SAND2020-3313PE

Battery Energy Storage Control: Modeling, Uncertainty, and Applications

PRESENTED BY

David Rosewater - 03 – 26 – 2020

Presented to the Faculty of the Graduate School of The University of Texas at Austin in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy

Supervisor:

Surya Santoso

Committee Members:

Ross Baldick

Alex Huang

Hao Zhu

Grani Hanasusanto

Raymond Byrne

Sandia National Laboratories is a multimission laboratory managed and operated by National Technology & Engineering Solutions of Sandia, LLC, a wholly owned subsidiary of Honeywell International Inc., for the U.S. Department of Energy's National Nuclear Security Administration under contract DE-NA0003525.

David Rosewater Vita

Educational Background

Montana Tech of the University of Montana

- Bachelor of Science degree in Electrical Engineering 2009
- Master of Science degree in Electrical Engineering 2011

PhD in ECE University of Texas at Austin – Since 2016 (PhD candidate since 2018)

Work Background

2009-2011 - Research intern at the Idaho National Laboratory developing advanced spectral impedance measurement techniques for hybrid vehicles batteries.

2011 – now - Research Scientist at the Sandia National Laboratories in Albuquerque, New Mexico

2014 Professional engineering licensure in the state of New Mexico #22275

IEEE Involvement

2008-2011 - IEEE Student Member

2011-2020 - IEEE Member

2020 - IEEE Senior Member

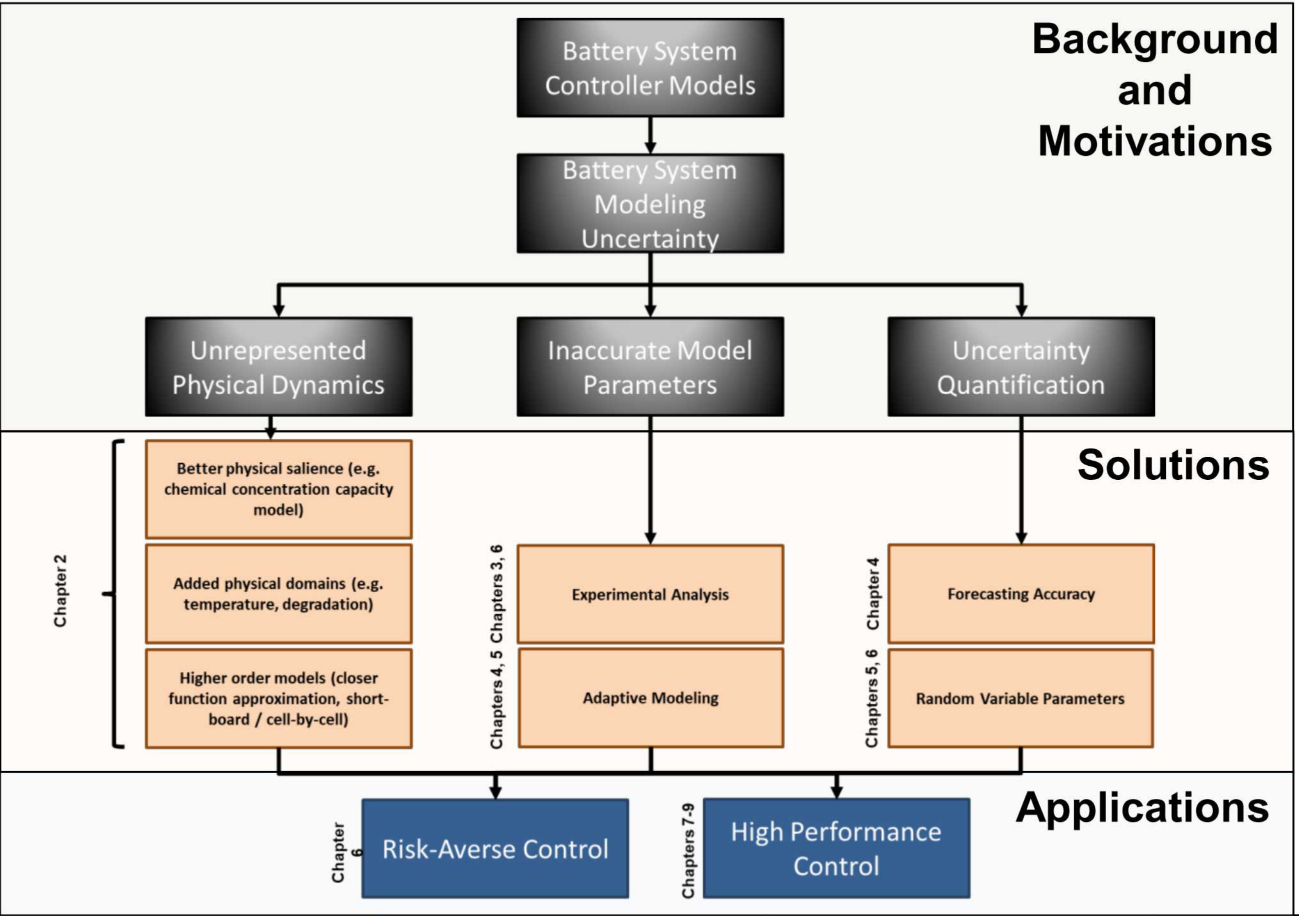
IEEE Standards Association

Started attending the IEEE ESSB Committee in 2013

Appointed as Chair of IEEE P2686 working group in 2018

Active contributor to IEEE 1547.9 since 2018

Summary of Contributions

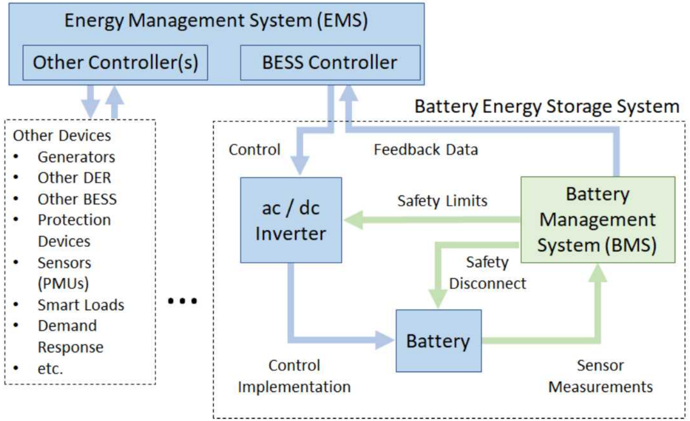


The goal of this dissertation is to understand, reduce, and control modeling uncertainty in battery energy management systems.

Battery Energy Storage Control

A BESS controller is the process responsible for deciding when to charge and discharge the batteries.

Energy storage services can be categorized as those where changes in value is **foreseeable** and those where it is **not foreseeable**.



Foreseeable e.g.
- Peak Saving
- TOU Price Arbitrage

Proactive control can improve effectiveness/value of storage

Not Foreseeable e.g.
- Frequency Regulation
- UPS Backup

Proactive control is either infeasible or trivial

Publications Outline

Part I: Models

- Chapter 2: D. Rosewater, D. Copp, T. Nguyen, R. Byrne, and S. Santoso, "Battery Energy Storage Models for Optimal Control" ***IEEE Access***, December 2019. Article DOI: 10.1109/access.2019.2957698, Code DOI: 10.24433/CO.6925148.v1
- Chapter 3: D. Rosewater, P. Scott, and S. Santoso, "Application of a uniform testing protocol for energy storage systems," in Proc. 2017 IEEE *Power & Energy Society General Meeting*, Chicago, IL, 2017, pp. 1-5. DOI: 10.1109/PESGM.2017.8274603
- Chapter 4: D. Rosewater, S. Ferreira, D. Schoenwald, J. Hawkins, and S. Santoso, "Battery Energy Storage State-of-Charge Forecasting: Models, Optimization, and Accuracy," ***IEEE Trans. Smart Grid***, vol. 10, no. 3, pp. 2453-2462, May 2019. DOI: 10.1109/TSG.2018.2798165

Part II: Uncertainty

- Chapter 5: D. Rosewater, B. Schenkman, and S. Santoso, "Adaptive Modeling Process for a Battery Energy Management System" in Proc. Symposium on Power Electronics, Electrical Drives, Automation and Motion, Sorrento, Italy, June 2020, to be published. [cavoite: not attending due to CDC travel advisory]

Part III: Applications

- Chapter 6: D. Rosewater, R. Baldick, and S. Santoso, "Risk-Averse model predictive control design for battery energy storage systems" ***IEEE Trans. Smart Grid***, September 2019. DOI: 10.1109/TSG.2019.2946130
- Chapter 7: D. Rosewater, Q. Nguyen, and S. Santoso, "Optimal Field Voltage and Energy Storage Control for Stabilizing Synchronous Generators on Flexible AC Transmission Systems," in Proc 2018 IEEE/PES Transmission and Distribution Conference and Exposition (T & D), Denver, CO, 2018, pp. 1-9. DOI: 10.1109/TDC.2018.8440436
- Chapter 8: P. Siratarnsophon, K. W. Lao, D. Rosewater, and S. Santoso, "A Voltage Smoothing Algorithm using Energy Storage PQ Control in PV-integrated Power Grid," in IEEE Transactions on Power Delivery. DOI: 10.1109/TPWRD.2019.2892611
- Chapter 9: D. Rosewater, A. Headley, F. Mier, and S. Santoso, "Optimal Control of a Battery Energy Storage System with a Charge-Temperature-Health Model" in *Proc. 2019 IEEE Power & Energy Society General Meeting*, August 2019

Part 1: Models

Elimination of Unrepresented Dynamics

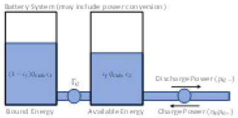
Major Contribution – Performed a comprehensive review of the mathematical models used for optimal control of battery energy storage devices.

D. Rosewater, D. Copp, T. Nguyen, R. Byrne, and S. Santoso, "Battery Energy Storage Models for Optimal Control" ***IEEE Access***, December 2019. Article DOI: 10.1109/access.2019.2957698, Code DOI: 10.24433/CO.6925148.v1

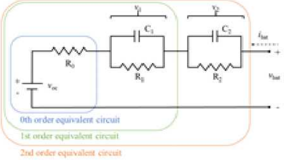
Illustration of the trade-off between model accuracy and complexity

- Parameters may be estimated through experimental analysis.
- Computationally simple enough for many real-time optimal control applications
- Can use generic parameters for chemistry type but this may not achieve desired accuracy level

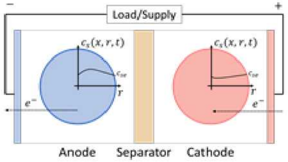
Currently too computationally complex for most control applications



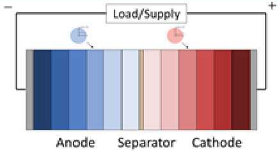
Energy Reservoir Model



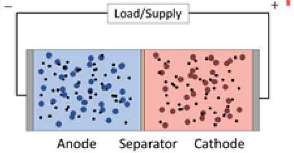
Charge Reservoir Model With Equivalent Circuit



Single Particle Model



Pseudo-Two-Dimensional Model



Detailed Electrochemical Simulation Models

- P3D stack/thermal
- P2D +Stress-strain
- P2D +Population balance
- MD, KMC, etc.

- May require information on battery construction and chemistry that manufacturer considers proprietary
- May be too computationally complex for some control applications

Model Accuracy

Computational Complexity

Battery Energy Storage Models for Optimal Control: Problem Statement

Consider a hypothetical commercial electrical customer billed for power under both time-of-use (TOU) and a \$50/kW demand charge.

Electric Bill without BESS

$$f_s = \Delta t\, \mathbf{w}^\top \mathbf{l} + \max(\mathbf{l})\, \nu$$

Electric Bill with BESS

$$f_s(\mathbf{p}) = \Delta t\, \mathbf{w}^\top (\mathbf{l} + \mathbf{p}) + \max(\mathbf{l} + \mathbf{p})\, \nu$$

where $\mathbf{p}$ is the battery system power that element wise subtracts from $\mathbf{l}$ when the battery system is discharging.

