SAND2018-10700C

Focus on ES Partnerships and Collaborations

PRESENTED BY

David Rosewater - 9 – 26 – 2018

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Focus on ES Partnerships and Collaborations with Industry & Academia

- David Reed - Pacific Northwest National Laboratory
  - Optimization and Controls for ES Safety
- Robb Thomson - National Institute of Standards and Technology
  - On the Role of Energy Storage in the Operation of Future Fossil Free Utilities
- Brian Berland - ITN Energy Systems
  - Demonstration of a kW Class Redox Battery Using an Advanced Bi-additive Vanadium Sulfate Electrolyte
- Mitch Anstey - Davidson College (North Carolina)
  - Improving Stability of Battery Additives and Electrolytes Using Redox Non-Innocent Ligand Complexes

University Projects (Through Sandia)

Davidson College	Ohio State University
University of Washington	University Texas Arlington
CUNY	New Mexico Tech
Northeastern University	University New Mexico
Stony Brook University	Washington University at S. L.
University of Kentucky	Michigan State University
UC Irvine	University of Utah
University of Alaska Fairbanks	South Dakota State University
University Texas at Austin	Clemson University
New Mexico State University	Southern Methodist University

$2.2M in funding to universities

Industry/Utility Partners (Through Sandia)

GeneSic Semiconductor

Creare

InnoCit

Mainstream Engineering

Powdermet

Urban Electric Power

Helix Power Corporation

Eugene Water and Electric Board

Cordova Electric Cooperative

Strategen

Mustang Prairie Energy

ANZA Electric

WattJoule

UniEnergy Technologies

Sterling Municipal Light Department

Public Service of New Mexico

National Rural Electric Cooperative Association

Hawaii Electric Light

Green Mountain Power

Electric Power Board of Tennessee

Electric Power Research Institute

Ecoult Battery

Demand Energy

Burlington Electric Department

Collaboration Highlight: The University of Texas at Austin

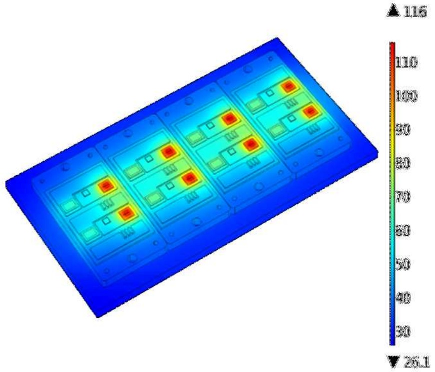
Low Voltage and High Current Bidirectional Converter for Grid-tied Flow Battery Energy Storage System

Alex Huang (UT Austin)
Stan Atcitty (Sandia)

- Task 1: Design, analysis and preliminary hardware development of a 45V/10kW level compact and efficient wide-band-gap-based converter.
- Task 2: Efficiency and thermal performance assessment and model validation along with converter design improvements.
- Task 2: Evaluation of parallel operation will ensure proper current sharing to achieve higher power. Plug-and-play installation and control configuration assessment.

Past Power Electronics Recognition at Sandia

- Four R&D100 Awards
- Three U.S. Patents, three pending
- Over 40 technical publications
- Power Electronics for Renewable & Distributed Energy Systems book

