Sandia National Laboratories

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Energy Storage Models for Risk-Averse Optimization

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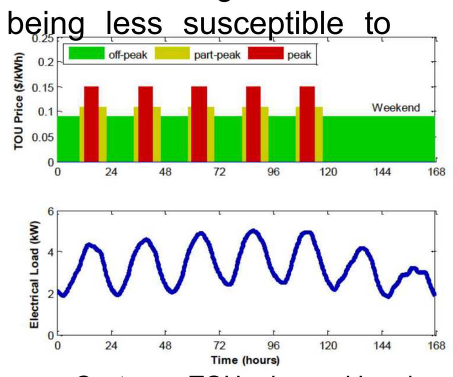
Self-guided-summary

Abstract—When batteries supply behind-the-meter services such as arbitrage or peak load management, an optimal controller can be designed to minimize the total electric bill. The limitations of the batteries, such as on voltage or state-of-charge, are represented in the model used to forecast the system's state dynamics. Control model inaccuracy can lead to an optimistic shortfall, where the achievable schedule will be costlier than the schedule derived using the model. To improve control performance and avoid optimistic shortfall, we develop a novel methodology for high performance, risk-averse battery energy storage controller design. Our method is based on two contributions. First, the application of a more accurate, but non-convex, battery system model is enabled by calculating upper and lower bounds on the globally optimal control solution. Second, the battery model is then modified to consistently underestimate capacity by a statistically selected margin, thereby hedging its control decisions against normal variations in battery system performance. The proposed model predictive controller, developed using this methodology, performs better and is more robust than the state-of-the-art approach, achieving lower bills for energy customers and being less susceptible to optimistic shortfall..

Problem Statement

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



Customer TOU price and Load

Electric Bill without

$$f_{\text{bill}} = \Delta t\, \mathbf{c}^T \mathbf{l} + \max(\mathbf{l})\, d$$

Electric Bill with

$$f_{\text{bill}} = \Delta t\, \mathbf{c}^T (\mathbf{l} + \mathbf{p}) + \max(\mathbf{l} + \mathbf{p})\, d$$

where p is the battery system power that element wise subtracts from l when the battery system is discharging. The problem is thus formulated: design a control algorithm to optimally calculate a vector of battery system power $\mathbf{p}$ that minimize f_{bill} the customer's bill without exceeding the battery's limits

Methods

We compare three controller models: the state-of-the-art energy reservoir model (ERM), a more accurate charge reservoir model (CRM), and a modified risk-averse CRM. To perform a **pseudo-empirical analysis** of the optimal schedules calculated from each model we simulate how the battery system would respond to each control signal using an extended CRM that incorporates additional constraints and parameters to improve its accuracy. The simulation model uses slightly different functions and parameters, enabling an analysis of the effects of model and parameter uncertainty on controller performance.

Simulation Results

The results of all three models, with open-loop and closed-loop implementation, are compared using a simulation model with either mean capacity, or extreme capacity. Total bill reduction is used to measure performance and optimistic short-fall is used to measure robustness.

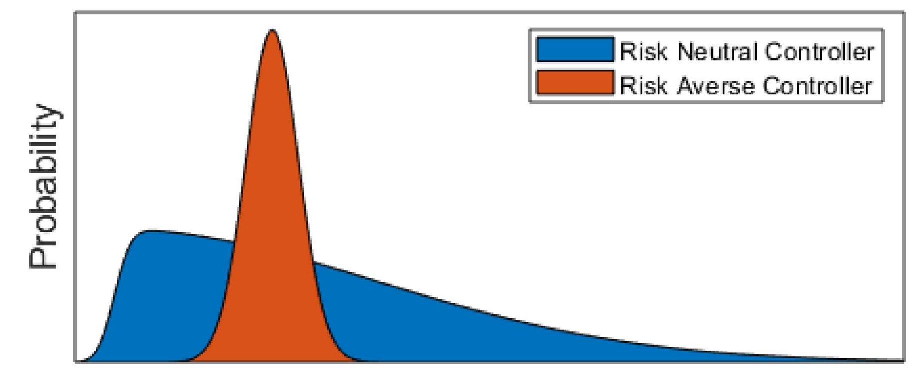
TABLE VI
SUMMARY OF RESULTS FROM SIMULATED CONTROL SCENARIOS

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	–	$235.35✓		
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

