An Energy Storage Cost Comparison: Li-ion Batteries vs Distributed Load Control

Not, "Pool Pumps for Peak Shaving and Valley Filling"

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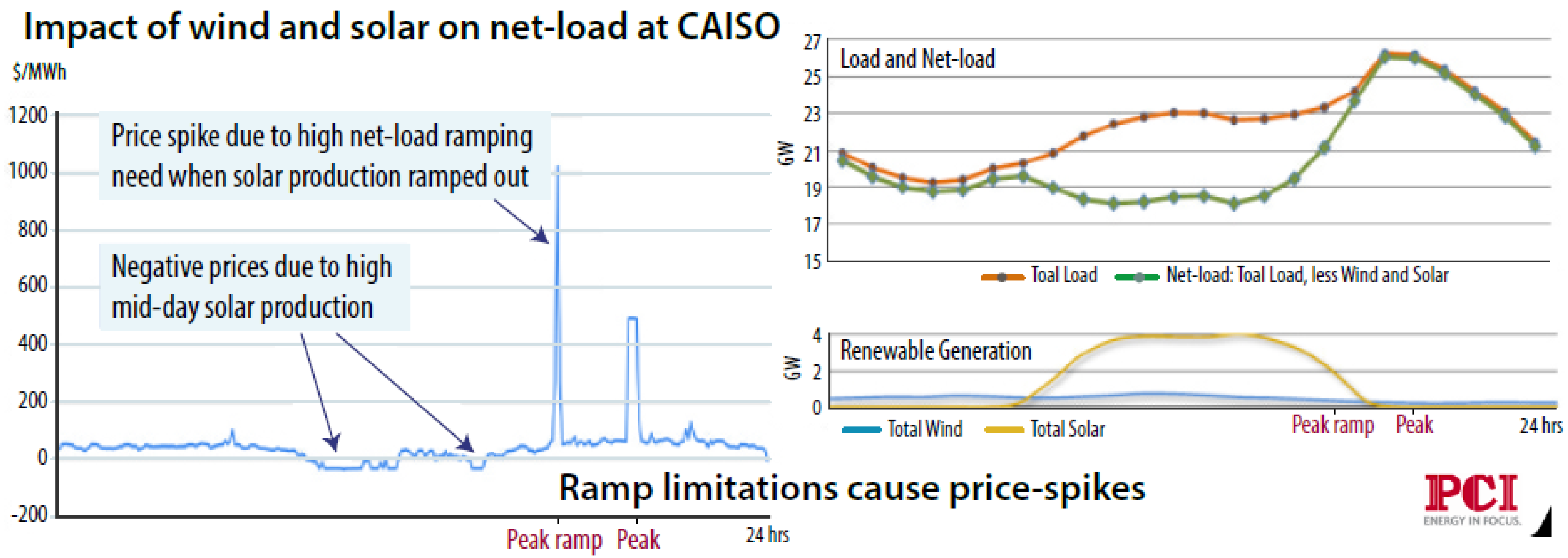
Outline

- Introduction
- Distributed Load Control (aka “Demand Dispatch”) What is it?
- How does it work?
- How does it perform?
- How do the costs compare to Battery Storage?

Introduction

- While the purpose in the past was different, today battery systems are being installed to counter the volatility of renewables



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Introduction

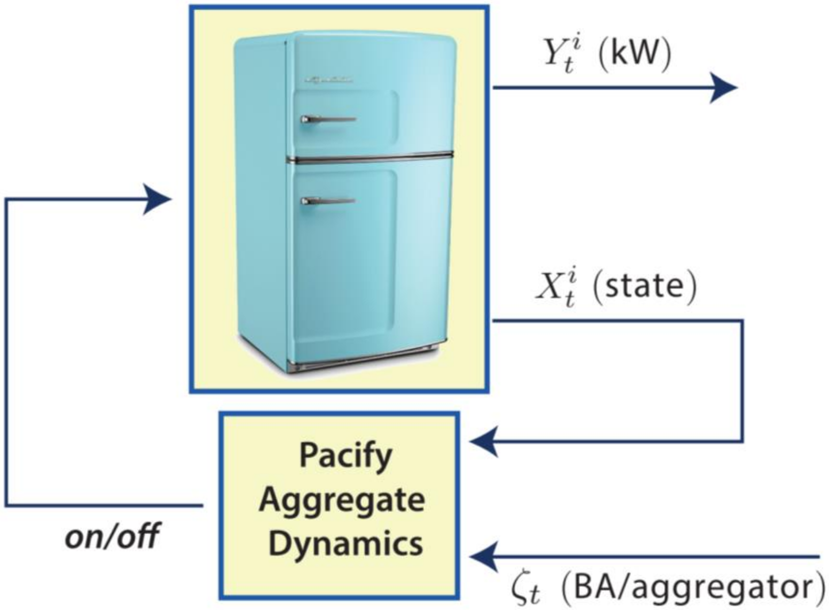
- But, battery costs are significant:
  - Cells need replacing every 5-10 years
  - Energy loss ~10% per cycle
  - A/C is required to cool battery cells
  - Grid-scale systems require lots of real estate

