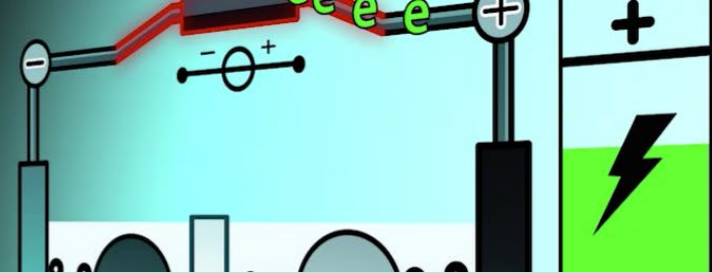




22<sup>nd</sup> Annual  
advanced  
automotive  
battery  
conference

DECEMBER 5 - 8, 2022  
HOTEL DEL CORONADO | SAN DIEGO, CA

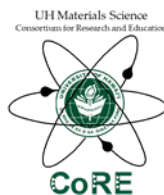


# Big Data in Diagnostics

## Data-Driven Direct Diagnosis of PV Connected Batteries

Matthieu Dubarry, David Beck, Nahuel Costa, & Dax Matthews

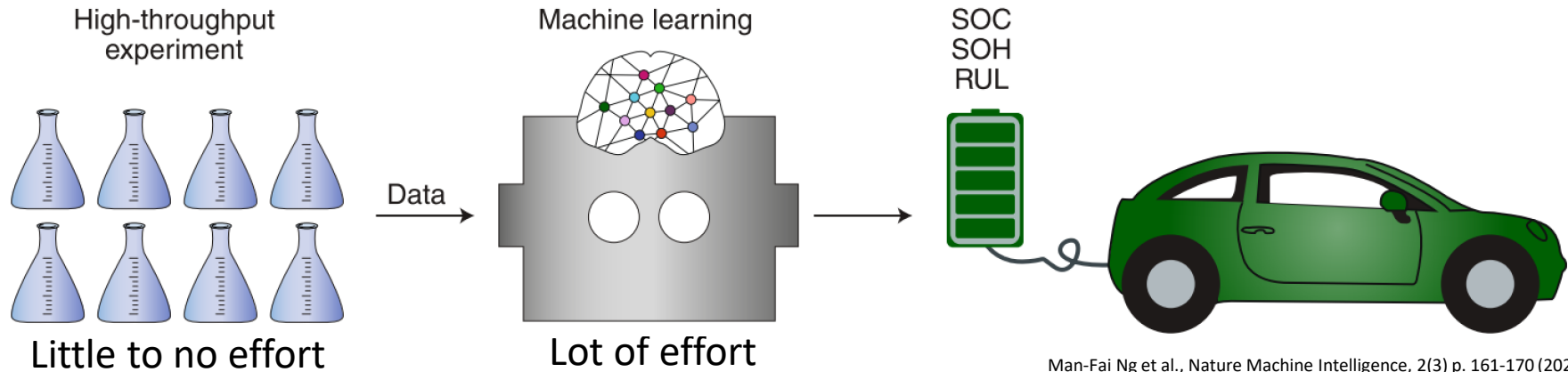
[matthieu@hawaii.edu](mailto:matthieu@hawaii.edu)



# Big Data for Li-Ion Diagnosis and Prognosis

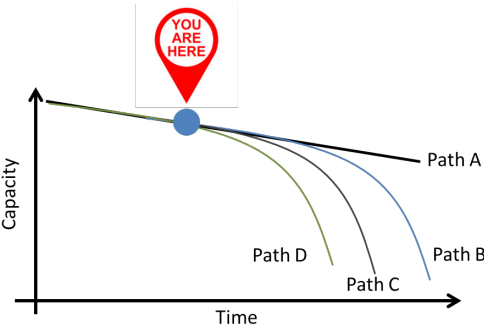
## Artificial Intelligence

### Objective/Significance

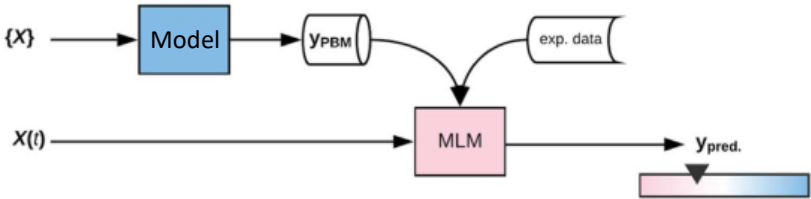


Man-Fai Ng et al., Nature Machine Intelligence, 2(3) p. 161-170 (2020)

