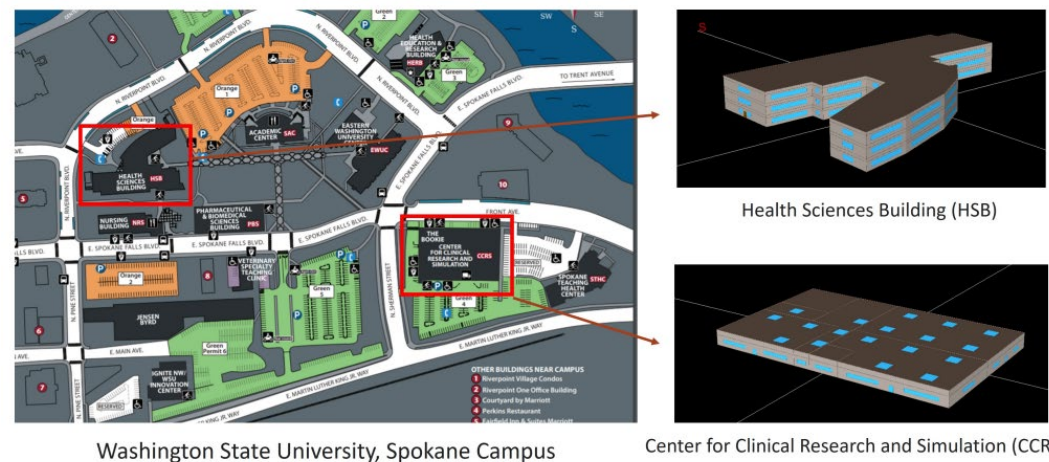


Energy Storage System Performance and Degradation Modeling from Shared Data

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PROJECT OVERVIEW

- Energy Storage System (ESS) time series data obtained from various utilities as part of the Washington Clean Energy Fund (WACEF)
- Additional ESS time series data obtained via collaboration with EPRI
- A performance model that also includes degradation mechanisms is essential to forecast battery economic benefits over battery's lifespan
- Single cell data used to model degradation, with lessons applied to the ESS level and single cell data used to constrain higher level ESS models

