Doctoral Dissertation Defense

Online Co-Estimation of State of Charge and Voltage Dynamics of Li-ion Batteries via Physics-Inspired Modeling

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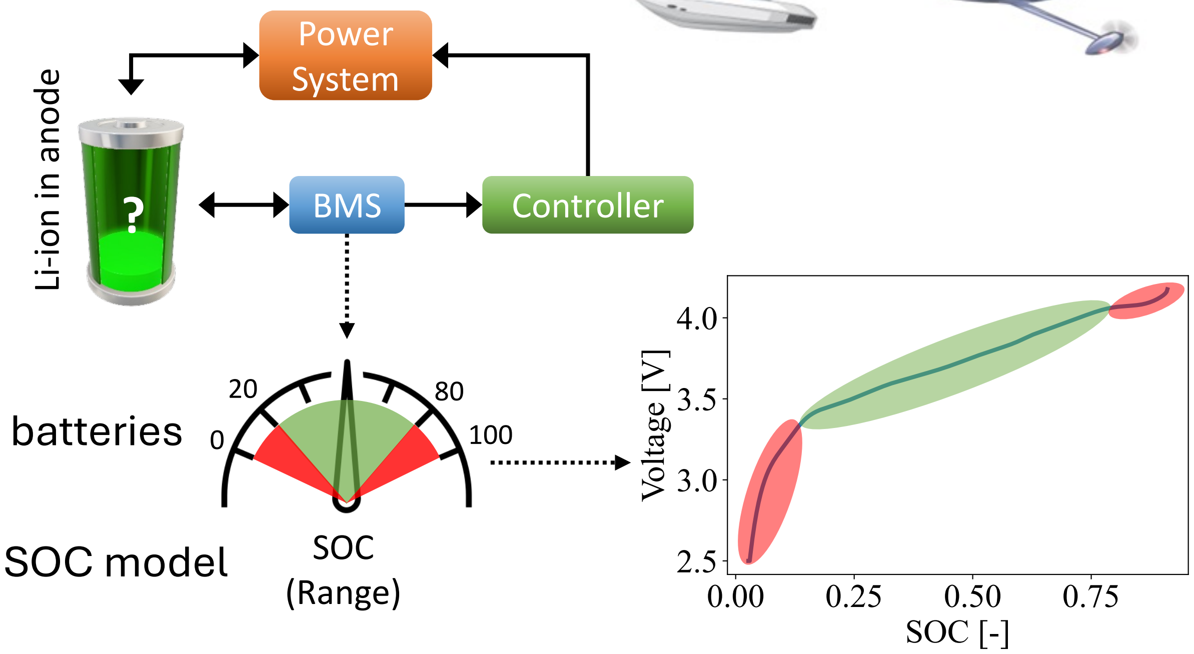
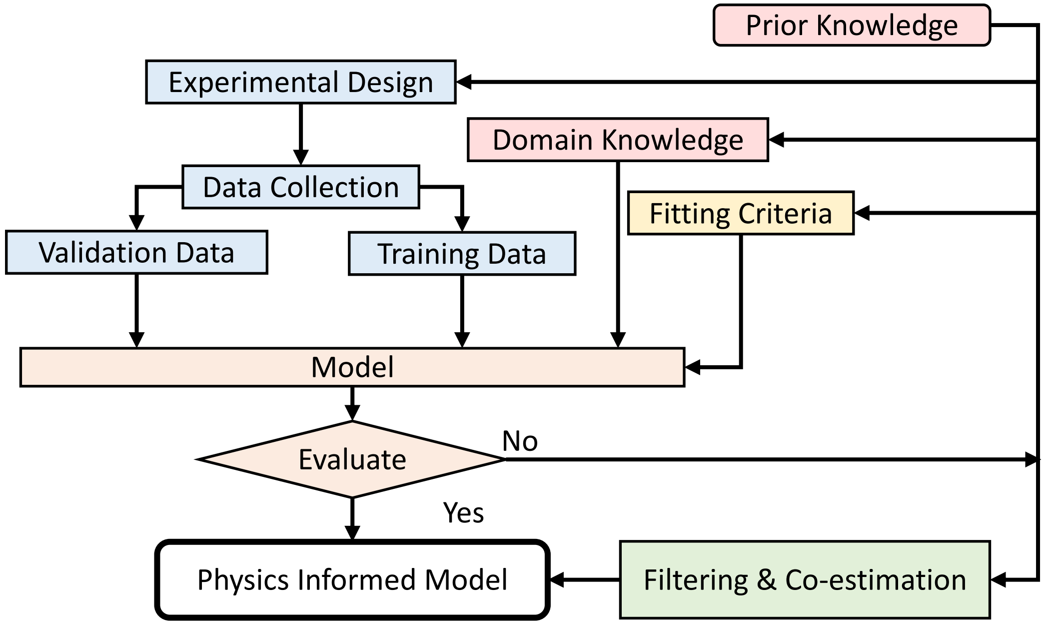
Introduction

- Li-ion batteries (LiBs) in modern life
  - High energy density
  - Low self-discharge
  - Rechargeable
- Battery Management Systems (BMS)
  - Performance
  - Safety
  - Reliability
- BMS need State-of-Charge (SOC)
  - SOC is the remaining charge in battery
  - Not measurable (Need to be estimated)
  - Complex dynamics (Need to be predicted)
  - Current technology limits the operating range of batteries
- ➢ Objective
  - Create accurate, efficient, and control-oriented SOC model
  - Develop algorithm to estimate SOC



Outline

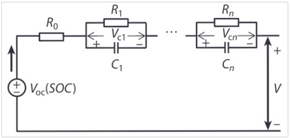
- Literature Review on SOC Estimation and Modeling
- Objectives
- Methods
  - Interpretable data-driven model
  - Physics-inspired model
  - Tuning parameters
  - Noise mitigation
  - Framework to estimate SOC
  - Experiments
- Results and Discussion
- Conclusion and Future work

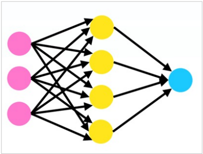


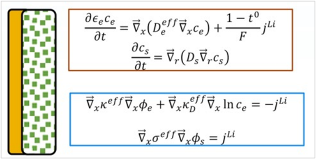
Battery Dynamics Modeling

SOC and Voltage have Complex Dynamics

Empirical Models | **Equivalent Circuit Models (ECM)** | **Machine Learning Models** | **Mechanistic Models**



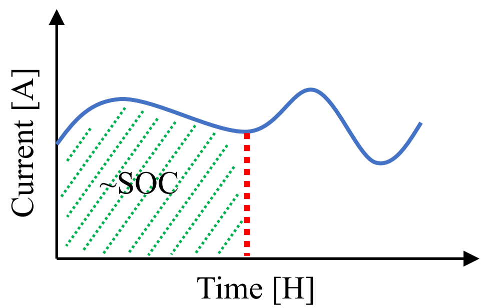




Simplicity ⟷ **Fidelity**

Battery Dynamics Modeling: Empirical Models

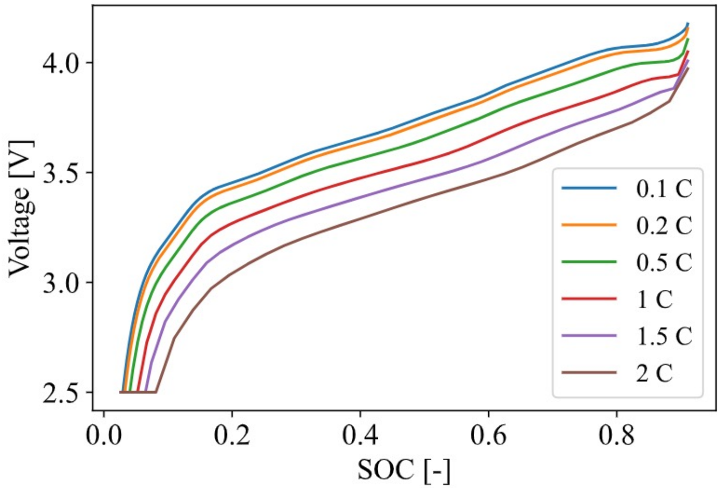
- Historical data
- Statistical methods
- **Coulomb counting**; e.g. Ghoulam et al., 2022
- **SOC-voltage mapping**; e.g. Xing et al., 2014



✓ Very simple

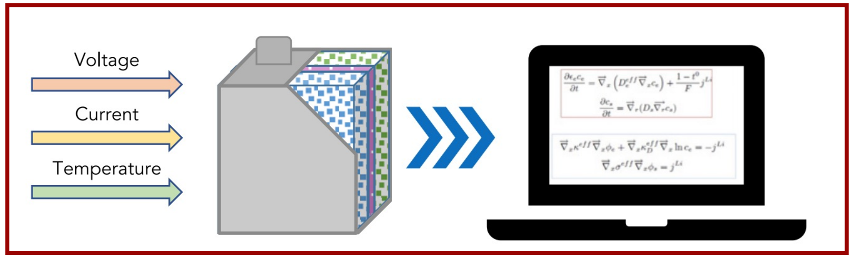
✗ Very sensitive to operating condition

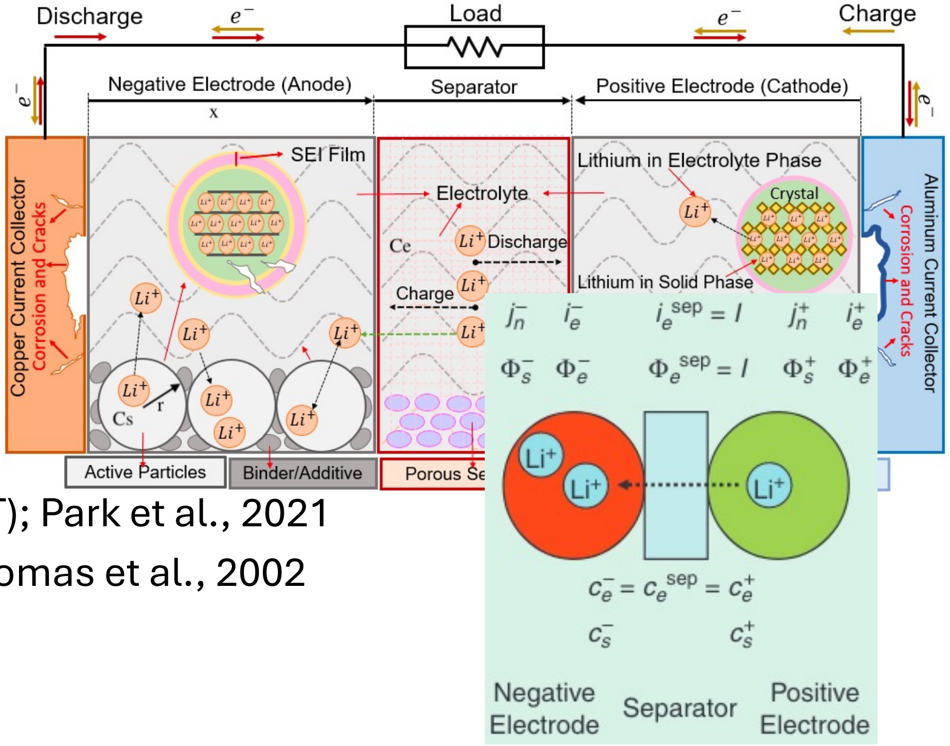
✗ Require large and high-quality datasets to build model



Battery Dynamics Modeling: Mechanistic Models (1)

- Express the process inside the battery with analytical equations
  - Electrochemical reactions
  - Heat and mass transport





➢ Porous Electrode Theory (Started by Newman's Group)
- Pseudo-two-Dimensional (P2D) model; Doyle et al., 1993
- P2D modeling with aging; Ramadass et al., 2004
- Doyle-Fuller-Newman (DFN) model with thermal dynamics; Thomas et al., 2002

✓ Suitable for analysis and diagnosis

➢ Simplified P2D models
- Single Particle Model (SPM); Guo et al., 2010
- Single Particle Model with electrolyte and Temperature (SPMeT); Park et al., 2021
- Multi-Particle Model (MPM); Majdabadi et al., 2015

✓ Suitable for control and optimization

Battery Dynamics Modeling: Mechanistic Models (2)

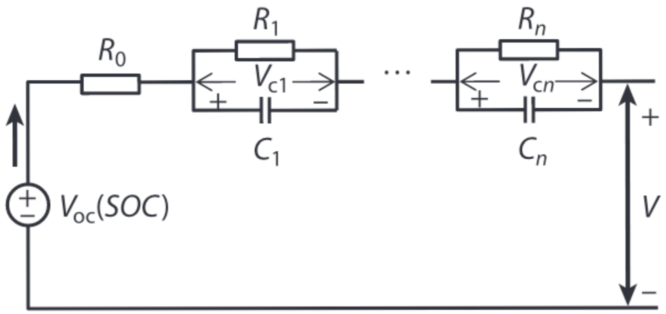
- ✓ Capture the dynamics of the modeled processes, detailed insight
- ✓ High interpretability, allow for design and performance optimization
- ✓ Extrapolatable to a wide range of conditions for complex models
- ✗ Require many parameters, several not available
- ✗ Based on idealized principles, not always apply
- ✗ Only predict the modeled phenomena
- ✗ Computationally expensive with added complexity

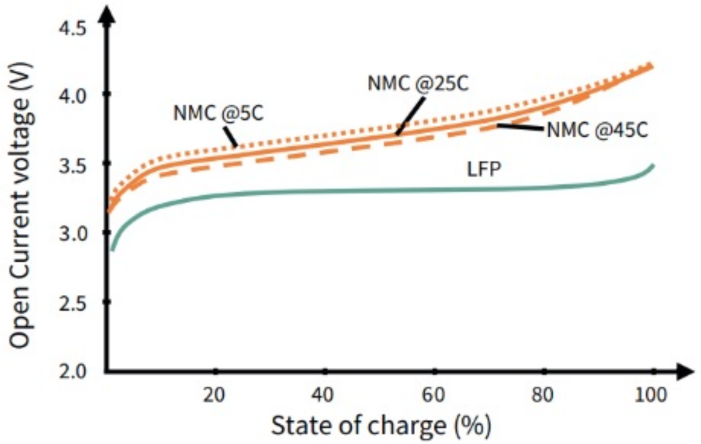
Model	Number of parameters	Computational Complexity
DFN	33	High
SPMeT	31	Medium
SPM	20	Low

Battery Dynamics Modeling: ECMs (1)

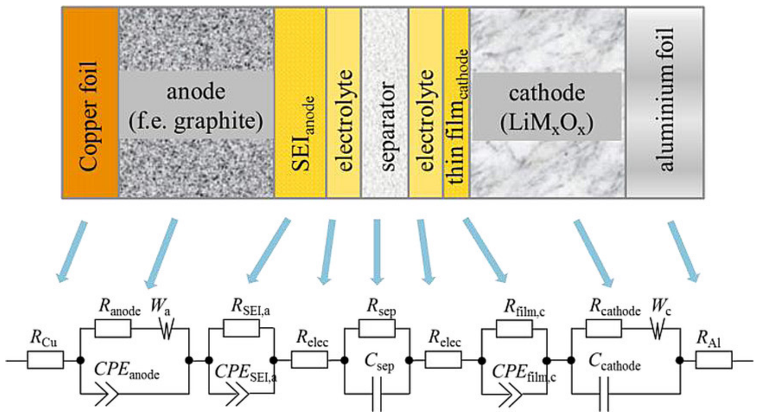
❖ Equivalent Circuit Model (ECM)

- Express the battery's dynamic with electrical components





- ECM with simple passive electrical elements; e.g. Schmidt et al., 2016
  - Determine Open circuit voltage (OCV) from voltage and current
  - Estimate SOC via SOC-OCV mapping
- ECM with fractional-order or distributed elements; Wildeuer et al., 2021
  - Using impedance spectra

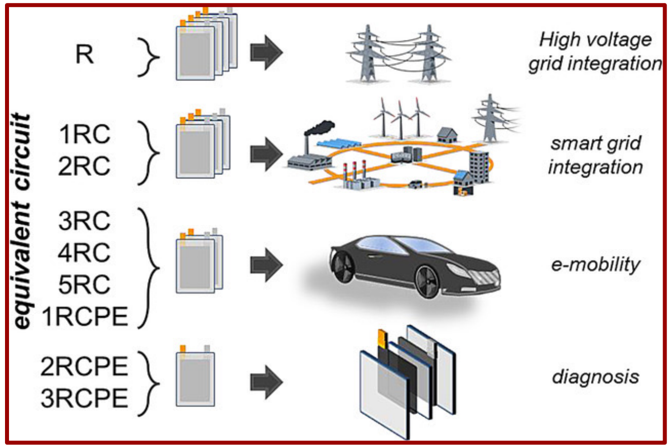


Battery Dynamics Modeling: ECMs (2)

