Energy Storage System Performance & Degradation Modeling & Validation

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Overview

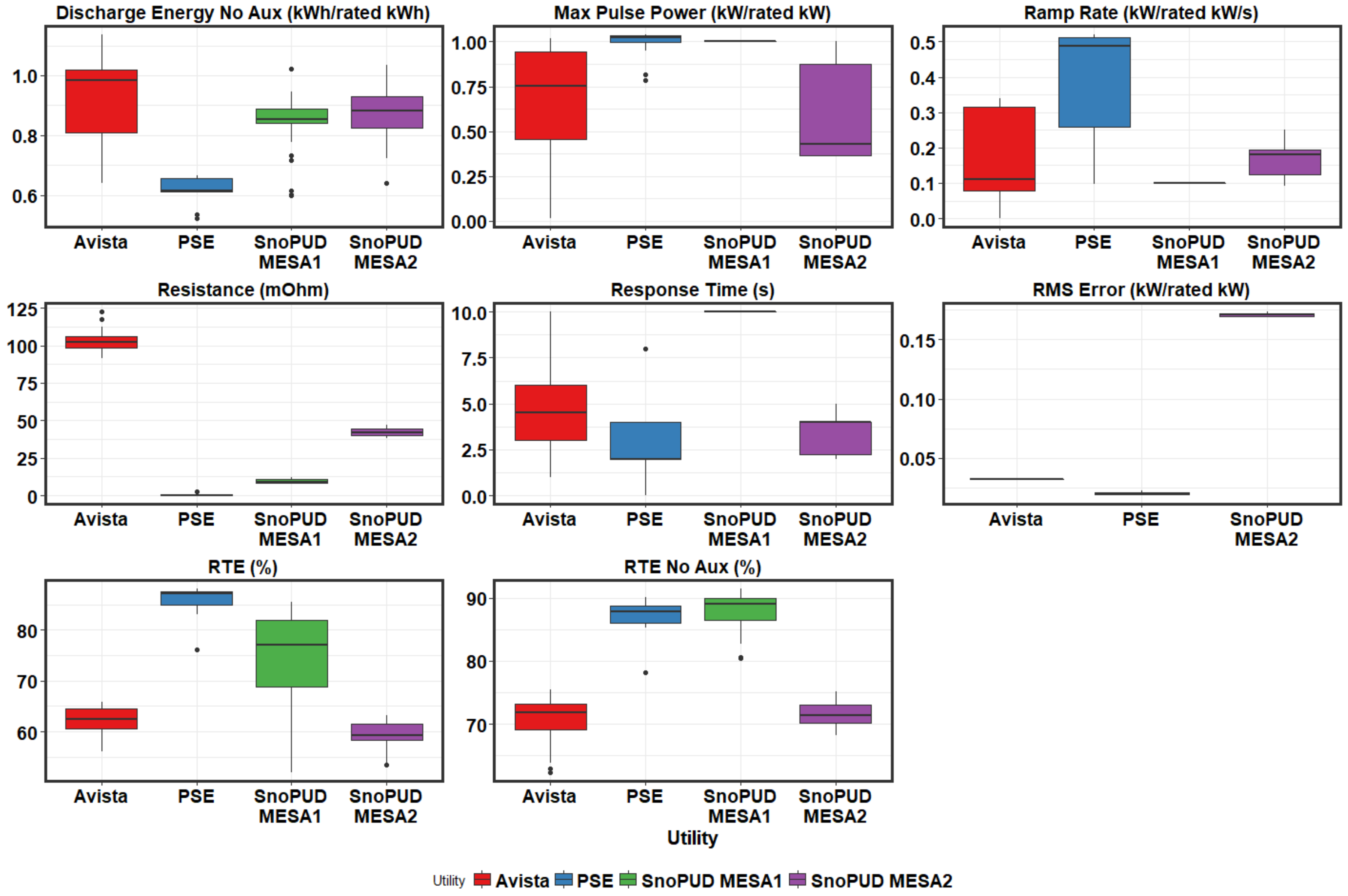
- Time series datasets from testing and real operation on the grid
- Performance modeling of battery energy storage systems
- State of health modeling for BESS, transferring insights from single cell to BESS level