The problem formulation can be expressed as: design an **optimal battery dispatch control scheme** that **minimizes the customer's total bill** subject to the constraints of the battery and the customer's system.

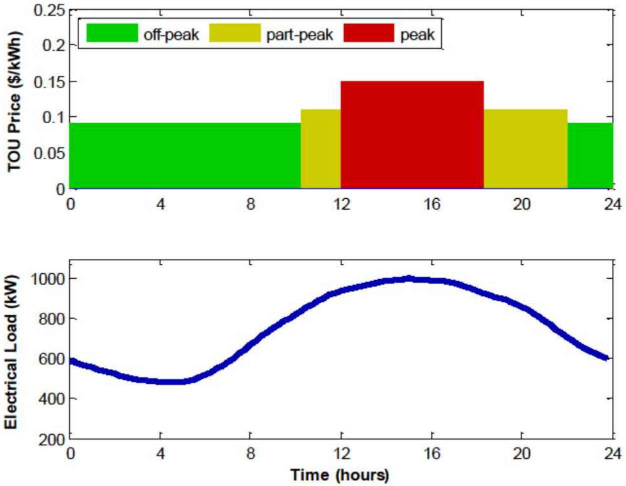


TABLE 1. Summary of case study assumptions.

Ownership	Commercial Electrical Customer
Load Profile	From the EPRI test circuit 'Ckt5' loadshape summer, scaled to a 1.0 MW peak [15].
ToU Tariff	9 ¢/kWh off-peak, 11 ¢/kWh partial-peak hours (9:00 to 21:00), 15 ¢/kWh peak (12:00 to 18:00) [13]
Demand Tariff	ν = \$50/kW based on peak net load [14].
Billing	Daily, 15 minute time steps.

SoC: Energy Reservoir Model

Energy reservoir model (ERM) is a term for the class of SoC models that define capacity in units of energy (kWh).

$$\min_{\mathbf{x}_{\mathrm{ERM}} \in \mathbb{R}^{3n+2}} \Delta t \mathbf{w}^\top (\mathbf{l} + \mathbf{p}^+ + \mathbf{p}^-) + \nu\tau$$

TOU Rate

Demand Charge

subject to:

$$Q_{\mathrm{cap}} \mathbf{D} \varsigma = \eta_e \mathbf{p}^+ + \mathbf{p}^- + p_{\mathrm{sd}}[\mathbf{1}]$$

Energy Reservoir

$$\varsigma_{[1]} = \varsigma_0$$
$$\varsigma_{[1]} = \varsigma_{[n]}$$

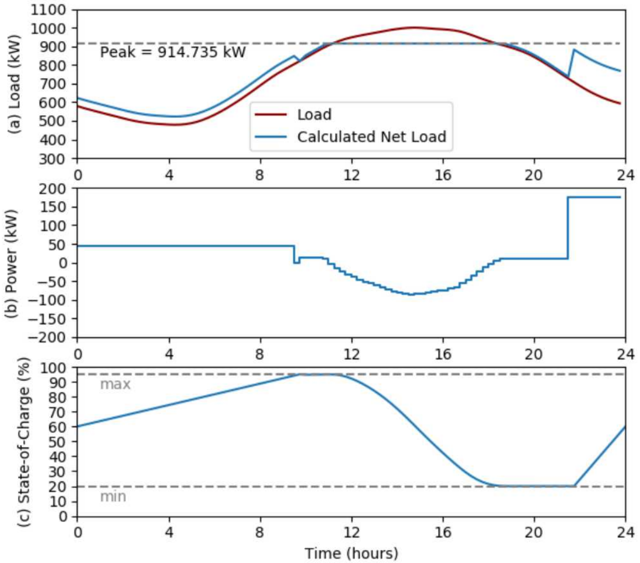
Initial and final SoC

$$p_{\min}[\mathbf{1}] \leq \mathbf{p}^+ + \mathbf{p}^- \leq p_{\max}[\mathbf{1}]$$
$$\varsigma_{\min}[\mathbf{1}] \leq \varsigma \leq \varsigma_{\max}[\mathbf{1}]$$
$$m_1 \varsigma + b_1[\mathbf{1}] \leq \mathbf{p}^+ + \mathbf{p}^- \leq m_2 \varsigma + b_2[\mathbf{1}]$$

Battery Management System Limits

$$\mathbf{l} + \mathbf{p}^+ + \mathbf{p}^- \leq \tau[\mathbf{1}]$$

Peak Power



SoC: Charge Reservoir Model

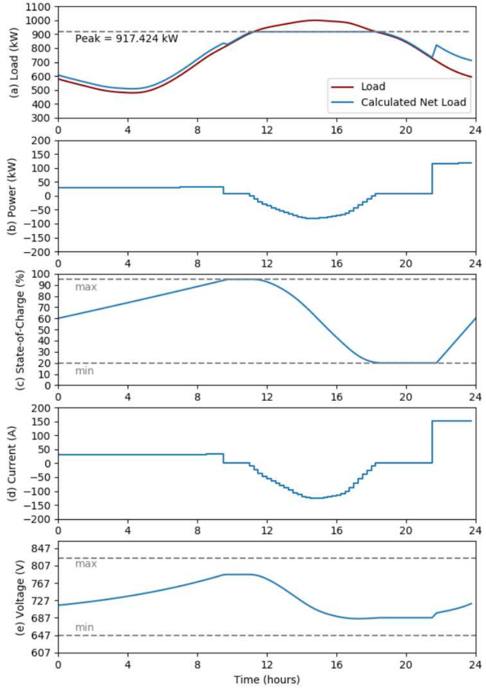
Charge reservoir model (CRM) is a term for the class of SoC models that define capacity in units of energy (Ah).

$$\min_{\mathbf{x}_{\text{CRM}} \in \mathbb{R}^{6n+2}} \quad \Delta t\, \mathbf{w}^\top (\mathbf{l} + \mathbf{p}) + \nu\tau$$

TOU Rate | Demand Charge

subject to:

$\mathbf{p}_{\text{dc}} = \phi_0 \mathbf{p}^2 + \phi_1 \mathbf{p} + \phi_2$	Inverter Efficiency
$\mathbf{p}_{\text{dc}} = (\mathbf{i}^+_{\text{bat}} + \mathbf{i}^-_{\text{bat}}) \mathbf{v}_{\text{bat}}$	Ohms Law
$\mathbf{v}_{\text{bat}} = \mathbf{v}_{oc[1:n]} + R_0 (\mathbf{i}^+_{\text{bat}} + \mathbf{i}^-_{\text{bat}})$	Equivalent Circuit
$\mathbf{v}_{\text{oc}} = \alpha \boldsymbol{\varsigma}^3 + \beta \boldsymbol{\varsigma}^2 + \gamma \boldsymbol{\varsigma} + \delta$	Open-Circuit Voltage
$C_{\text{cap}} \mathbf{D} \boldsymbol{\varsigma} = \eta_c \mathbf{i}^+_{\text{bat}} + \mathbf{i}^-_{\text{bat}}$	Charge Reservoir
$\varsigma_{[1]} = \varsigma_0$, $\varsigma_{[1]} = \varsigma_{[n]}$	Initial and final SoC
$p_{\min}[\mathbf{1}] \le \mathbf{p} \le p_{\max}[\mathbf{1}]$, $\varsigma_{\min}[\mathbf{1}] \le \boldsymbol{\varsigma} \le \varsigma_{\max}[\mathbf{1}]$, $v_{\min}[\mathbf{1}] \le \mathbf{v}_{\text{bat}} \le v_{\max}[\mathbf{1}]$, $i_{\min}[\mathbf{1}] \le \mathbf{i}^-_{\text{bat}} \le [\mathbf{0}]$, $[\mathbf{0}] \le \mathbf{i}^+_{\text{bat}} \le i_{\max}[\mathbf{1}]$	Battery Management System Limits
$\mathbf{l} + \mathbf{p} \le \tau[\mathbf{1}]$	Peak Power



SoC: Single Particle Model (SPM)

TOU Rate | Demand Charge

Single Particle Model (SPM) is a subclass of concentration based SoC models that define capacity in units of energy (mol/cm[3]).

$$\min_{\mathbf{x}_{\text{SPM}} \in \mathbb{R}^{18n+13}} \quad \Delta t\, \mathbf{w}^\top (\mathbf{1}+\mathbf{p}) + \nu\tau \tag{40a}$$

subject to:

$$\mathbf{p}_{\text{dc}} = \phi_0 \mathbf{p}^2 + \phi_1 \mathbf{p} + \phi_2 \tag{40b}$$

$$\mathbf{p}_{\text{dc}} = \mathbf{i}_{\text{bat}} \mathbf{v}_{\text{bat}} \tag{40c}$$

$$\mathbf{v}_{\text{bat}} = \mathbf{\Phi}_{p[1:n]} - \mathbf{\Phi}_{n[1:n]} + \eta_p - \eta_n + R_0 \mathbf{i}_{\text{bat}} \tag{40d}$$

$$\mathbf{\Phi}_j = v^0_{bat} + \frac{RT}{F} \ln\left(\frac{c_{j,max} - \mathbf{c}_{j,0}}{\mathbf{c}_{j,0}}\right) + \sum_{k=0}^{N} \frac{A_k}{F}\left[\left(\frac{2\mathbf{c}_{j,0}}{c_{j,max}} - 1\right)^{k+1} - \frac{2\mathbf{c}_{j,0} k (c_{j,max} - \mathbf{c}_{s,j,0})}{c_{j,max}\left(2\frac{\mathbf{c}_{j,0}}{c_{j,max}} - 1\right)^{1-k}}\right] \tag{40e}$$

$$\frac{\mathbf{i}_{\text{bat}}}{a_{s,j} A_{s,j} L_{s,j}} = k_{s,j} c_{j,max} c_e^{0.5} (-\mathbf{c}_{j,0[1:n]})^{0.5} \mathbf{c}^{0.5}_{j,0[1:n]} \times \left\{\exp\left(\frac{0.5\,F}{RT}\eta_j\right) - \exp\left(-\frac{0.5\,F}{RT}\eta_j\right)\right\} \tag{40f}$$

$$V_{j,0} \mathbf{D} \mathbf{c}_{j,0} = \frac{S_{j,0}\, \mathbf{i}_{\text{bat}}}{F\, a_{s,j} A_{s,j} L_{s,j}} - \frac{D_{s,j} S_{j,1} (\mathbf{c}_{j,1[1:n]} - \mathbf{c}_{j,0[1:n]})}{dr} \tag{40g}$$

$$\frac{dr\, V_{j,1}}{D_{s,j}} \mathbf{D}\mathbf{c}_{j,1} = S_{j,1}(\mathbf{c}_{j,0[1:n]} - \mathbf{c}_{j,1[1:n]}) + S_{j,2}(\mathbf{c}_{j,2[1:n]} - \mathbf{c}_{j,1[1:n]})$$

$$\frac{dr\, V_{j,2}}{D_{s,j}} \mathbf{D}\mathbf{c}_{j,2} = S_{j,2}(\mathbf{c}_{j,1[1:n]} - \mathbf{c}_{j,2[1:n]}) + S_{j,3}(\mathbf{c}_{j,3[1:n]} - \mathbf{c}_{j,2[1:n]})$$

$$\frac{dr\, V_{j,3}}{D_{s,j}} \mathbf{D}\mathbf{c}_{j,3} = S_{j,3}(\mathbf{c}_{j,2[1:n]} - \mathbf{c}_{j,3[1:n]}) + S_{j,4}(\mathbf{c}_{j,4[1:n]} - \mathbf{c}_{j,3[1:n]})$$