❖ ECM

- ✓ Use measurable data (current and voltage)

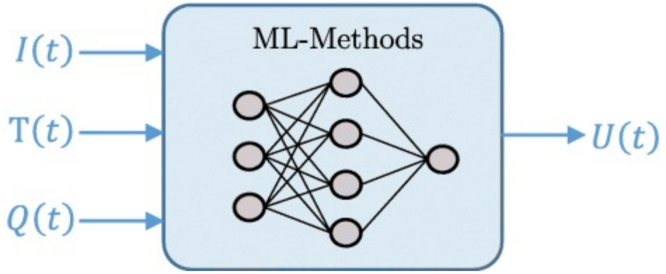
- ECM with passive electrical components:
  - ✓ Simple with low computational cost
  - ✗ Narrow operating range due to lack of physics-based information
  - ✗ Need to use look-up tables with many sets, still limited due to being linear
- ECM with fractional-order or distributed elements:
  - ✓ Connections to internal processes of LiBs
  - ✓ Larger operating conditions
  - ✗ Require impedance spectra
  - ✗ Need specific devices with careful experimental control
  - ✗ Not suitable for real-time applications



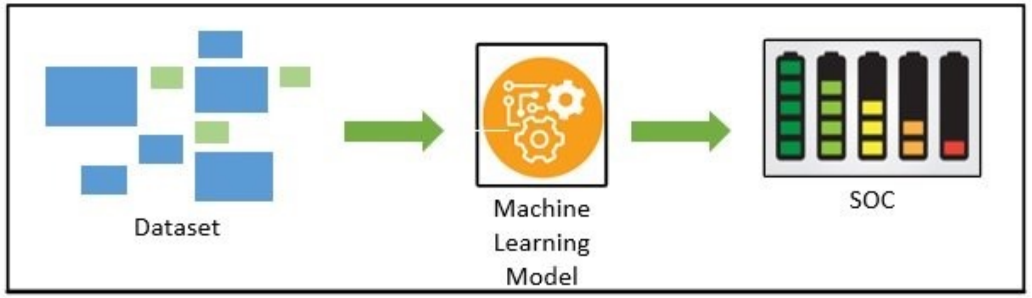
Battery Dynamics Modeling: ML (1)

❖ **Data-driven Model/Machine Learning**

- Express the battery's dynamic from measurable data
- Black box modeling



- Support vector machine (SVM); Feng et al., 2019
- Clustering with genetic algorithm; Hu et al., 2016
- Neural network (NN); How et al., 2020
  - Recurrent NN; Vidal et al., 2022
  - Long short-term memory recurrent NN; Chemali et al., 2018



Battery Dynamics Modeling: ML (2)

❖ **Data-driven Model/Machine Learning**

✓ No need for internal parameters (using measurable data)

✓ Adaptable to new chemistries or conditions by retraining

✓ Can use novel features instead of traditional metrics (e.g., voltage, current)

✓ Low implementation cost, suitable for real-time applications

✗ Require rich and informative dataset to capture operating conditions

✗ Needs an extensive set of data to build model

✗ Risk of overfitting with complex algorithms

✗ Can lead physically inconsistent results and lack interpretability (no connection to physics)

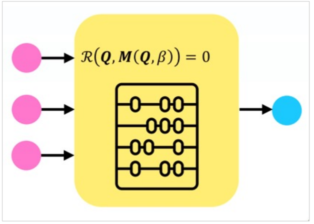
✗ Too many features reduce stability (ill-conditioned problem due to correlated terms)

Battery Dynamics Modeling

- Empirical Models
- Equivalent Circuit Models (ECM)
- Machine Learning Models
- Mechanistic Models

Hybrid

- ECM+ML
- Mechanistic+ML



Battery Dynamics Modeling: Hybrid Models (1)

- ECM: Increasing operating range and accuracy
  - ECM + Machine learning
    - ECM + deep learning; Su et al., 2023
    - ECM + NN; Borah et al., 2024
  - ECM + Kalman filter; Yao et al., 2024

✓ Refine estimates; suitable for aggressive input

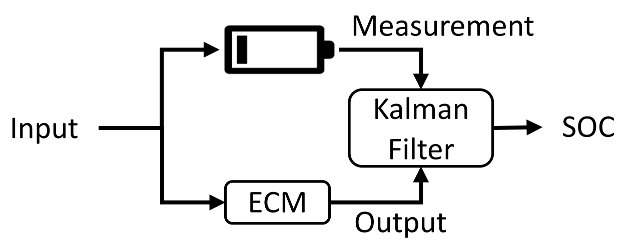
✓ Mitigate noise effect

✓ Extend ECM operating range

✗ Lack of interpretability

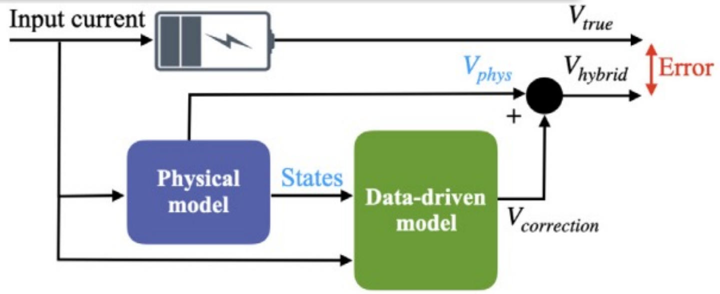
✗ Require large datasets for training

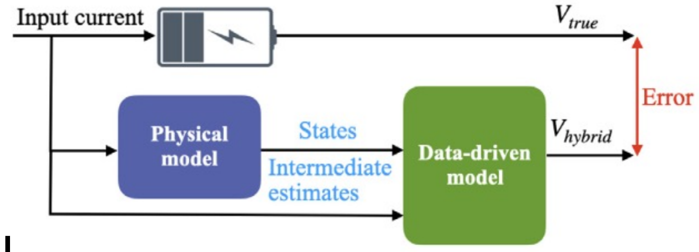
✗ Limited accuracy in low SOC regions



Battery Dynamics Modeling: Hybrid Models (2)

- Mechanistic: Increasing accuracy and reducing computational time
  - SPM + Machine learning
    - SPM + recurrent NN; Saehong Park et al., 2017
    - SPM with thermal dynamics + feed forward NN; Tu et al., 2023
  - Mechanistic models + Kalman filter
    - SPM + Kalman filter; Fang et al., 2014
    - P2D + Kalman filter; Smiley et al., 2018
  - Physics-informed NN, Hofmann et al., 2023
  - Solving SPM with electrolyte equations with NN; Xue et al., 2023





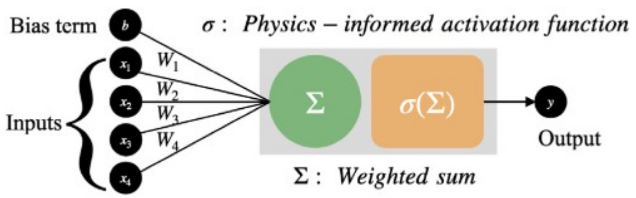
✓ Improve accuracy by capturing complex unmodeled dynamics with ML

✓ Extend operating range of simplified model (ECM and SPM)

✗ Require large datasets for training machine learning

✗ Need many internal parameters for mechanistic models

✗ Increase complexity in balancing mechanistic and machine learning components



Proposed Approach

- **Desired Model:**

✓ Interpretable and control-oriented data-driven model
  - Uncover governing equations not fitting data only

✓ Connection to physics

✓ Perform well in unseen data

- **Interpretable input/output modeling techniques:**
- Dynamic mode decomposition (DMD); Tu, 2013
  - Approximate linear system
- Sparse identification of nonlinear dynamics (SINDy); Brunton et al., 2016
  - Nonlinear reduced order model through sparsification of a library of potential terms
  - Require remarkably less data comparing to NN

✗ Dynamics of LiB is highly nonlinear

SINDy challenges:

✗ Selecting library terms

✗ Selecting sparsification parameters

Objective

- **Main objective:** Develop a tractable data-driven model to discover the governing equations of Li-ion batteries

- **Hypothesis:** Voltage and SOC dynamics can be represented by a few terms from the measured data, and SOC levels can be accurately estimated via these learned dynamics

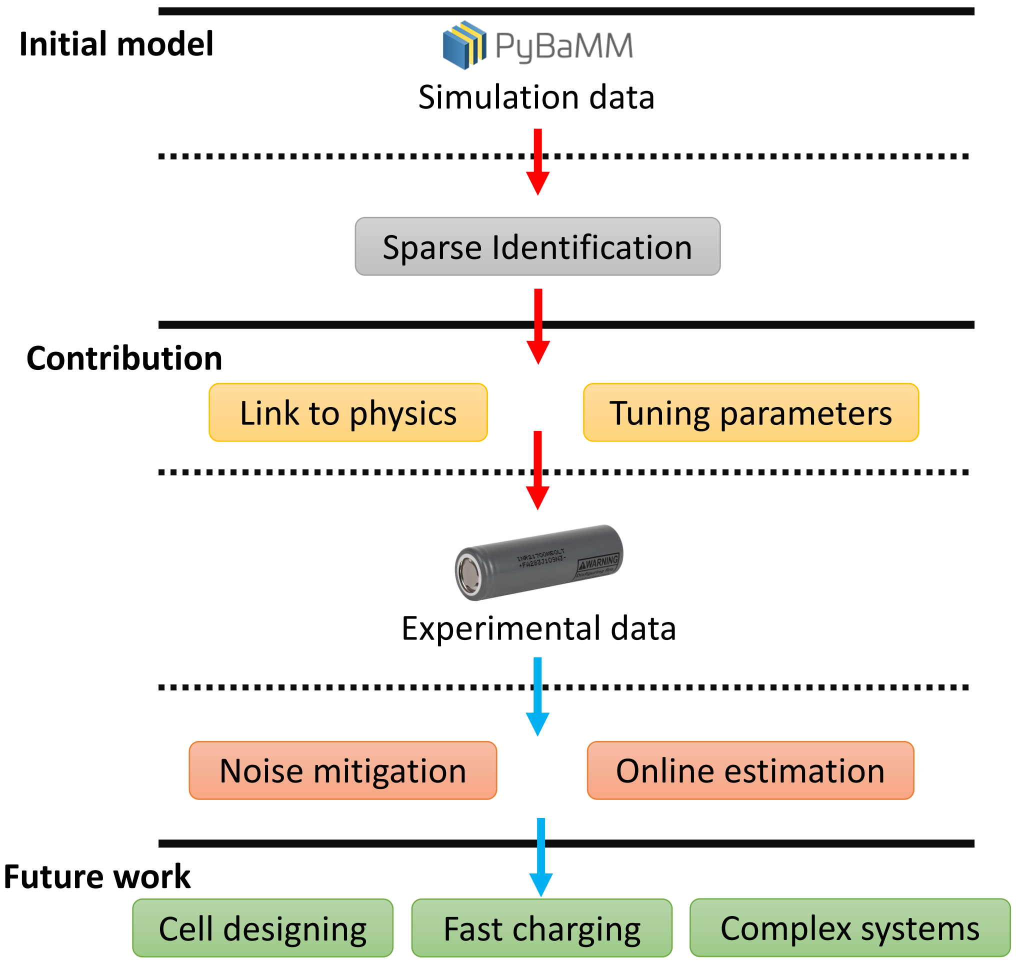
- **Aim 1: Discovering Battery's Voltage and SOC dynamics**
  - Create a nonlinear interpretable data-driven model for Li-ion battery
  - Enhance the modeling technique by including physics-inspired terms
  - Formulate a multi-objective cost function to capture the dynamics

- **Aim 2: Robust Modeling with Noisy Data**
  - Extend data-driven model using a Joint Unscented Kalman Filter to mitigate noise effects
  - Develop a co-estimation framework to update model parameters using measurement data

- **Aim 3: Data Generation and Model Development**
  - Generate data from a detailed cylindrical cell battery model
  - Design experiments on a single cell at different temperatures
  - Conduct experimental studies and collect data

Roadmap

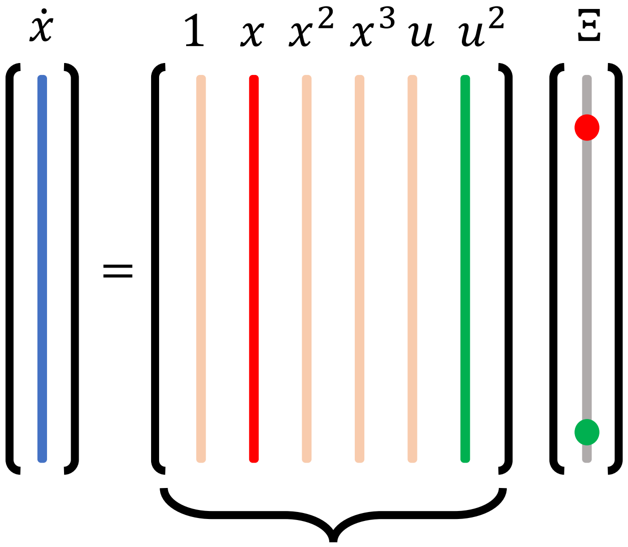
- Discover governing equation of Li-ion batteries
  - Using the measurable data
  - Physics-inspired
  - Generalizability
- Reduce measurement noise effect
  - Using Joint Unscented Kalman Filter
- Co-estimation framework



Sparse Identification of Nonlinear Dynamics

- SINDy is based on sparse linear regression; Brunton et al., 2016
    - Results in reduced order nonlinear model
    - Detect the governing equation
- Notable extensions to SINDy
- SINDy with control (SINDyC); Brunton et al., 2016
- AIC-inspired on training data; Mangan et al., 2017
- Constraint dynamics; Loiseau & Brunton, 2018
- Including switching dynamic; Li et al., 2019; Mangan et al., 2019
- PDE; Messenger & Bortz, 2021
- MPC; Fasel et al., 2021
- Sensitivity analysis: Naozuka et al., 2022
- Ensemble model; Fasel et al., 2022

$$\dot{x} = x + 3u^2$$



Library: $\Theta(X, U)$

- There are several extensions; however, they mostly left the choice of library terms and sparsification parameters which based on the original formulation overfits the model

Sparse Identification Method

$$x[k+1] = f(x[k],u[k]) \; : \; \overset{0}{\cancel{a}}x[k] + \overset{1}{\cancel{b}}x^2[k] + \overset{0}{\cancel{c}}u[k] + \overset{4}{\cancel{d}}x[k]u[k] + \overset{-1.4}{\cancel{e}}x^2[k]u^2[k] + \overset{0}{\cancel{f}}\sin[k]$$

Library of potential terms: $\boxed{x[k+1] = x^2[k] + 4x[k]u[k] - 1.4x^2[k]u^2[k]}$

$$\Theta(\mathrm{X,U}) = \begin{bmatrix} \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ X & X^2 & U & XU & X^2U^2 & \sin(X) \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix}$$

$$X = [x[k] \quad x[k+1] \quad \cdots \quad x[k+m-1]]^T, X' = [x[k+1] \quad x[k+2] \quad \cdots \quad x[k+m]]^T$$

$$U = [u[k] \quad u[k+1] \quad \cdots \quad u[k+m-1]]^T$$

- By defining sparse vector of coefficients Ξ:

$$X' = \Theta(X,U)\Xi$$

Identifying Sparse Vector of Coefficients Ξ

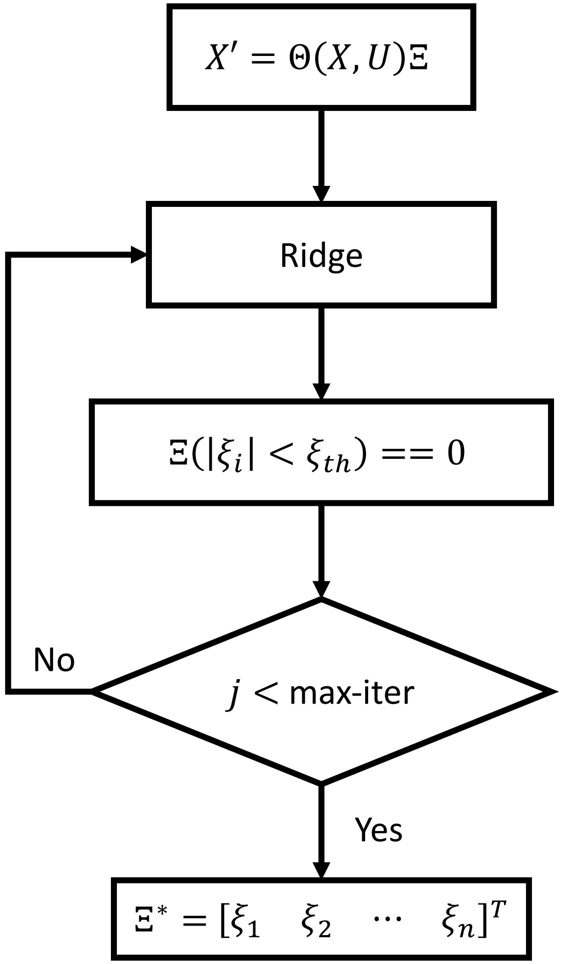
$$\Xi = [\xi_1 \quad \xi_2 \quad \cdots \quad \xi_n]^T$$

- Ridge Regularization problem:

$$\Xi^* = \mathrm{argmin}_{\Xi} \|X' - \Theta\Xi\|_2 + \lambda\|\Xi\|_2 + \underline{\xi_{th}\|\Xi\|_0}$$

λ: regularization parameter

- Suitable for correlated terms
- Promoting sparsity: Sequentially thresholded ridge regression (STRidge)
  - ξ_{th}: if $|\xi_i| < \xi_{th} \Rightarrow \xi_i = 0$



Tuning Sparsification Parameters (λ, ξ_{th})

- **Original Approach:** Akaike information criterion (AIC)-inspired loss function:

$AIC = 2N - 2\ln(\hat{L})$, $\hat{L}$ is the maximum value of the likelihood function

$$\boxed{\mathcal{L}(\Xi) = N \ln\left(\frac{\|X' - \Theta(X,U)\Xi\|_2^2}{N} + \epsilon\right) + 2K}$$

k is the number of nonzero coefficients in Ξ, and N is the number of measured data in time.
$\epsilon \ll 1$ to avoid overfitting the data.