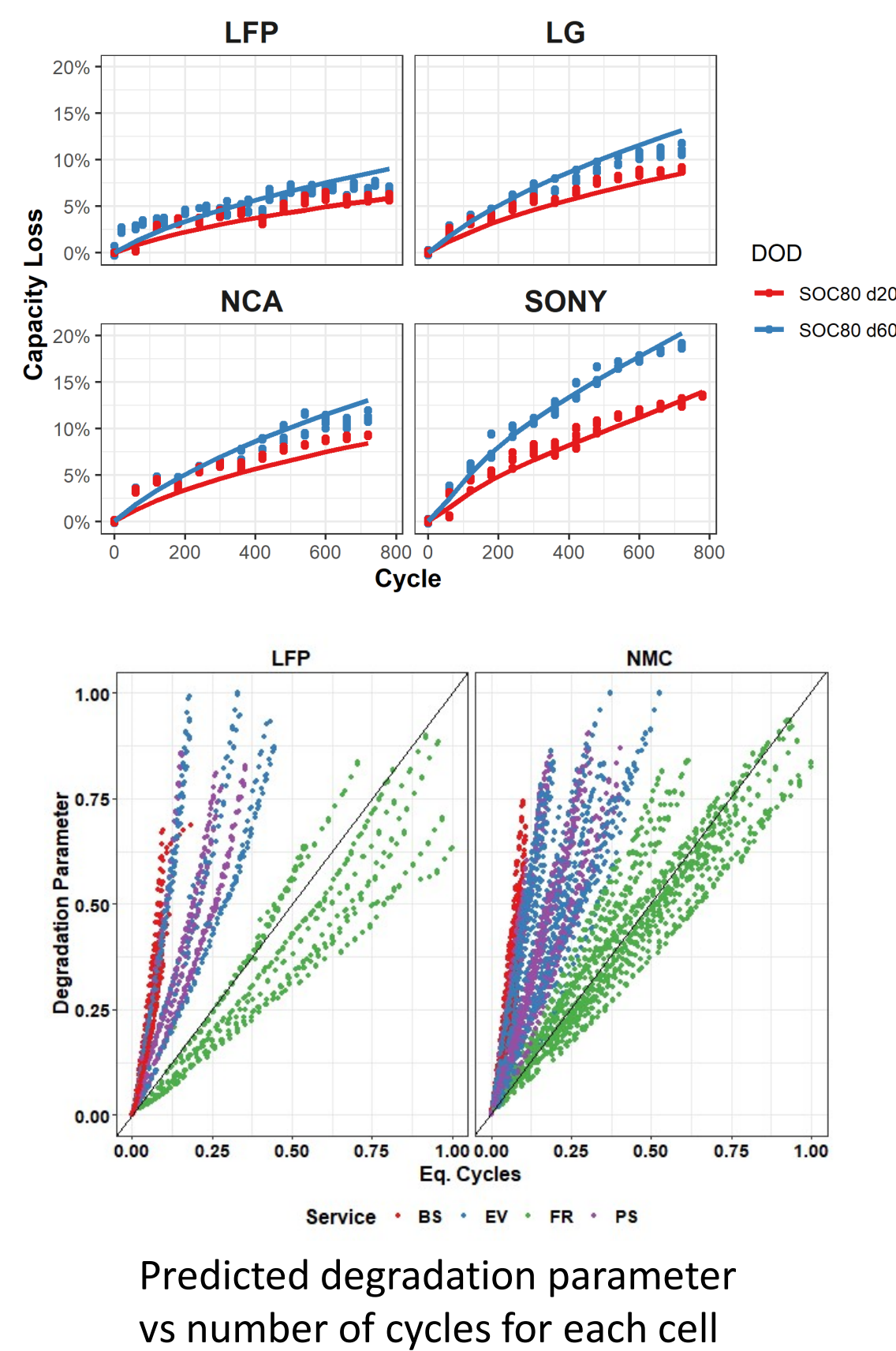
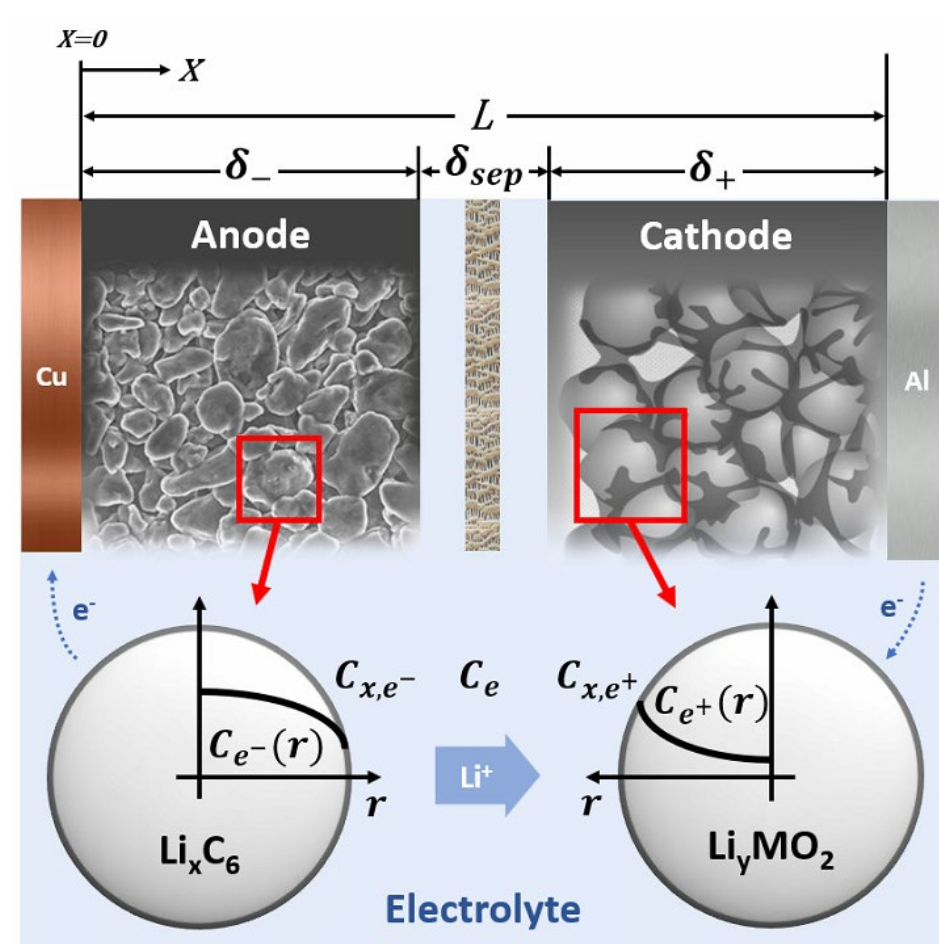


- Shared Energy Economy Microgrid (Spokane, WA)
- Operated by Avista
- Lithium Iron Phosphate (LFP)

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
EPRI Li-Ion 3	LFP	Anonymous	Anonymous	4.0
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
WACEF Li-Ion 5	LFP	668	1840	2.8