$$\frac{dr\, V_{j,4}}{D_{s,j}} \mathbf{D}\mathbf{c}_{j,4} = S_{j,4}(\mathbf{c}_{j,3[1:n]} - \mathbf{c}_{j,4[1:n]})$$

$$\mathbf{c}_{j,\{0:4\},[1]} = \mathbf{c}_{j,\text{init}}[\mathbf{1}]$$

$$\mathbf{c}_{j,\{0:4\},[n]} = \mathbf{c}_{j,\text{init}}[\mathbf{1}]$$

$$p_{\min}[\mathbf{1}] \le \mathbf{p} \le p_{\max}[\mathbf{1}]$$

$$v_{\min}[\mathbf{1}] \le \mathbf{v}_{\text{bat}} \le v_{\max}[\mathbf{1}]$$

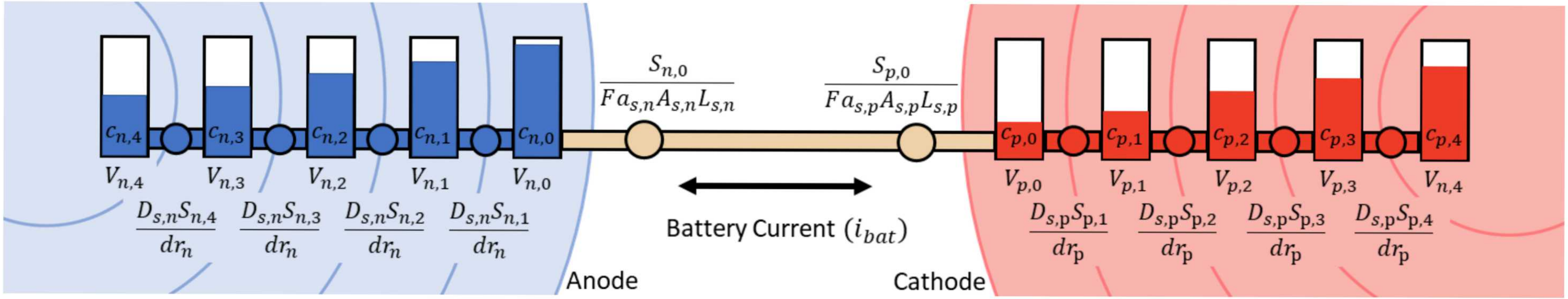
$$i_{\min}[\mathbf{1}] \le \mathbf{i}_{\text{bat}} \le i_{\max}[\mathbf{1}]$$

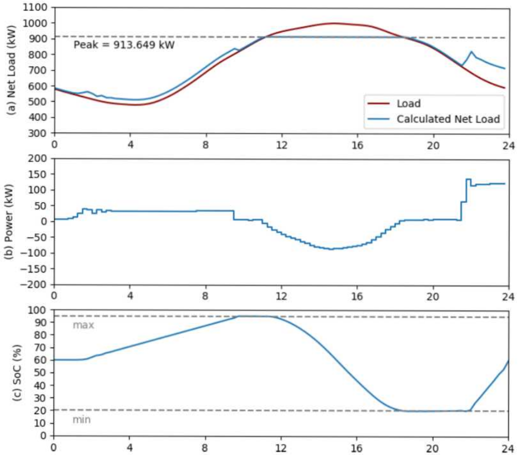
$$[\mathbf{0}] \le \mathbf{c}_{j,\{0:4\}} \le c_{j,max}[\mathbf{1}]$$

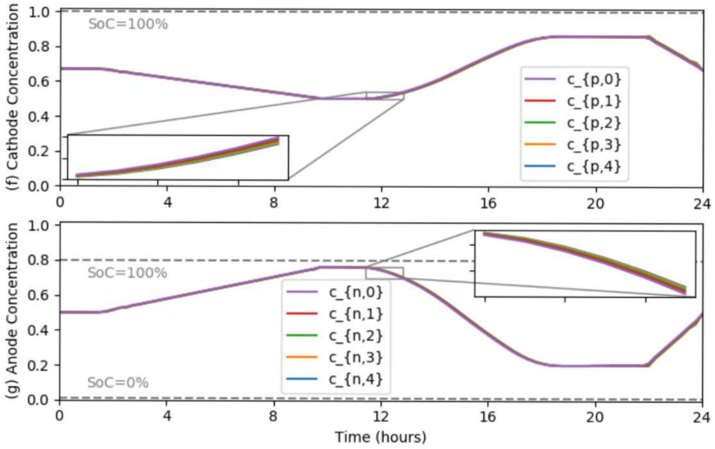
$$\mathbf{1} + \mathbf{p} \le \tau[\mathbf{1}]$$

- Inverter Efficiency
- Ohms Law
- Cell Voltage
- Chemical potential
- Butler-Volmer equation
- Concentration Model
- Initial and final SoC
- Battery Management System Limits
- Peak Power

SoC: Single Particle Model (SPM)

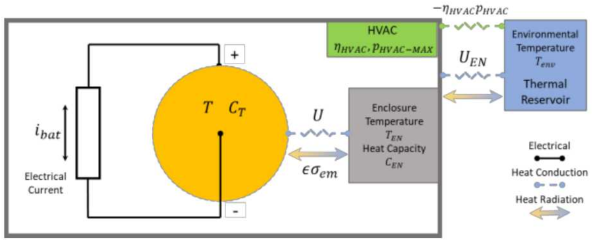






Temperature

An enclosure can also be modeled using the heat generation and transfer discussed above. Heat is generated in the hottest cell in the system, transferred to the enclosure, then transferred to the environment.



$$\min_{\mathbf{x}_T \in \mathbb{R}^{9n+5}} \quad \Delta t\, \mathbf{w}^\top(\mathbf{l} + \mathbf{p} + \mathbf{p}_{\text{HVAC}}) + \nu\tau \tag{55a}$$

subject to:

$\vdots$ in addition to the constraints in (28)

$$\mathbf{l} + \mathbf{p} + \mathbf{p}_{\text{HVAC}} \le \tau \tag{55b}$$

$$C_T \mathbf{D}\mathbf{T} = R_0(\mathbf{i}_{\text{bat}})^2 + U(\mathbf{T}_{\text{EN}[1:n]} - \mathbf{T}_{[1:n]}) \tag{55c}$$

$$C_{\text{EN}} \mathbf{D}\mathbf{T}_{\text{EN}} = K_{\text{H}}(\mathbf{T}_{[1:n]} - \mathbf{T}_{\text{EN}[1:n]}) + U_{\text{EN}}(\mathbf{T}_{\text{env}} - \mathbf{T}_{\text{EN}[1:n]}) - \eta_{\text{HVAC}}\mathbf{p}_{\text{HVAC}} \tag{55d}$$

$$\mathbf{T}_{[1]} = T_0 \tag{55e}$$

$$\mathbf{T}_{\text{EN}[1]} = T_0 \tag{55f}$$

$$\mathbf{T} \le T_{\max}[\mathbf{1}] \tag{55g}$$

$$[\mathbf{0}] \le \mathbf{p}_{\text{HVAC}} \le p_{\text{HVAC-max}}[\mathbf{1}] \tag{55h}$$

TOU Rate

Demand Charge

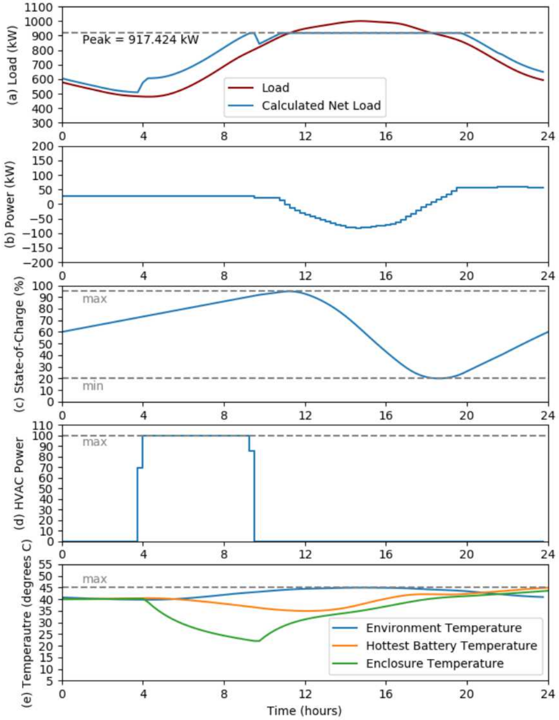
Peak Power

Hottest Cell Temperature

Enclosure Temperature

High Temperature Limit

HVAC Power Limit



Degradation

Rainflow counting is a recursive algorithm and so is not simple to incorporate into optimization. However, if we assume only one cycle in the control horizon, it can be simplified.

$$\min_{\mathbf{x}_{\mathrm{H}} \in \mathbb{R}^{9n+12}} \quad \Delta t\, \mathbf{w}^\top (\mathbf{l} + \mathbf{p} + \mathbf{p}_{\mathrm{HVAC}}) + \nu\tau + \mathrm{C}_{\mathrm{EoL}}\, \dot{\varrho}$$

TOU Rate

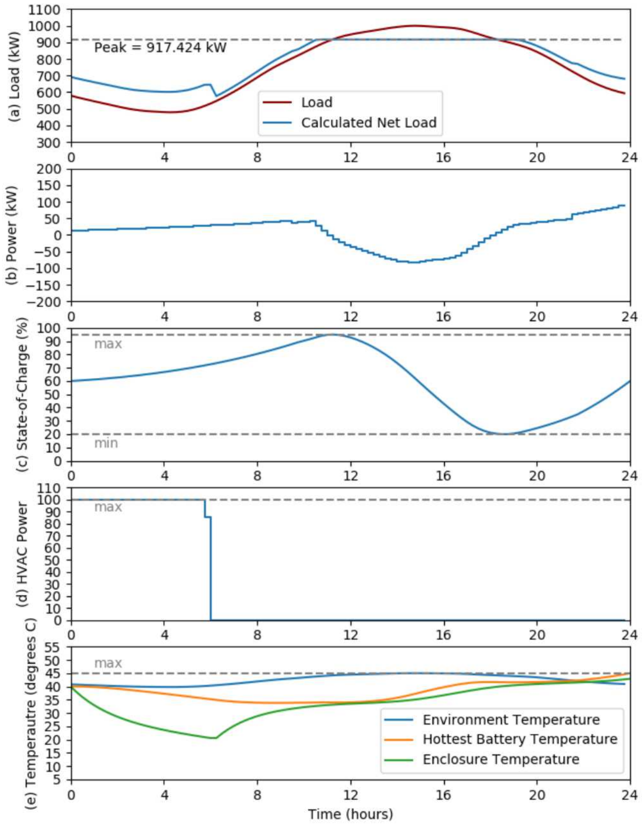
Demand Charge

Degradation Cost

subject to:

$\vdots$ in addition to the constraints in (28) and (55)

$\dot{\varrho} = -k_{\mathrm{t}}\, S_{\varsigma}\, S_{\mathrm{T}}\, e^{-\mathfrak{f}_{\mathrm{d}}}$	Degradation Rate
$\mathfrak{f}_{\mathrm{d}} = S_{\mathrm{t}}\, S_{\varsigma}\, S_{\mathrm{T}} + S_{\delta}\, S_{\varsigma}\, S_{\mathrm{T}}$	Driving Function
$S_{\mathrm{t}} = k_{\mathrm{t}}\, n\, \Delta t$	Time Stress Factor
$S_{\varsigma} = e^{k_{\varsigma}\left(\frac{\lVert\varsigma\rVert_1}{n} - \varsigma_{\mathrm{ref}}\right)}$	SoC Stress Factor
$S_{\mathrm{T}} = e^{k_{\mathrm{T}}(\lVert\mathbf{T}\rVert_1 - T_{\mathrm{ref}})\frac{T_{\mathrm{ref}}}{\lVert\mathbf{T}\rVert_1}}$	Temperature Stress Factor
$\delta = \max(\varsigma) - \min(\varsigma)$ $S_{\delta} = a\,\delta^4 + b\,\delta^3 + c\,\delta^2 + d\,\delta + e$	Depth-of-Discharge Stress Factor

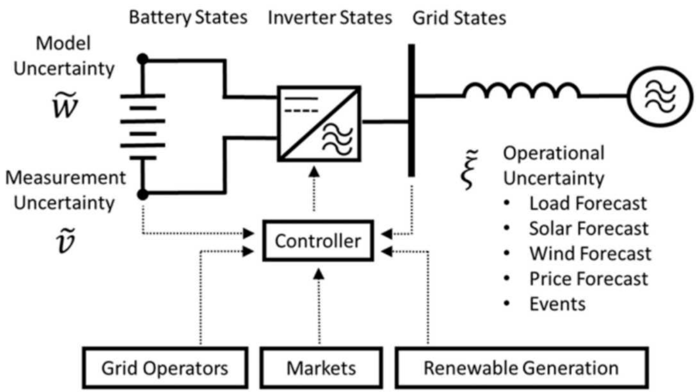


Part II: Uncertainty

Modeling Error Minimization

Minor Contribution – Develops a process for the EMS to calculate and improve the accuracy of its control model using the operational data produced by the battery system

D. Rosewater, B. Schenkman, and S. Santoso, “Adaptive Modeling Process for a Battery Energy Management System” in Proc. Symposium *on Power Electronics, Electrical Drives, Automation and Motion*, Sorrento, Italy, June 2020, to be published.