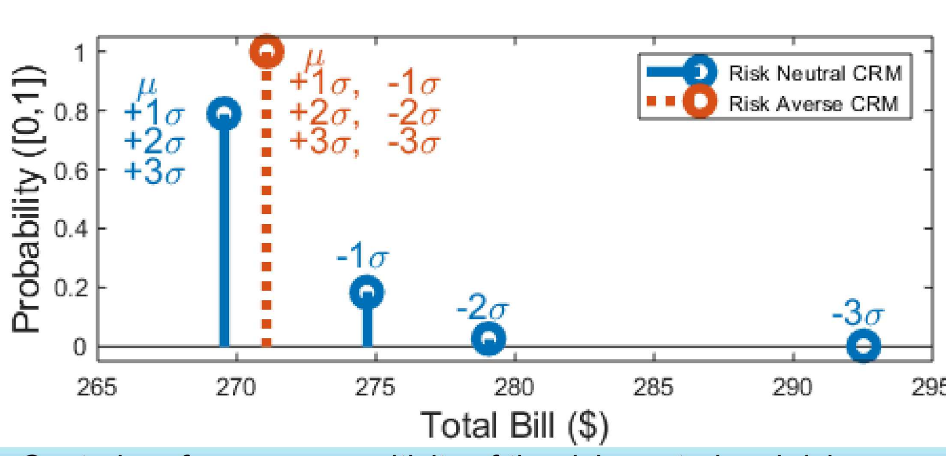
✓denotes that the solution to the non-convex problem satisfies the bound
* The extended CRM is used to simulate the BESS being controlled. It's parameters are selected to represent average behavior 'mean', or 'extreme case' lower than normal available energy as described in Section VI
** Optimistic Shortfall 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

Main idea

This proposed BESS controller **performs better** and/or is **more robust** to fluctuating capacity than the state-of-the-art controllers.



Notional examples of risk-neutral and risk-averse control bill savings probability density functions



Control performance sensitivity of the risk-neutral and risk-averse CRM based model predictive controllers.

Conclusions

- In this paper we develop and demonstrate an advanced methodology for designing BESS controllers under ToU price arbitrage and peak demand charge management applications.
- The proposed CRM based model predictive controller outperforms the ERM, but is sensitive to BESS capacity.
- The risk-averse CRM still outperforms the ERM, but is more robust to variations in BESS performance
- This methodology for can be applied wherever the risk profile of a scheduled service is asymmetric.
- Incremental improvements in controller performance can reduce the cost of deploying storage to make the grid more efficient and resilient.

Models

Energy Reservoir Model (ERM)

$$\min_{\mathbf{x}_e \in \mathbb{R}^{3n+2}} \Delta t\, \mathbf{c}^T (\mathbf{l} + \mathbf{p}^+ + \mathbf{p}^-) + \tau\, d + \Pi_1 ||\mathbf{p}^+ + \mathbf{p}^-||_2^2 \quad (3a)$$

$$\text{subject to: } Q_{\text{cap}} \mathbf{D} \boldsymbol{\varsigma} = \eta_e \mathbf{p}^+ + \mathbf{p}^-$$

$$\varsigma_{[1]} = \varsigma_0 \quad (3b)$$

$$\varsigma_{[1]} = \varsigma_{[n]} \quad (3c)$$

$$[\mathbf{0}] \le \mathbf{p}^+ \le p_{\max}[\mathbf{1}] \quad (3d)$$

$$p_{\min}[\mathbf{1}] \le \mathbf{p}^- \le [\mathbf{0}] \quad (3e)$$

$$\varsigma_{\min}[\mathbf{1}] \le \boldsymbol{\varsigma} \le \varsigma_{\max}[\mathbf{1}] \quad (3f)$$

$$\mathbf{l} + \mathbf{p}^+ + \mathbf{p}^- \le \tau[\mathbf{1}] \quad (3g)$$

where $\mathbf{x}_e = \{\mathbf{p}^+, \mathbf{p}^-, \boldsymbol{\varsigma}, \tau\} \in \mathbb{R}^{3n+2}$, $\mathbf{p}^+ \in \mathbb{R}^n_+$ is the ac electrical power provided to charge battery system, $\mathbf{p}^- \in \mathbb{R}^n_-$ is the ac electrical power discharged from the battery system, $\boldsymbol{\varsigma} \in \mathbb{R}^{n+1}$ is the battery SoC, $\tau \in \mathbb{R}$ is the peak demand power and the differential matrix $\mathbf{D}$ is shown in (4).

$$\mathbf{D} = \frac{1}{\Delta t} \begin{bmatrix} -1 & 1 & 0 & . & . & 0 \\ 0 & -1 & 1 & 0 & . & . \\ & & . & . & & \\ & & & . & . & \\ 0 & & & 0 & -1 & 1 \end{bmatrix}_{n \times (n+1)} \quad (4)$$

Charge Reservoir Model (CRM)