- One alternative: ***Demand Dispatch*** – a set of load adjustment techniques that go far beyond traditional demand response to provide battery-like services

- We compare the cost of the largest Li-ion battery system in the US with an equivalent amount of demand dispatch.
  - ❖ 30 MW, 120 MWh installation by SDG&E

Distributed Control Architecture

- A common signal is broadcast to each class of loads where *local control* considers the command signal and its own state to compute the probability of changing the power mode.
- Randomization eliminates synchronization and enables local control
  - Reduces computation/communication
  - Guarantees Quality of Service (QoS)
- Aggregate behavior can be described as a ***virtual battery***
- ***What is the capacity of a "virtual battery"?***



Calculating Capacity

- The generalized battery model from [4] is used to estimate the capacity for water heaters to provide grid services.

Energy Capacity	$C = N\Delta C_{th} / 2$
Discharge power limit	$n_{+} = NP_{o}$
Charge power limit	$n_{-} = N(P_{m} - P_{o})$

- Parameters for typical electric water heaters are taken from [4-6]

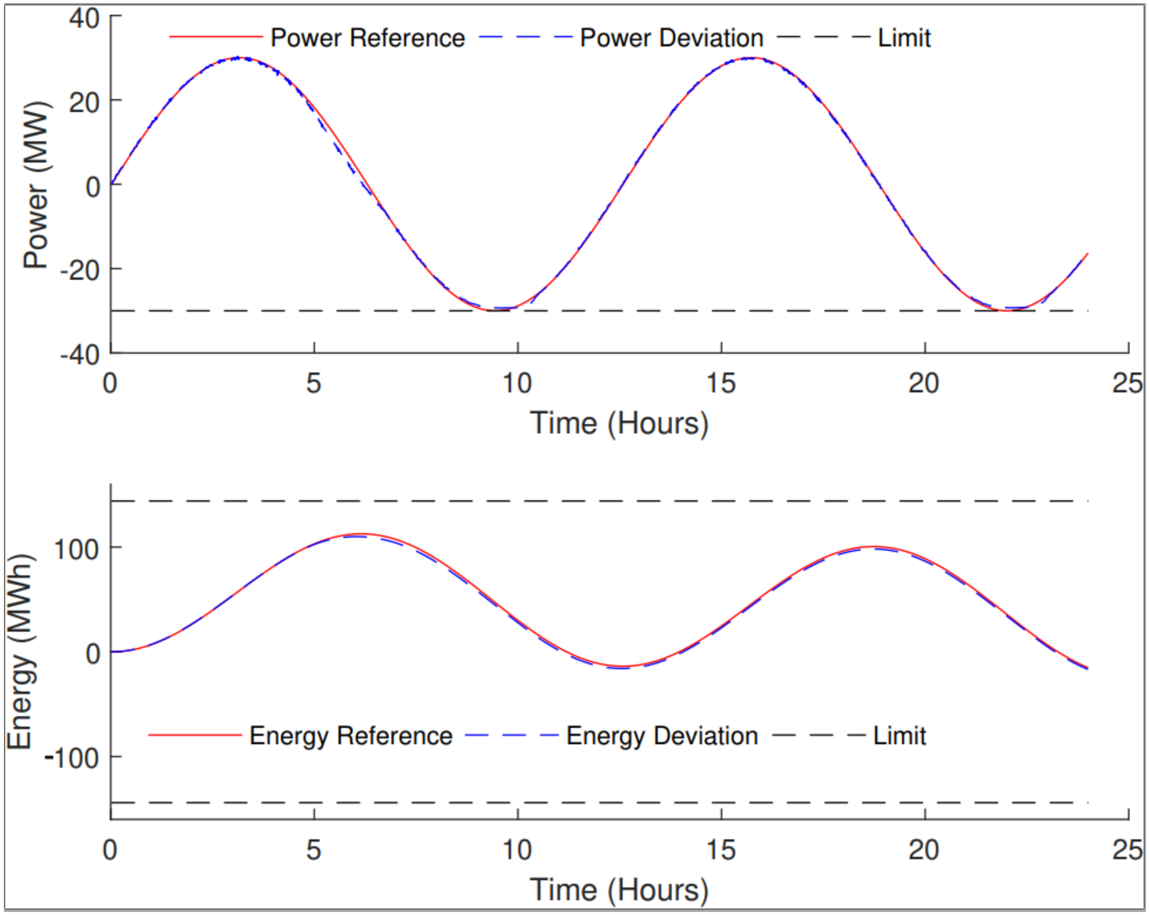
Deadband	Δ = 2-10 °C
Thermal Capacitance	C_{th} = 0.2 – 0.6 kWh/°C
Max Power	P_{m} = 4-5 kW
Average power	P_{o} = 0.2 – 0.3 kW