Dataset Overview

Alias	Chemistry	Rated Power (kW)	Rated Energy (kWh)	Energy/Power Ratio (kWh/kW)
EPRI Flow 1	Vanadium Flow (VRF)	90	270	3.0
EPRI Li-Ion 1	NMC	1000	2000	2.0
EPRI Li-Ion 2	NMC	1000	1000	1.0
WACEF Flow 1	Vanadium Flow (VRF)	1000	3200	3.2
WACEF Flow 2	Vanadium Flow (VRF)	2200	8000	3.6
WACEF Li-Ion 1	LMO/NMC	2000	1000	0.5
WACEF Li-Ion 2	LFP	2000	4400	2.2
WACEF Li-Ion 3	LFP	1000	2000	2.0
WACEF Li-Ion 4	LFP	1000	5500	5.5

- All datasets contain 1-2 years of real operational data on the grid
- WACEF datasets are from BESSs tested for Washington Clean Energy Fund
- EPRI datasets are from BESSs collected from EPRI collaboration

Metrics Analyzed WACEF



- Results come from reference performance tests – capacity, FR, pulse

WACEF II Systems Tested

- Horn Rapids ESS (Richland, WA)
- Operated by Energy Northwest
- CATL Battery
- 1.0 MW / 5.5 MWh LFP
- 77-83% RTE

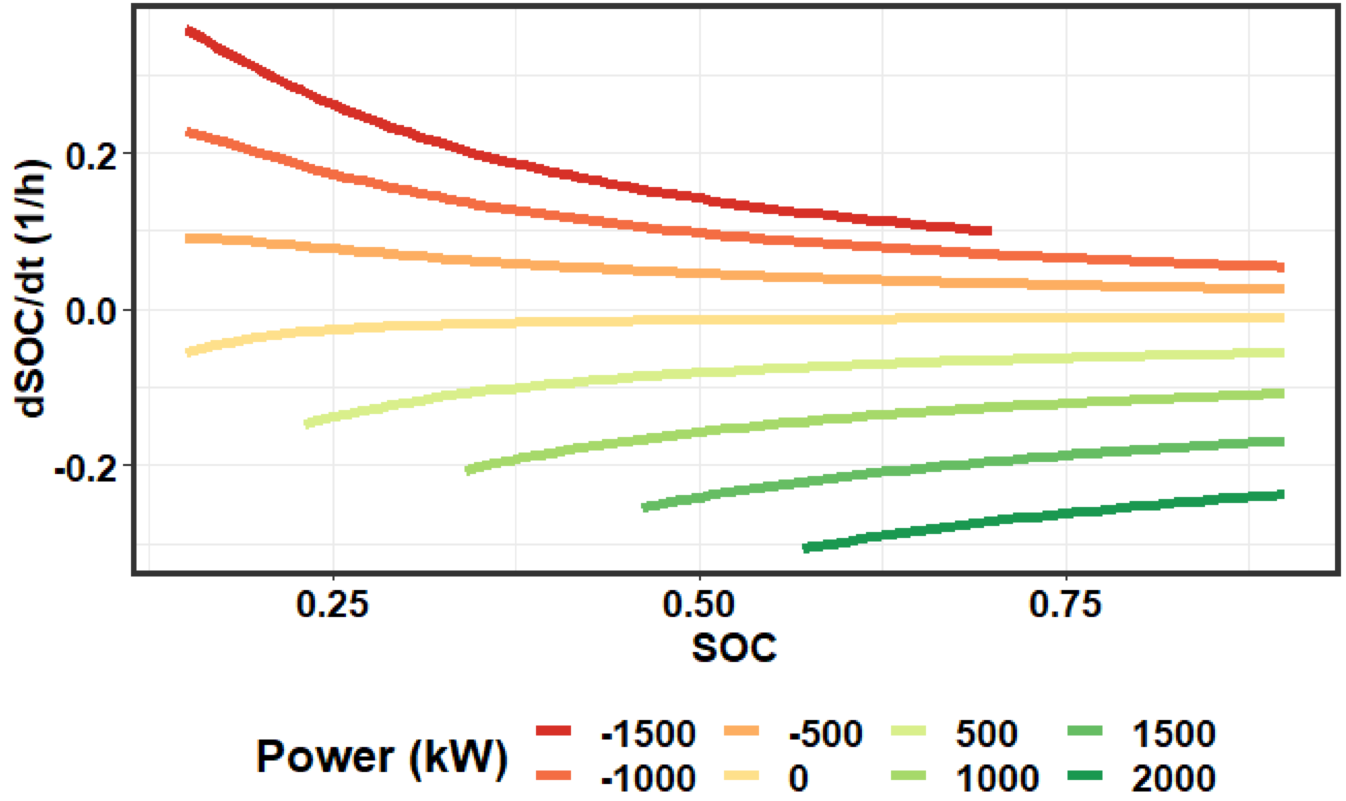
- Decatur Island ESS (Decatur, WA)
- Operated by OPALCO
- Powin Battery
- 1.0 MW / 2.0 MWh LFP
- 87-93% RTE