Sources of Model Uncertainty

<u>Unrepresented dynamics</u>
e.g.
Modeling Assumption:
Open circuit voltage is a function of state of charge.

Source of Uncertainty:
Open circuit voltage is also a function of temperature

<u>Inaccurate parameters</u>
e.g.
Modeling Assumption:
Battery capacity is 100 Ah at a 10 A discharge rate

Source of Uncertainty:
Aging reduces battery capacity to 90 Ah

Parameter Estimation Methodologies

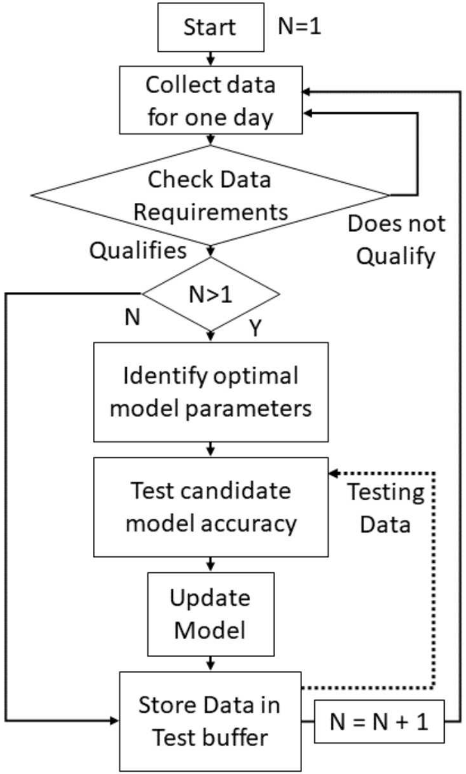
Specifications:
Prior to a system being built the manufacture can supply specifications of the system's expected performance
Pro: easy, quick
Con: aspirational or conservative values, mismatch between expected and actual use

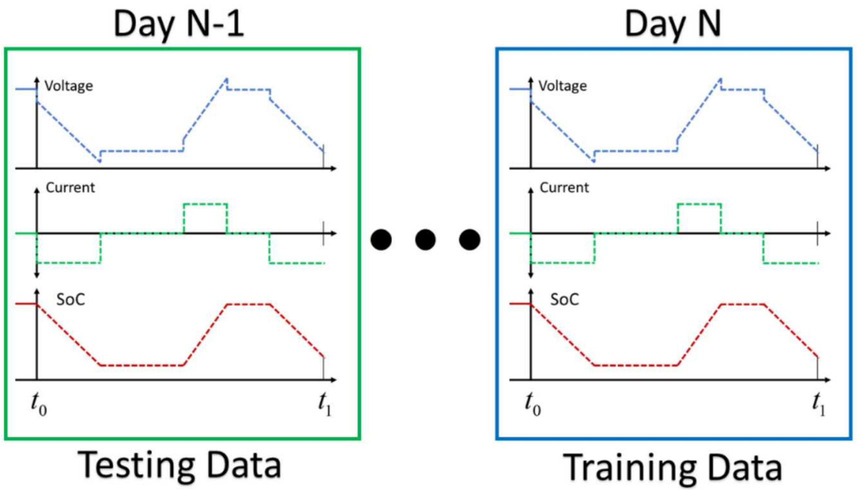
Testing Metrics: See Chapter 3
As soon as a system is built tests can be performed to estimate performance metrics that are relevant to the SoC forecasting model
Con: mismatch between expected and actual use

Operational Data:
Once a BESS is installed and operational, the data collected from it can be used to further improve forecasting accuracy.

Operational Data

We reduce the prior knowledge of the battery that the EMS needs to get started, improve the prediction accuracy over alternatives methods, and to calculate and track modeling uncertainty such that the model can be used for risk-averse or robust state estimation and control.





Model Training

Step 1: Identify optimal Model Parameters

Capacity and Efficiency

$$\min_{\mathbf{x}_1 \in \mathbb{R}^{n+3}} ||\varsigma - \hat{\varsigma}||_2^2$$

subject to :

$$\hat{C}_{\text{cap}} \mathbf{D} \hat{\varsigma} = \hat{\eta}_c \mathbf{i}^+ + \mathbf{i}^-$$

$$\mathbf{x}_1 = \left\{ \hat{\varsigma}, \hat{\eta}_c, \hat{C}_{\text{cap}} \right\} \in \mathbb{R}^{n+3}$$

$\hat{\varsigma}$

OCV and Equivalent Circuit

$$\min_{\mathbf{x}_2 \in \mathbb{R}^{3n+12}} ||\mathbf{v} - \hat{\mathbf{v}}||_2^2$$

subject to :

$$\hat{\mathbf{v}} = \hat{\mathbf{v}}_{oc\,[1:n]} + \hat{\mathbf{v}}_{1\,[1:n]} + \hat{R}_c^+ \mathbf{i}^+ + \hat{R}_d^- \mathbf{i}^-$$

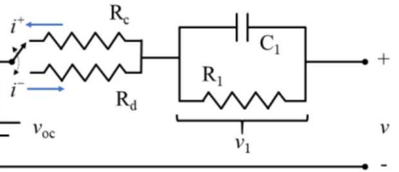
$$\mathbf{D}\hat{\mathbf{v}}_1 = -\frac{\hat{\mathbf{v}}_{1\,[1:n]}}{\hat{R}_1 \hat{C}_1} + \frac{\mathbf{i}^+ + \mathbf{i}^-}{\hat{C}_1}$$

$$\hat{\mathbf{v}}_{\text{oc}} = \hat{\alpha}\hat{\boldsymbol{\varsigma}}^3 + \hat{\beta}\hat{\boldsymbol{\varsigma}}^2 + \hat{\gamma}\hat{\boldsymbol{\varsigma}} + \hat{\delta}$$

$$v_{\text{oc-max}} = \hat{\alpha}\varsigma_{\text{max}}^3 + \hat{\beta}\varsigma_{\text{max}}^2 + \hat{\gamma}\varsigma_{\text{max}} + \hat{\delta}$$

$$v_{\text{oc-min}} = \hat{\alpha}\varsigma_{\text{min}}^3 + \hat{\beta}\varsigma_{\text{min}}^2 + \hat{\gamma}\varsigma_{\text{min}} + \hat{\delta}$$

$$3\hat{\alpha}\varsigma_{\text{hold}}^2 + 2\hat{\beta}\varsigma_{\text{hold}} + \hat{\gamma} \geq 0$$



$$\mathbf{x}_2 = \left\{ \hat{\mathbf{v}}, \hat{\mathbf{v}}_{oc}, \hat{\mathbf{v}}_1, \hat{R}_c, \hat{R}_d, \hat{R}_1, \hat{C}_1, \hat{\alpha}, \hat{\beta}, \hat{\gamma}, \hat{\delta} \right\} \in \mathbb{R}^{3n+12}$$

Model Testing and Update

Step 2: Calculate Model Error on Testing Data

$$\varepsilon_{\text{RMS}} = \sqrt{\frac{\sum_{k=1}^{n}(v_k - \hat{v}_k)^2}{n}}$$

$$\varepsilon_{\%} = \sum_{k=1}^{n} \frac{|v_k - \hat{v}_k|}{v_k}$$

$\varepsilon_{\%}$

Step 3: Update equivalent circuit, capacity, and efficiency parameters

Learning Rate

$$\Gamma = \min\left\{\frac{0.05}{\varepsilon_{\%}}, 0.25\right\}$$

Equivalent Circuit Model Parameter Update

$$R_c = (1-\Gamma)R_c + \Gamma \hat{R}_c$$
$$R_d = (1-\Gamma)R_d + \Gamma \hat{R}_d$$
$$R_1 = (1-\Gamma)R_1 + \Gamma \hat{R}_1$$
$$C_1 = (1-\Gamma)C_1 + \Gamma \hat{C}_1$$

Capacity and Efficiency Update

$$C_{cap} = (1-\Gamma)C_{cap} + \Gamma \hat{C}_{cap}$$
$$\eta_c = (1-\Gamma)\eta_c + \Gamma \hat{\eta}_c$$

Model Testing and Update

Step 4: Update open circuit voltage holding values

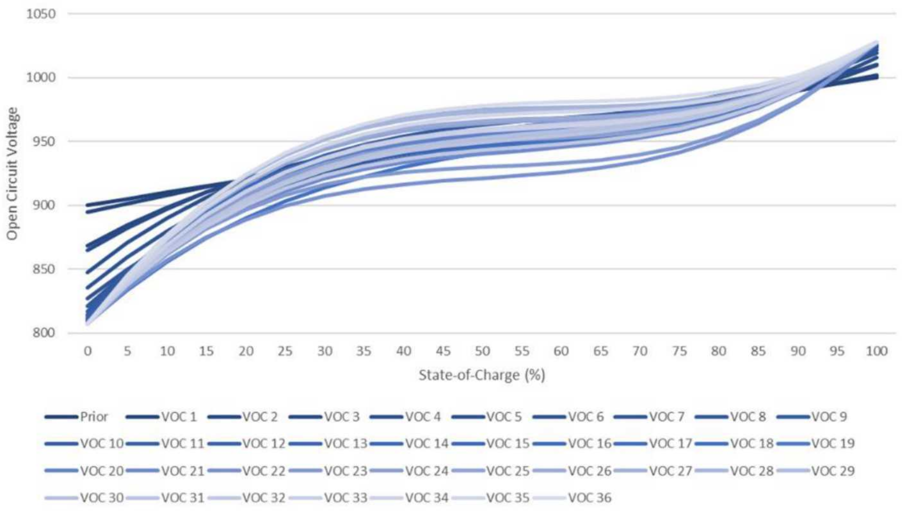
$$v_{oc-\text{hold}}(\varsigma) \mathrel{+}= \frac{\Gamma}{m}\sum_{k=1}^{m}\mathcal{N}(\varsigma - \varsigma_{\text{hold-k}})\left(\hat{\alpha}\varsigma_{\text{hold-k}}^{3} + \hat{\beta}\varsigma_{\text{hold-k}}^{2} + \hat{\gamma}\varsigma_{\text{hold-k}}^{3} + \hat{\delta}\right)$$