PHYSICS-BASED MODELING

- In house data of four types of commercial cells
 - Two types of Nickel Manganese Cobalt (NMC)
 - Nickel Cobalt Aluminum (NCA)
 - Iron Phosphate (LFP)
- Cells subjected to one of 13 types of 24 hour signal
 - Calendar aging
 - Peak shaving
 - Frequency regulation
 - Electric vehicle drive cycle
- Three cells for each experiment for total of 156 cells.
- Every 40 cycles, capacity test is performed to measure cell capacity
- Physics based model used to predict battery capacity degradation
 - Lithium lost to solid electrolyte interface (SEI) layer growth is primary mechanism
 - SEI layer cracks as graphite contracts, increasing rate of SEI layer growth
 - SEI layer thickness decreases rate of SEI layer growth due to diffusion
 - Cathode dissolution
 - Heat generation interacts with chemistry
- Parameters such as diffusion rate coefficient, kinetic rate constants, fit to data.
- Physics based model gives functionality of degradation parameters with respect to current, state of charge, and battery history.
- Simplified version of physics-based model used for ESS modeling, and used to predict cell performance at same time.



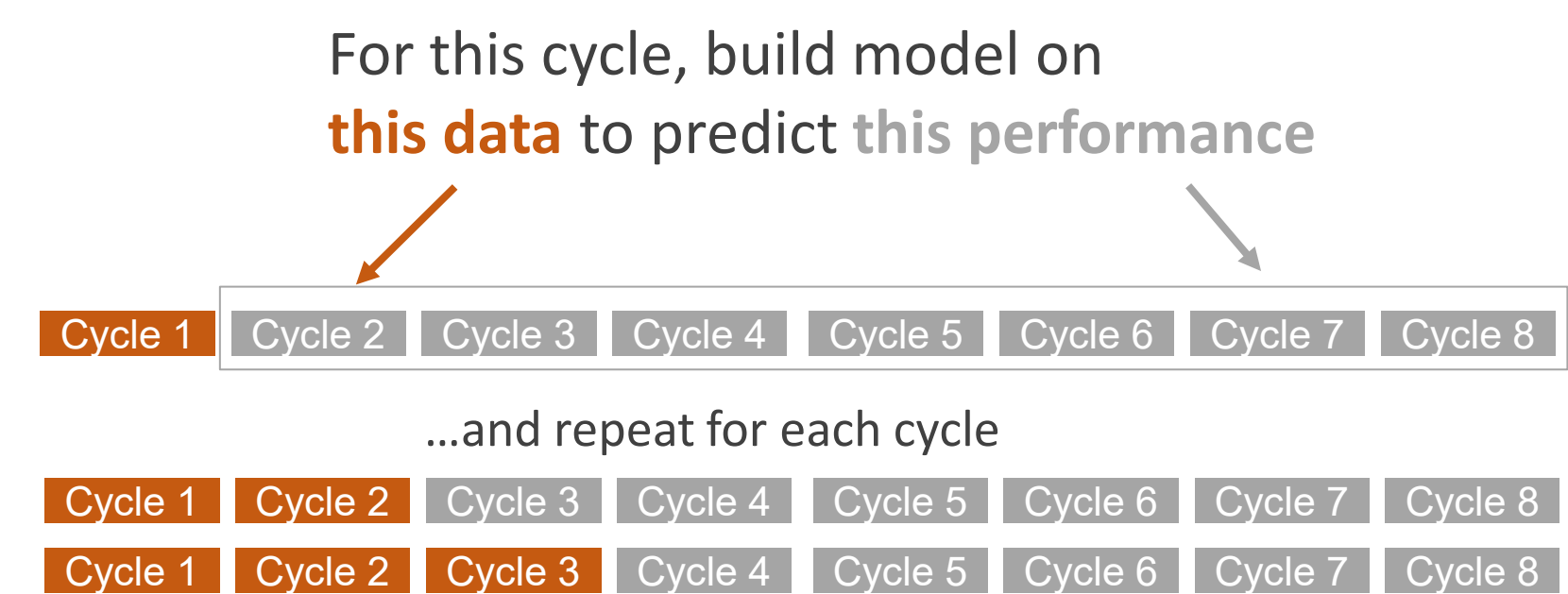
PNNL/EPRI Data Sharing



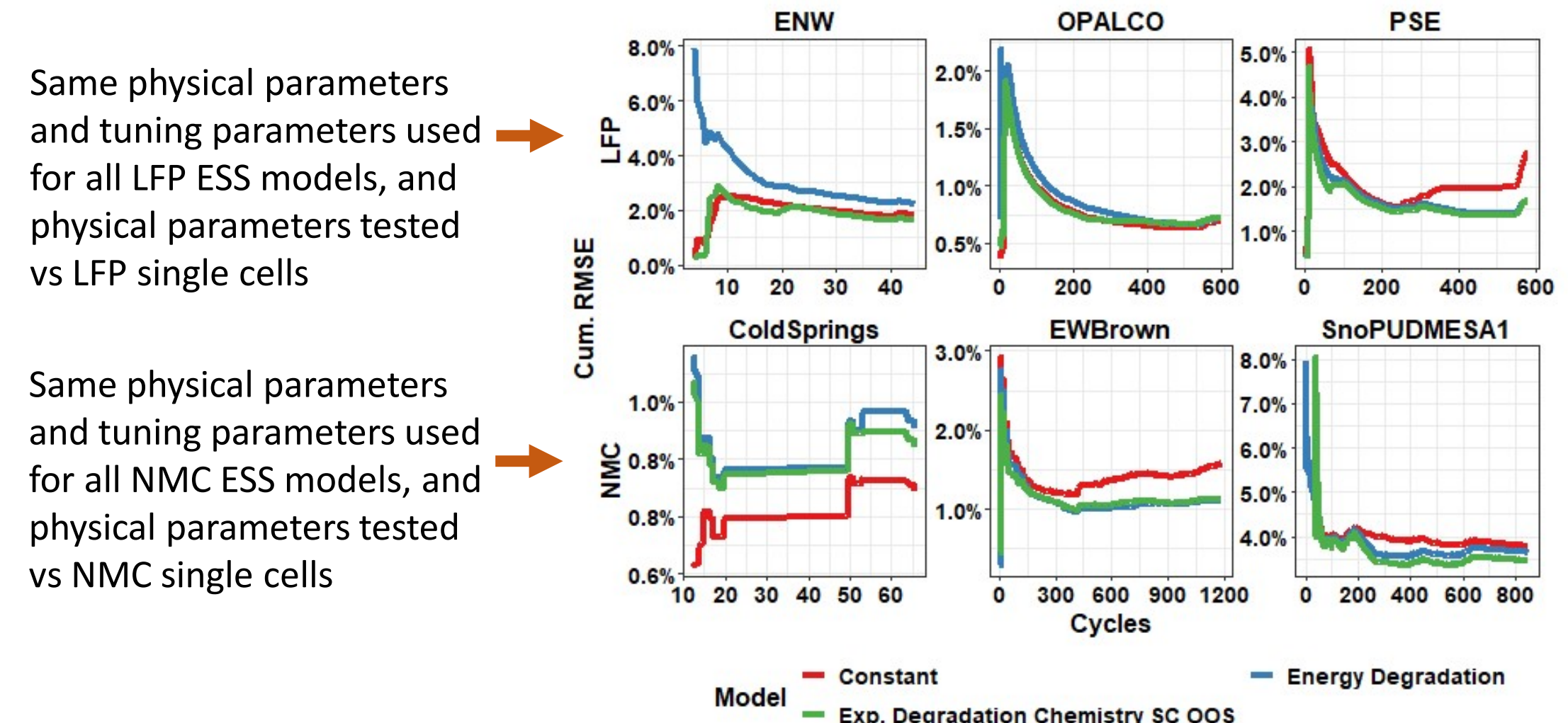
- EPRI has stored several ESS's time series operational data in an internal database, and shared data with PNNL via an automated data pipeline.
- Data time frame ranges from 1-5 years, and includes information such as power and reactive measured at various meters, battery state of charge (SOC), AC/DC current, AC/DC voltage, state of health (SOH). This data is recorded at various levels such as at the ESS level, the string level, and the module level. Some single cell data is available.
- Representatives from PNNL and EPRI meet regularly to collaborate and discuss analysis of data and share techniques/insights in evaluating ESS performance and degradation metrics