- Using the generalized battery model and the given parameters, we calculate that ***N* = *120,000*** water heaters are needed to provide 30 MW, 120 MWh of capacity

Validating Capacity Estimates

- Power *deviation* of the collection can track a reference signal

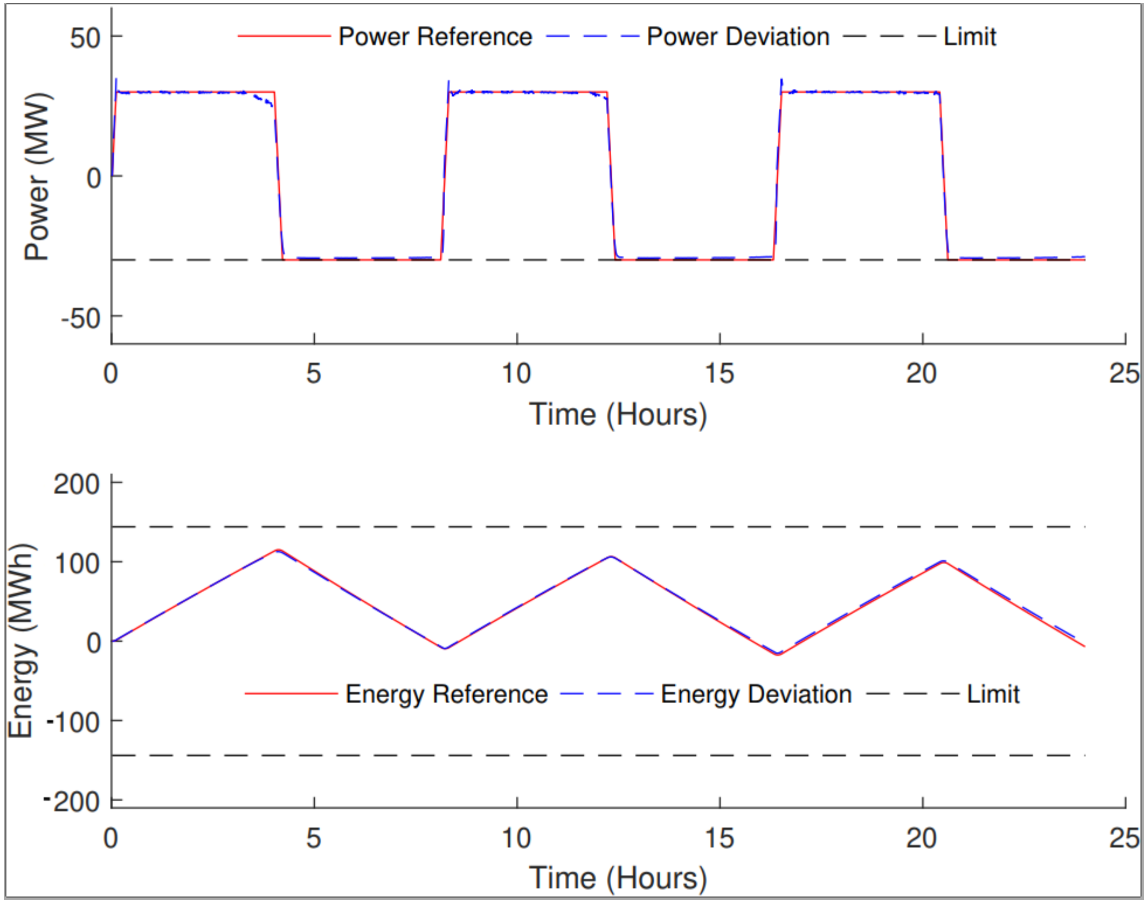
- 120,000 water heaters tracking a 30 MW, 120 MWh sinusoidal signal