Performance Model Theory

- We want to predict the rate at which the battery's vendor defined SOC changes as a function of power and SOC
- General model setup:

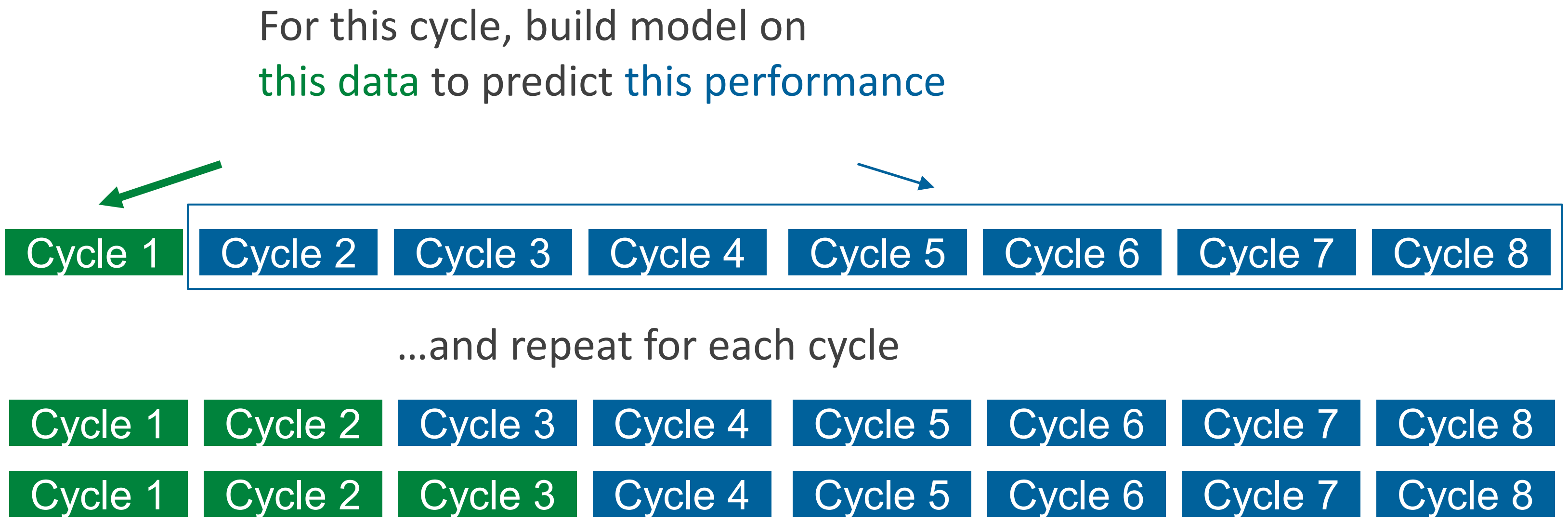
$$\frac{dSOC}{dt} = f(P, SOC)$$

- For a basic linear model, dSOC/dt is just linear with the battery power
- For nonlinear models, more terms including power, SOC, and their interactions are incorporated



