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Model Uncertainty in Grid Connected Battery Energy Storage Systems

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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

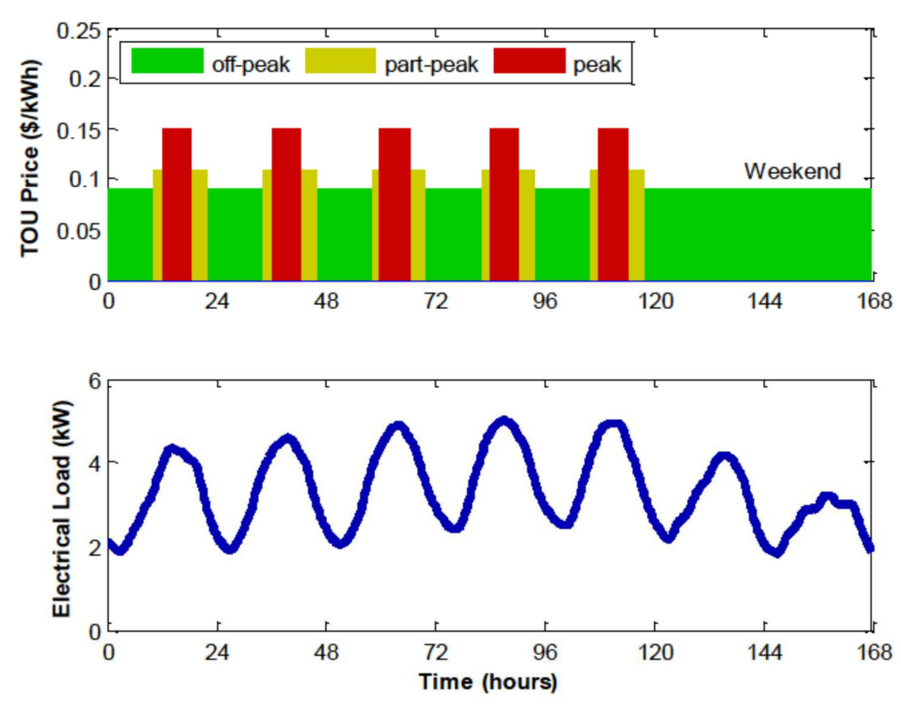
$$\boldsymbol{c}^{\dagger}\boldsymbol{l} + \$50\max(\boldsymbol{l})$$

Electric Bill with BESS

$$\boldsymbol{c}^{\dagger}(\boldsymbol{l}+\boldsymbol{p}_e) + \$50\max(\boldsymbol{l}+\boldsymbol{p}_e)$$

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

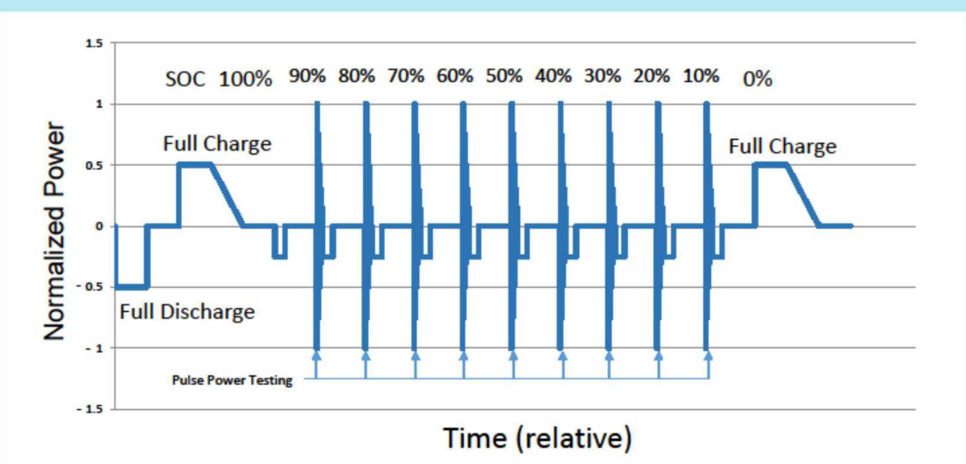
Design a control algorithm to optimally calculate a vector of battery system power that minimizes the customer's cost without exceeding the battery's limits.