- Goal is to balance accuracy and complexity

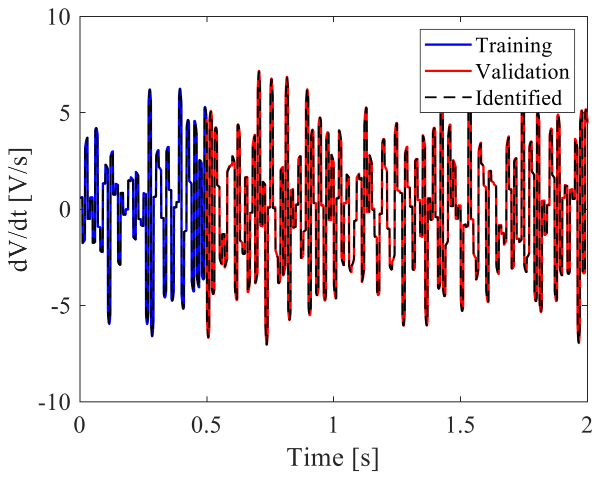
$$\boxed{\Xi^* = \mathrm{argmin}_{\Xi}\left\|\dot{X} - \Theta\Xi\right\|_2 + \lambda\|\Xi\|_2 + \xi_{th}\|\Xi\|_0}$$

Limitations of Generic Model

- Preliminary results using SINDy: predict voltage with generic terms and AIC cost function
- Very limited operating condition
  - Lack of connection to physics
  - Exact terms to be included in the library
    - Adding too many terms results in ill-conditioned problems with correlated terms
  - Cost function using only training data

Next Steps

- ✓ Create physics-inspired library
- ✓ Design multi-objective cost function
- ✓ Predict both voltage and SOC simultaneously



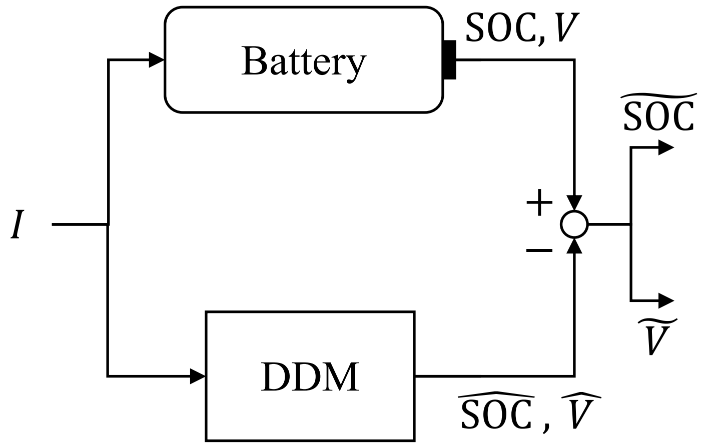
NL Control-Oriented Model of Batteries

- Measurable data
  - Voltage and SOC are the states ($[V \quad \mathrm{SOC}] \equiv X$)
  - Current is the input ($I \equiv U$)

$$[V_{k+1}, \mathrm{SOC}_{k+1}] = f(V_k, \mathrm{SOC}_k, I_k)$$

$$V_{k+1} = \Theta(V_k, \mathrm{SOC}_k, I_k)\Xi_1$$

$$\mathrm{SOC}_{k+1} = \Theta(V_k, \mathrm{SOC}_k, I_k)\Xi_2$$



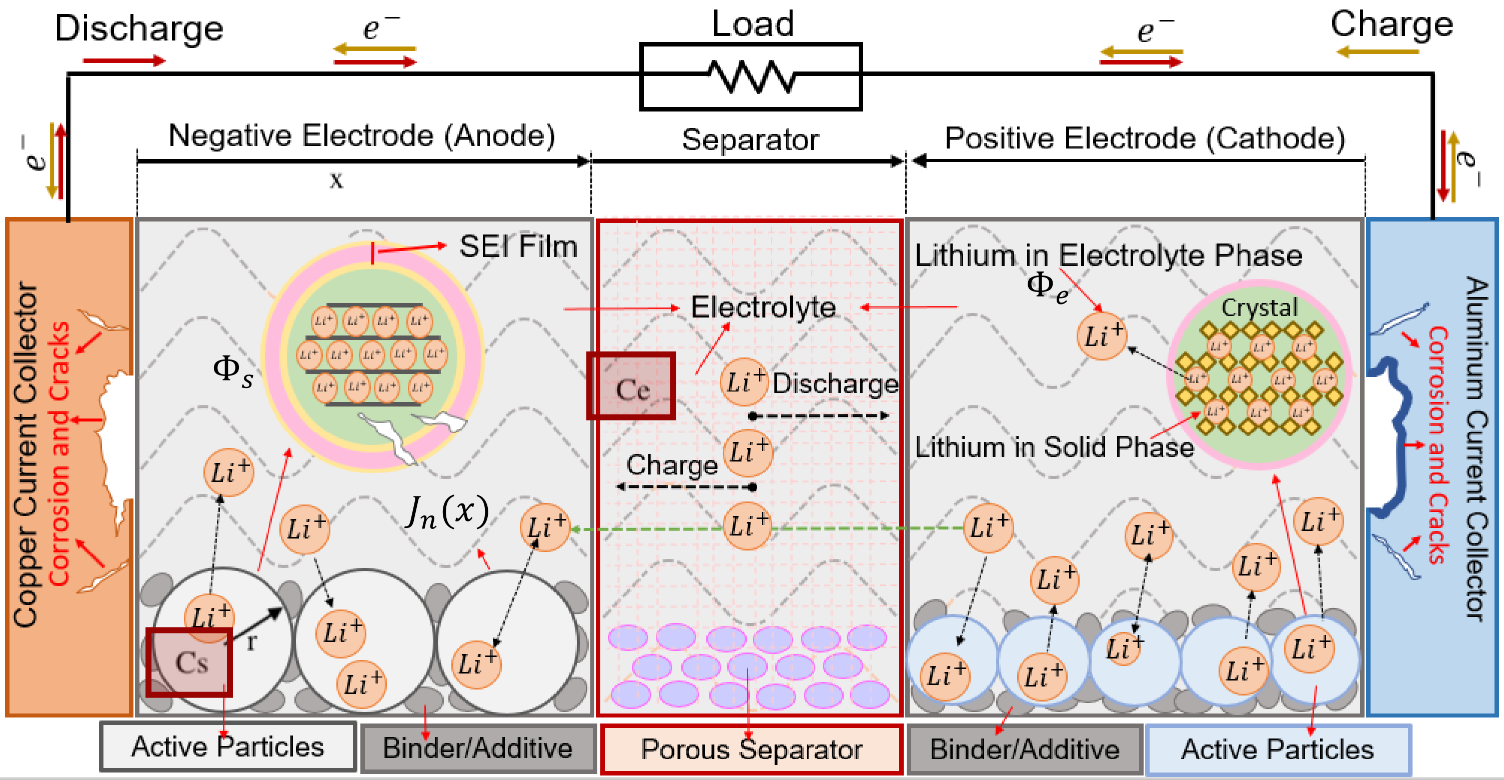
- Data to create the data-driven models
  - Python Battery Mathematical Modelling (PyBaMM)
  - 21700 cylindrical Li-ion cell with material NMC 811 parameters set (5000 mAh)
  - DFN Model

- First step: determine a library based on battery physics

Physics-Informed Library (1)

- DFN model
- Solid and electrolyte concentrations:

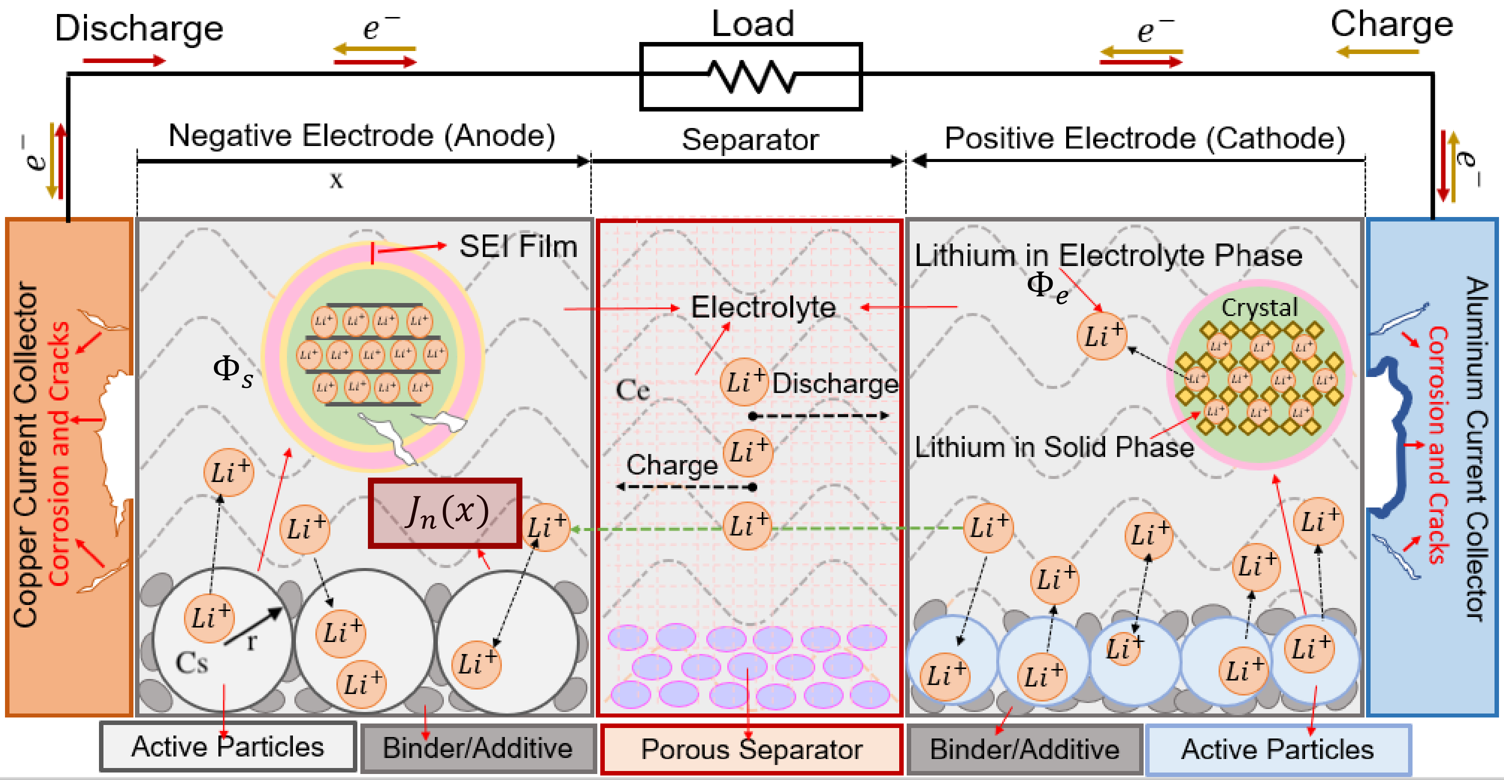
$$\frac{\partial c_s^{\pm}}{\partial t}(x,r,t) = \frac{1}{r^2}\frac{\partial}{\partial r}\left(D_s^{\pm} r^2 \frac{\partial c_s^{\pm}}{\partial r}(x,r,t)\right)$$
$$\frac{\partial c_e}{\partial t}(x,t) = \frac{\partial}{\partial x}\left[D_e \frac{\partial c_e}{\partial x}(x,t)\right] + \frac{1-t_c^0}{\epsilon_e F L^{\pm}} I(t)$$



Physics-Informed Library (2)

- DFN model: $\sin(\cdot),\ \exp(\cdot)$
- Overpotential (Butler-Volmer):

$$j_n^{\pm}(x,t) = \frac{1}{F} i_0^{\pm}(x,t)\left[\sinh \frac{\alpha_a F}{RT}\eta^{\pm}(x,t)\right]$$



Physics-Informed Library (3)

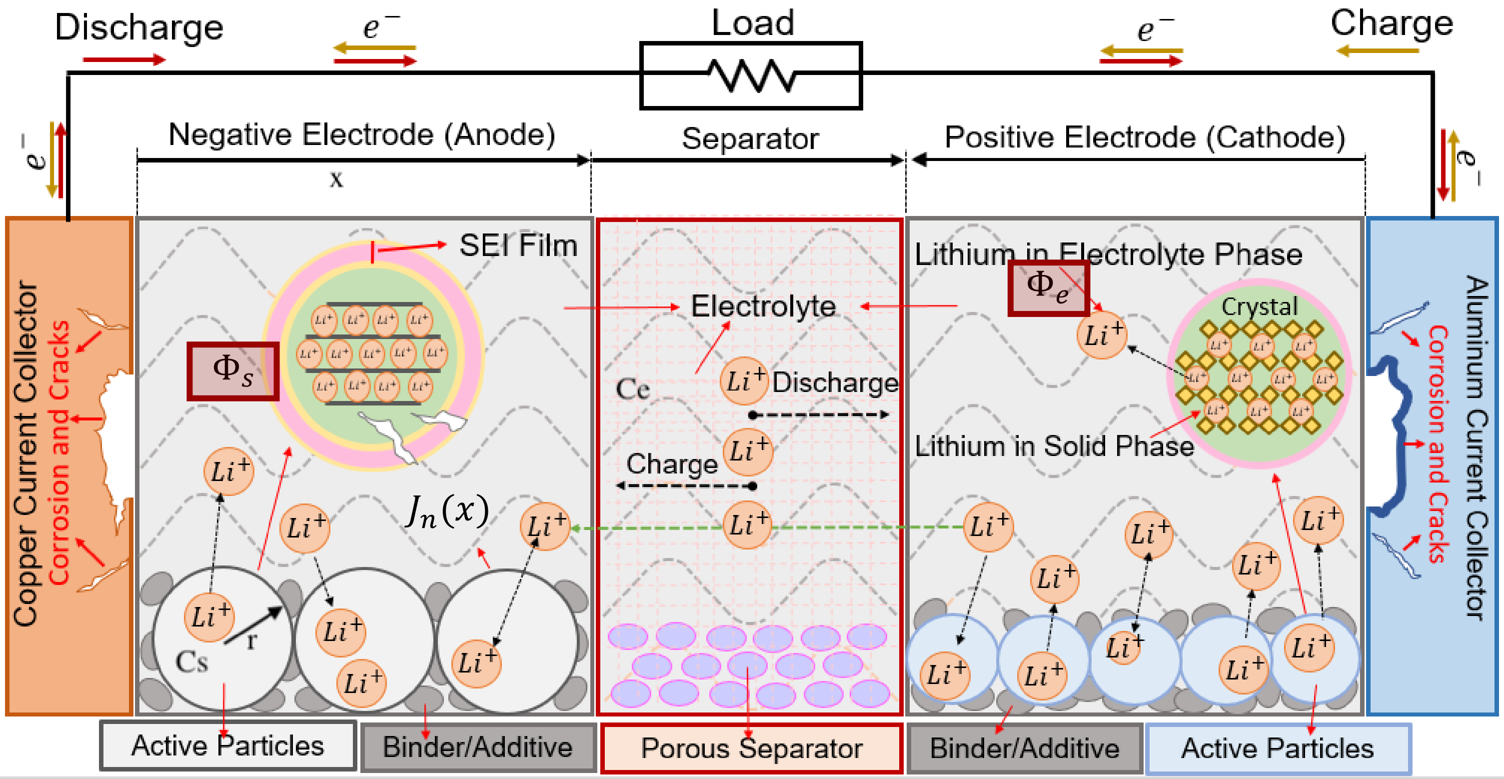
- DFN model: $\sin(\cdot),\ \exp(\cdot),\ \sinh(\cdot)$
- Electrolyte's electric potential:
- Solid electric potential:
- SOC:

$$\frac{\partial \phi_e}{\partial x}(x,t) = \frac{2RT}{F}(1-t_c^0)\left(1+\frac{d\ln f_{\frac{c}{a}}}{d\ln c_e}(x,t)\right)\partial \ln\frac{c_e}{\partial x}(x,t) - \frac{i_e^{\pm}(x,t)}{\kappa}$$

$$\phi_s^{\pm}(x,t) = \eta^{\pm}(x,t) + \phi_e(x,t) + U^{\pm}(c_{ss}^{\pm}) - FR_f^{\pm} j_n^{\pm}(x,t)$$