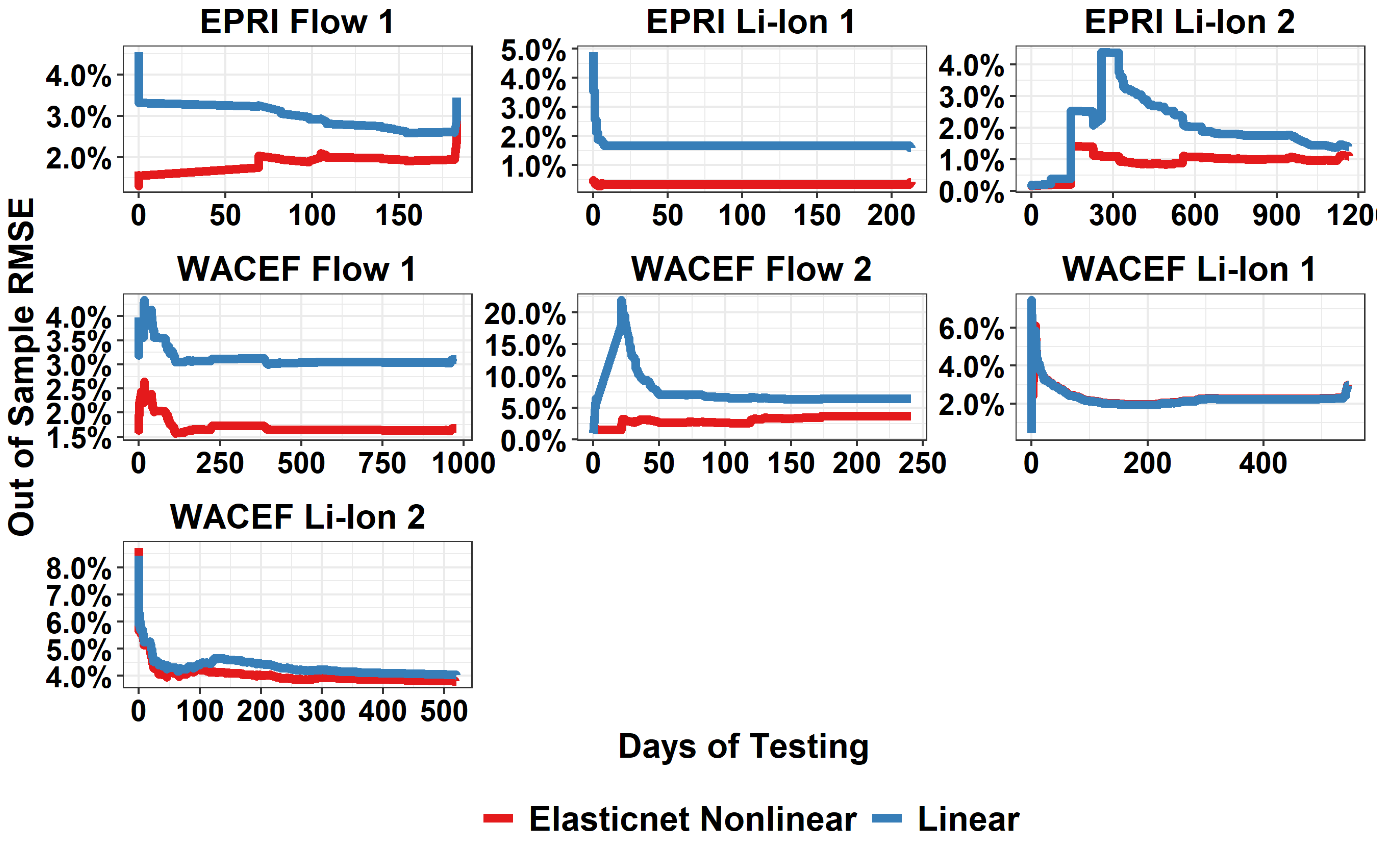
Performance Model Validation

- For validation, we split the data up by charge/discharge cycle. We loop through every cycle and build a model built on all data previous to that cycle. Then, we predict the SOC change during the cycle. This tests the model's ability to predict performance.
- For tuning hyperparameters, we see what minimizes out of sample error.