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

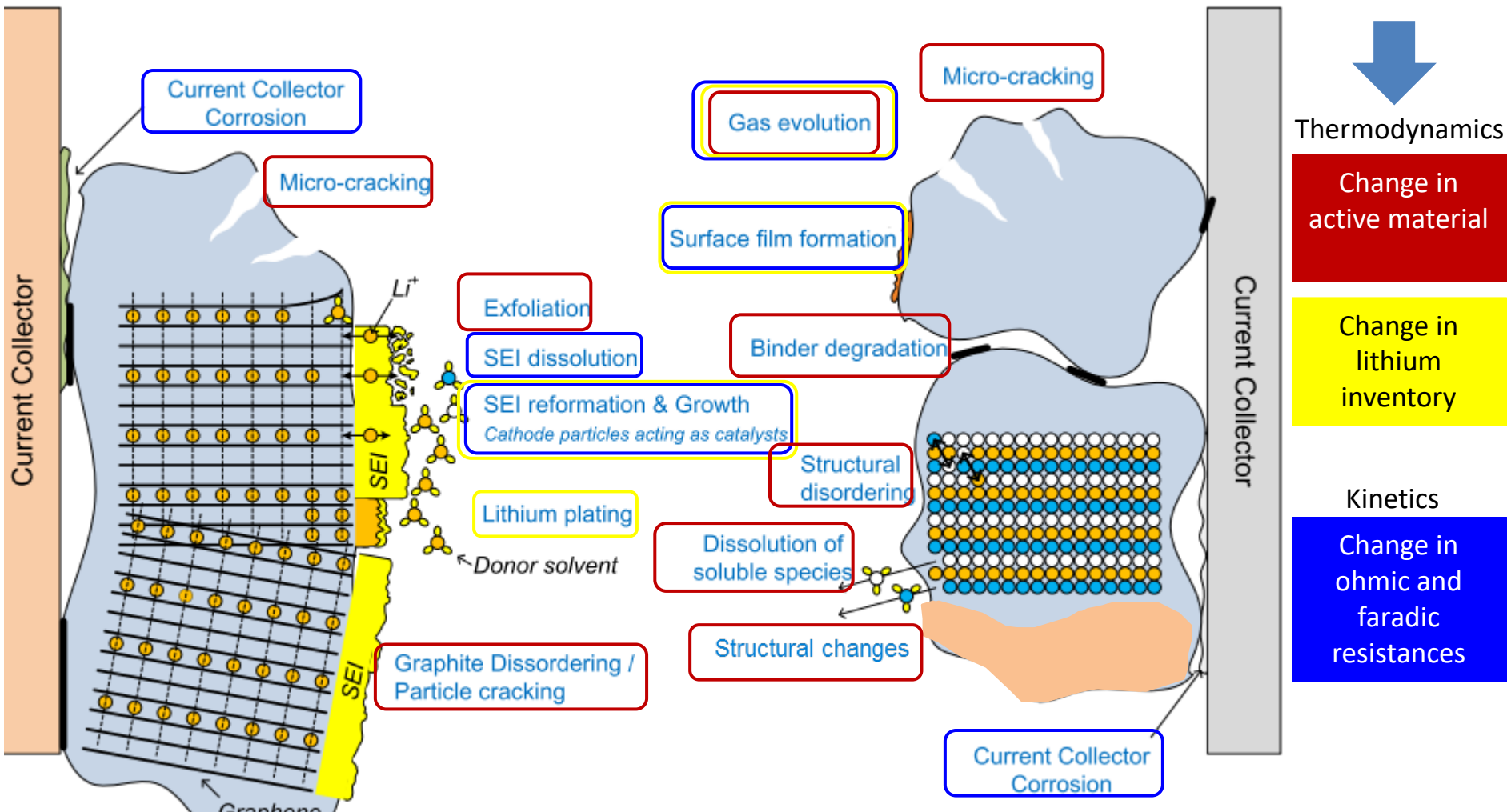


Solution: Transfer Learning  
Create synthetic training datasets

# Big Data for Li-Ion Diagnosis and Prognosis

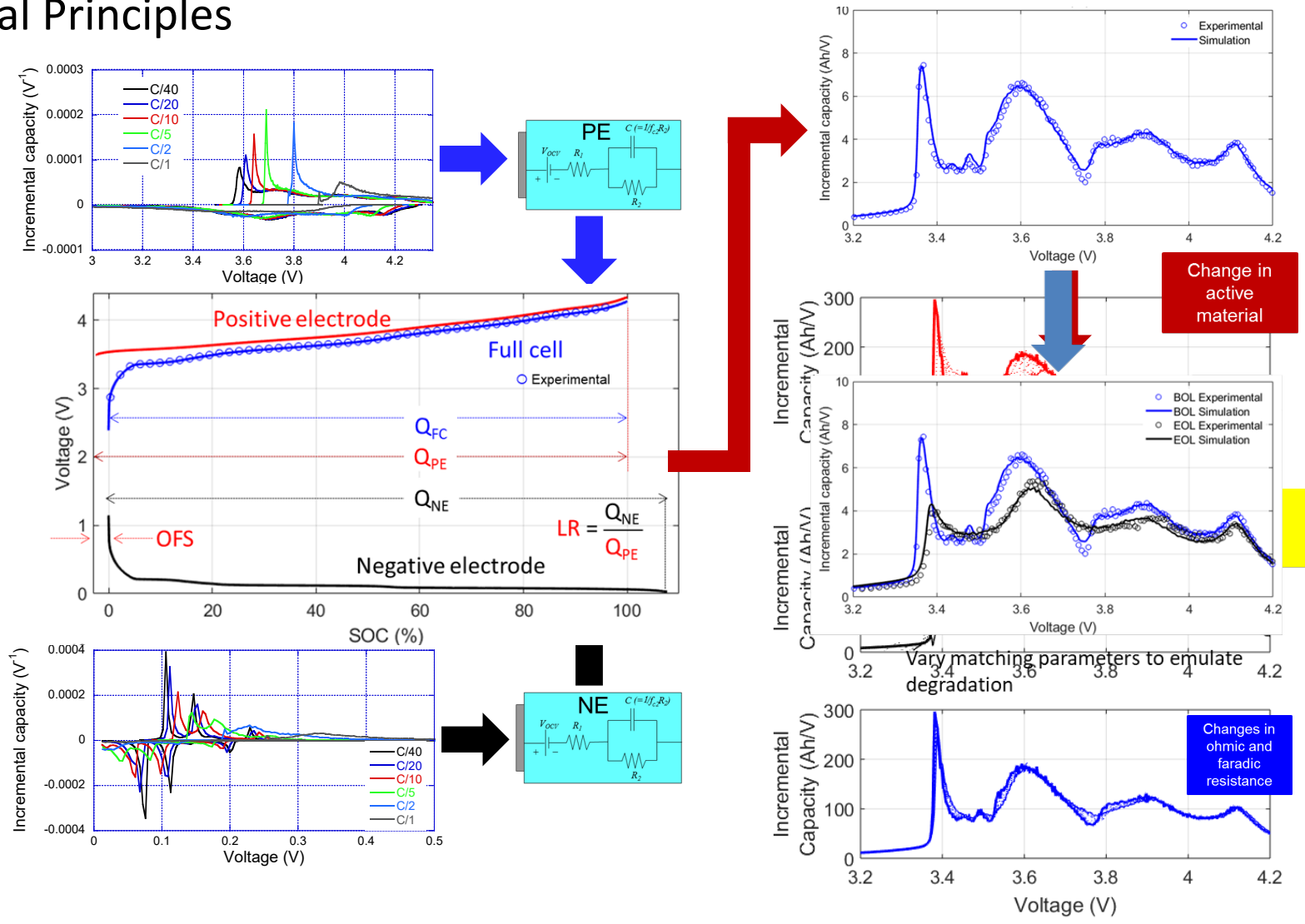
Li-ion batteries are complex systems

Lithium ion battery degradation mechanisms