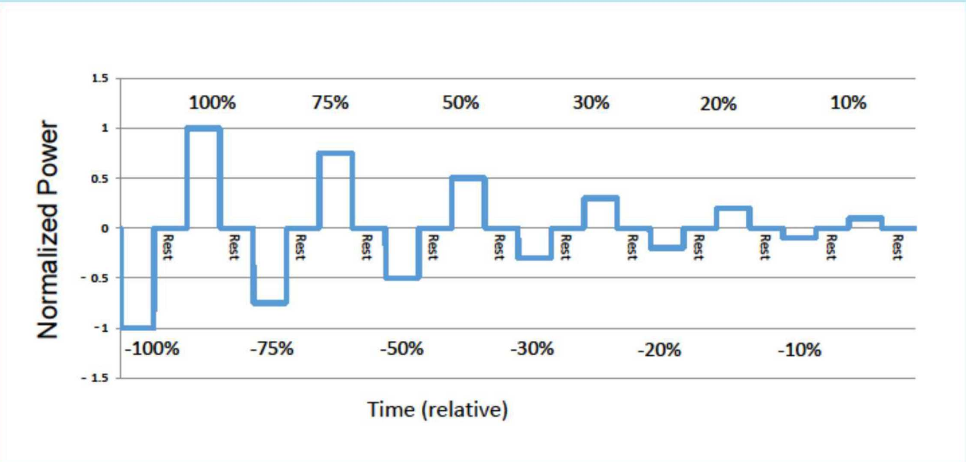
Reducing Model Uncertainty Through Testing

Energy Storage Pulsed Power Characterization (ESPPC) Test

Experimental procedure takes the BESS through a wide operational range to calculate accurate model parameters.



1. Discharge the system at p_{nom} until ς_{min} has been reached
2. Float at $p_e \approx 0$ for 1 hour
3. Charge the system at p_{nom} until ς_{max} has been reached
4. Float at $p_e \approx 0$ for 1 hour
5. Discharge the system at p_{nom} until 10% of of the usable charge ($\varsigma_{max}-\varsigma_{min}$) has been removed from the battery
6. Float at $p_e \approx 0$ for 1 hour
7. Perform pulsed power testing
   i. Discharge at p_{min} for 1 minute
   ii. Float at $p_e \approx 0$ for 1 minute
   iii. Charge at p_{max} for 1 minute
   iv. Float at $p_e \approx 0$ for 1 minute
   v. Repeat i through iv using 75%, 50%, 30%, 20%, and 10% of p_{max} and p_{min}
8. Repeat steps 5 through 7 until ς_{min} has been reached (collecting impedance and conversion efficiency curves at nine total states of charge)
9. Charge the system at p_{nom} until ς_{max} has been reached



Model Comparison

Energy Reservoir Model

$$\min_{\boldsymbol{x}_e \in \mathbb{R}^n} \quad \boldsymbol{c}^{\dagger}(\boldsymbol{l}+\boldsymbol{p}_e) + \$50\tau + \Pi||\boldsymbol{p}_e||_2^2$$

subject to:

$$Q_{cap}D\boldsymbol{\varsigma} = \min(\boldsymbol{p}_e, 0) + \eta_e \max(\boldsymbol{p}_e, 0) + p_{sd}$$
$$\boldsymbol{\varsigma}(1) - \varsigma_0 = 0$$
$$\boldsymbol{\varsigma}(1) - \boldsymbol{\varsigma}(n) = 0$$
$$p_{min} \le \boldsymbol{p}_e \le p_{max}$$
$$\varsigma_{min} \le \boldsymbol{\varsigma} \le \varsigma_{max}$$
$$m_1\boldsymbol{\varsigma} + b_1 \le \boldsymbol{p}_e \le m_2\boldsymbol{\varsigma} + b_2$$
$$\boldsymbol{l} + \boldsymbol{p}_e \le \tau$$

The CRM is includes more dynamics so it has the potential for higher accuracy.

Name	Symbol	Mean	σ
Energy Capacity*	Q_{cap}	5.944 kWh	0.096 kWh
Energy Efficiency*	η_e	61.7 %	2.63%
Maximum Power Discharge	p_{max}	7 kW	
Maximum Power Charge	p_{min}	7 kW	
Maximum SoC	ς_{max}	95 %	
Minimum SoC	ς_{min}	20 %	

* derived from experimental analysis using a least-square fit

Optimal parameters are derived for both models from ESPPC testing.