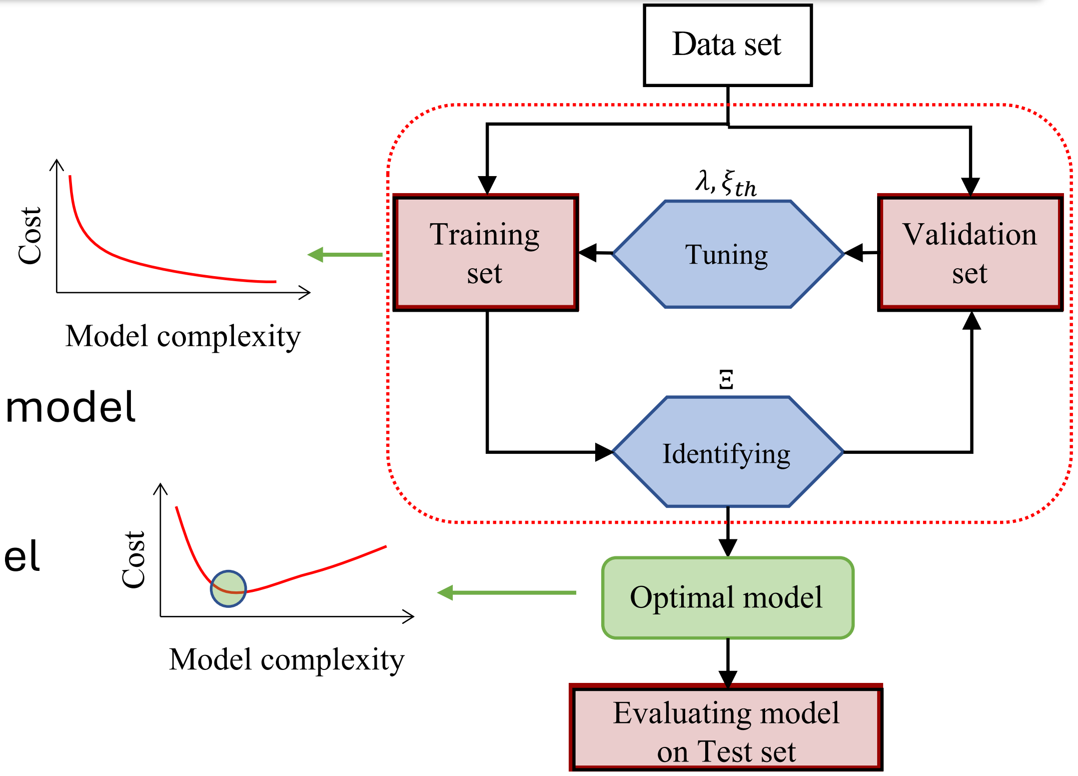
$$V(t) = \phi_s^{+}(0^{+},t) - \phi_s^{-}(0^{-},t)$$

$$SOC(t) = SOC(0) - \frac{1}{C_a}\int_0^t \eta I d\tau$$



Automated Optimization Algorithm

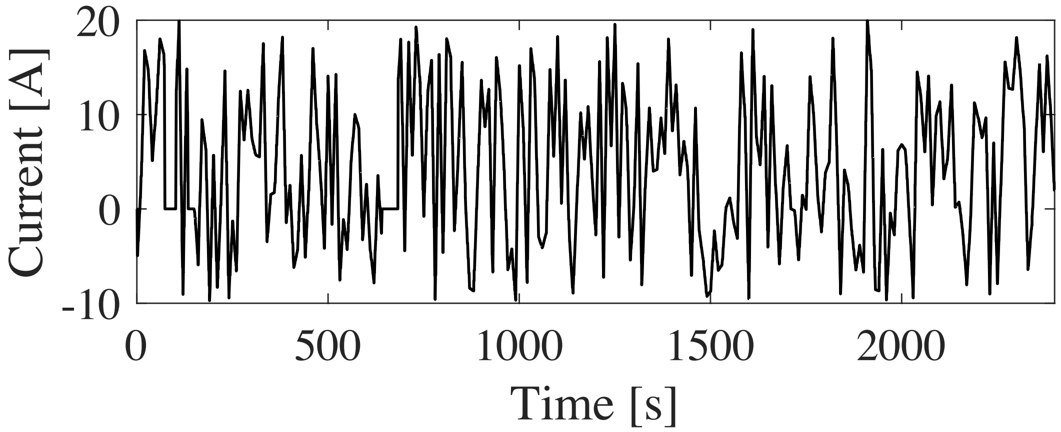
- Three datasets for modeling:
- Training dataset:
  - Building the model
  - Input and output of this set are known
- Validation dataset:
  - Optimizing the hyperparameters of the identified model
- Test dataset:
  - Evaluating the performance of the identified model

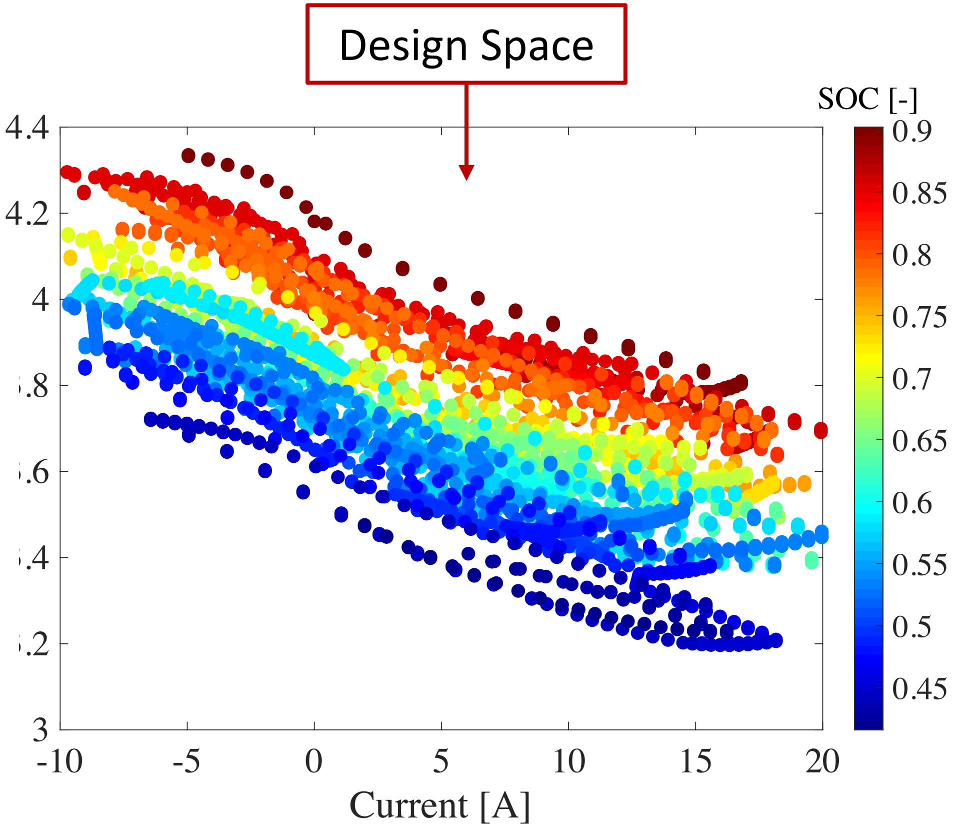


$$\Xi^* = \mathrm{argmin}_{\Xi} \|X' - \Theta\Xi\|_2 + \lambda\|\Xi\|_2 + \xi_{th}\|\Xi\|_0$$

Training Dataset

- Electrical current is employed to generate data
- Stochastic current signal up to 2C/4C-rate charge/discharge with 50 ms sampling time

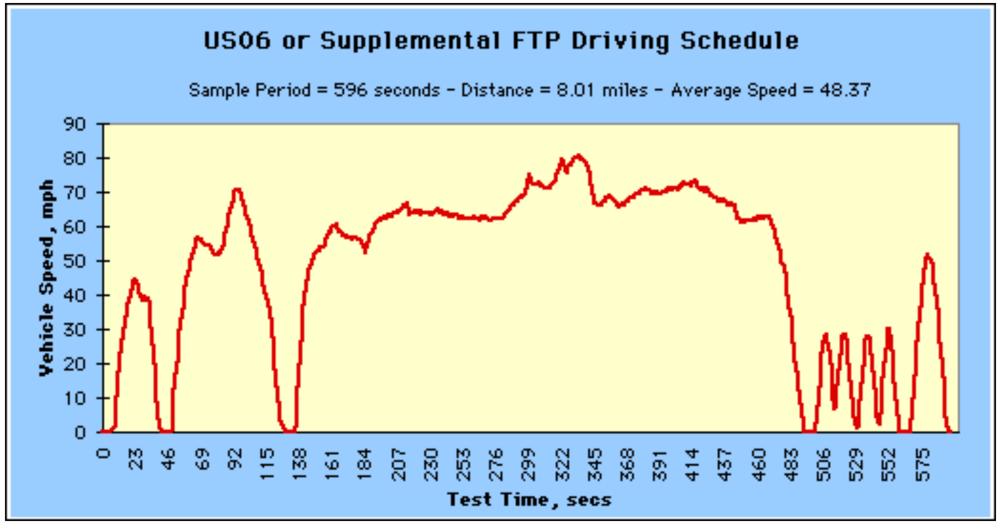




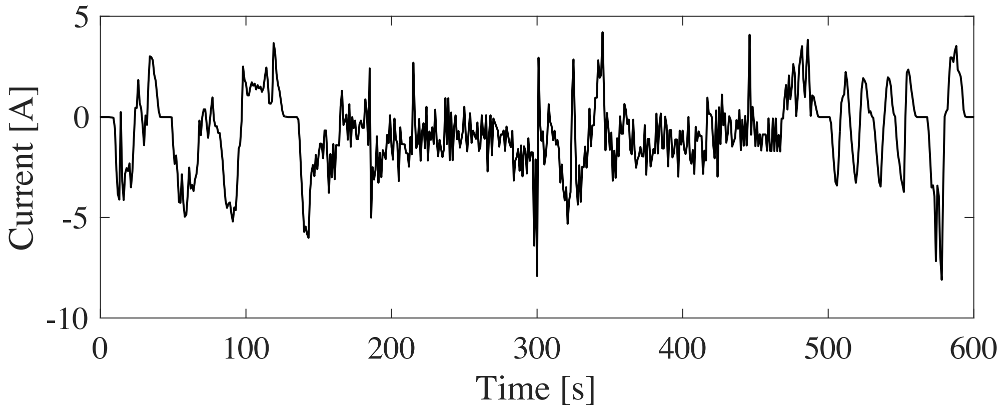
Validation Dataset

EPA aggressive highway drive cycles for validation

- US06 drive cycle



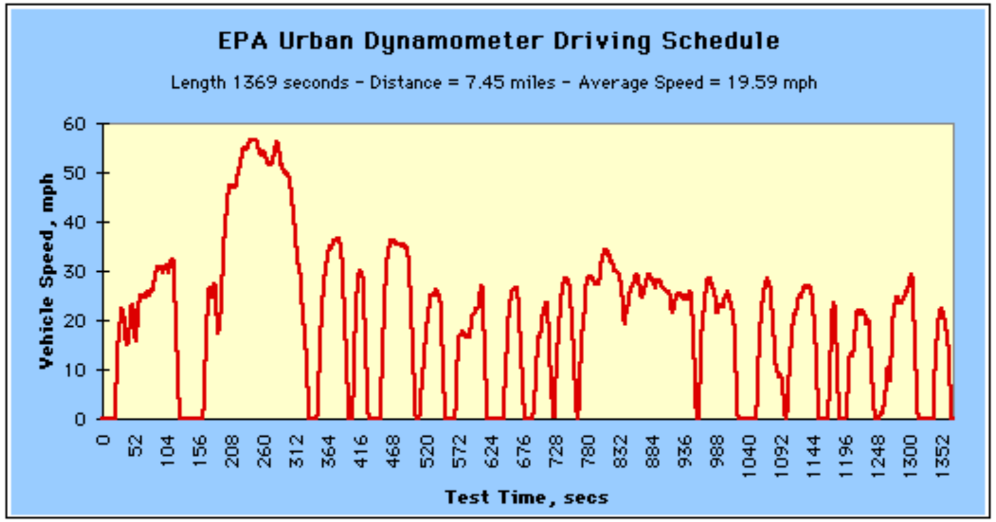
- Current profile



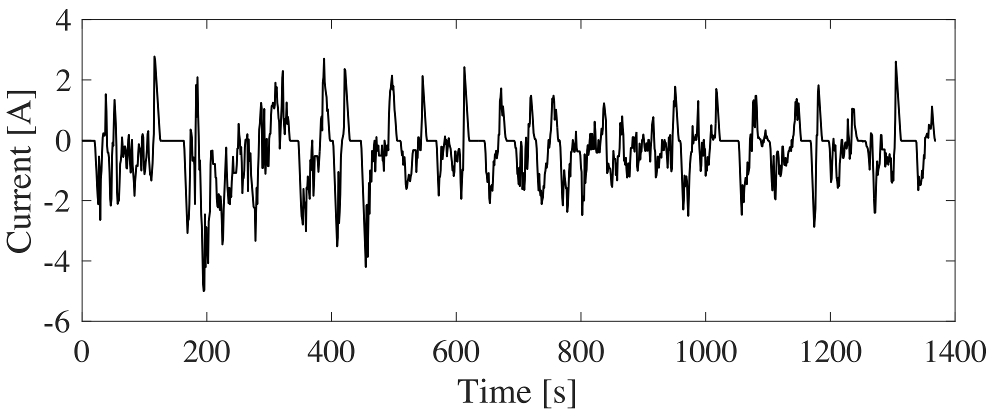
Test Dataset

EPA urban drive cycles for test

- Urban Dynamometer Driving Schedule (UDDS)



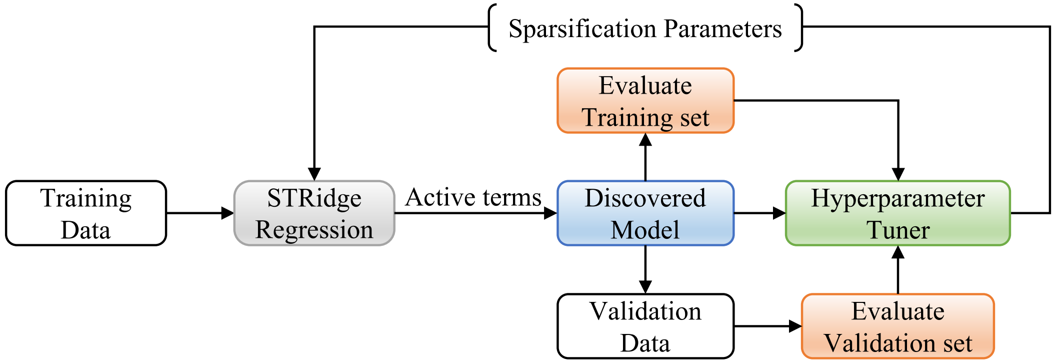
- Current profile



Introducing Hyperparameter Formulation

- The sparsification parameters are tuned with the training, validation set and number of terms