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

### General Principles



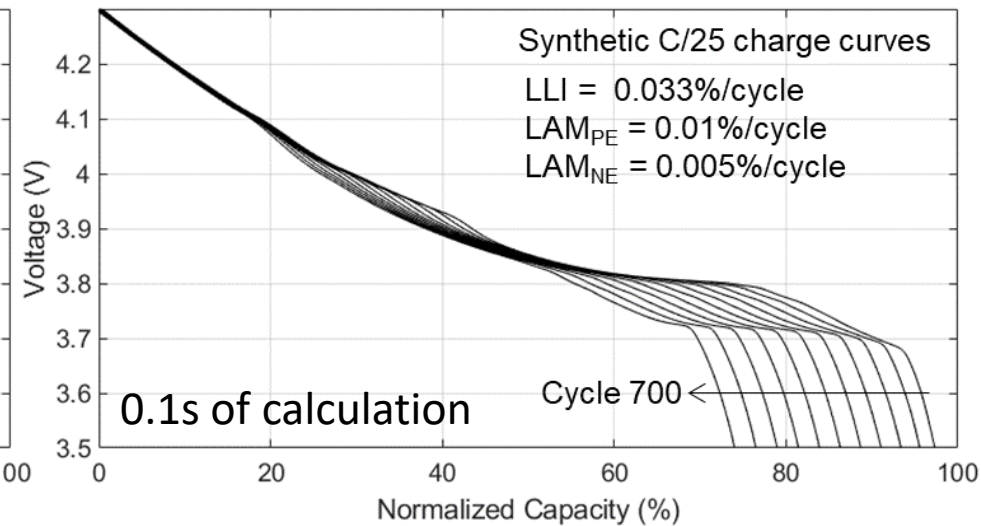
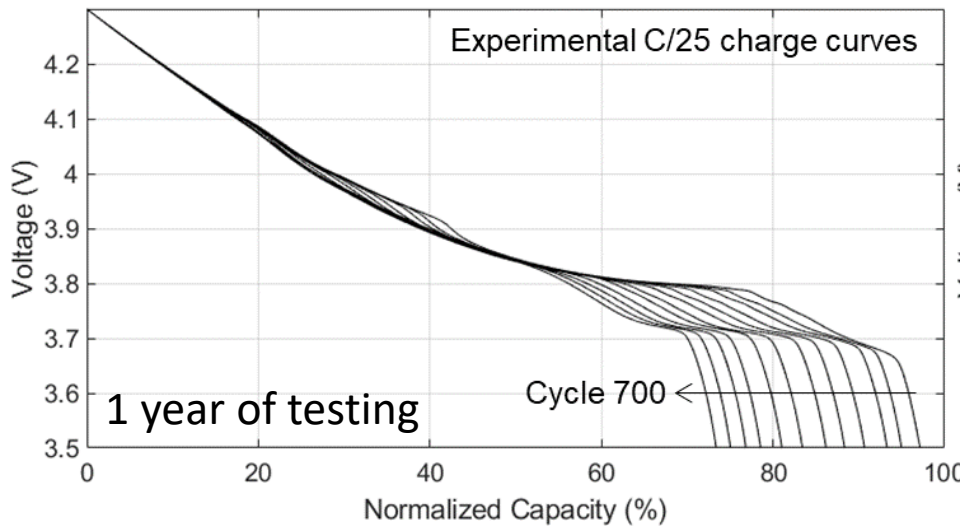
# Big Data for Li-Ion Diagnosis and Prognosis

Simulate any possible degradation

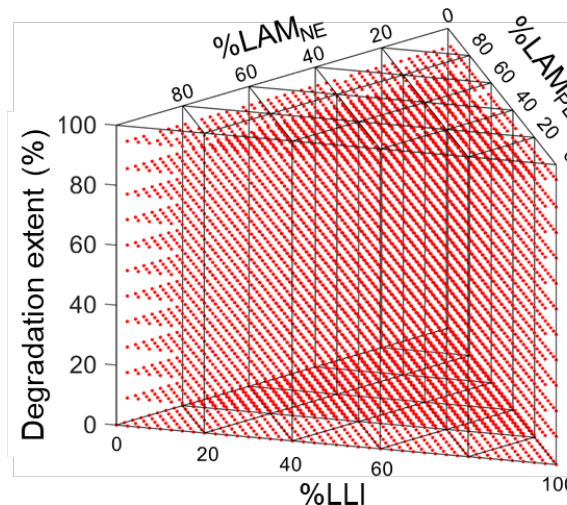
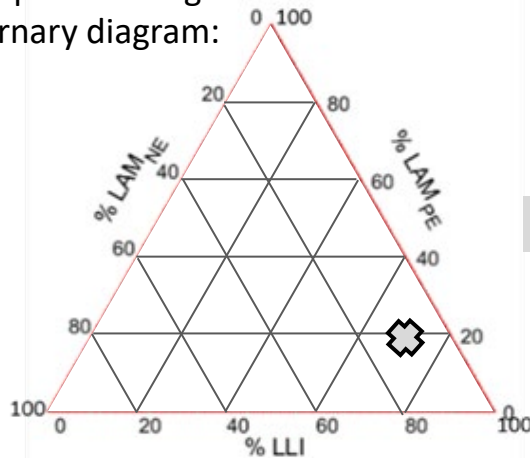