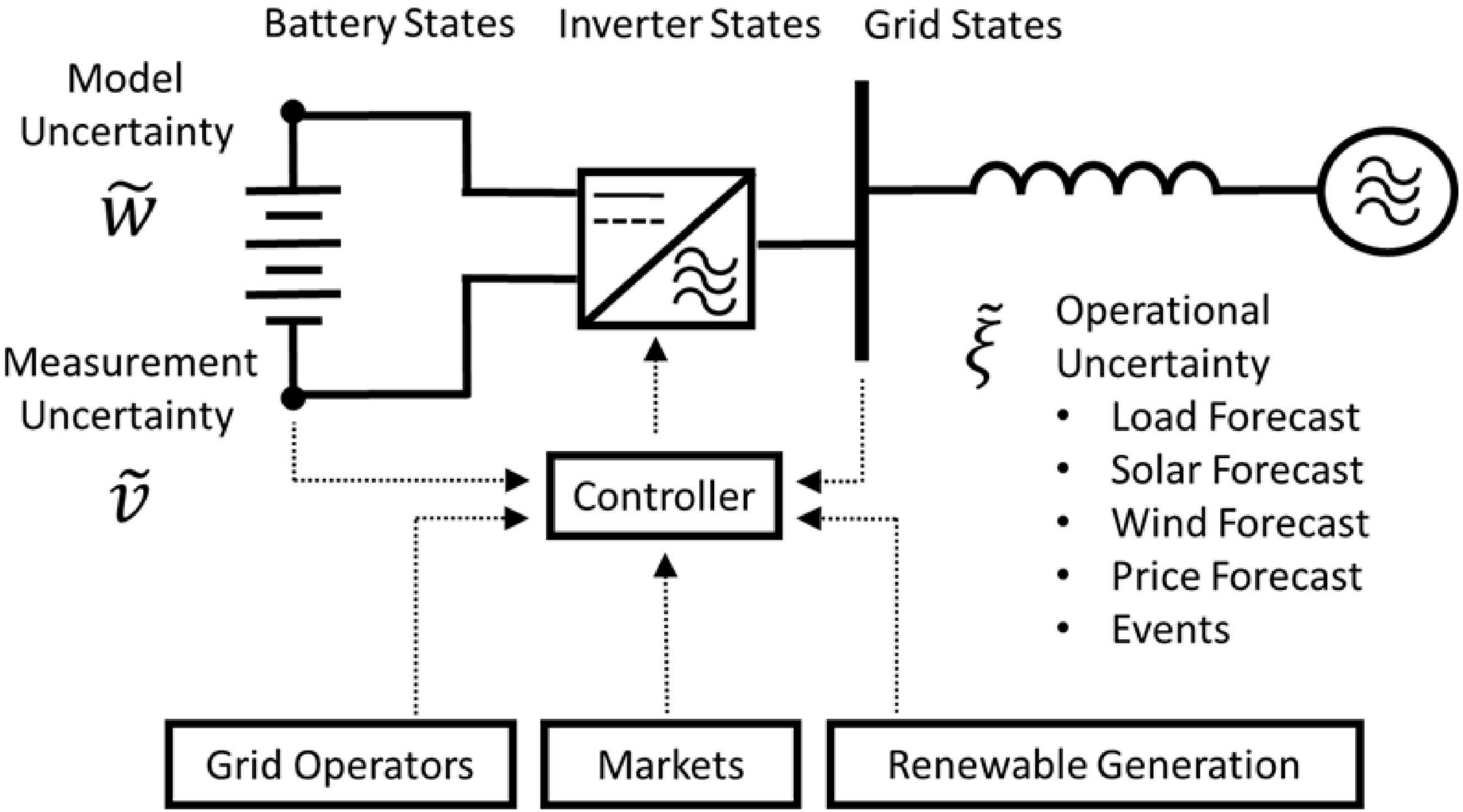


APEI
15kV Discrete SiC Multichip Module

Collaboration Highlight: The University of Texas at Austin

Optimal control of battery energy storage: Reducing and Shaping Model Uncertainty to Improve Control Performance

David Rosewater (Sandia)
Surya Santoso (UT Austin)
Ross Baldick (UT Austin)



Model uncertainty stems from unrepresented model dynamics, inaccurate parameters, abnormal operational conditions, or state disturbance injections.

