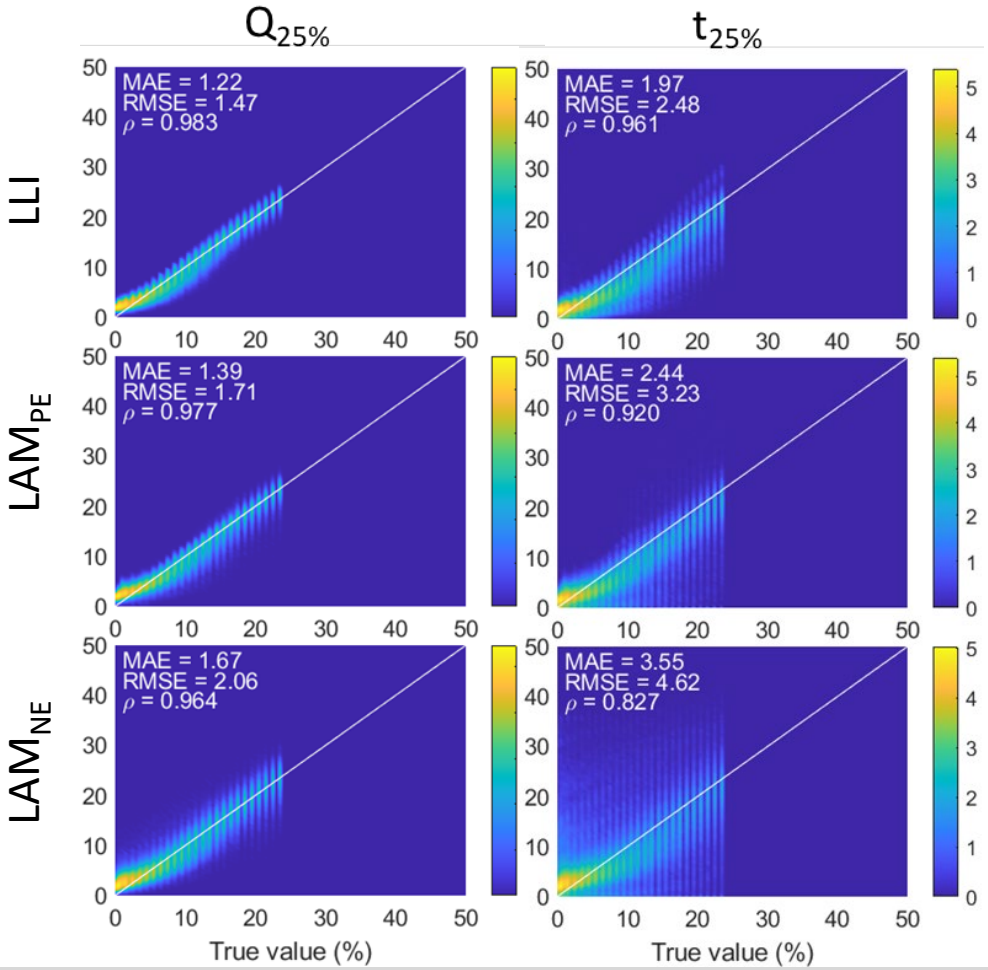
Diagnosability tested on 1 ML algorithms for 2 years of data

720 days, 10000 degradation paths, up to 25% degradation in 1% increments.

Impact of composition (> 50% clear sky)



Impact of extent (> 50% clear sky)



Dubarry M., Costa N., & Matthews D., Nature Communications, In press
Dubarry M., Yasin F., Costa N., & Matthews D., Batteries, In preparation

Data-Driven Diagnosis for PV Connected Batteries

PV connected batteries will undergo sporadic usage which will prevent the application of traditional diagnosis methods.

This work proposes a **new methodology** for **opportunistic diagnosis** using machine learning algorithms trained directly on PV battery charging data.

The training was performed on synthetic voltage data under different degradations calculated from **clear-sky model irradiance data**. Validation was performed on synthetic voltage responses calculated from **plane of array irradiance observations** for a photovoltaic system located in Maui, HI, USA.

An **average RMSE of 1.75%** was obtained for more than 10,000 different degradation paths with 25% or less degradation on the cells and 50% or more clear sky.

Significant benefits for **using synthetic data** to understand the expected variations of voltage response **as real data is not yet available**.

Future work will address packs and additional usage on the cells.

Dubarry M., Costa N., & Matthews D., Nature Communications, In press
Dubarry M., Yasin F., Costa N., & Matthews D., Batteries, In preparation

Acknowledgments

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SAFETY & RELIABILITY FORUM

Thank you!

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