## Emulation of battery electrochemical response

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



# 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**

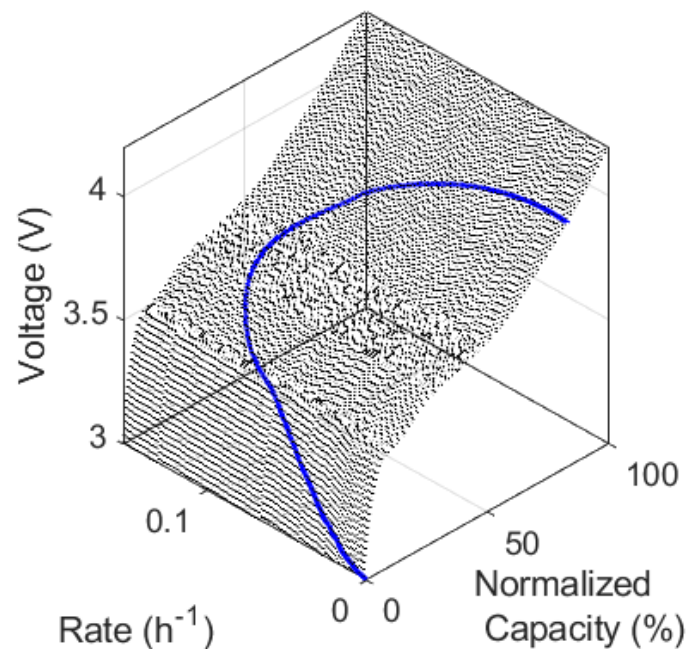
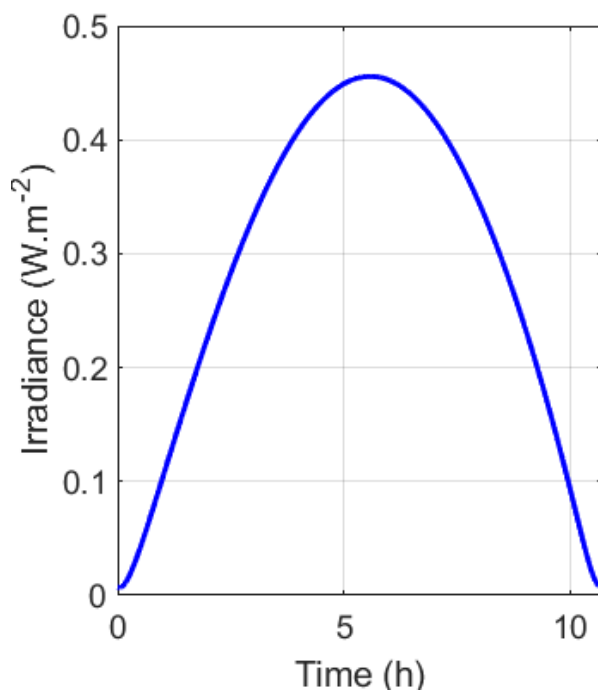
It is still essential, and the only way, to decipher which conditions cater to specific degradation.

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

Dubarry M. et al., Energies, 2021, 14(9), 2371

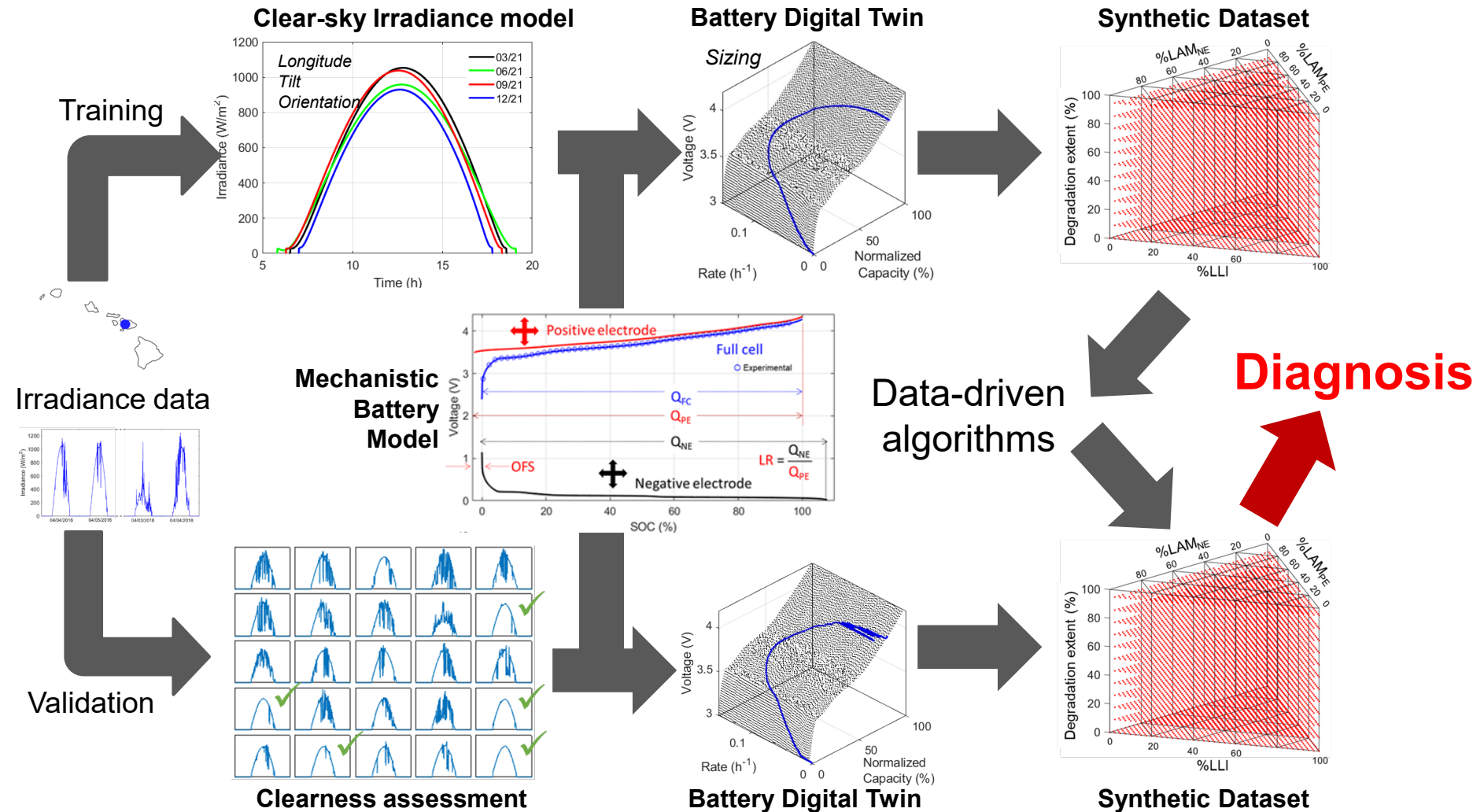
## Data-Driven Diagnosis for PV Connected Batteries