Collaboration Highlight: The University of Texas at Austin

Problem Statement

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

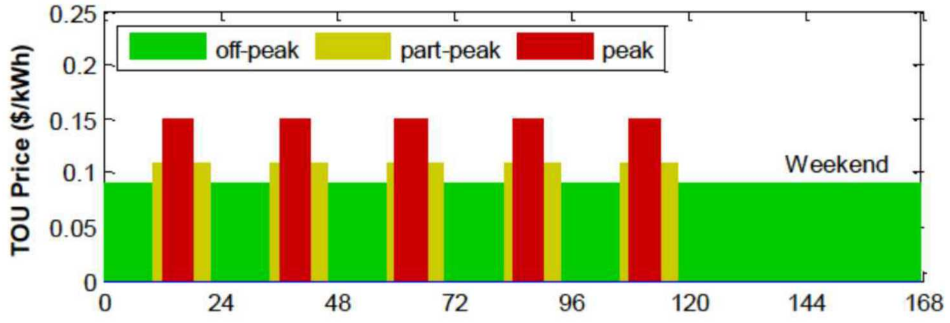
Electric Bill without BESS

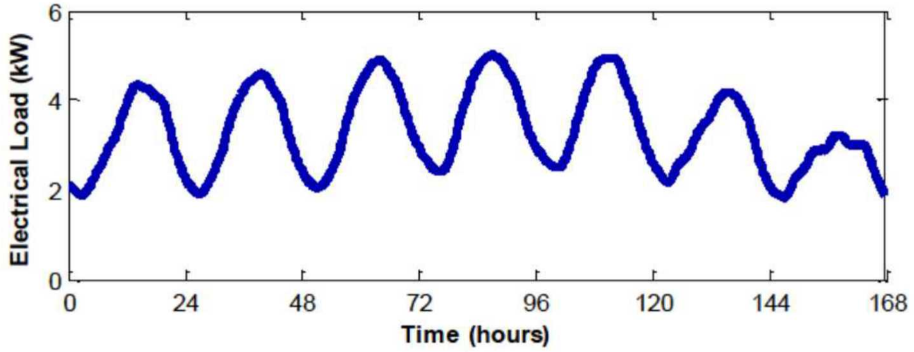
$$\boldsymbol{c}^{\dagger}\boldsymbol{l} + \$50\max(\boldsymbol{l})$$

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.





The problem is thus formulated: design a control algorithm to optimally calculate a vector of battery system power $\boldsymbol{p}_e$ that minimizes the customer's cost without exceeding the battery's limits.

Collaboration Highlight: The University of Texas at Austin

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:

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

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

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:

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

Optimal parameters are derived for both models from expirementation.

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

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	

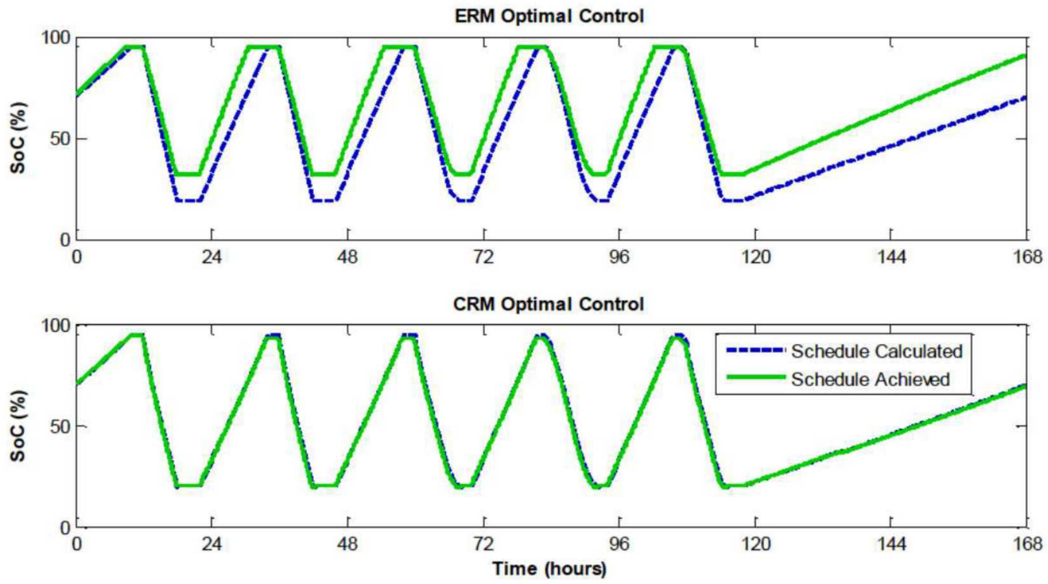
Cubic Polynomial Fit*	α	β	γ	δ
$0.2 \leq \varsigma \leq 0.95$	13.48	-10.04	5.74	49.23