Charge Reservoir Model

$$\min_{\boldsymbol{x}_c \in \mathbb{R}^m} \quad \boldsymbol{c}^{\dagger}(\boldsymbol{l}+\boldsymbol{p}_e) + \$50\tau + \Pi||\boldsymbol{p}_e||_2^2$$

subject to:

$$\boldsymbol{p}_{dc} - \phi_0\boldsymbol{p}_e^2 - \phi_1\boldsymbol{p}_e - \phi_2 = 0$$
$$\boldsymbol{p}_{dc} - \boldsymbol{i}_{bat}\boldsymbol{v}_{bat} = 0$$
$$\boldsymbol{v}_{bat} - \boldsymbol{v}_{oc} - R_0\boldsymbol{i}_{bat} = 0$$
$$\boldsymbol{v}_{oc} - \alpha\boldsymbol{\varsigma}^3 - \beta\boldsymbol{\varsigma}^2 - \gamma\boldsymbol{\varsigma} - \delta = 0$$
$$C_{cap}D\boldsymbol{\varsigma} - \eta_c \max(\boldsymbol{i}_{bat}, 0) - \min(\boldsymbol{i}_{bat}, 0) = 0$$
$$\boldsymbol{\varsigma}(1) - \varsigma_0 = 0$$
$$\boldsymbol{\varsigma}(1) - \boldsymbol{\varsigma}(n) = 0$$
$$p_{min} \le \boldsymbol{p}_e \le p_{max}$$
$$\varsigma_{min} \le \boldsymbol{\varsigma} \le \varsigma_{max}$$
$$v_{min} \le \boldsymbol{v}_{bat} \le v_{max}$$
$$i_{min} \le \boldsymbol{i}_{bat} \le i_{max}$$
$$\boldsymbol{l} + \boldsymbol{p}_e \le \tau$$

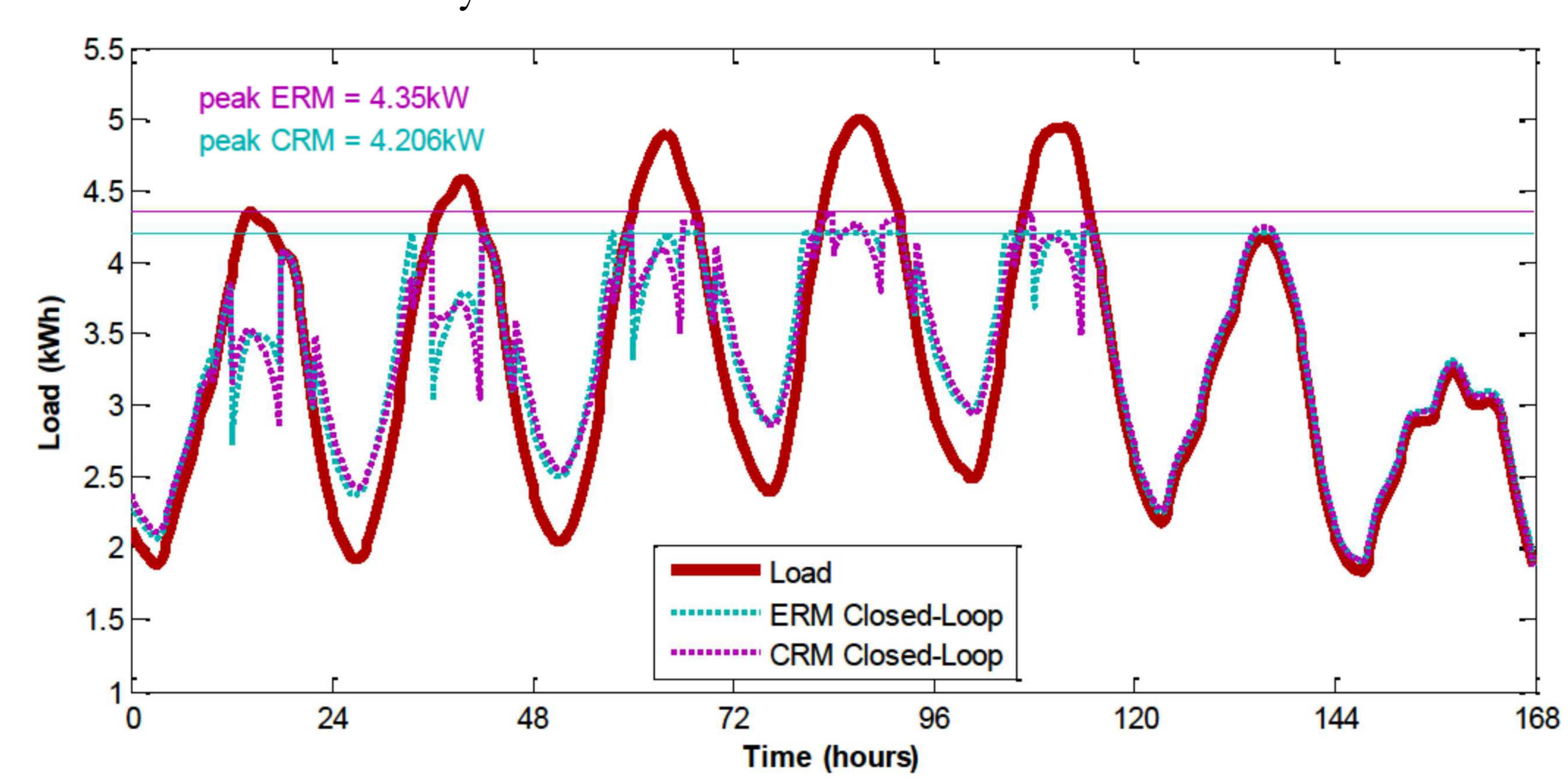
Name	Symbol	Mean	σ
Charge Capacity*	C_{cap}	135.2 Ah	2.6 Ah
Coulombic Efficiency*	η_c	94.6 %	0.74%
Inverter Efficiency Coefficient*	ϕ_0	-4.7865e-07	
Inverter Efficiency Coefficient*	ϕ_1	0.99107	
Inverter Efficiency Coefficient*	ϕ_2	-0.0721	
Battery Internal Resistance*	R_0	15.35 mΩ	0.34 mΩ
Maximum Power Discharge	p_{max}	7 kW	
Maximum Power Charge	p_{min}	7 kW	
Maximum SoC	ς_{max}	95 %	
Minimum SoC	ς_{min}	20 %	
Maximum Battery Voltage	v_{max}	58.8 V	
Minimum Battery Voltage	v_{min}	46.2 V	
Maximum Current Discharge	p_{max}	150 A	
Maximum Current Charge	p_{min}	150 A	