- 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



## Data-Driven Diagnosis for PV Connected Batteries

Mechanistic model can be applied outside of constant current data

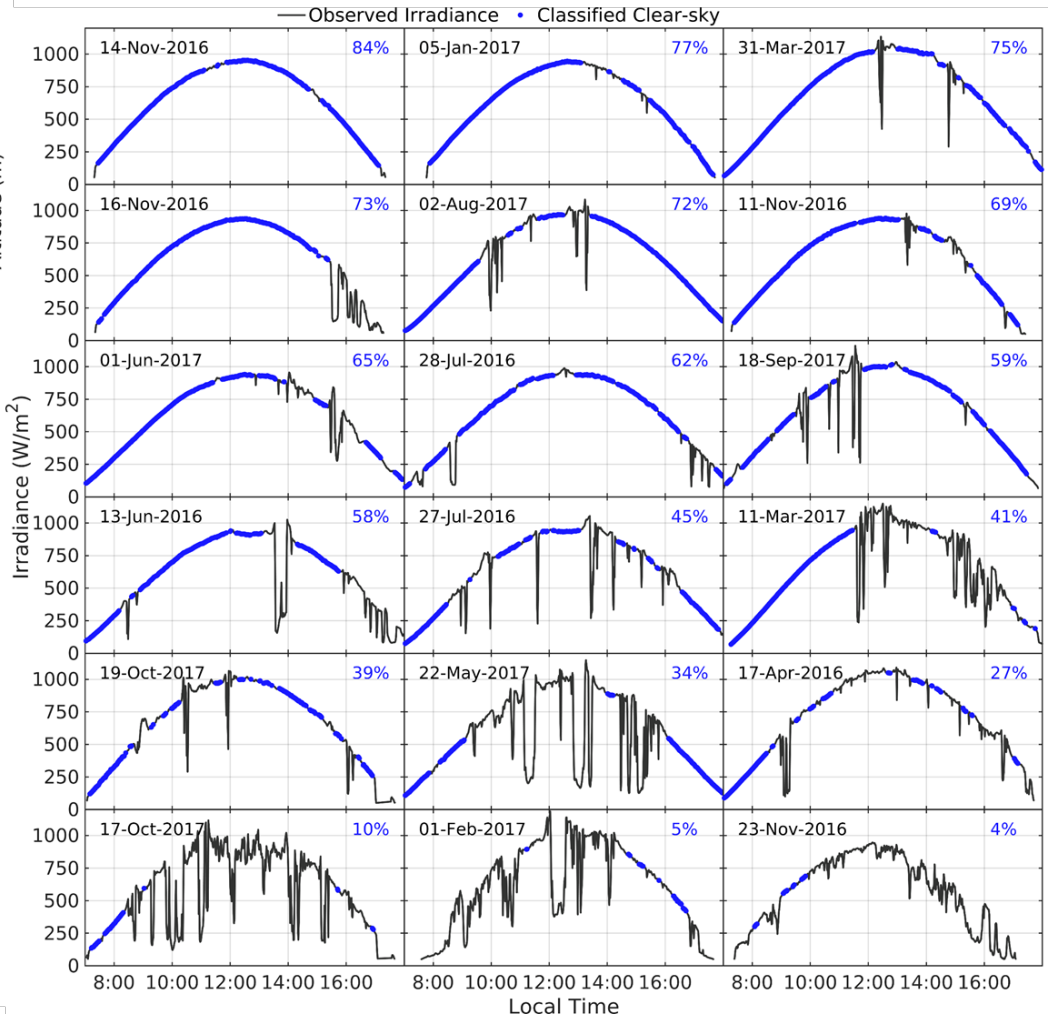
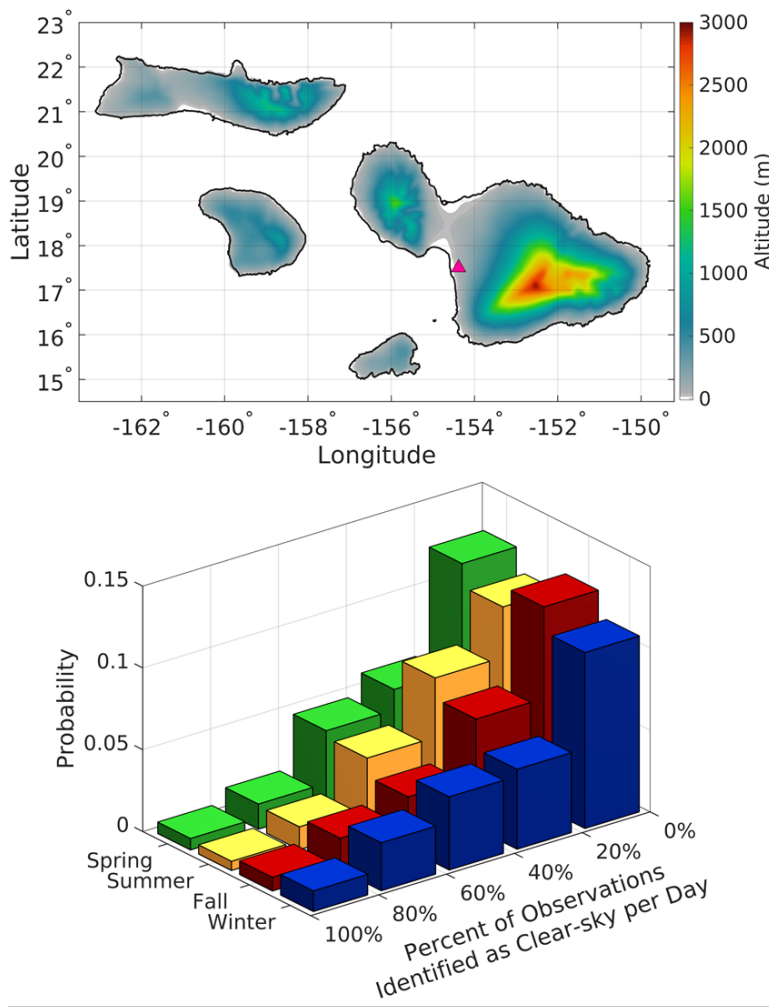