Learning Rate

Probability that the SoC equals the holding SoC

Estimated Parameters from Step 3

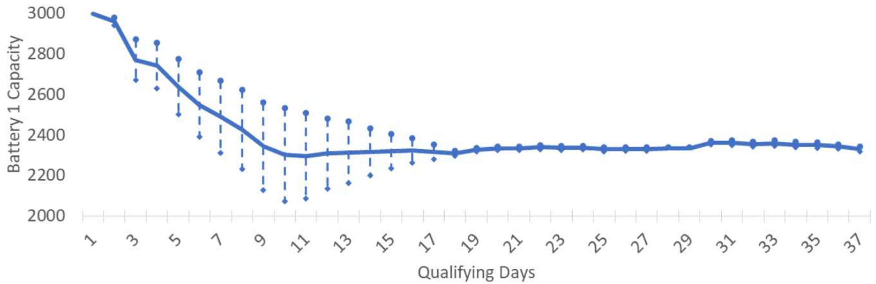
Step 5: Re-fit the holding values to update OCV function

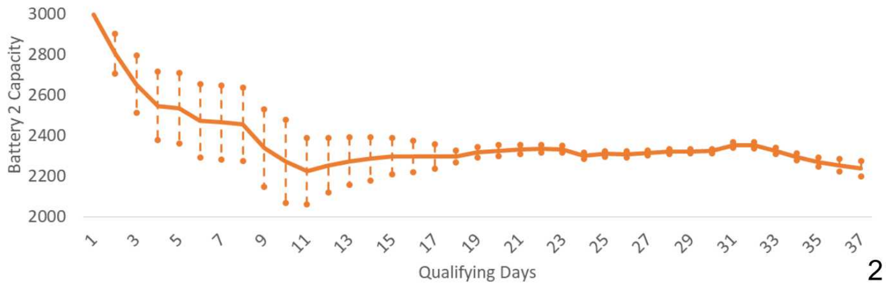


Results for Data Collected in 2019-2020

Sterling MA

Parameter uncertainty is calculated as the standard deviation of the previous ten estimates.





Part III: Applications

Risk-Averse Optimal Control

Major Contribution – Enabled the application of a more accurate, but non-convex, battery system model by calculating upper and lower bounds on the globally optimal control solution.

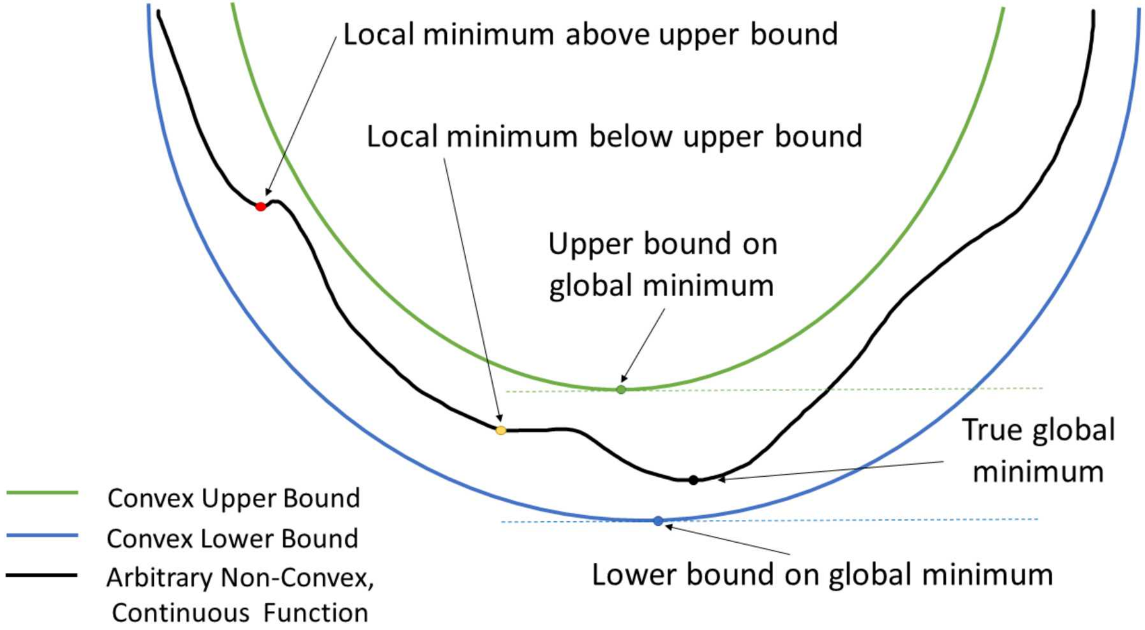
Major Contribution – Modified battery controller model to consistently underestimate capacity by a statistically selected margin, thereby hedging its control decisions against normal variations in battery system performance.

D. Rosewater, R. Baldick, and S. Santoso, "Risk-Averse model predictive control design for battery energy storage systems" ***IEEE Trans. Smart Grid***, September 2019. DOI: 10.1109/TSG.2019.2946130

Problem 1: The CRM is non-convex

CRM-based control is a non-convex problem, meaning gradient based optimization solvers are not guaranteed to produce the global minimum.

Approach: Bound the Solution to the CRM-based optimal control problem between two related convex problems



Lower Bound (constraint relaxation)

Original non-convex problem

$$\min_{\mathbf{x}_c \in \mathbb{R}^{8n+3}} \quad \Delta t\, \mathbf{c}^T(\mathbf{l}+\mathbf{p}) + \tau\, d + \Pi_1 ||\mathbf{p}||_2^2 + \Pi_2 ||\mathbf{v}_s||_1 \quad (5a)$$

subject to:

$$\phi_0 \mathbf{p}^2 + \phi_1 \mathbf{p} + \phi_2 \geq \mathbf{p}_{\text{dc}} \quad (5b)$$

$$\mathbf{p}_{\text{dc}} = (\mathbf{i}^+_{\text{bat}} + \mathbf{i}^-_{\text{bat}})\mathbf{v}_{\text{bat}} \quad (5c)$$

$$\mathbf{v}_{\text{bat}} = \mathbf{v}_{oc\,[1:n]} + R_0(\mathbf{i}^+_{\text{bat}} + \mathbf{i}^-_{\text{bat}}) + \mathbf{v}_s \quad (5d)$$

$$\mathbf{v}_{\text{oc}} = \alpha \boldsymbol{\varsigma}^3 + \beta \boldsymbol{\varsigma}^2 + \gamma \boldsymbol{\varsigma} + \delta \quad (5e)$$

$$C_{\text{cap}} \mathbf{D} \boldsymbol{\varsigma} = \eta_c \mathbf{i}^+_{\text{bat}} + \mathbf{i}^-_{\text{bat}} \quad (5f)$$

$$\varsigma_1 = \varsigma_0 \quad (5g)$$

$$\varsigma_1 = \varsigma_{n+1} \quad (5h)$$

$$p_{\min}[\mathbf{1}] \leq \mathbf{p} \leq p_{\max}[\mathbf{1}] \quad (5i)$$

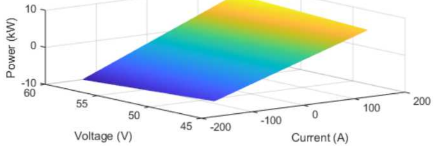
$$\varsigma_{\min}[\mathbf{1}] \leq \boldsymbol{\varsigma} \leq \varsigma_{\max}[\mathbf{1}] \quad (5j)$$

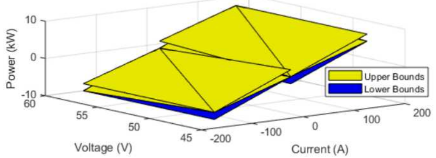
$$v_{\min}[\mathbf{1}] \leq \mathbf{v}_{\text{bat}} \leq v_{\max}[\mathbf{1}] \quad (5k)$$

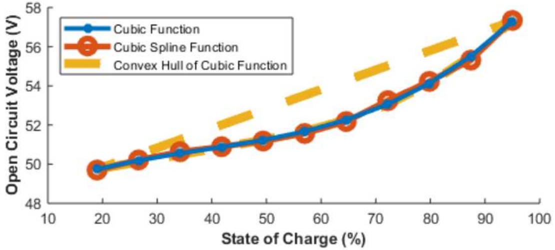
$$[\mathbf{0}] \leq \mathbf{i}^+_{\text{bat}} \leq i_{\max}[\mathbf{1}] \quad (5l)$$

$$i_{\min}[\mathbf{1}] \leq \mathbf{i}^-_{\text{bat}} \leq [\mathbf{0}] \quad (5m)$$

$$\mathbf{l} + \mathbf{p} \leq \tau[\mathbf{1}] \quad (5n)$$







$$\min_{\substack{\mathbf{x}_c \in \mathbb{R}^{8n+3} \\ \mathbf{p}^+_{\text{dc}} \in \mathbb{R}^n_+ \\ \mathbf{p}^-_{\text{dc}} \in \mathbb{R}^n_-}} \quad \Delta t\, \mathbf{c}^T(\mathbf{l}+\mathbf{p}) + \tau\, d + \Pi_1 ||\mathbf{p}||_2^2 + \Pi_2 ||\mathbf{v}_s||_1$$

subject to: $\vdots$ (5d) and (5f) through (5n) unchanged

relaxing (5b) $\phi_0 \mathbf{p}^2 + \phi_1 \mathbf{p} + \phi_2 \geq \mathbf{p}^+_{\text{dc}} + \mathbf{p}^-_{\text{dc}}$ (7a)

relaxing (5c) $\mathbf{A}_1[\mathbf{i}^+_{\text{bat}}, \mathbf{v}_{\text{bat}}, \mathbf{p}^+_{\text{dc}}]^T \leq \mathbf{b}_1[\mathbf{1}]_{1\times n}$ (7b)

$\mathbf{A}_2[\mathbf{i}^-_{\text{bat}}, \mathbf{v}_{\text{bat}}, \mathbf{p}^-_{\text{dc}}]^T \leq \mathbf{b}_2[\mathbf{1}]_{1\times n}$ (7c)

relaxing (5e) $\mathbf{A}_3[\boldsymbol{\varsigma}, \mathbf{v}_{\text{oc}}]^T \leq \mathbf{b}_3[\mathbf{1}]_{1\times n}$ (7d)

Upper Bound (constraint restriction)

Original non-convex problem

$$\min_{\mathbf{x}_c \in \mathbb{R}^{8n+3}} \Delta t\, \mathbf{c}^T(\mathbf{l}+\mathbf{p}) + \tau\, d + \Pi_1||\mathbf{p}||_2^2 + \Pi_2||\mathbf{v}_s||_1 \quad (5a)$$

subject to:

$$\phi_0\mathbf{p}^2 + \phi_1\mathbf{p} + \phi_2 \geq \mathbf{p}_{\text{dc}} \quad (5b)$$

$$\mathbf{p}_{\text{dc}} = (\mathbf{i}_{\text{bat}}^+ + \mathbf{i}_{\text{bat}}^-)\mathbf{v}_{\text{bat}} \quad (5c)$$

$$\mathbf{v}_{\text{bat}} = \mathbf{v}_{oc\,[1:n]} + R_0(\mathbf{i}_{\text{bat}}^+ + \mathbf{i}_{\text{bat}}^-) + \mathbf{v}_s \quad (5d)$$

$$\mathbf{v}_{\text{oc}} = \alpha\boldsymbol{\varsigma}^3 + \beta\boldsymbol{\varsigma}^2 + \gamma\boldsymbol{\varsigma} + \delta \quad (5e)$$

$$C_{\text{cap}}\mathbf{D}\boldsymbol{\varsigma} = \eta_c\mathbf{i}_{\text{bat}}^+ + \mathbf{i}_{\text{bat}}^- \quad (5f)$$

$$\varsigma_1 = \varsigma_0 \quad (5g)$$

$$\varsigma_1 = \varsigma_{n+1} \quad (5h)$$

$$p_{\text{min}}[\mathbf{1}] \leq \mathbf{p} \leq p_{\text{max}}[\mathbf{1}] \quad (5i)$$