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

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

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

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

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

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

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

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

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

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

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

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

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

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

where $\mathbf{x}_c = \{\mathbf{p}, \mathbf{p}_{\text{dc}}, \mathbf{i}^+_{\text{bat}}, \mathbf{i}^-_{\text{bat}}, \mathbf{v}_{\text{bat}}, \mathbf{v}_s, \mathbf{v}_{\text{oc}}, \boldsymbol{\varsigma}, \tau\} \in \mathbb{R}^{8n+3}$, $\mathbf{p}_{\text{dc}} \in \mathbb{R}^n$ is the dc electrical power provided to battery, $\mathbf{v}_{\text{bat}} \in \mathbb{R}^n$ is the battery terminal voltage, $\mathbf{v}_s \in \mathbb{R}^n_+$ is the slack voltage used in calculation of an upper bound, $\mathbf{v}_{\text{oc}} \in \mathbb{R}^{n+1}$ is the battery open-circuit voltage, and $\tau \in \mathbb{R}$ is the peak power demand.

Risk-Averse Capacity (value at

$$(C_{\text{cap}} + \tilde{C}_{\text{cap}}) D \boldsymbol{\varsigma} = \eta_c \mathbf{i}^+_{\text{bat}} + \mathbf{i}^-_{\text{bat}} \quad (9)$$

where $\tilde{C}_{\text{cap}} \sim \mathcal{N}(\mu = 0, \sigma = 2.6\text{Ah})$ is the random component of the battery's capacity, assumed to be a zero-mean, normal distribution.

$$\hat{C}_{\text{cap}} = \min\{C_{\text{cap}} \in \mathbb{R} \,|\, \mathbb{P}(\tilde{C}_{\text{cap}} \le C_{\text{cap}}) \ge 0.13\%\} \quad (10)$$

Bounding the Global Minimum

The CRM is a non-convex, non-pseudoconvex problem, hence we cannot grantee that a gradient based solver will find the globally optimal solution. An upper bound to a minimization problem can be found by restricting the feasible set (adding additional constraints) while a lower bound can be calculated by expanding the feasible set (relaxing or removing constraints).

Lower Bound (convex relaxation)

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

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

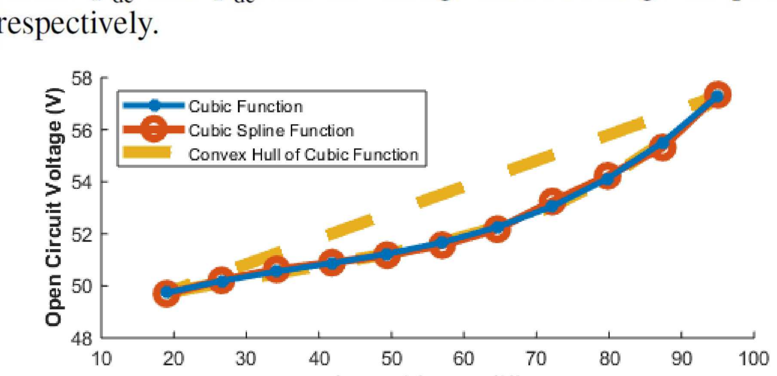
$$\text{relaxing (5b)} \quad \phi_0 \mathbf{p}^2 + \phi_1 \mathbf{p} + \phi_2 \ge \mathbf{p}^+_{\text{dc}} + \mathbf{p}^-_{\text{dc}} \quad (7a)$$

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

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

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

where $\mathbf{p}^+_{\text{dc}}$ and $\mathbf{p}^-_{\text{dc}}$ are the charge and discharge dc powers respectively.



Upper Bound (convex restriction/approximation)

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

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

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

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

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

$$\boldsymbol{\varsigma} = \varsigma_{\min}[\mathbf{1}] + \boldsymbol{\varsigma}_1 + \boldsymbol{\varsigma}_2 + \boldsymbol{\varsigma}_3 + \boldsymbol{\varsigma}_4 + \boldsymbol{\varsigma}_5 \quad (8d)$$

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

$$\varsigma_{\text{seg}} \mathbf{w}_1 \le \boldsymbol{\varsigma}_1 \le \varsigma_{\text{seg}} \quad (8f)$$

$$\varsigma_{\text{seg}} \mathbf{w}_2 \le \boldsymbol{\varsigma}_2 \le \varsigma_{\text{seg}} \mathbf{w}_1 \quad (8g)$$

$$\varsigma_{\text{seg}} \mathbf{w}_3 \le \boldsymbol{\varsigma}_3 \le \varsigma_{\text{seg}} \mathbf{w}_2 \quad (8h)$$

$$\varsigma_{\text{seg}} \mathbf{w}_4 \le \boldsymbol{\varsigma}_4 \le \varsigma_{\text{seg}} \mathbf{w}_3 \quad (8i)$$

$$0 \le \boldsymbol{\varsigma}_5 \le \varsigma_{\text{seg}} \mathbf{w}_4 \quad (8j)$$

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