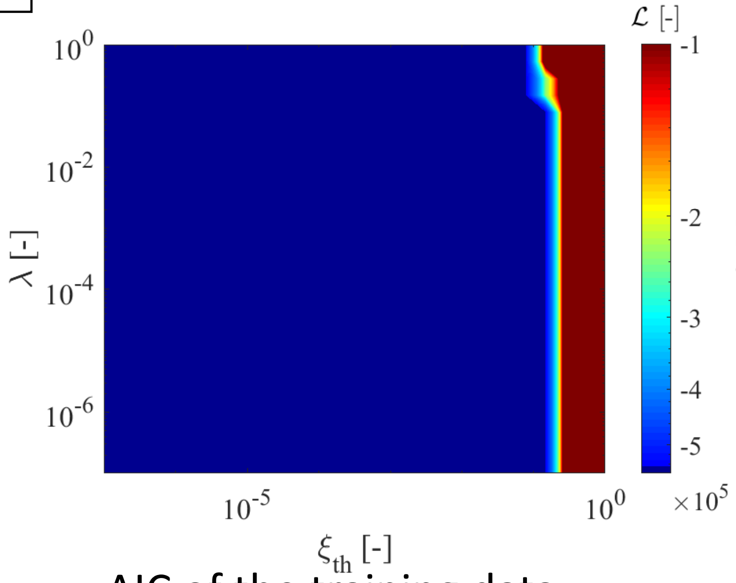
$$\min_{\lambda,\xi_{th}} \mathcal{J}(\Xi) \coloneqq \rho_1 \mathrm{E}_t(x,\hat{x}) + \rho_2 \mathrm{E}_v(x,\hat{x}) + \rho_3 K$$



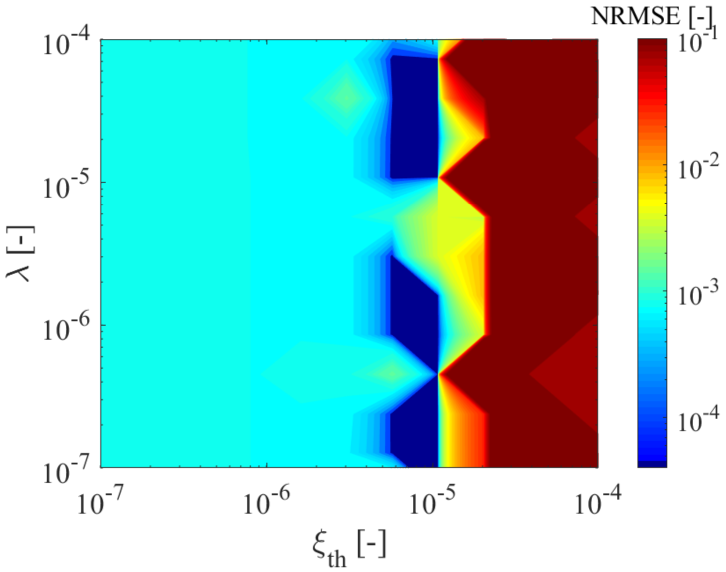
$$\Xi^* = \mathrm{argmin}_\Xi \|X' - \Theta\Xi\|_2 + \lambda\|\Xi\|_2 + \xi_{th}\|\Xi\|_0$$

AIC: $\mathcal{L}(\Xi) = m \ln\left(\frac{\|X' - \Theta(X,U)\Xi\|_2^2}{m} + \epsilon\right) + 2K$

$$E(x,\hat{x}) = \sqrt{\frac{1}{m}\sum_{k=1}^{m}\left(\frac{x[k]-\hat{x}[k]}{x[k]}\right)^2}$$



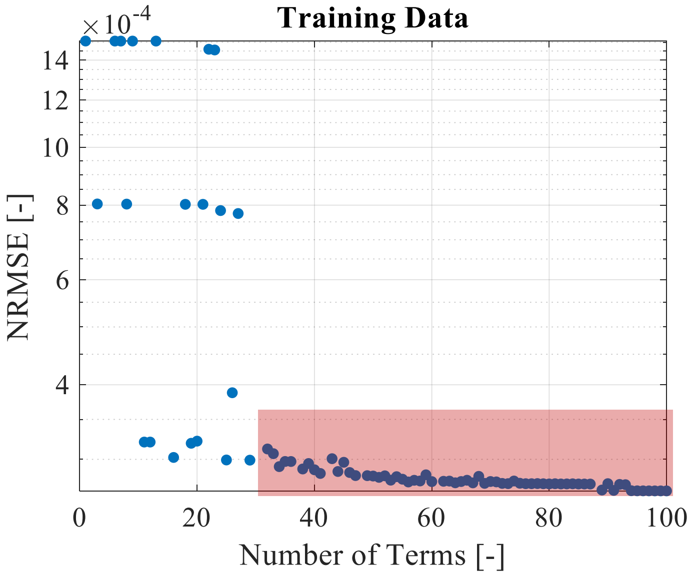
AIC of the training data

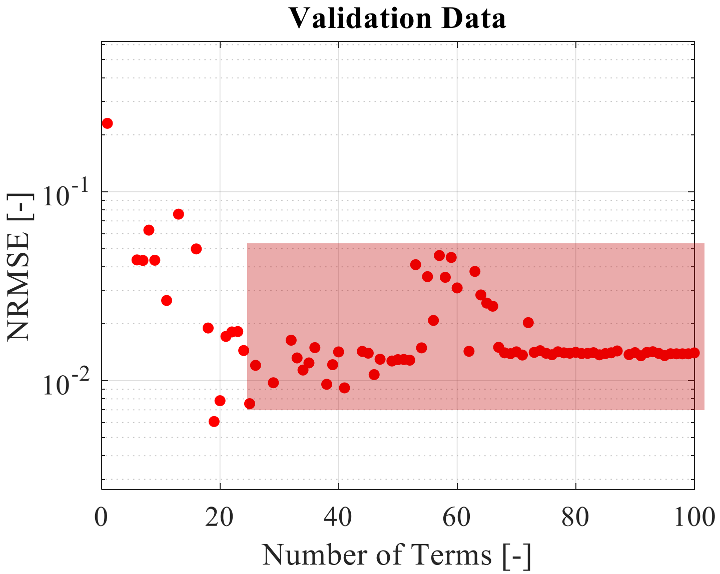


NRMSE of the validation data

Optimal Voltage Dynamics Model

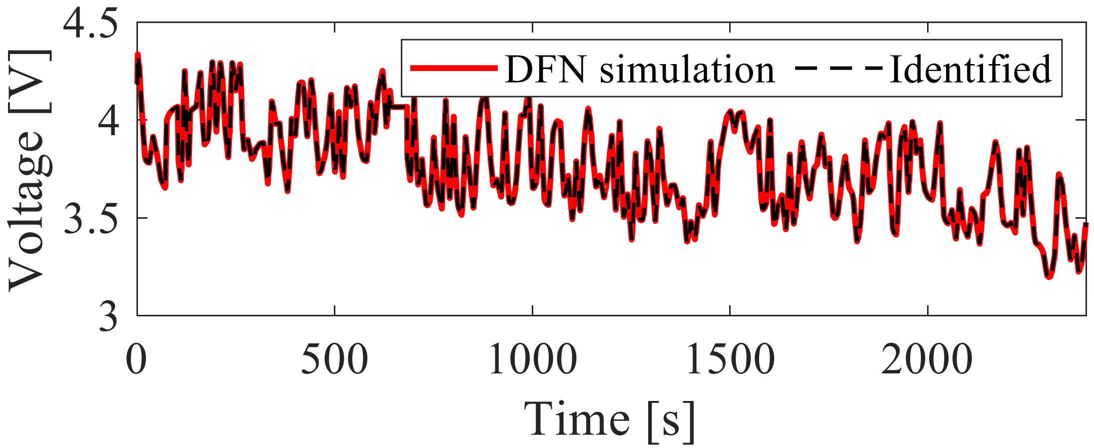
- Number of active terms depends on the hyperparameters (λ, ξ_{th})
- Red region suggests diminishing returns

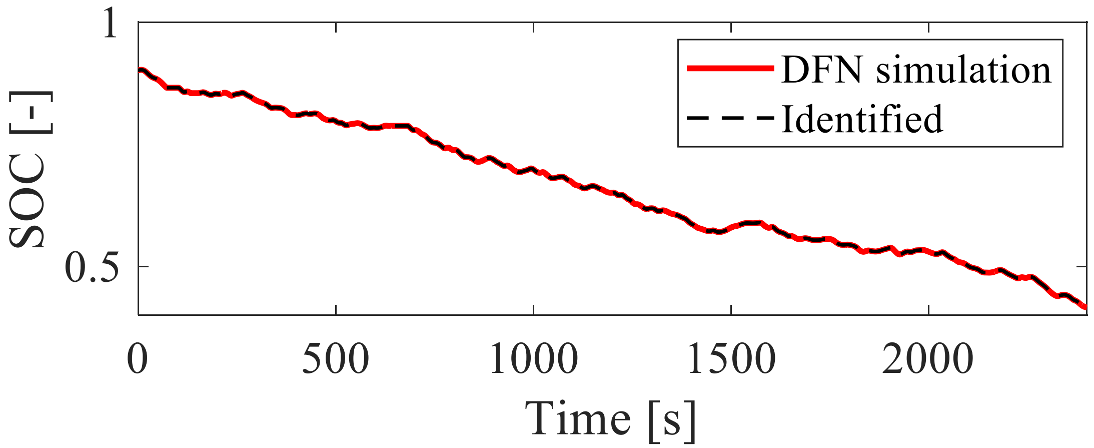




Simulation Results (1)

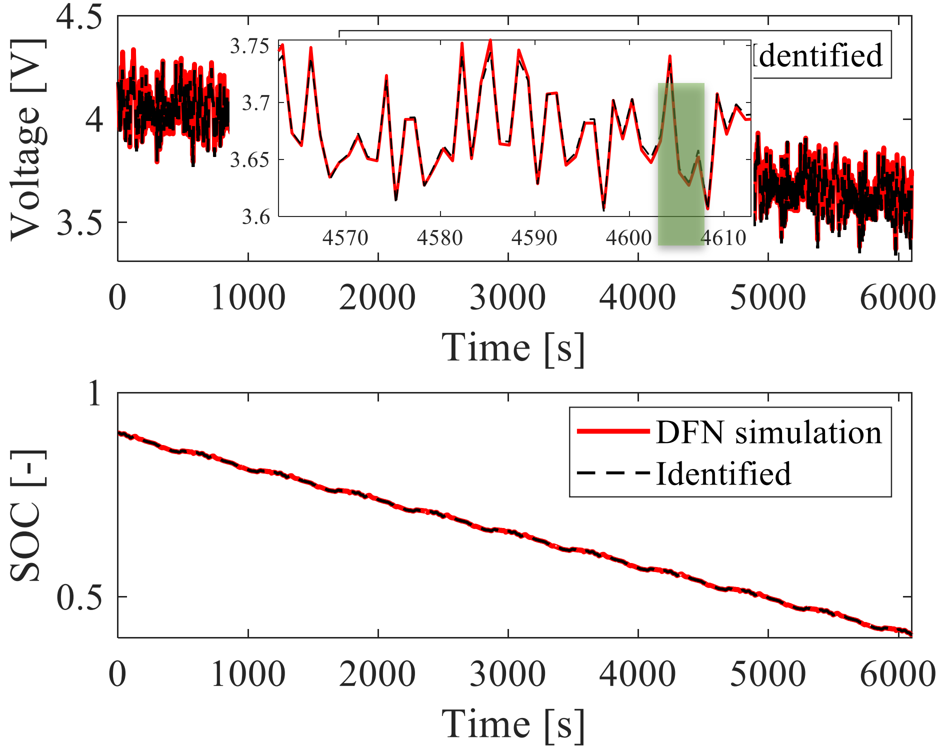
- Voltage and SOC are calculated simultaneously
- Training data NRMSE
  - Voltage: 3.2×10^{-4}
  - SOC: 10^{-8}



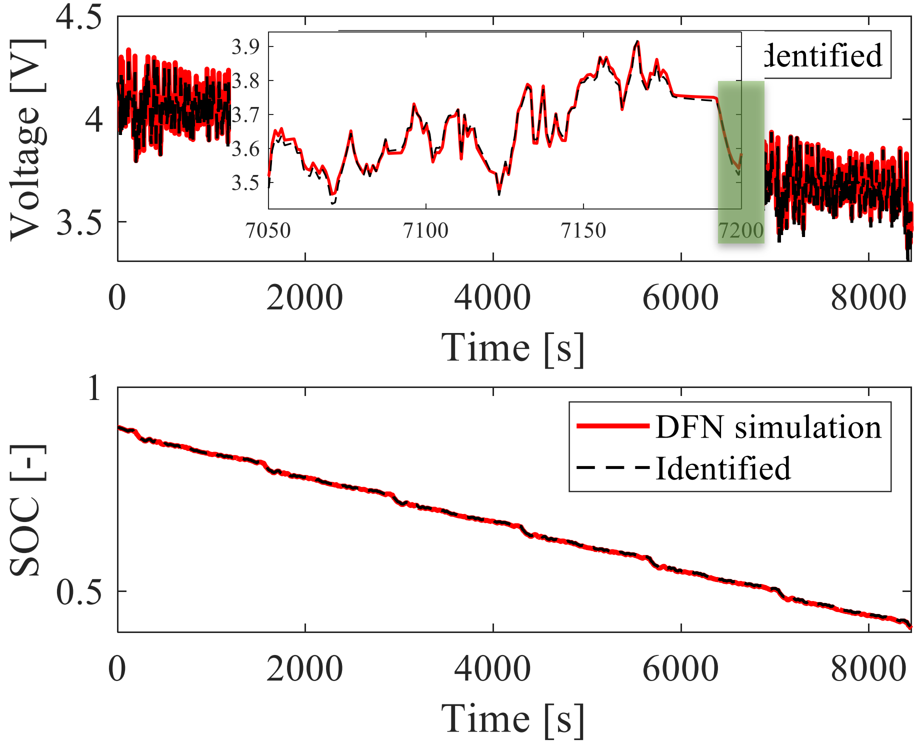


Simulation Results (2)

- US06 validation data NRMSE:
  - Voltage: 6.1×10^{-3}
  - SOC: 2.2×10^{-5}



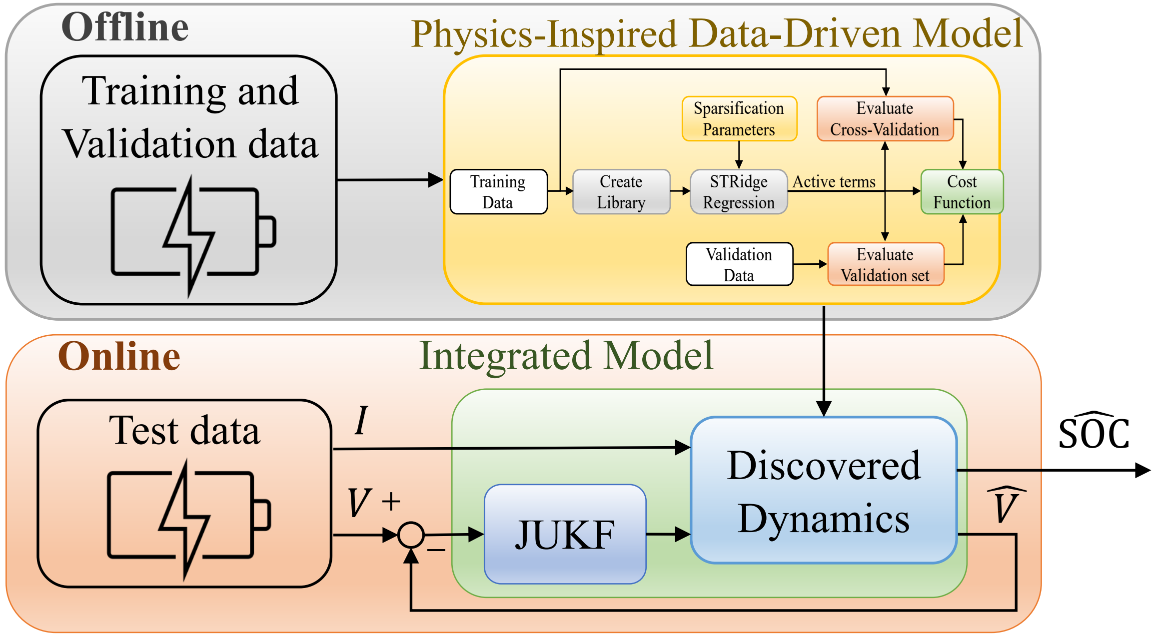
- UDDS test data NRMSE:
  - Voltage: 6.3×10^{-3}
  - SOC: 2.8×10^{-3}