Cubic Polynomial Fit*	α	β	γ	δ
$0.2 \le \varsigma \le 0.95$	13.48	-10.04	5.74	49.23

* derived from experimental analysis using a least-square fit

Results

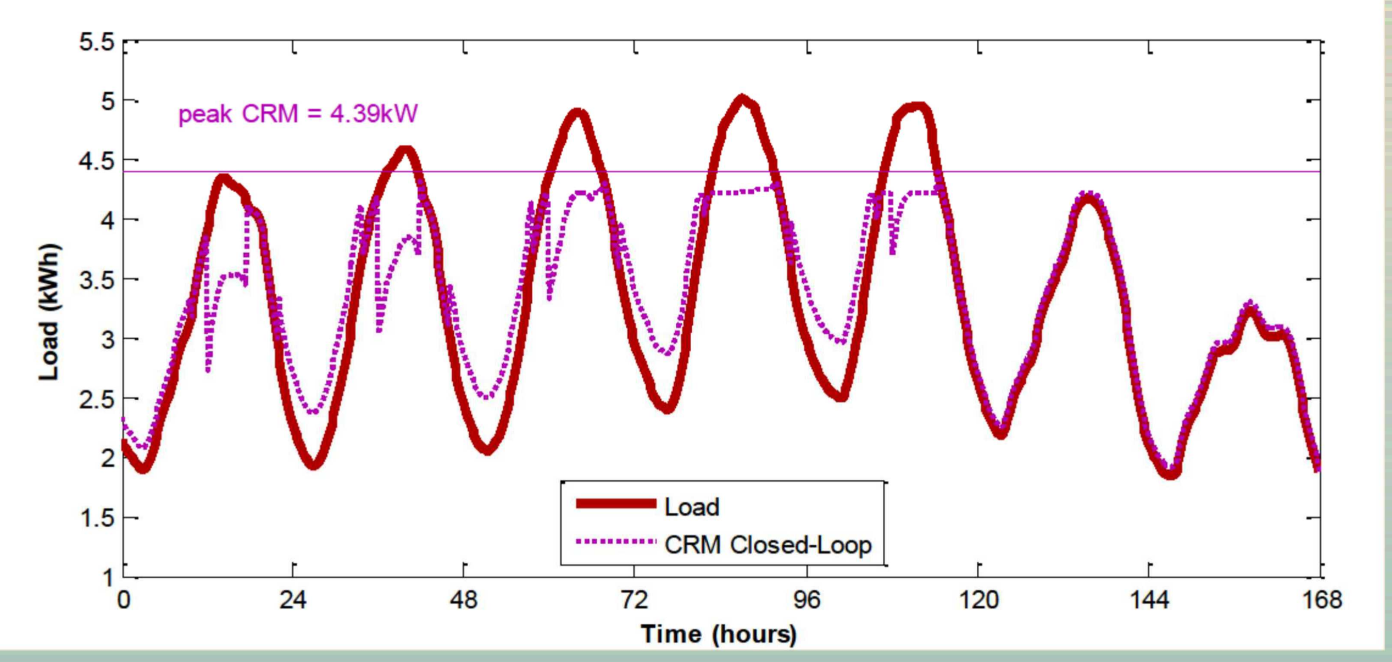
In closed-loop control the optimal CRM based controller reduces the customer's bill by 12.8% better than the ERM based controller.