Performance Model Validation Results

- We improved the model using the elasticnet algorithm, which has the advantage of choosing which features are most important automatically.



Lithium Ion State of Health

- Battery performance changes over time due to changes in the battery’s state of health. To model this, we adjust the model:

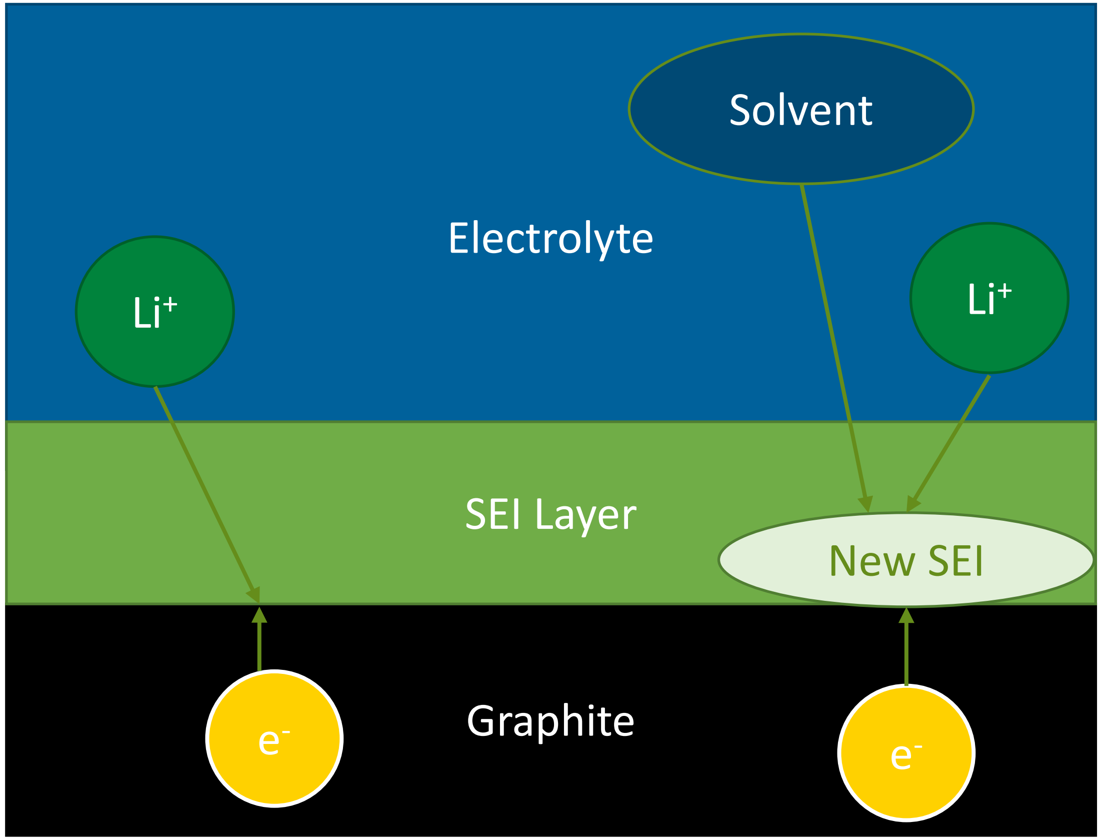
$$\frac{dSOC}{dt} = f(P, SOC, D)$$

- We use our knowledge of the physics of lithium-ion degradation to figure out how to incorporate the battery’s history. We incorporate an SOH term D from our physics-based modeling to represent the degradation:

$$\frac{dD}{dt} = f(P, SOC)$$

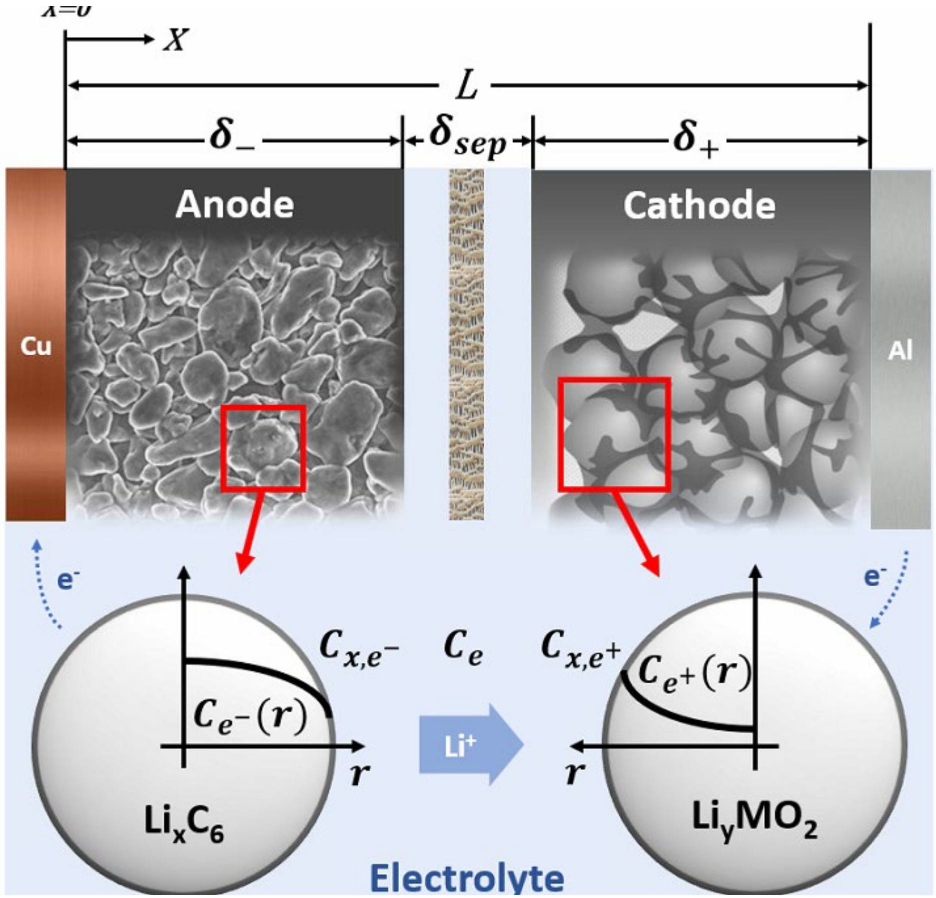
Lithium Ion Degradation Mechanisms

- SEI (solid electrolyte interphase) Layer formation is primary mechanism of capacity loss, lithium at the anode reacts with solvent to produce SEI. Capacity is lost from loss of lithium to SEI and increased internal resistance from SEI.
- Diffusion through SEI layer limits rate of SEI formation
- Graphite expands and contracts while charging and discharging, this cracks the SEI layer and speeds up formation
- Nickel dissolved in the cathode makes its way over and speeds up reaction



Finite Element Modeling

- Modeling uses COMSOL finite element analysis software
- Newman's pseudo 2d model is foundation
- Modeled heat generation and its interaction with the chemistry



BESS Level SOH Modeling

- Start with linear model so we can focus on SOH effect:

$$\frac{dSOC}{dt} = c_0 + c_{dis}P_{dis} + c_{chg}P_{chg}$$

Equivalent to 1/discharge capacity

Equivalent to 1/charge capacity

- Add SOH interaction term:

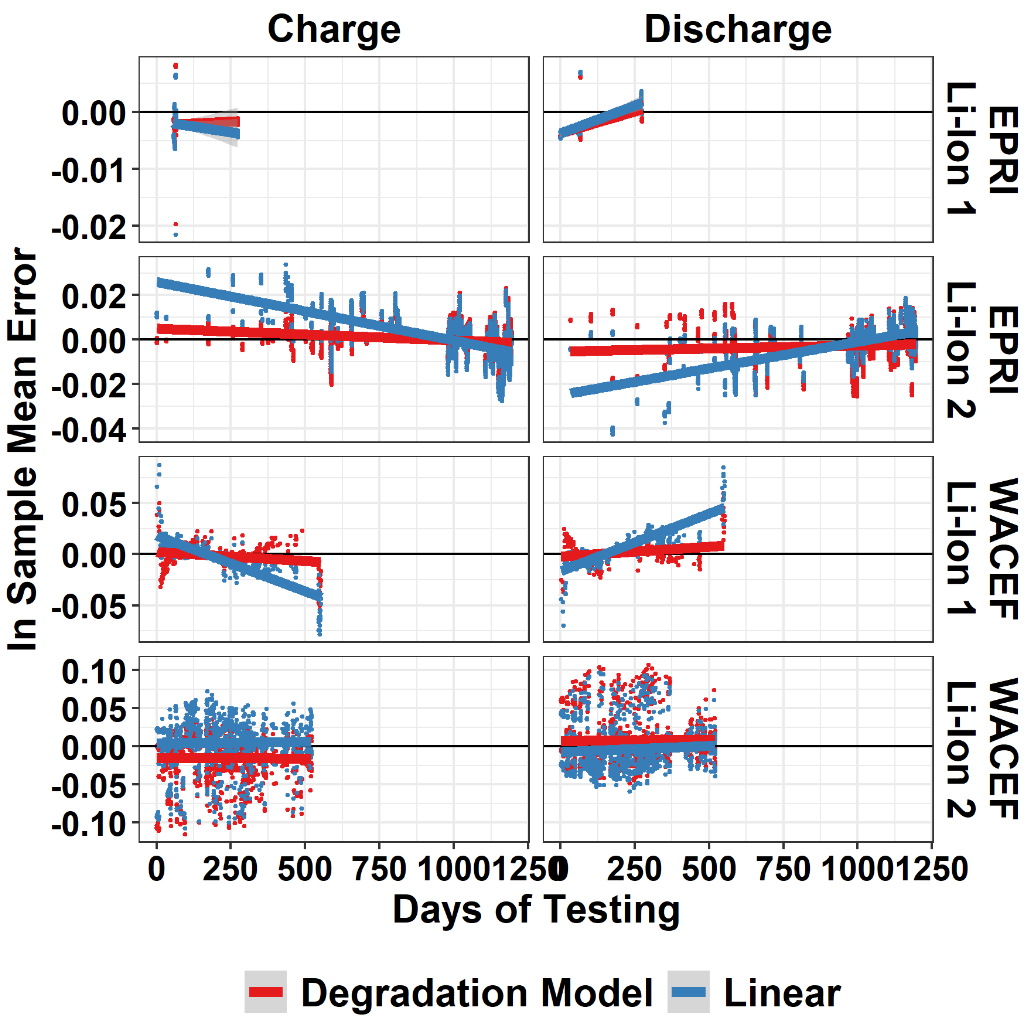
$$\frac{dSOC}{dt} = c_0 + (c_{dis} + c_{SOH,dis}D)P_{dis} + (c_{chg} + c_{SOH,chg}D)P_{chg}$$

- SOH model used from physics insights:

$$\frac{dD}{dt} = exp(cSOC + aP + bP^2)$$

Performance Model State of Health Validation

- On the right are the out of sample mean error vs time for a model without degradation (blue) and with degradation (red).
- The degradation model requires more data to work well, but accurately predicts how the battery's performance changes over time
- The model without degradation is overly pessimistic during the start of testing, and overly optimistic during the end of testing – this is because it is not capturing degradation. This is important to capture for long term modeling.



Conclusions and Future Work

- Methodology developed and validated for predictive modeling of BESSs including degradation
- Incorporate results from new datasets
- Incorporate more physical insights from the SOH model
- Incorporate more analysis from single cell data to transfer to ESS level

Acknowledgements

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Thank you