Enhancing Model

- Current Model
  - ✓ Works for perfect measurement
  - ✓ No uncertainty (e.g., with simulated data)

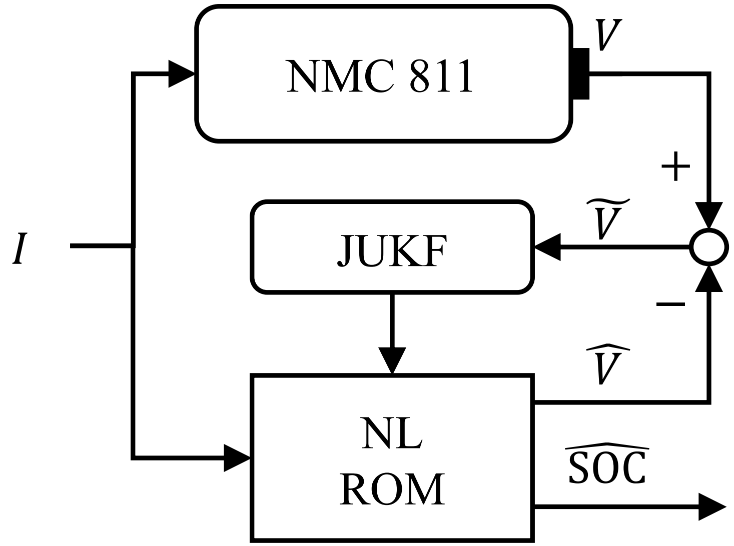
- Issue on actual implementation
  - Noisy data both in training and validation
  - Error in estimations
- Solution for noisy data and improve estimation
  - Kalman Filter → Adapt the model
    - ✓ Mitigate noise effect
    - ✓ Connect SOC dynamics and SOC-Voltage map



Joint Unscented Kalman Filter

- Avoid needs for linearization, suitable for nonlinear systems
- Address uncertainty in voltage state and coefficients concurrently

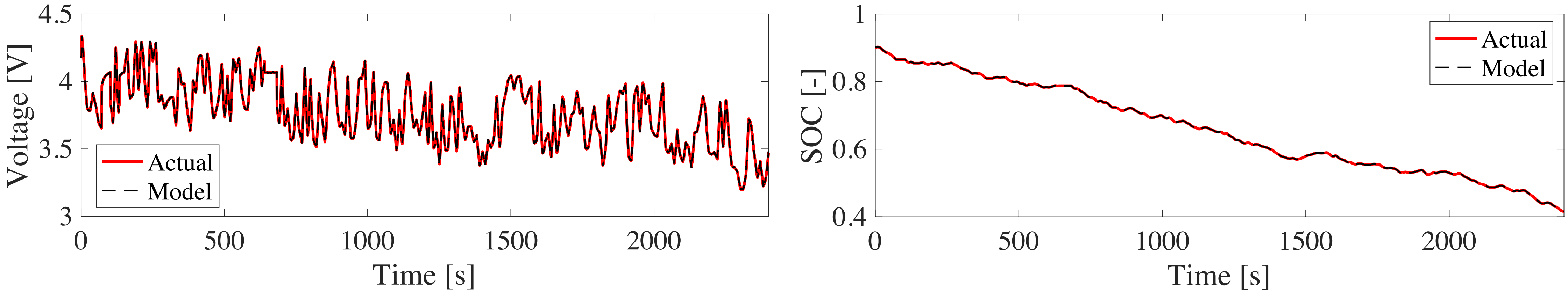
- $\Xi_{r,1}[k+1] = \Xi_{r,1}[k] + w_{\Xi}[k]$ Nonzero sparse coefficients
- $V[k+1] = \theta_{r,1}[k]\Xi_{r,1}[k] + w_V[k]$ Voltage dynamics
- $V_o[k] = V[k] + v_V[k]$ Noisy voltage data



- Update V and $\Xi_{r,1}$ with the noisy output (Voltage)
- Utilize the updated voltage for the SOC prediction
- $\mathrm{SOC}[k+1] = \theta_{r,2}[k]\Xi_{r,2}[k]$

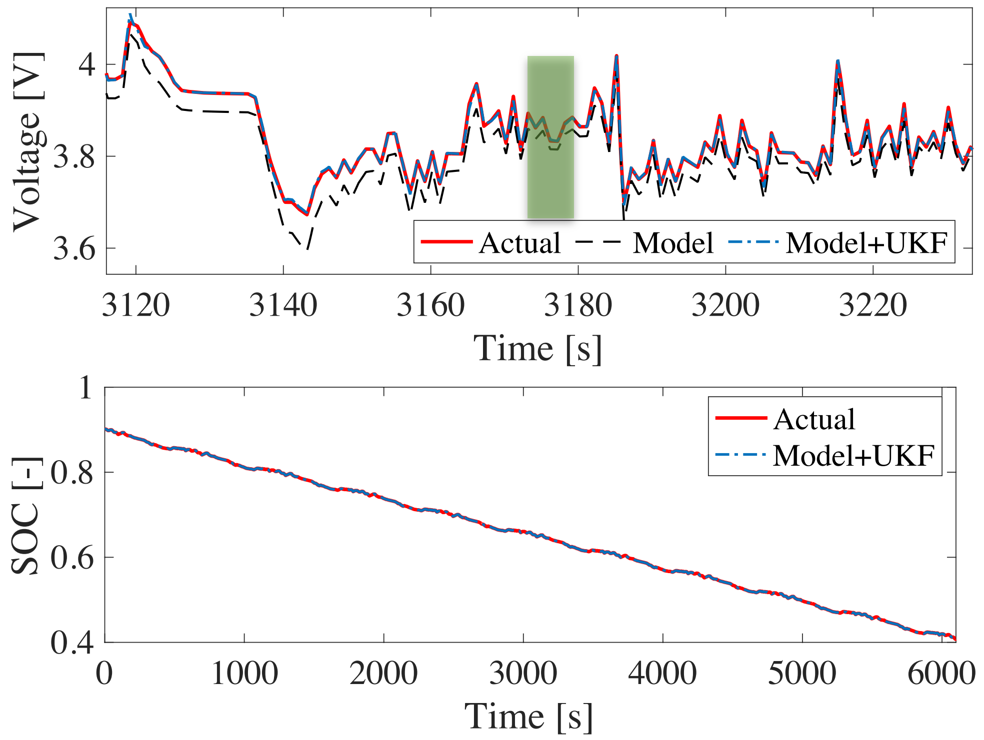
Simulation Results with Added Noise (1)

- Voltage data has 5% Gaussian noise as a measurement noise
- Training data NRMSE
  - Voltage: 10^{-3}
  - SOC: 1.008×10^{-7}

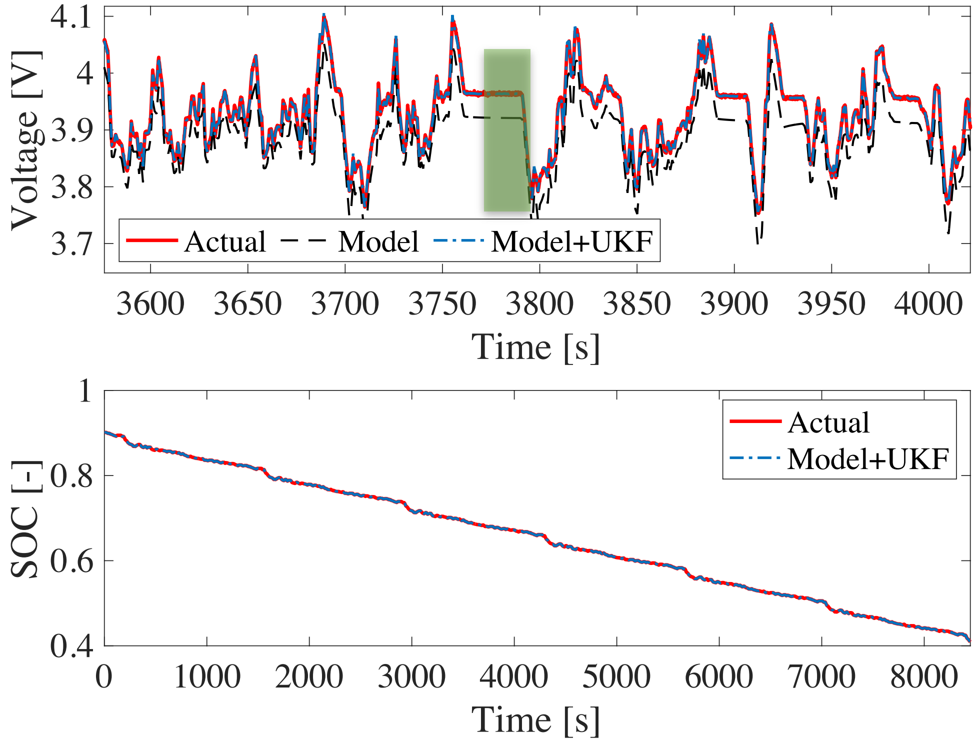


Simulation Results with Added Noise (2)

- US06 validation data NRMSE:
  - Voltage: 1.1×10^{-3}
  - SOC: 5.0963×10^{-5}

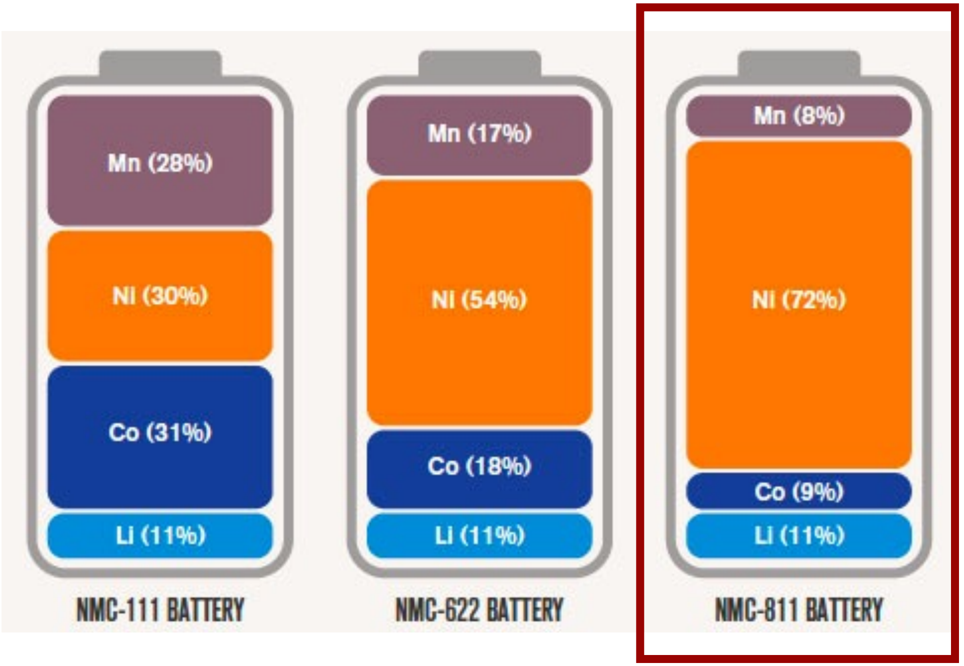


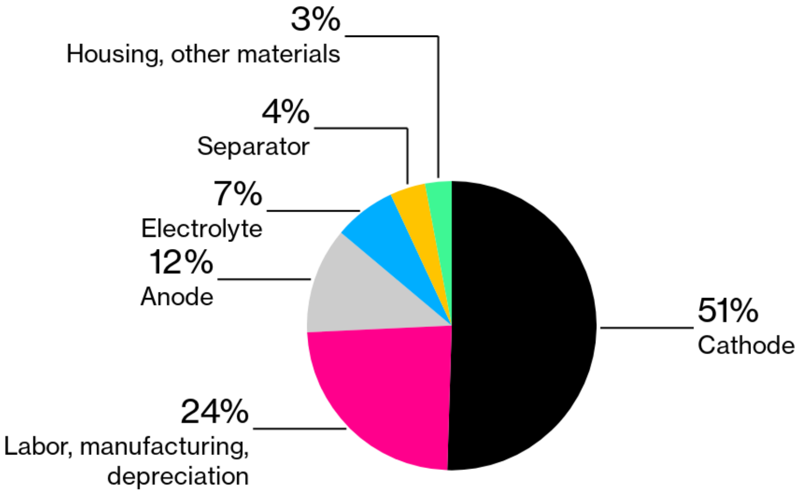
- UDDS test data NRMSE:
  - Voltage: 9.0568×10^{-4}
  - SOC: 1.1585×10^{-4}



Selecting Battery for Experiment

- NMC batteries: Efficient, dependable
  - Less Cobalt: Reduce price
  - Increasing Nickel: Higher capacity and lower weight
- LGM50 21700 cylindrical cell with NMC 811 cathode





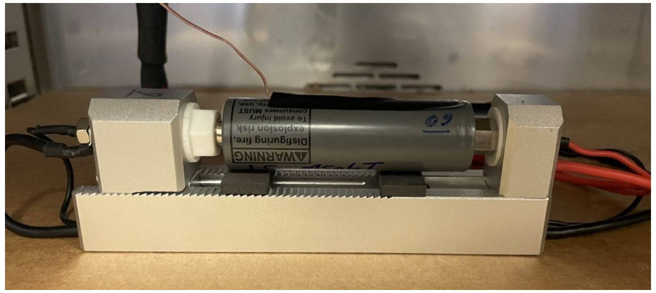
Average cost structure of Li-ion cell
https://www.bloomberg.com/news/newsletters/2021-09-14/ev-battery-prices-risk-reversing-downward-trend-as-metals-surge

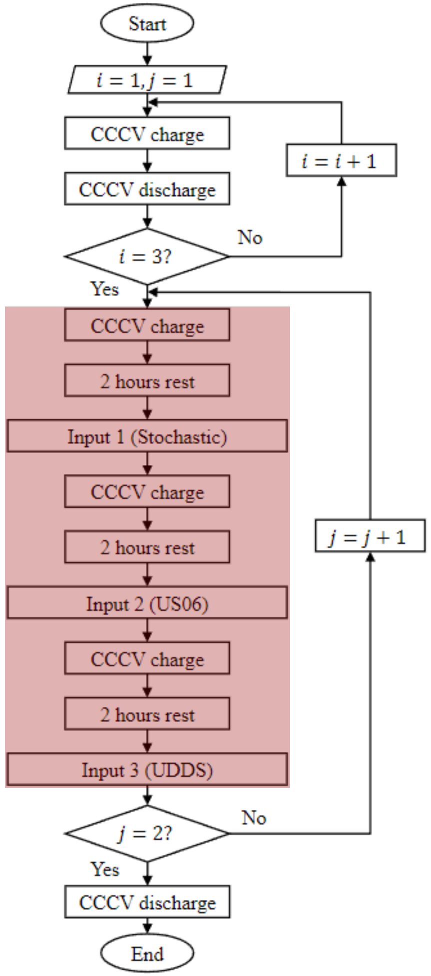
Designing Experiment

- Electrical current is employed to generate data
- 1C-rate: 4.8 A, fully charge the battery in 1 hour with constant current