ESS STATISTICS BASED MODELING

- High level regression-based model required for ESS level modeling



- Take ESS datasets from WACEF and EPRI, and build an elasticnet based model predicting how SOC changes with time based on power applied to the battery and SOH of the battery. SOH also estimated from history of power and SOC. Economic modeling can use SOC and SOH as state variables.
- For models including degradation, we combine ESSs with same chemistries, and use the same electrochemical and tuning parameters for all of them. The electrochemical parameters are also used to predict degradation in our single cell data to ensure robustness. This gives degradation rate as a function of power and SOC across a diverse set of operating conditions.
- Out of sample error compared for **base model with no degradation**, a **simple energy-based degradation model**, and the **physics based degradation models**



- Physics based degradation model improves model performance without overfit

CONCLUSIONS AND FUTURE WORK

- Methodology for predicting battery performance vindicated with real operational data, and methodology for degradation incorporated into ESS predictions
- Data sharing allows for validating generalized ESS modeling methodology across multiple datasets
- Increasing model complexity by adding degradation mechanisms improves model performance without overfit, and is made more robust via single cell data
- Future work will apply this methodology to more datasets as we acquire them via WACEF and EPRI
- Physics-based model to include more interaction of cathode dissolution with SEI layer formation, and lithium plating.
- More degradation mechanisms such as SEI layer diffusion limitation, cathode dissolution, and graphite particle stress to be added to ESS model

Acknowledgements

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