$$\varsigma_{\text{min}}[\mathbf{1}] \leq \boldsymbol{\varsigma} \leq \varsigma_{\text{max}}[\mathbf{1}] \quad (5j)$$

$$v_{\text{min}}[\mathbf{1}] \leq \mathbf{v}_{\text{bat}} \leq v_{\text{max}}[\mathbf{1}] \quad (5k)$$

$$[\mathbf{0}] \leq \mathbf{i}_{\text{bat}}^+ \leq i_{\text{max}}[\mathbf{1}] \quad (5l)$$

$$i_{\text{min}}[\mathbf{1}] \leq \mathbf{i}_{\text{bat}}^- \leq [\mathbf{0}] \quad (5m)$$

$$\mathbf{l} + \mathbf{p} \leq \tau[\mathbf{1}] \quad (5n)$$

$$\min_{\substack{\mathbf{x}_c \in \mathbb{R}^{8n+3} \\ \boldsymbol{\nu}_{1-5} \in \mathbb{R}_+^{n+1} \\ \varsigma_{1-5} \in \mathbb{R}_+^{n+1} \\ \mathbf{w}_{1-5} \in \{0,1\}^{n+1}}} \Delta t\, \mathbf{c}^T(\mathbf{l}+\mathbf{p}) + \tau\, d + \Pi_1||\mathbf{p}||_2^2 + \Pi_2||\mathbf{v}_s||_1$$

subject to: ⋮ (5b) and (5f) through (5n) unchanged

restricting (5c) $\mathbf{p}_{\text{dc}} = (\mathbf{i}_{\text{bat}}^+ + \mathbf{i}_{\text{bat}}^-)v_{\text{ocmin}}$ (8a)

restricting (5d) $v_{\text{ocmin}}[\mathbf{1}] = \mathbf{v}_{oc\,[1:n]} + R_0(\mathbf{i}_{\text{bat}}^+ + \mathbf{i}_{\text{bat}}^-) + \mathbf{v}_s$ (8b)

Constant Battery Voltage

approx. (5e) $\mathbf{v}_{\text{oc}} = v_{\text{ocmin}}[\mathbf{1}] + \boldsymbol{\nu}_1 + \boldsymbol{\nu}_2 + \boldsymbol{\nu}_3 + \boldsymbol{\nu}_4 + \boldsymbol{\nu}_5$ (8c)

$$\boldsymbol{\varsigma} = \varsigma_{\text{min}}[\mathbf{1}] + \varsigma_1 + \varsigma_2 + \varsigma_3 + \varsigma_4 + \varsigma_5 \quad (8d)$$

$$[\boldsymbol{\nu}_1, \boldsymbol{\nu}_2, \boldsymbol{\nu}_3, \boldsymbol{\nu}_4, \boldsymbol{\nu}_5]^T = \mathbf{A}_4[\varsigma_1, \varsigma_2, \varsigma_3, \varsigma_4, \varsigma_5]^T \quad (8e)$$

$$\varsigma_{\text{seg}}\mathbf{w}_1 \leq \varsigma_1 \leq \varsigma_{\text{seg}} \quad (8f)$$

$$\varsigma_{\text{seg}}\mathbf{w}_2 \leq \varsigma_2 \leq \varsigma_{\text{seg}}\mathbf{w}_1 \quad (8g)$$

$$\varsigma_{\text{seg}}\mathbf{w}_3 \leq \varsigma_3 \leq \varsigma_{\text{seg}}\mathbf{w}_2 \quad (8h)$$

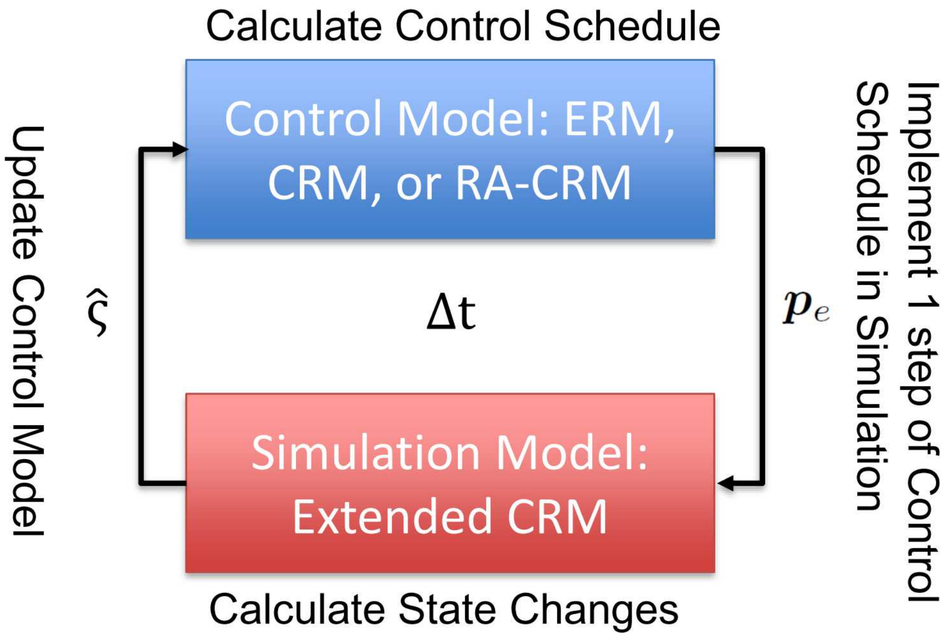
$$\varsigma_{\text{seg}}\mathbf{w}_4 \leq \varsigma_4 \leq \varsigma_{\text{seg}}\mathbf{w}_3 \quad (8i)$$

$$0 \leq \varsigma_5 \leq \varsigma_{\text{seg}}\mathbf{w}_4 \quad (8j)$$

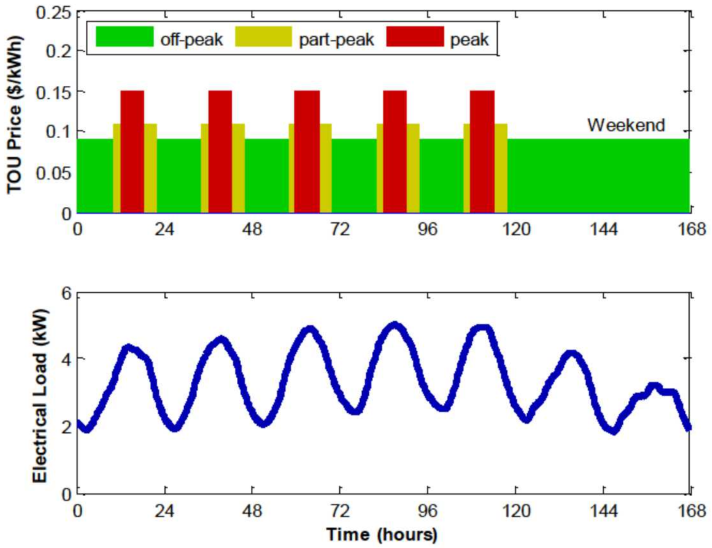
Piecewise-linear OCV approximation

Pseudo-empirical analysis of optimal control performance

- Model parameters calculated through lab testing
- ERM used as state-of-the-art baseline

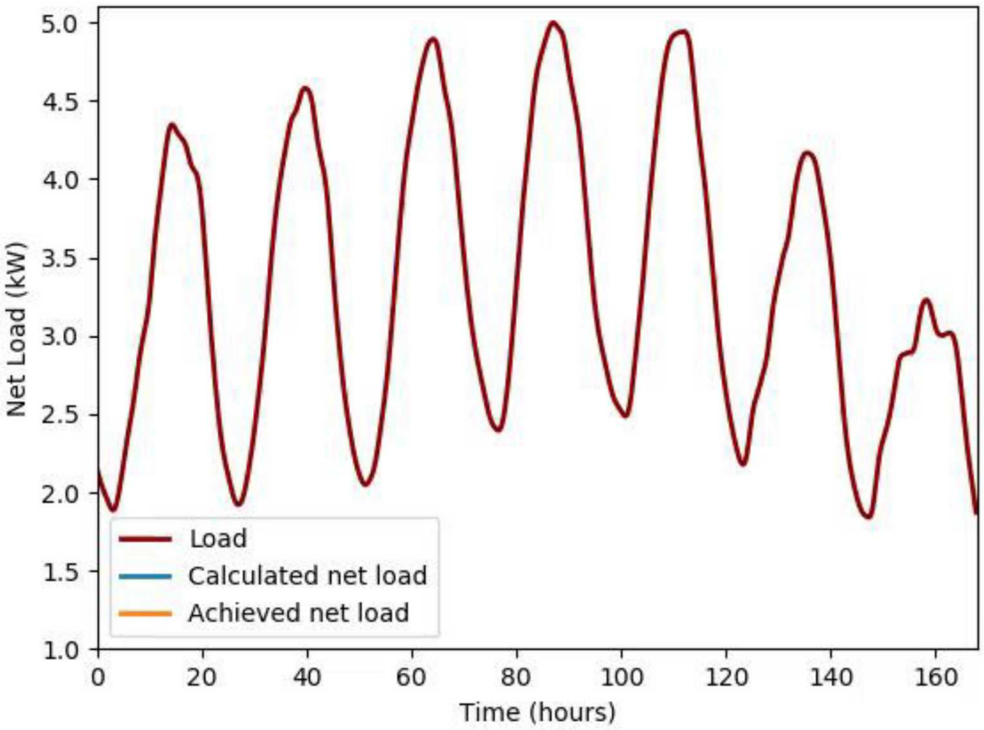


Modified controller objective (1 week):



Closed-loop control: Available Energy Overestimation

Example of model overestimation with closed loop control



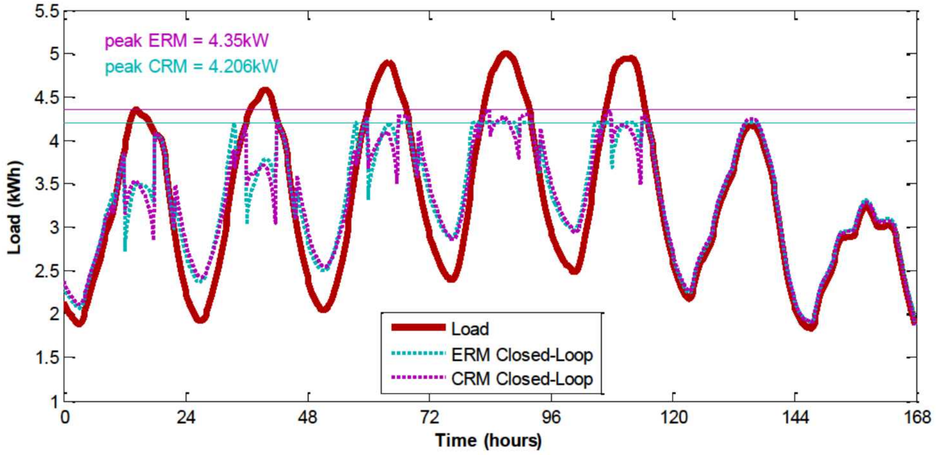
Performance Improvement From the CRM

The baseline customer electrical bill for this time is **$310.88**

For the example system parameterized with experimental data, we find that

1. The closed-loop ERM reduces this by **11.6%** to **$274.91**, and
2. 2. the closed-loop CRM reduces the bill by **13.3%** to **$269.55**

While a **$5 per month** improvement in savings over the ERM does not sound significant in absolute terms, it is important to remember the scale of power systems. **With approximately 5 million commercial customers in the U.S. currently eligible for tariffs with a demand charge rate of at least $15/kW (McLaren_2017) a 14.6% improvement in cost savings, over the ERM, from a simple change in software would have a significant impact.**



J. McLaren and S. Mullendore, "Identifying potential markets for behind-the-meter battery energy storage: A survey of U.S. demand charges," National Renewable Energy Laboratory, Tech. Rep., 2017.