❖ Max current for constant current charging: 0.3C-rate

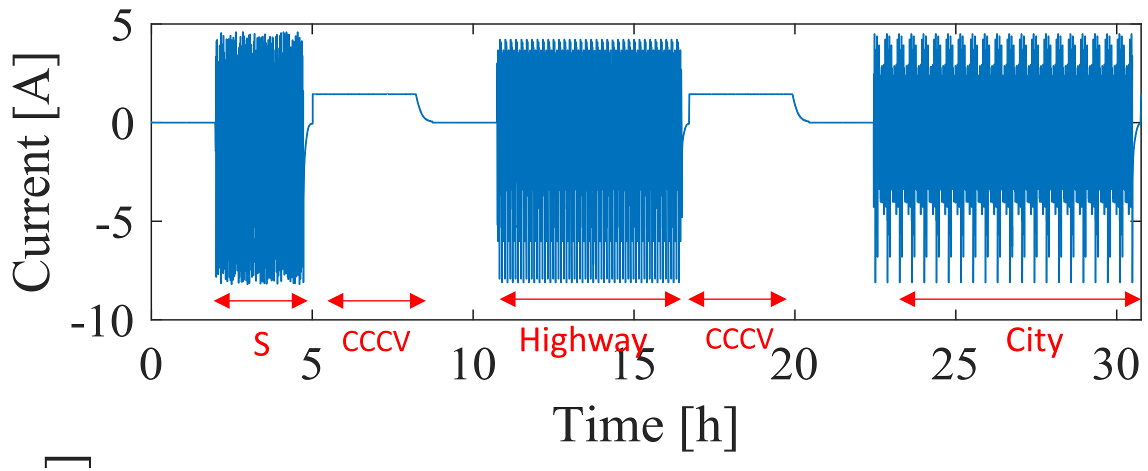
- $T = 10°\mathrm{C}, 25°\mathrm{C}, 40°\mathrm{C}$

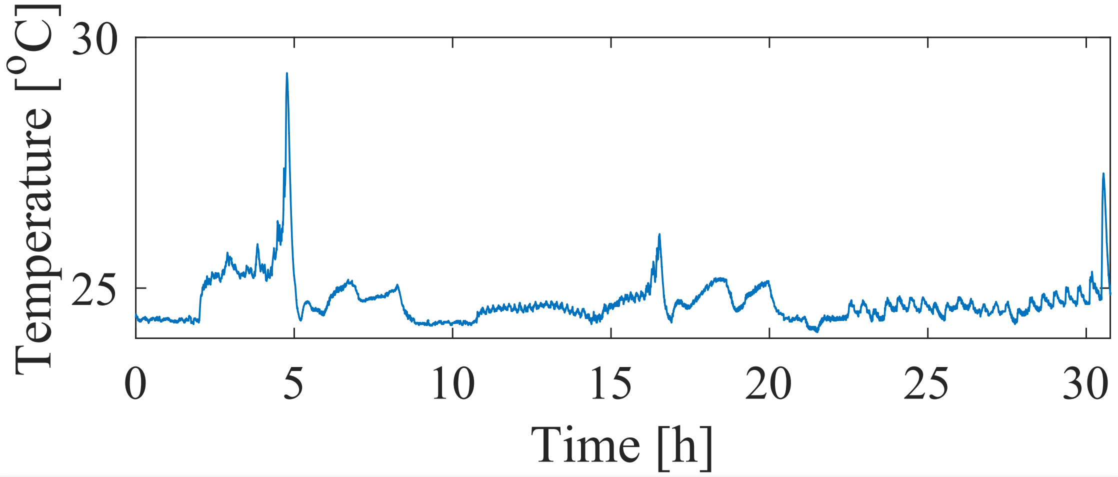


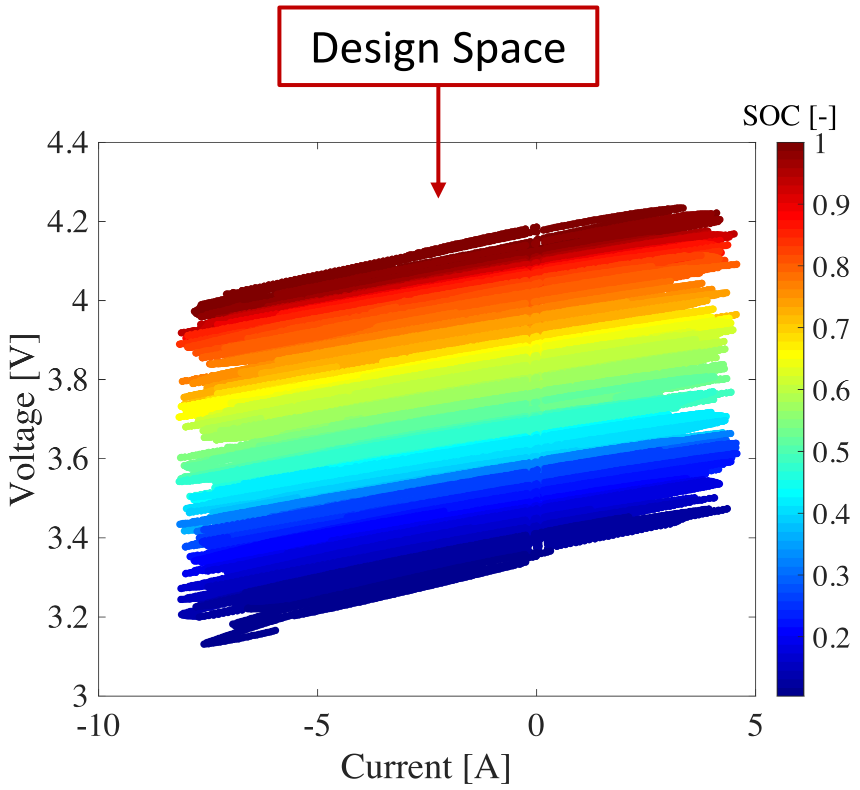


Experimental Results

- Stochastic electrical current signal up to 1C/2C-rate charge/discharge with 50 ms sampling time



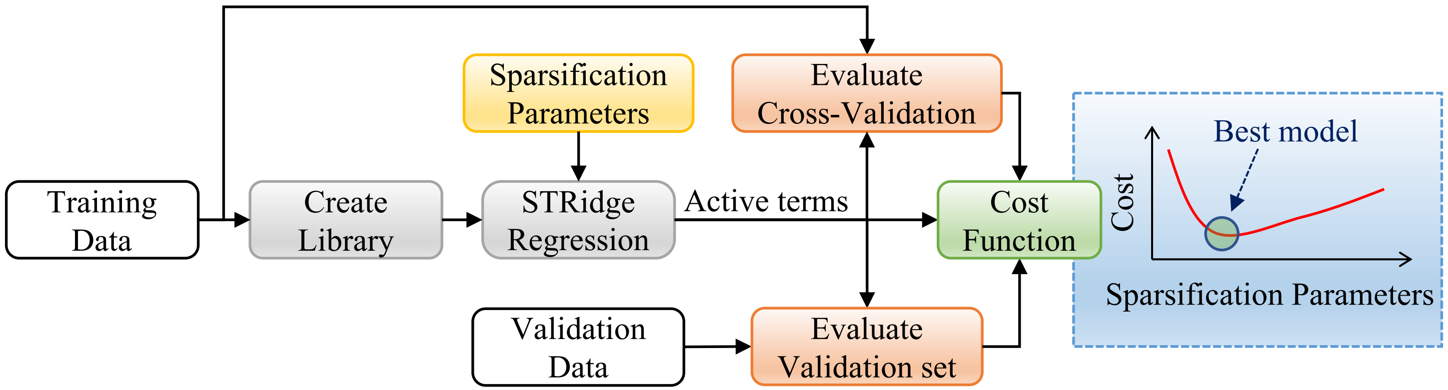


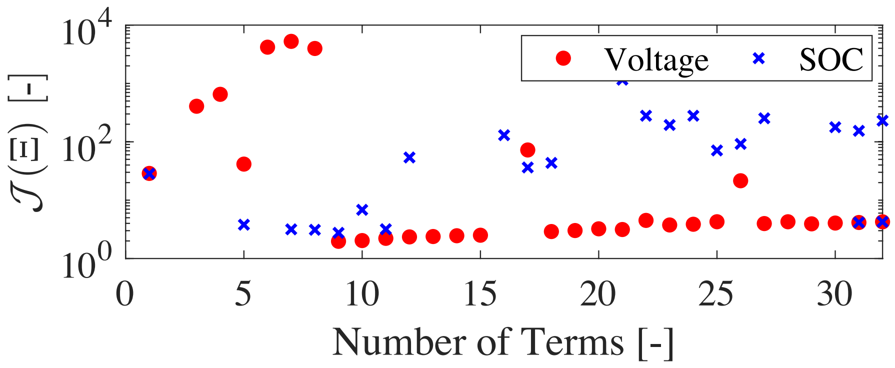


Tuning Sparsification Hyperparameters

- Multi-objective cost function

$$\min_{\lambda,\xi_{th}} \mathcal{J}(\Xi) \coloneqq \rho_1 \mathrm{E}_t(x,\hat{x}) + \rho_2 \mathrm{E}_v(x,\hat{x}) + \rho_3 K$$





	Value for SOC	Value for Voltage
Number of terms	9	9

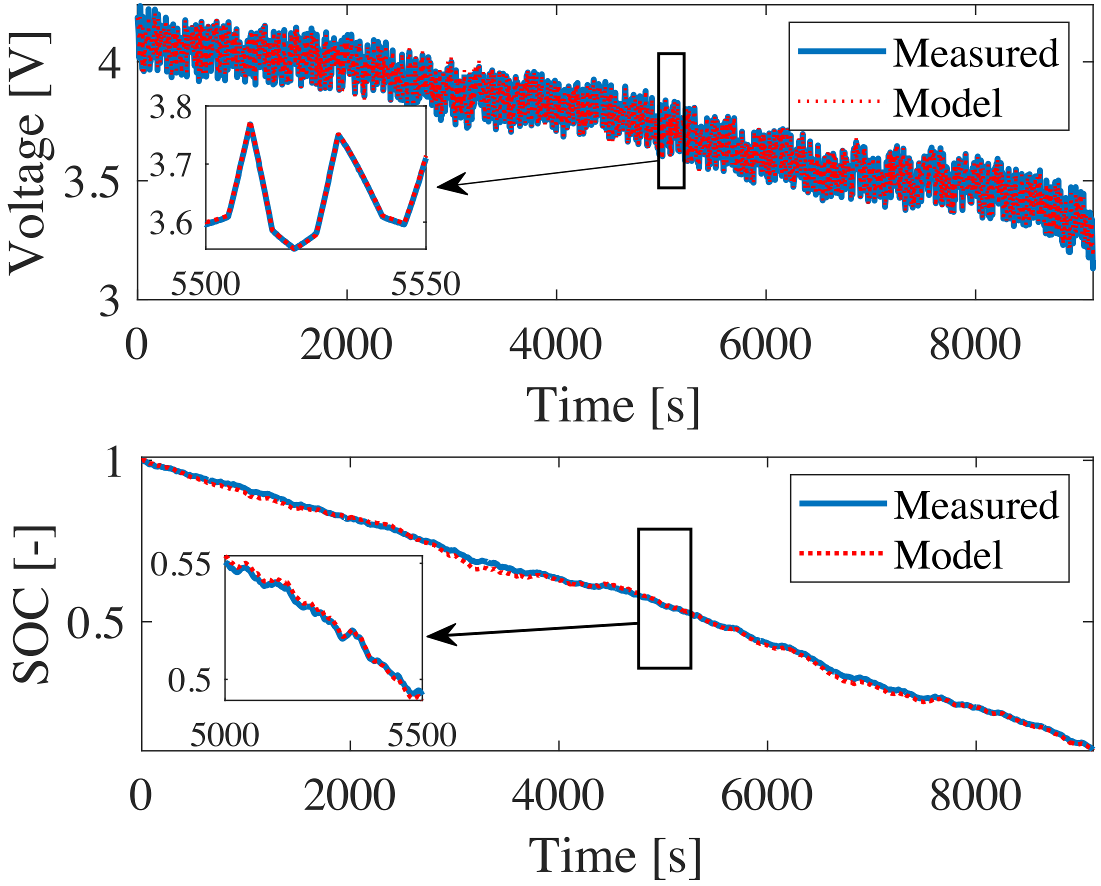
Model Using Experimental Data (1)

- calculate SOC with Coulomb counting:

$$\mathrm{SOC(t)} = \mathrm{SOC(0)} - \frac{1}{Q}\int_0^t \eta_c I d\tau$$

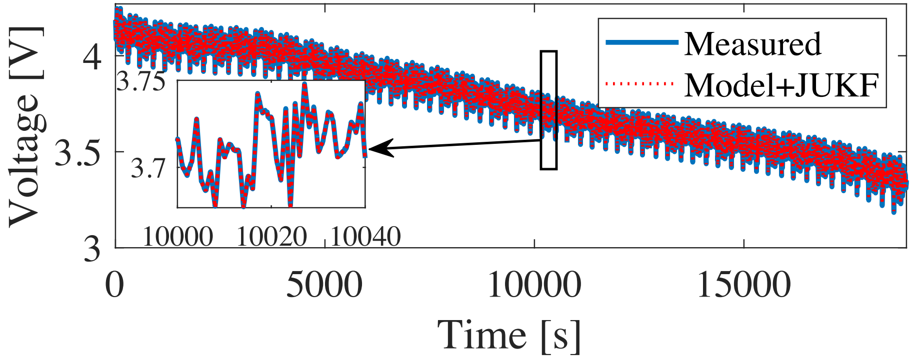
- η_c: $\frac{Q_{discharged}}{Q_{charged}}$

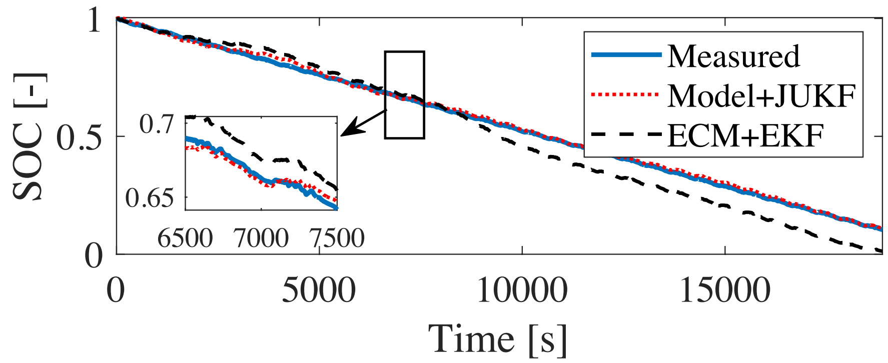
- Training data RMSE
  - Voltage: 2.1×10^{-3}V
  - SOC: 8.6×10^{-3}



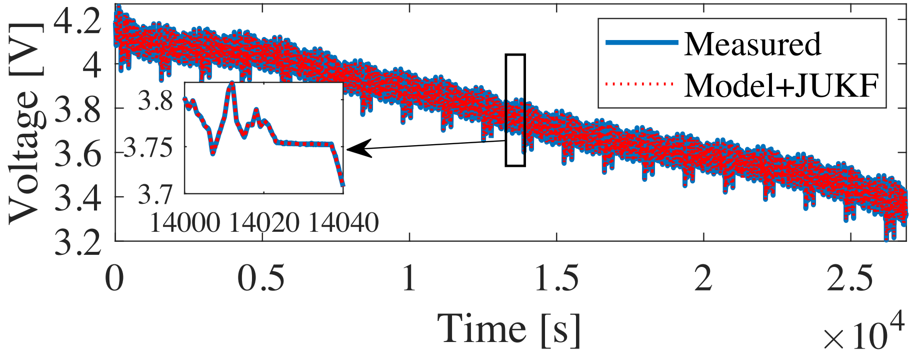
Model Using Experimental Data (2)

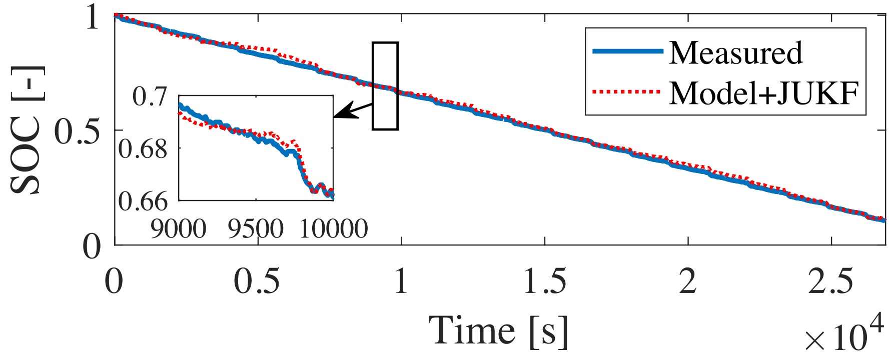
- Aggressive highway validation data RMSE:
  - Voltage: 8×10^{-4} V
  - SOC: 9.9×10^{-3} (ECM+EKF: 6.3×10^{-2})