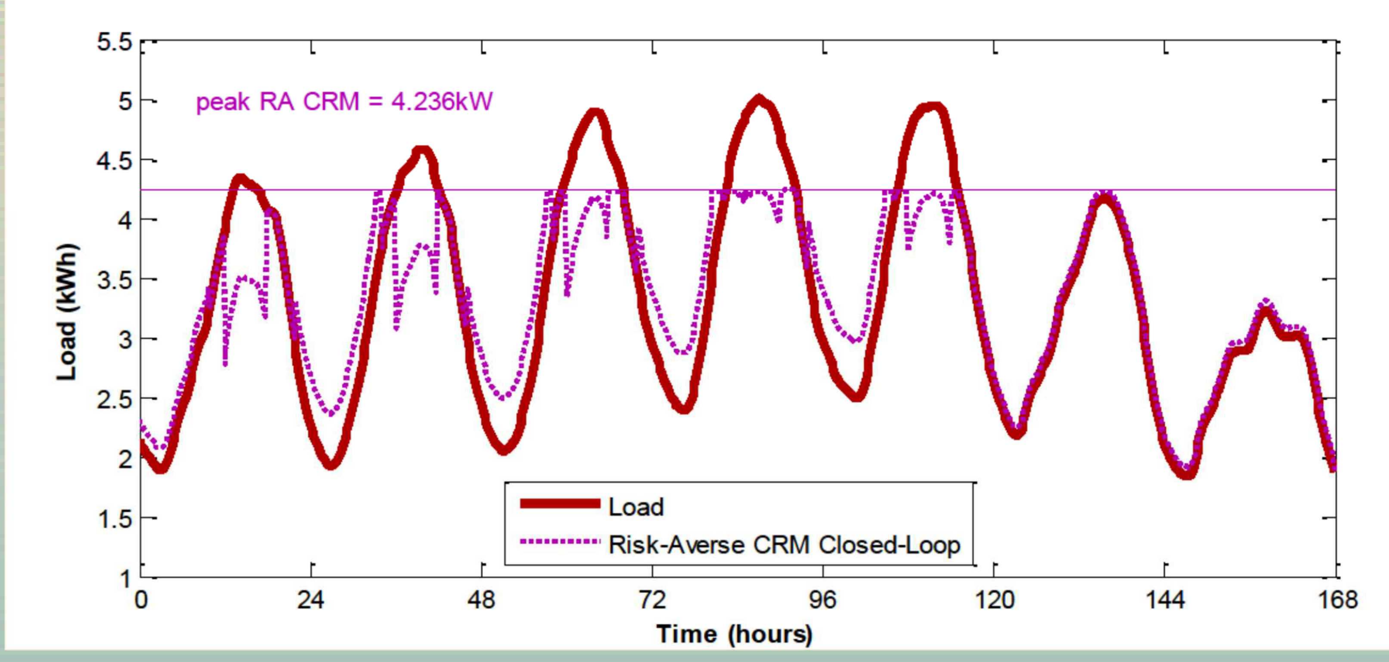
Shaping Model Uncertainty to Improve Controller Robustness

To explore the effects of model uncertainty we adjust the parameters of the Extended CRM to create an intentional parameter mismatch between the controller model and the controlled system. This demonstrates that the CRM is vulnerable to model uncertainty, yielding a \$9.63 optimistic short-fall.

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.



Controller Scenario	Sim-Model*	Total Bill	% Savings	Optimistic Short-fall**
Baseline	–	\$311.01	–	
ERM OL Cal	–	\$274.42	11.7%	–
ERM OL Ach	mean	\$274.42	11.7%	\$0.00
ERM CL Ach	mean	\$273.67	12.0%	-\$0.75
ERM CL Ach	extreme	\$273.81	12.0%	-\$0.61
CRM OL Cal	–	\$269.67	13.2%	–
CRM OL Ach	mean	\$275.10	11.6%	\$5.43
CRM CL Ach	mean	\$269.94	13.2%	\$0.27
CRM CL Ach	extreme	\$279.30	10.3%	\$9.63
RA CRM OL Cal	–	\$271.33	12.8%	–
RA CRM OL Ach	mean	\$271.33	12.8%	\$0.00
RA CRM CL Ach	mean	\$271.19	12.8%	-\$0.14
RA CRM CL Ach	extreme	\$271.44	12.7%	\$0.11



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