# Big Data for Li-Ion Diagnosis and Prognosis

## Data-Driven Diagnosis for PV Connected Batteries

### Clear-sky assessment

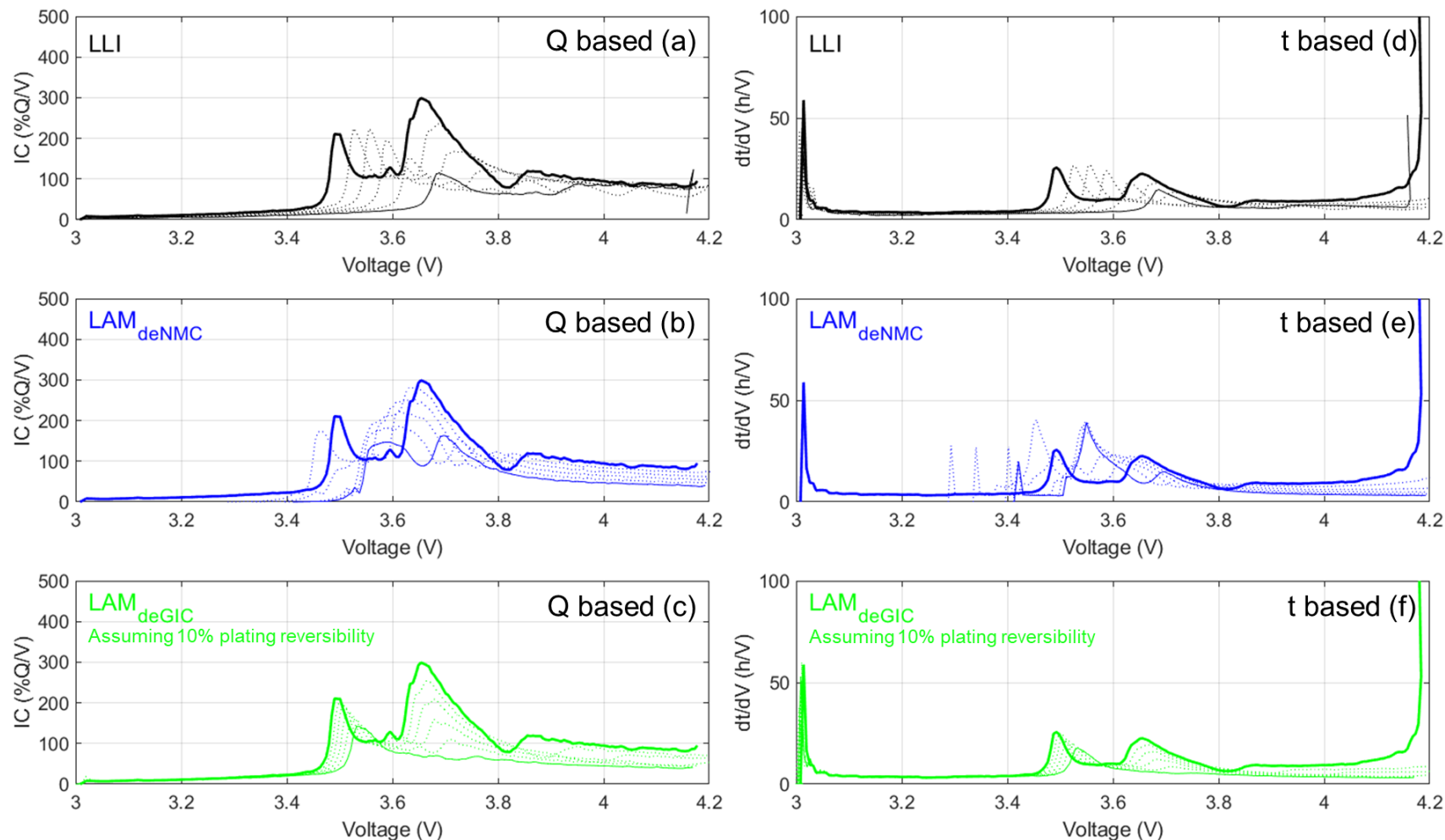


# Big Data for Li-Ion Diagnosis and Prognosis

## Data-Driven Diagnosis for PV Connected Batteries

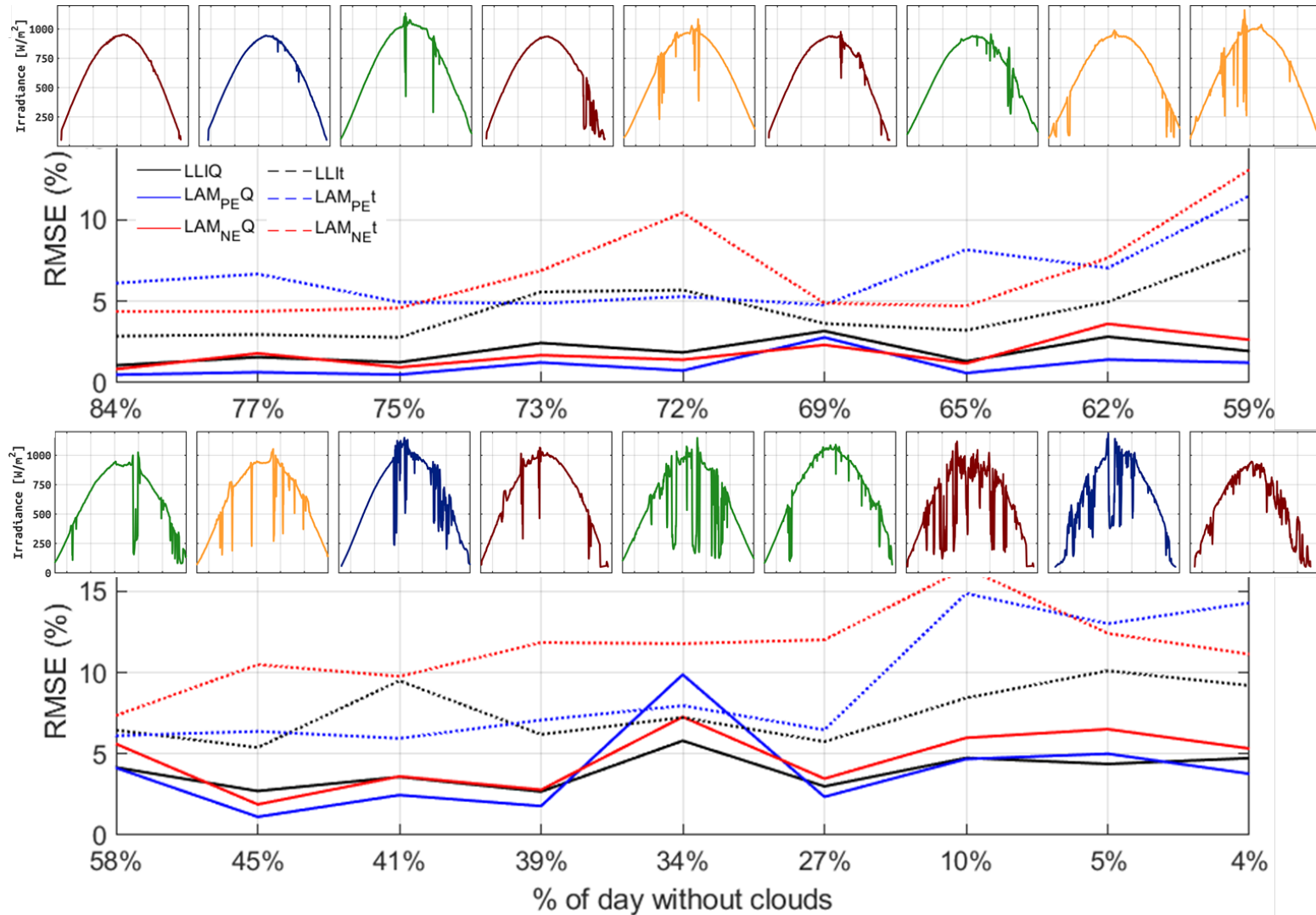
Capacity vs. Time

Uncorrelated because not constant current



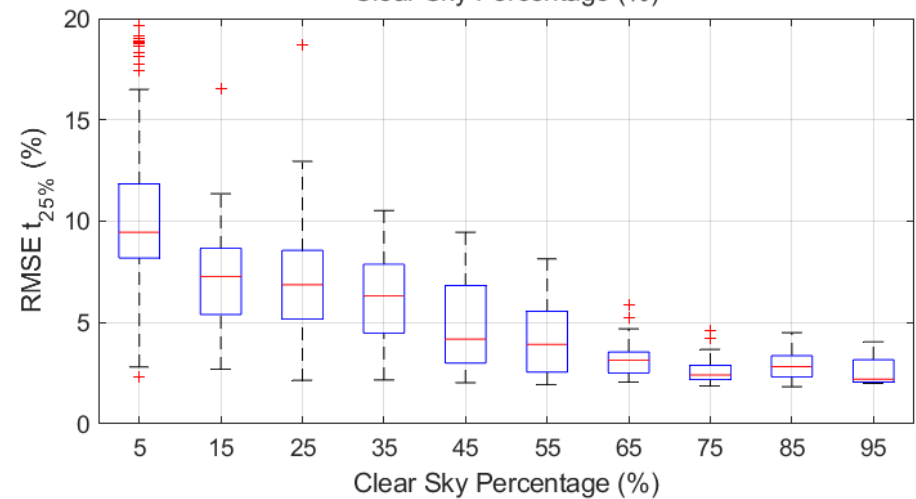
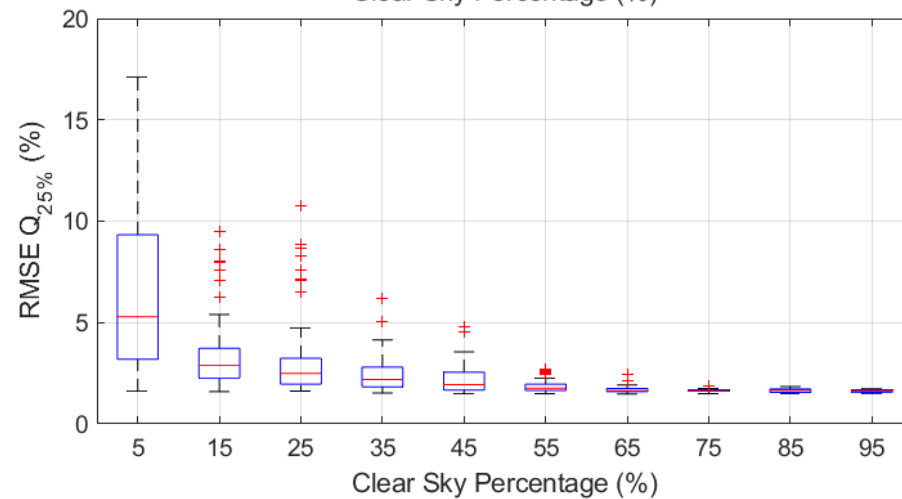