Problem 2: Risk-Averse Control

Some energy storage services have asymmetric controller model risk, where overestimating capacity is much worse underestimating capacity.

When to use risk averse control?

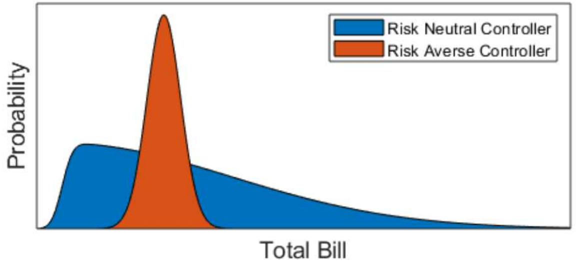
Approach: develop a method for risk-averse optimal control using a value-at-risk battery capacity

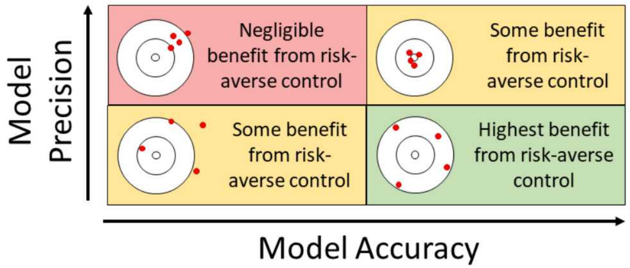
Criteria 1: The application has asymmetric risk

E.g. peak shaving

Criteria 2: The battery model is accurate but imprecise.

e.g. A simplistic model with optimal parameters





Value-at-Risk Battery Capacity: $\hat{C}_{\text{cap}} = \min\{C_{\text{cap}} \in \mathbb{R} \mid \mathbb{P}(\tilde{C}_{\text{cap}} \leq C_{\text{cap}}) \geq 0.13\%\}$

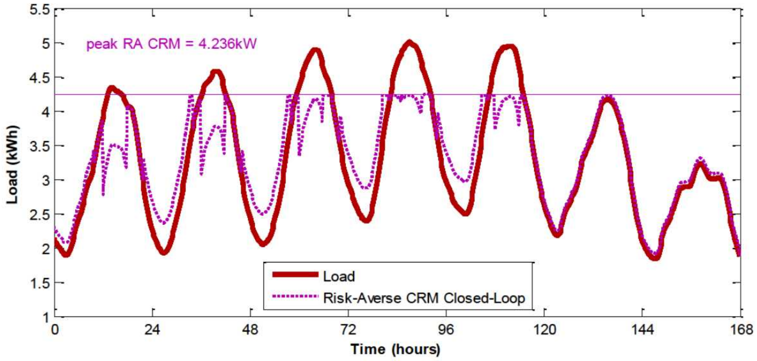
Risk-Averse Model

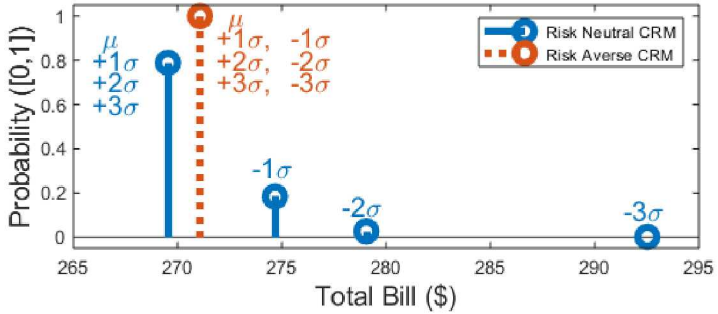
By choosing parameters to consistently underestimate available energy (overestimating SoC) we shape the CRM's uncertainty profile to make the controller more robust to variations in battery performance.

SUMMARY OF RESULTS FROM SIMULATED CONTROL SCENARIOS

Controller Scenario	Sim-Model*	Total Bill	% Savings	Optimistic Short-fall**
Baseline	–	\$310.88	–	
ERM OL Cal	–	\$274.91	11.6%	–
ERM OL Ach	mean	\$273.93	11.9%	-\$0.98
ERM CL Ach	mean	\$273.56	12.0%	-\$1.35
ERM CL Ach	extreme	\$273.69	12.0%	-\$1.22
–upper bound	–	\$272.72✓		
CRM OL Cal	–	\$269.55	13.3%	–
–lower bound	–	\$228.89✓		
CRM OL Ach	mean	\$274.98	11.5%	\$5.43
CRM CL Ach	mean	\$269.55	13.3%	\$0.00
CRM CL Ach	extreme	\$292.53	5.9%	\$22.98
–upper bound	–	\$274.21✓		
RA CRM OL Cal	–	\$271.22	12.8%	–
–lower bound	–	\$230.41✓		
RA CRM OL Ach	mean	\$271.17	12.8%	-\$0.05
RA CRM CL Ach	mean	\$271.08	12.8%	-\$0.14
RA CRM CL Ach	extreme	\$271.21	12.8%	-\$0.01

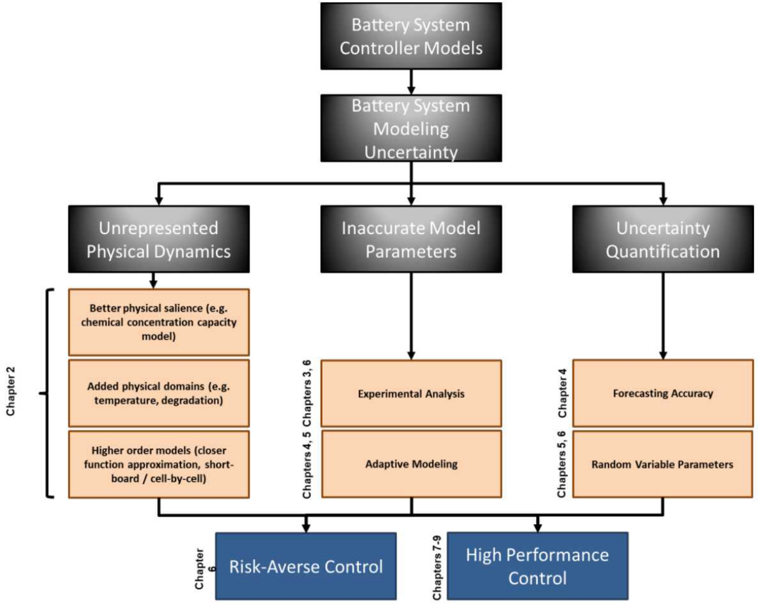
✓denotes that the solution to the non-convex problem satisfies the bound
* The extended CRM is used to simulate the BESS being controlled. It's parameters are selected to represent average behavior 'mean', or 'extreme case' lower than normal available energy as described in Section VI
** Optimistic Shortfall compares the bill achieved by applying control action to the simulated BESS to the open-loop calculated bill from each controller
Cal - calculated, Ach - achieved, OL - open-loop, CL - closed-loop, RA - risk-averse





Conclusions

This dissertation has achieved its goal to understand, reduce, and control modeling uncertainty in battery energy management systems.



Objectives / Contributions

Provides a review of the battery system model selection options for optimal controllers

- **Major** – Provides an complete review of the range of battery energy storage models used in optimal control design Minor – Compares each model's relative strengths and weaknesses
- Minor – Identifies gaps in the state-of-the-art of battery modeling that can serve as opportunities for future research

Develops new methods for uncertainty minimization using experimental and operational data

- **Major** – Develops a new method for selecting optimal parameter values based on operational data presented
- Minor – Applies a uniform test protocol to a grid scale energy storage system to reduce performance uncertainty
- Minor – Develops new energy storage performance metrics that provide more information to the device owner
- Minor – Reformulates two SoC forecasting models to be conducive to parameter optimization
- Minor – Develops a new framework for quantifying model accuracy
- Minor – Develops a process for the EMS to calculate and improve the accuracy of its control model using the operational data produced by the battery system
- Minor – Demonstrates the effectiveness of the adaptive modeling process using real world data

Develops a high performance, risk-averse control system for battery energy storage devices

- **Major** – Enables the application of a more accurate, but non-convex, battery system model by calculating upper and lower bounds on the globally optimal control solution
- **Major** – Modifies battery controller model to consistently underestimate capacity by a statistically selected margin, thereby hedging its control decisions against normal variations in battery system performance

Demonstrates the effectiveness of controller improvements for maximizing the value of grid energy storage assets

- Minor – Designs and demonstrates an advanced controller that is able to optimally stabilize a synchronous generator, over a rang of frequencies, using both field voltage and a co-located energy storage system
- Minor – Designs and demonstrates an advanced controller to smooth grid voltage using energy storage in distribution systems with high penetration PV
- Minor – Designs and demonstrates an advanced control system to optimally reduce a customer's electrical bill using a BESS, subject to a minimum operational life constraint

Questions?

Backup Slides

Battery Energy Storage Models for Optimal Control: State-of-Charge

Misconception: If you know state-of-charge, you essentially also know how much energy is left in the battery.

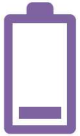
Reality: Because of the nonlinear relationship between power an energy SoC can be retroactively changed if you are not carful in the definition.

$$\text{State of Charge} \triangleq \frac{\text{Remaining Capacity}}{\text{Nominal Capacity}}$$

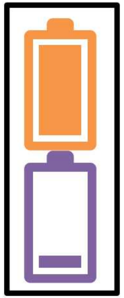
Thought Experiment

SoC = 90%

SoC = 10%



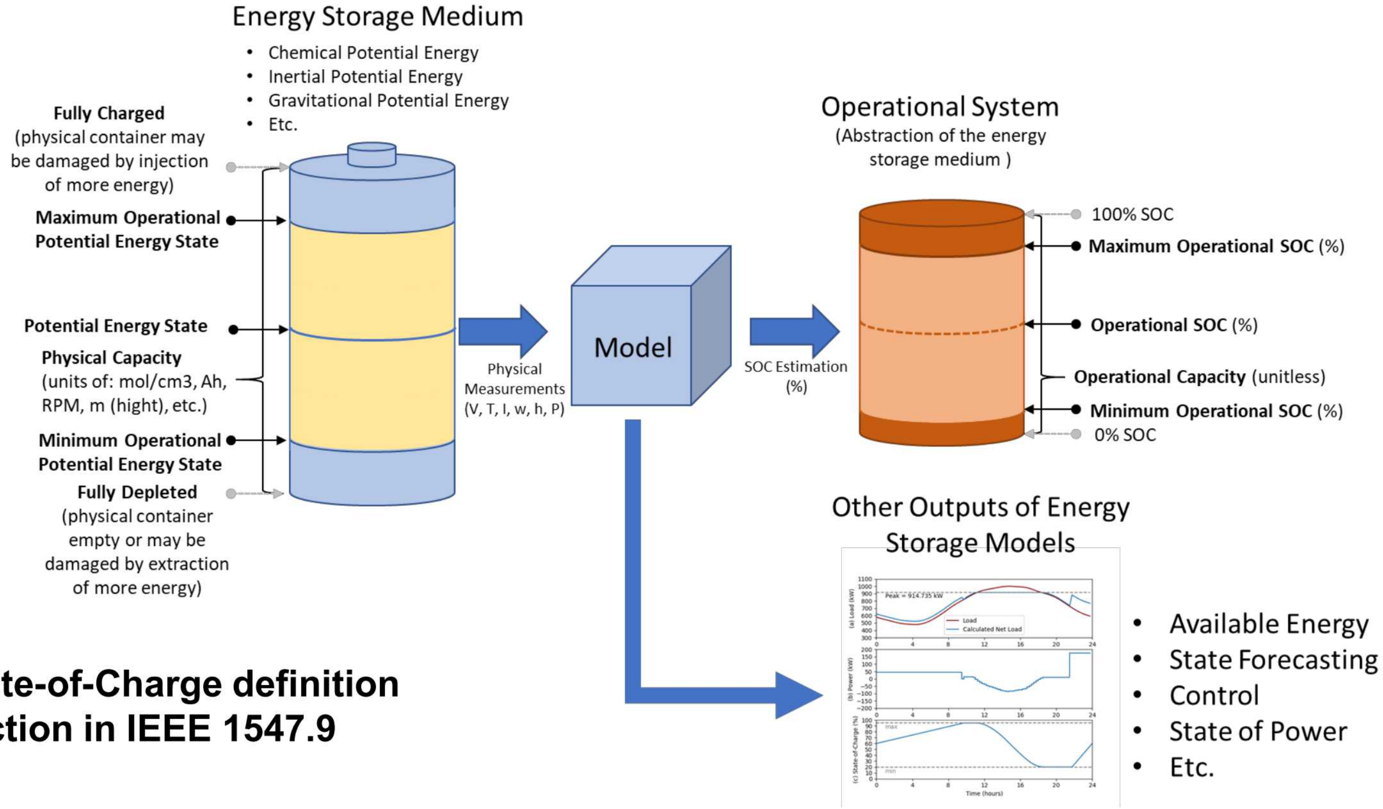
SoC = ?%



Bottom Line:

- SoC is a useful fiction
- It has no physical meaning in large systems
- It is still a useful proxy variable for an aggregated uncertain state of an electrochemical reaction

Battery Energy Storage Models for Optimal Control: State-of-Charge



State-of-Charge definition section in IEEE 1547.9

Operational Data: Method 1

ERM | CRM

Original Model

ERM:

$$\varsigma(n) = \hat{\varsigma}_0 - \frac{\Delta t}{Q}\sum_{k=1}^{n}(p_d(k) + \eta_e p_c(k) + p_{sd})$$
$$p_c = \min(p_e, 0)$$
$$p_d = \max(p_e, 0)$$
$$\varsigma_{min} \le \varsigma(k) \le \varsigma_{max}$$

CRM:

$$\varsigma(n) = \hat{\varsigma}_0 - \frac{\Delta t}{C}\sum_{k=1}^{n}(i_d(k) + \eta_c i_c(k) + i_{sd})$$
$$i_c = \min(i_e, 0)$$
$$i_d = \max(i_e, 0)$$
$$\varsigma_{min} \le \varsigma(k) \le \varsigma_{max}$$

Define

ERM:

$$x = \frac{-1}{Q}\begin{bmatrix} 1 \\ \eta_e \\ p_{sd} \end{bmatrix} \quad P = \begin{bmatrix} \Delta t p_d(1) & \Delta t p_c(1) & \Delta t \\ \Delta t(p_d(1) + p_d(2)) & \Delta t(p_c(1) + p_c(2)) & 2\Delta t \\ \vdots & \vdots & \vdots \\ \Delta t \sum_{k=1}^{n} p_d(k) & \Delta t \sum_{k=1}^{n} p_c(k) & n\Delta t \end{bmatrix}$$

CRM:

$$y = \frac{-1}{C}\begin{bmatrix} 1 \\ \eta_c \\ i_{sd} \end{bmatrix} \quad I = \begin{bmatrix} \Delta t i_d(1) & \Delta t i_c(1) & \Delta t \\ \Delta t(i_d(1) + i_d(2)) & \Delta t(i_c(1) + i_c(2)) & 2\Delta t \\ \vdots & \vdots & \vdots \\ \Delta t \sum_{k=1}^{n} i_d(k) & \Delta t \sum_{k=1}^{n} i_c(k) & n\Delta t \end{bmatrix}$$

Reformulated Model

$$\varsigma = Px + \hat{\varsigma}_0 \qquad \varsigma = Iy + \hat{\varsigma}_0$$

Parameter Optimization: find the parameters that minimize the error of each model's forecast

$$\min_{x \in \mathbb{R}^3} \quad ||Px + \hat{\varsigma}_0 - \hat{\varsigma}_{\text{BMS}}||_2^2 \qquad \min_{y \in \mathbb{R}^3} \quad ||Iy + \hat{\varsigma}_0 - \hat{\varsigma}_{\text{BMS}}||_2^2$$

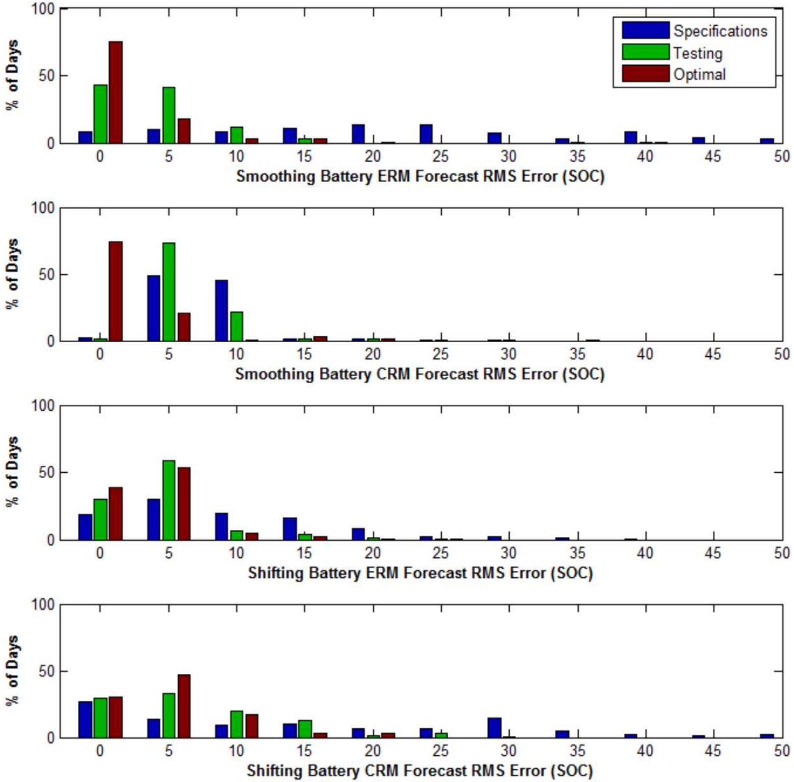
Albuquerque NM

Photo Source: DOE Global Energy Storage Database https://www.energystorageexchange.org/

State-of-Charge Forecasting Error Metrics

Battery	Model	Selection Method	90% High	Mean RMS	90% Low
Smooth	ERM	S	94.99	25.61	-10.83
Smooth	ERM	T	18.13	4.29	-7.42
Smooth	ERM	O	11.39	2.58	-8.09
Smooth	CRM	S	0.10	7.67	-15.62
Smooth	CRM	T	0.12	6.88	-13.42
Smooth	CRM	O	6.61	2.67	-3.42
Shift	ERM	S	41.57	9.64	-33.07
Shift	ERM	T	23.89	4.53	-12.10
Shift	ERM	O	19.60	3.79	-12.16
Shift	CRM*	S	64.00	16.01	-73.23
Shift	CRM*	T	32.80	6.89	-24.33
Shift	CRM*	O	23.71	5.05	-18.83

* a dynamic battery model was not used for the shifting battery

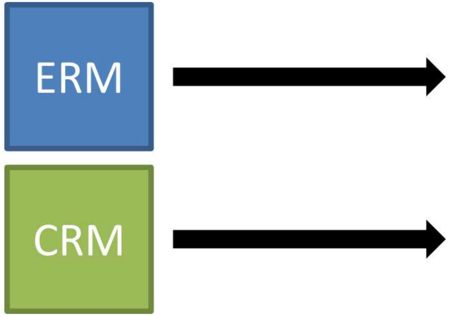


State-of-Charge Forecasting RMS Error

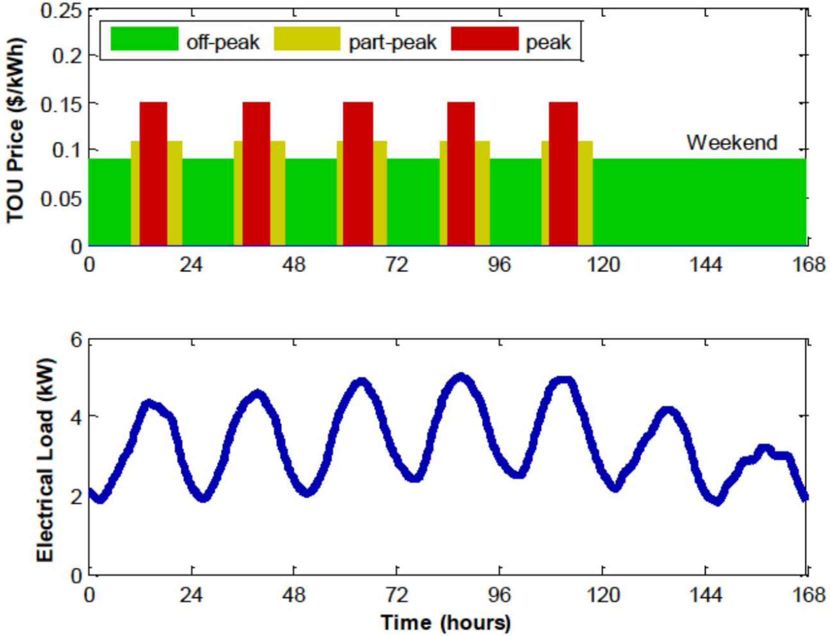
Effects of Model Uncertainty

Definition: “**optimistic shortfall**”, where the achievable schedule will be costlier than the schedule derived from optimal control.

Approach:
Apply both models to solve the same problem to determine the performance improvement from the more accurate CRM



Modified controller objective (1 week):

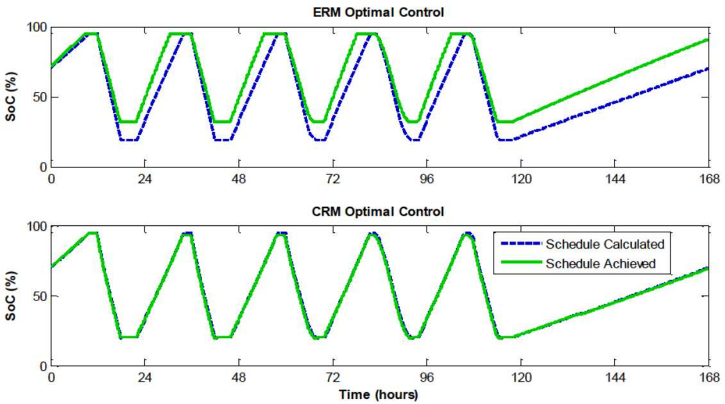


We use an **Extended CRM** model with more parameters and dynamics represented to do a pseudo-empirical analysis of controller performance.

Open-loop Control: Illustration of Asymmetric Risk

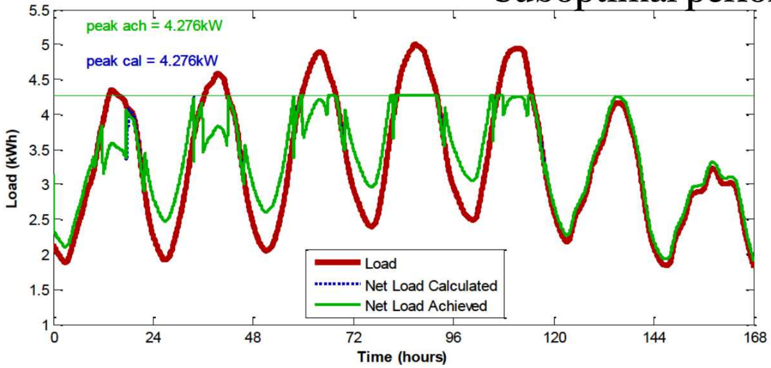
Available Energy

Underestimation -> Suboptimal control
Overestimation -> Optimistic shortfall



Demand Charge management has an asymmetric risk profile, meaning it is much worse to overestimate available energy than to underestimate it.

Suboptimal performance



Optimistic shortfall