* derived from experimental analysis using a least-square fit

Open-loop Control: Illustration of Asymmetric Risk

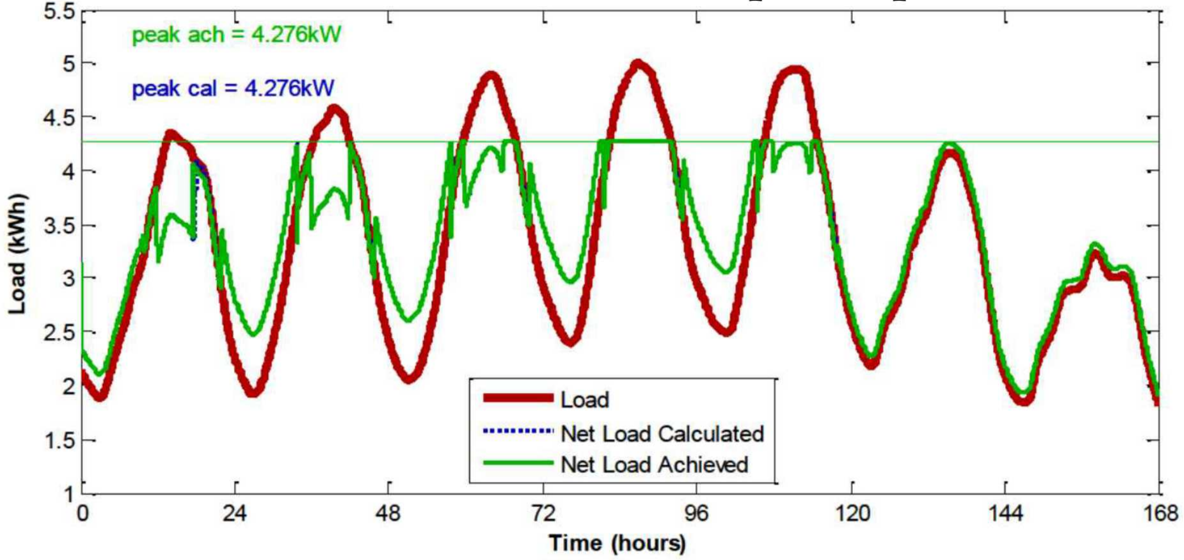
Available Energy

Underestimation -> Suboptimal control
Overestimation -> Optimistic shortfall

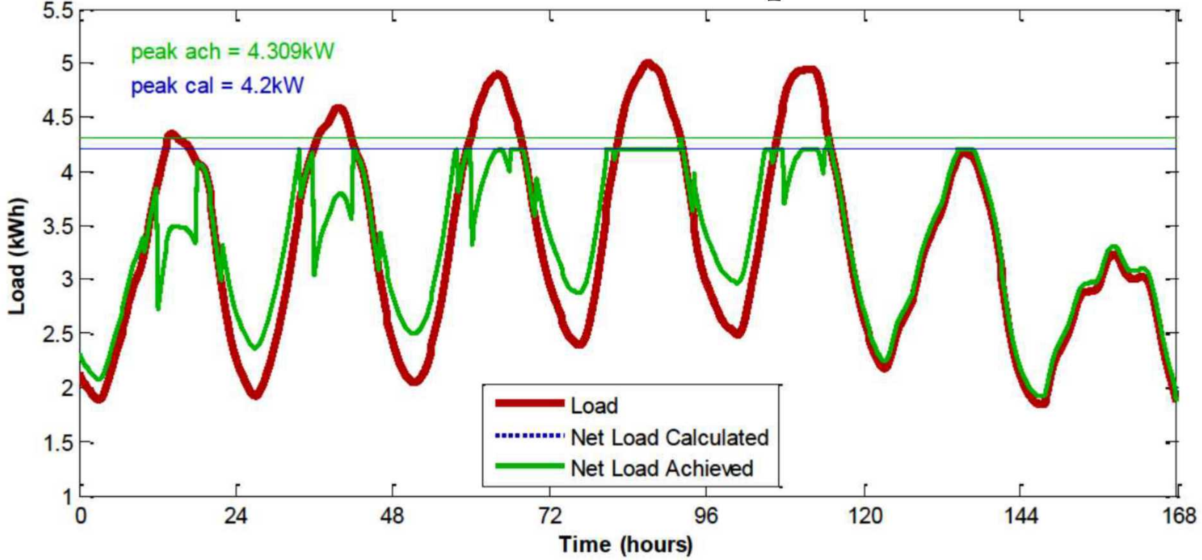


Demand Charge management has an asymmetric risk profile, meaning it is much worse to overestimate available energy than to underestimate it.