- City test data RMSE:
  - Voltage: 6×10^{-4} V
  - SOC: 1.2×10^{-2}



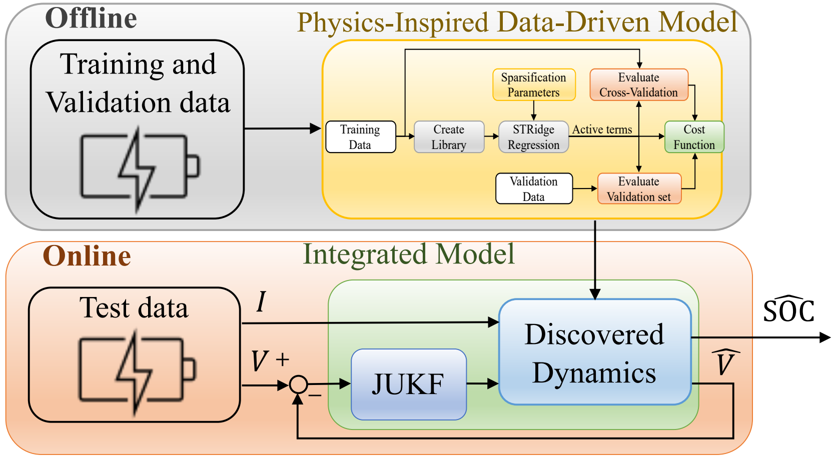


SOC Estimation: Co-estimation Framework

- Adding uncertainty in SOC dynamics due to noisy current and unknown initial value
- Address uncertainty in both states and coefficients concurrently

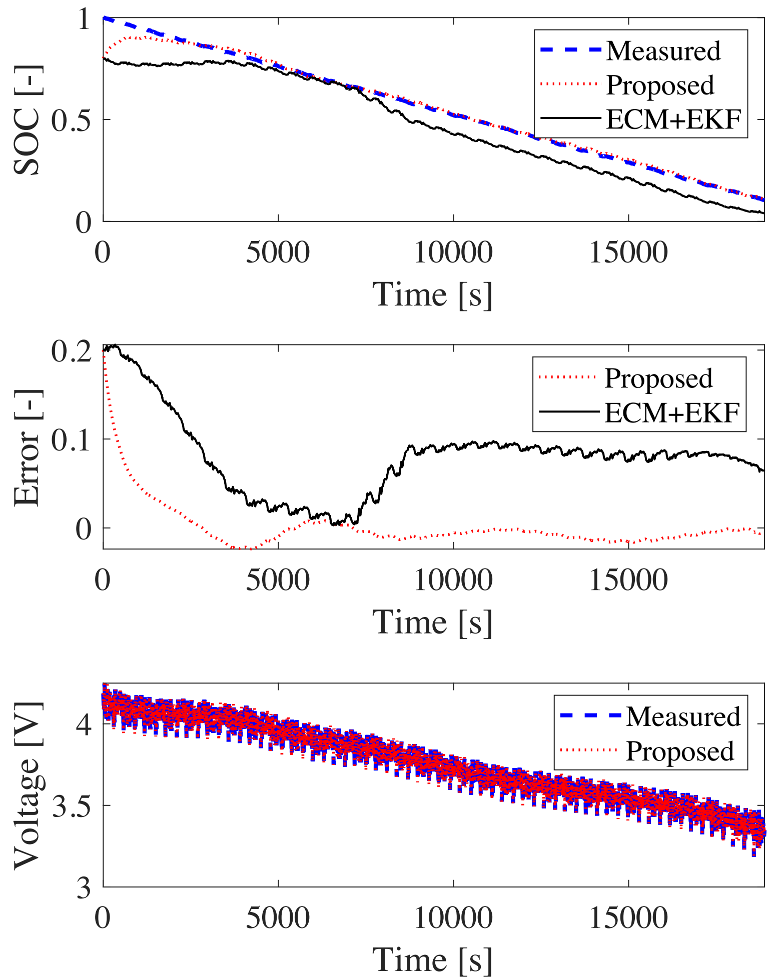
- $\Xi_{r,1}[k+1] = \Xi_{r,1}[k] + w_{\Xi}[k]$ Nonzero sparse coefficients
- $V[k+1] = \theta_{r,1}[k]\Xi_{r,1}[k] + w_V[k]$ SOC-Voltage map
- $\mathrm{SOC}[k+1] = \theta_{r,2}[k]\Xi_{r,2}[k] + w_S[k]$ SOC dynamics
- $V_o[k] = V[k] + v_V[k]$ Noisy voltage data

- Update V, SOC and $\Xi_{r,1}$ with the noisy output (Voltage)



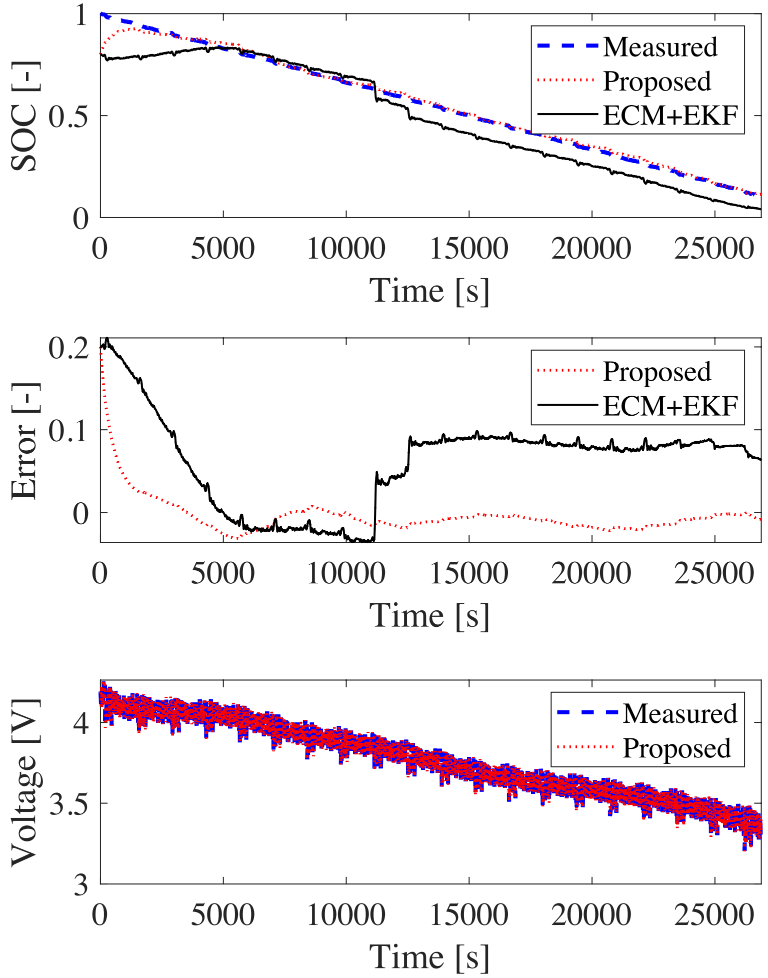
Co-estimation Results (1)

- US06 Validation data
- Initial SOC: 0.8 (20% uncertainty)
- SOC RMSE after convergence: 0.0102
- ECM+EKF fails to estimate SOC
- Voltage RMSE: 0.0008V



Co-estimation Results (2)

- UDDS Test data
- Initial SOC: 0.8 (20% uncertainty)
- SOC RMSE after convergence: 0.0130
- ECM+EKF fails to estimate SOC
- Voltage RMSE: 0.0006V

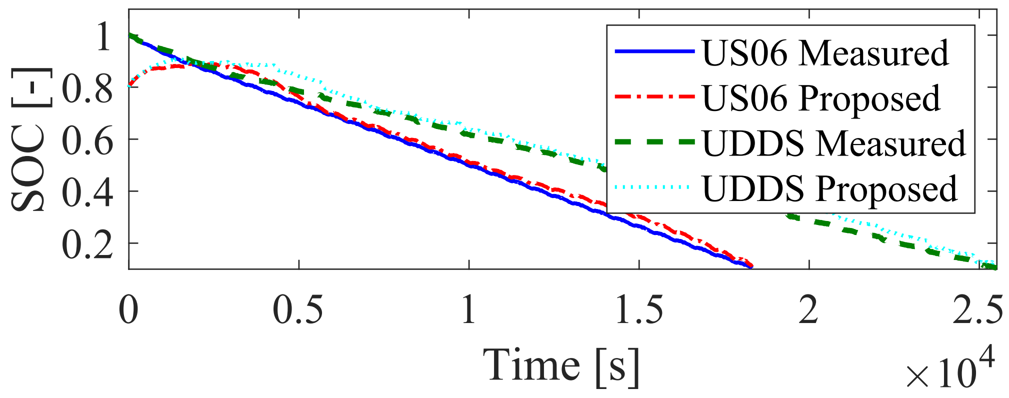


- Battery tester voltage accuracy: ±0.02% full-scale range (±0.0004V)
- Similar to maximum absolute error of voltage (0.0004V)

Co-estimation Result on Different Conditions

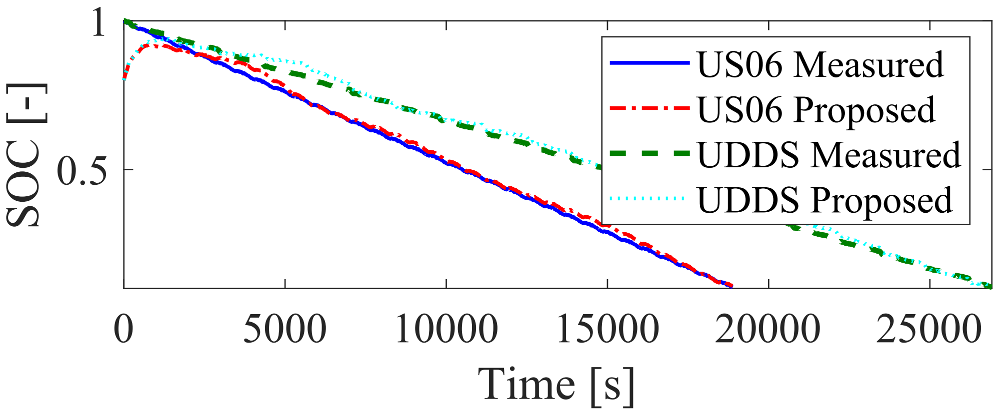
Evaluate the transferability of the model to cold and warm environments by only adjusting the coefficients

- Temperature:10℃



RMSE	SOC	Voltage
US06	0.0283	0.0026 V
UDDS	0.0325	0.0019 V

- Temperature:40℃



RMSE	SOC	Voltage
US06	0.0144	0.0006 V
UDDS	0.0158	0.0005 V

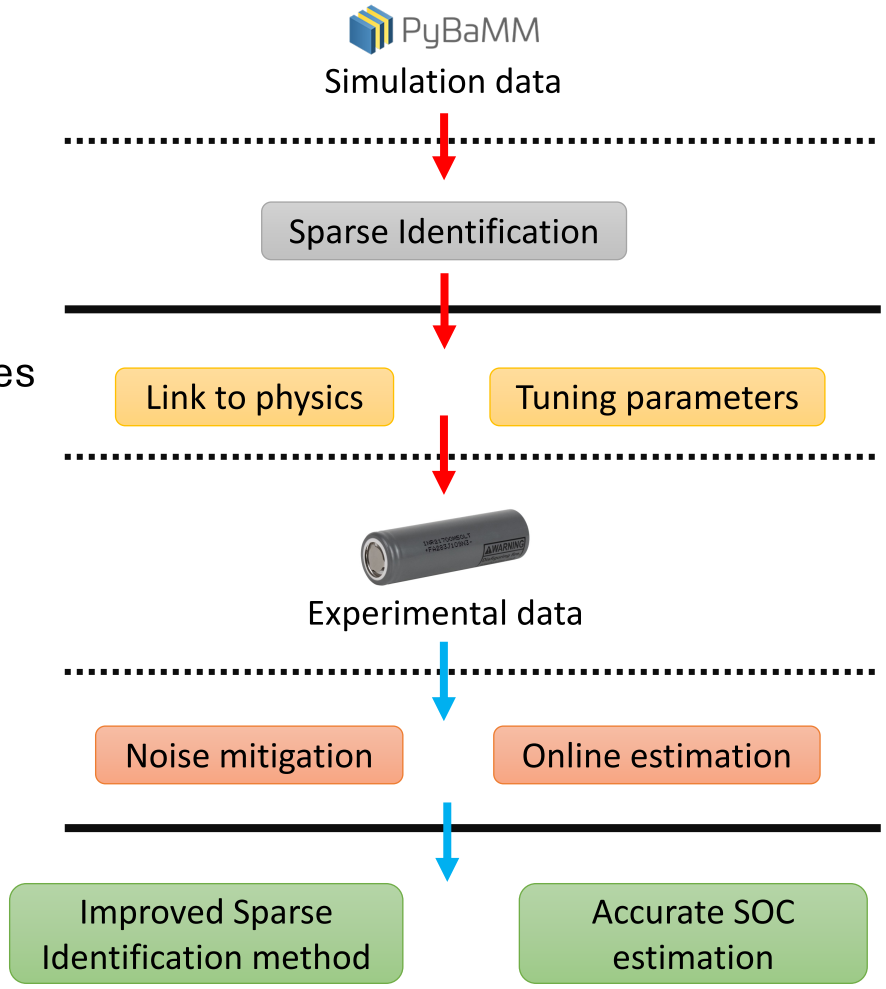
Conclusion

Developed tractable data-driven modeling techniques for complex systems:

- Formulating nonlinear sparse modeling with hyperparameters
- Tuning of sparsification hyperparameters via a novel cost function
- Augmented the technique with a joint unscented Kalman filter to work with noisy data and co-estimation

Contributions to energy storage systems:

- Detailed analysis of complex electrochemical models of Li-ion batteries to determine physics-informed library terms
- Validated the modeling technique on DFN models
- Designed and conducted experiments to generate modeling data
- Created a control-oriented, tractable, interpretable battery model
- Developed a technique to determine voltage-SOC mapping to replace the currently used look-up tables from extensive experiments
- Online SOC estimation via introduced co-estimation framework
- Validated performance across diverse operating ranges, proving robustness and adaptability



Future Work

- **Testing in other Operating Conditions**: Assess model performance in extreme conditions
- **Fast Charging**: Design optimal current profile using the model to reduce charging time
- **Applications to other Cell Chemistries**: Evaluate and extend the model to other chemistries (e.g., sodium-ion)
- **Ensemble Machine Learning**: Improve model accuracy and generalizability
- **Adaptive Modeling**: Evaluate model's online adaption on aged cells

Publications

Journals:

- "Augmented Sparse Nonlinear Identification of Nonlinear Dynamics (aSINDy)," *SIAM Journal on Optimization*, (In Preparation)
- "Online Co-Estimation of State of Charge and Voltage Dynamics of Li-ion Batteries via Physics-Inspired Modeling," *IEEE Trans. Transp. Electrif*, (Under Review), **IF: 7.2**
- "Homogenized Mechanical-Electrochemical-Thermal Model of a Lithium-ion Cell," *eTransportation,* (Under Review), **IF: 15**
- "The Impact of Lightweighting and Battery Technologies on the Sustainability of Electric Vehicles: A Comprehensive Life Cycle Assessment," *Environmental Impact Assessment Review* (2024), **IF: 9.8**
- "A Data-Driven Framework for Learning Governing Equations of Li-ion Batteries and Co-Estimating Voltage and State-of-Charge," *Journal of Energy Storage* (2024), **IF: 8.9**
- "Data-driven Discovery of Lithium-Ion Battery State of Charge Dynamics," *Journal of Dynamic Systems, Measurement, and Control* (2023)

Conferences:

- "Bootstrap-Based Sparse Modeling for Temperature-dependent State-Of-Charge Prediction of Batteries," *2025 American Control Conference (ACC'25)*, (Under Review)
- "Real-time Internal Short Circuit Detection in Li-ion Battery Modules During Field Use," *ACC'24*
- "A Physic-Inspired Machine Learning Nonlinear Model of Li-ion Batteries," *ACC'23*
- "Sparse Modeling of Energy Storage Systems in Presence of Noise," *IFAC-PapersOnLine* (2023)
- "Discovering Governing Equations of Li-ion Batteries Pertaining State of Charge Using Input-Output Data," *ACC'23*
- "Modeling of Li-ion batteries for real-time analysis and control: A data-driven approach," *ACC'22*