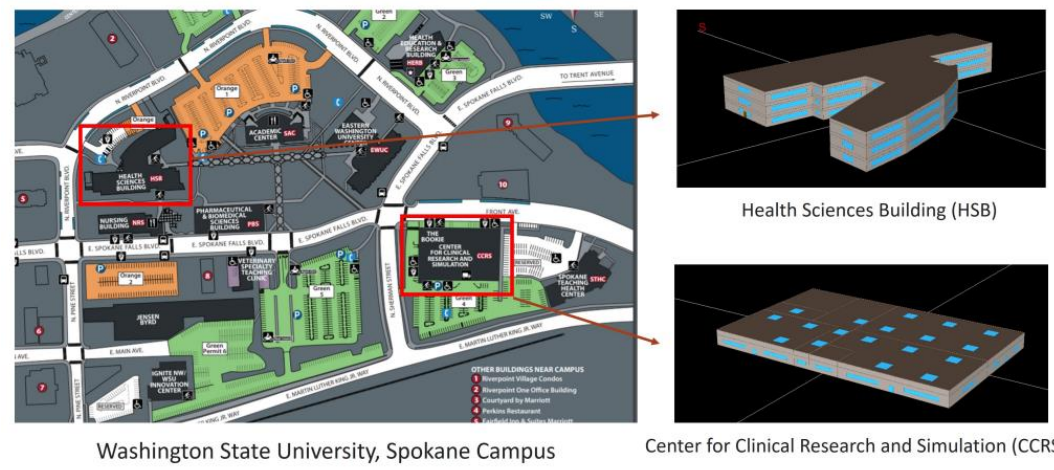


Energy Storage System Performance and Reliability Modeling

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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
EPRI Li-Ion 4	LFP	10000	30000	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

SINGLE-CELL MODELING

Objective: Develop a comprehensive and robust physics-based model to predict battery capacity degradation, emphasizing the effects of the Solid Electrolyte Interface (SEI) layer. This model aims to incorporate additional degradation mechanisms, including SEI layer diffusion limitations, cathode dissolution, and graphite particle stress. The approach involves gradually increasing model complexity by sequentially adding these degradation mechanisms to enhance model accuracy and performance. Future work will involve implementing the model to simulate real data results and comparing these results for validation.

Approach:

1. Dimensionality

- **Pseudo 2-Dimensional:** This model uses two dimensions, one along the particle radius and one along the electrode thickness. This model was found to be too complex to be useful in investigating degradation mechanisms, and using a simpler 0-dimensional model produced more accurate results with faster computation
- **Single Particle 1-Dimensional:** This model uses one dimension, the particle radius, and calculates lithium concentration distribution along the particle radius. This is the model we are currently focusing the most on.
- **0-Dimensional:** This model treats the battery having constant concentration along the particle radius, constant current distribution within the electrode, so quantities do not vary along any dimension. This predicted degradation well, but may be overly simplistic.

2. Electrochemical Dynamics Integration:

- **Solid Phase Diffusion:** Utilize the finite difference method for simulating lithium-ion diffusion in spherical particles. Implement diffusion equations for both positive and negative electrodes.
- **Solid phase dynamics:** Molar flux within solid electrode phases based on current density and electrode properties.
- **Reaction Kinetics:** Model the charge transfer reactions at the electrode-electrolyte interfaces. Include Butler-Volmer kinetics to capture the electrochemical reaction rates.

3. SEI Layer Growth and Degradation:

- **Lithium Consumption:** Simulate lithium loss due to SEI formation, considering reaction rates and lithium inventory.
- **SEI Layer Evolution:** Model the growth kinetics of the SEI layer, accounting for cracking and repair mechanisms. Include effects of SEI layer thickness on ionic and electronic conductivities.
- **Degradation Mechanisms:** Integrate mechanisms such as SEI layer thickening, loss of active material, and electrolyte decomposition. Model the impact of these mechanisms on capacity fade and internal resistance increase.

CONCLUSIONS AND FUTURE WORK

Future Work:

- **Thermal Effects:** Incorporates temperature-dependent parameters to account for heat generation and dissipation.
- **Model Calibration:** Use experimental data to calibrate model parameters. Perform sensitivity analysis to identify critical parameters affecting degradation.
- **Prediction:** Predict capacity degradation, voltage profiles, and thermal behavior over the battery lifecycle.
- **Validation:** Compare simulation results with experimental data for validation. Refine the model to improve accuracy and reliability.

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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, 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

For this cycle, build model on **this data** to predict **this performance**



...and repeat for each cycle



- 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.
- Degradation rate is predicted as a function of power and SOC from physics-based modeling – simplifying assumptions are made and major mechanisms identified to translate physics-based model to system level inputs. We focus on loss of lithium due to SEI layer formation while ignoring SEI diffusion limitations and SEI layer cracking. Future work will include SEI diffusion limitation, SEI layer cracking, and cathode dissolution
- Out of sample error compared for **base model with no degradation**, a **simple energy-based degradation model**, and the **physics based degradation models**

Same physical parameters and tuning parameters used for all LFP ESS models, and physical parameters tested vs LFP single cells

Same physical parameters and tuning parameters used for all NMC ESS models, and physical parameters tested vs NMC single cells