Suboptimal performance



Optimistic shortfall

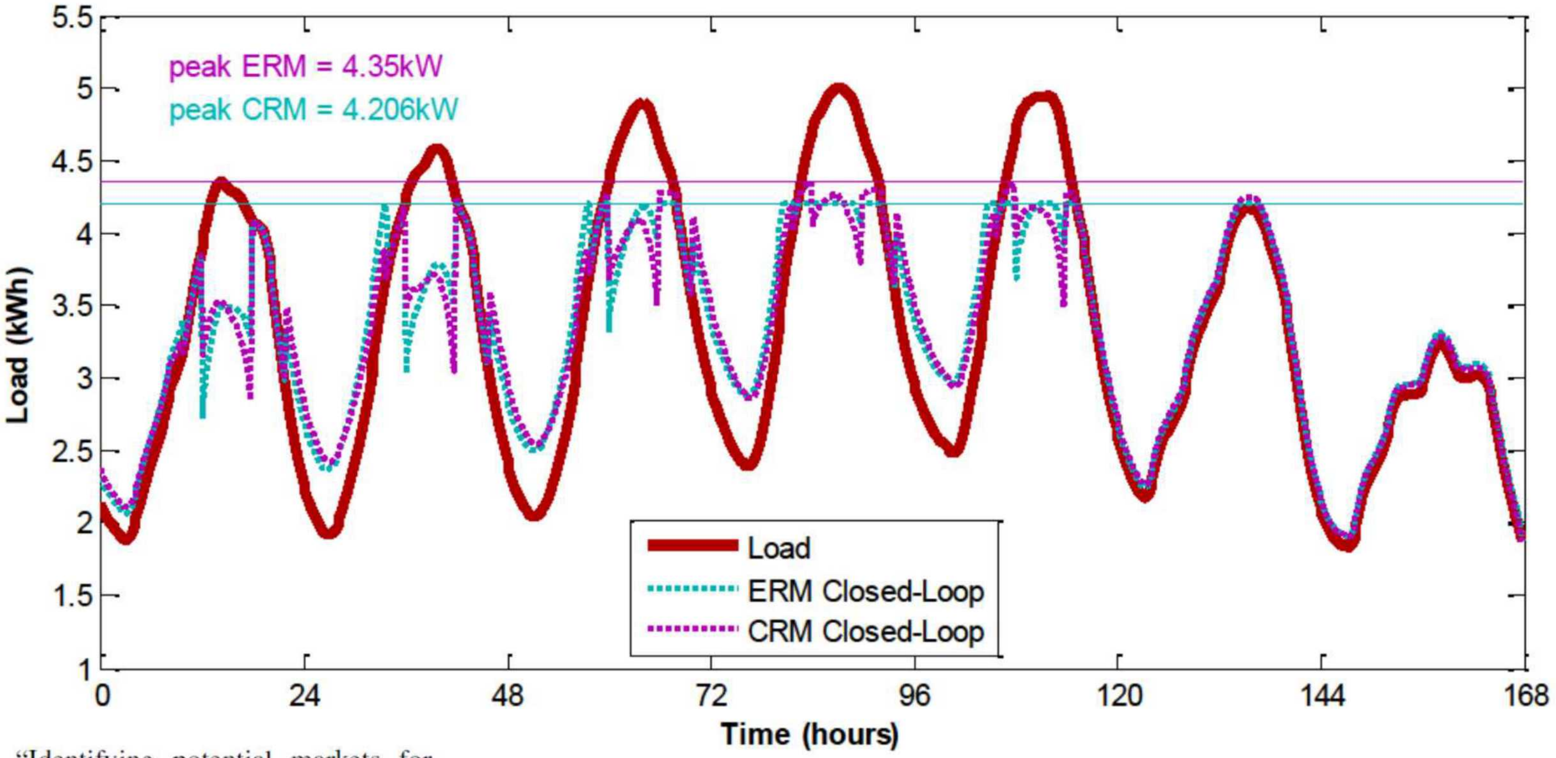


Performance Improvement From the CRM

The baseline customer electrical bill for this time is $311.01

For the example system parameterized with experimental data, we find that 1. the closed-loop ERM reduces this by 12.0% to $273.81, and 2. the closed-loop CRM reduces the bill by 13.2% to $269.94

While a $4 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 12.8\% 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.

Collaboration Highlight: The University of Texas at Austin

- Inaccurate models can lead to suboptimal control
- Model uncertainty can create either suboptimal control or an optimistic shortfall
- Some services have asymmetric risk, where overestimating future states has greater or lower impact on the objective than underestimating it.

Acknowledgements:

Supervisor:

- Dr. Surya Santoso

Committee Members:

- Dr. Ross Baldick
- Dr. Glenn Masada
- Dr. Alex Huang
- Dr. Hao Zhu
- Dr. Raymond Byrne

This research highlight illustrates one example of broad research portfolio that is intrinsically integrated with industry and academia