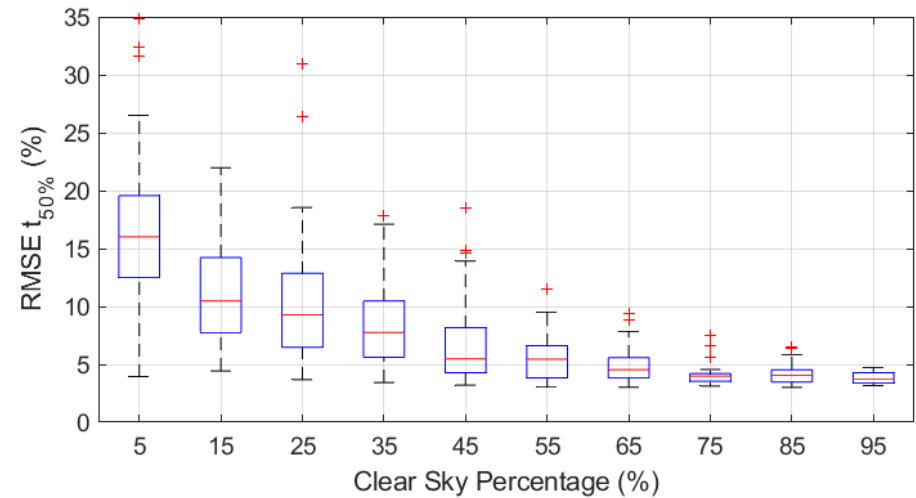
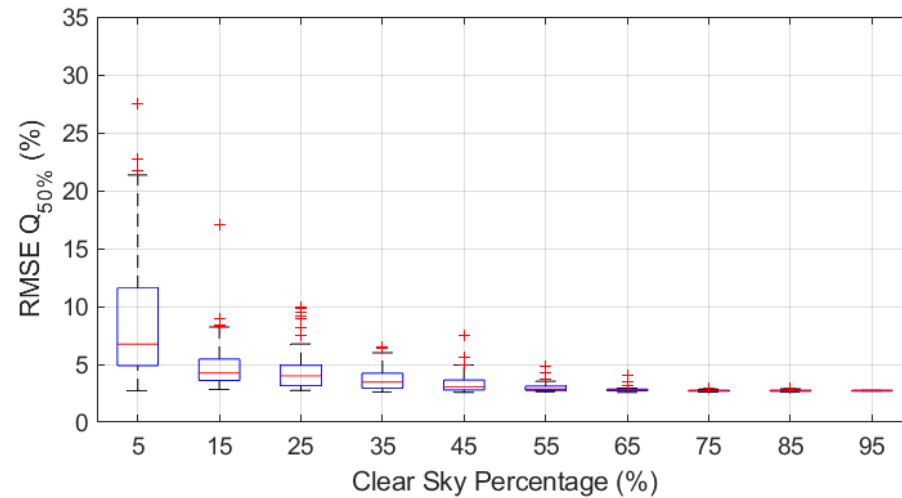
## Data-Driven Diagnosis for PV Connected Batteries

Diagnosability tested on 5 state of the art ML algorithms



## Data-Driven Diagnosis for PV Connected Batteries

Diagnosability tested on 1 ML algorithms for 2 years of data



## 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 2.75%** was obtained for more than 10,000 different degradation paths with 25% or less degradation on the cells.

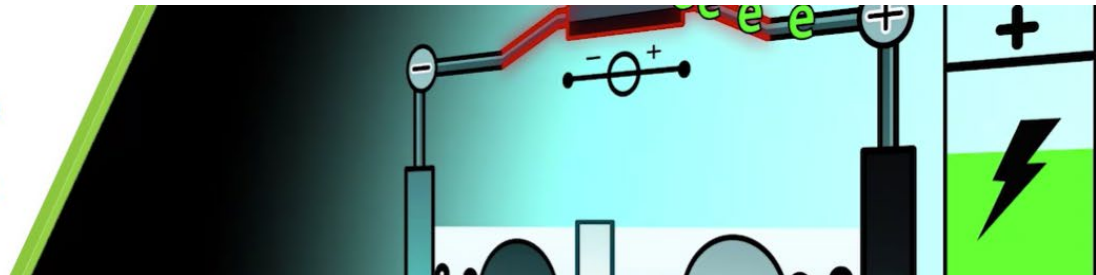
Significant benefits for **using synthetic data** to understand the expected variations of voltage response **as real data is not yet available**.

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



# Acknowledgments

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*Thank you!*



[matthieu@hawaii.edu](mailto:matthieu@hawaii.edu)