- **Tracking is nearly perfect when the capacity limits of the collection are respected**

Validating Capacity Estimates

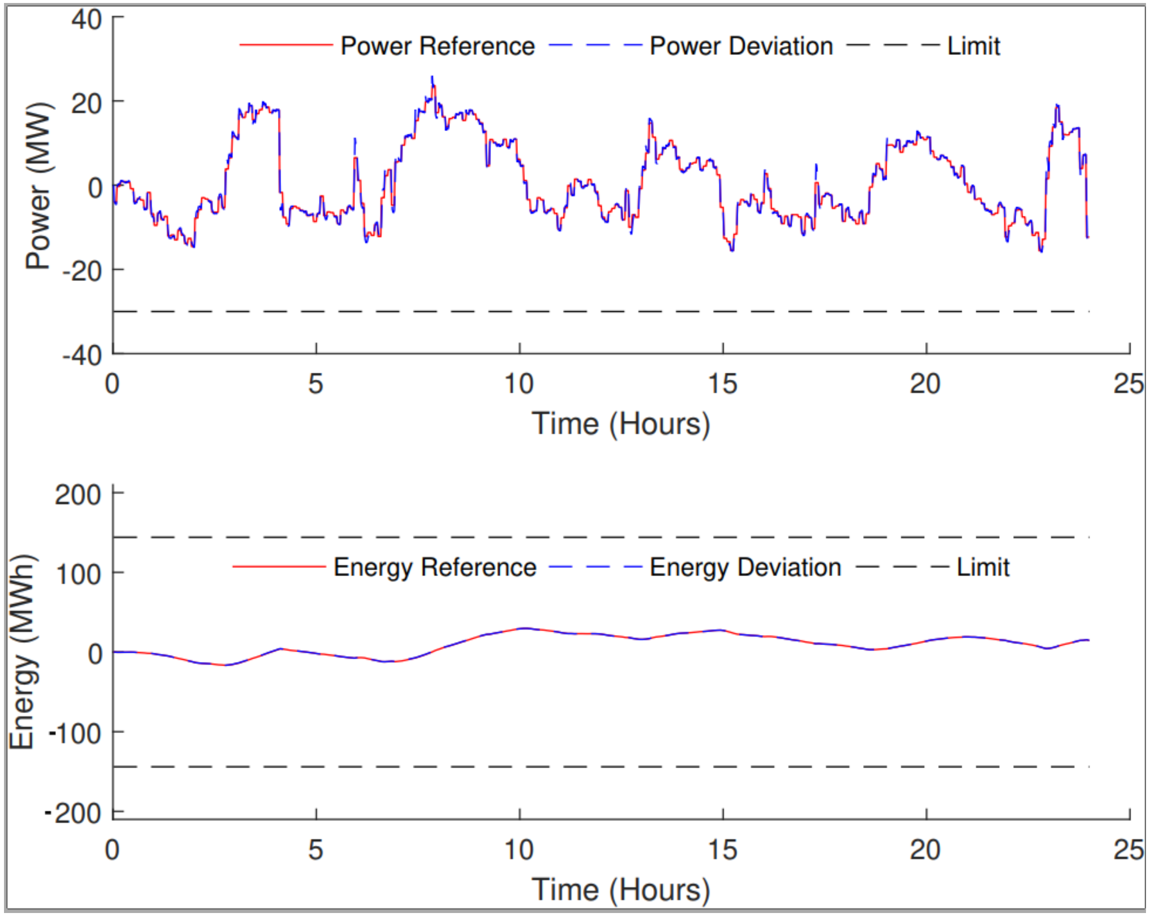
- Power *deviation* of the collection can track a reference signal
- 120,000 water heaters tracking a 30 MW signal for four hours



- **Tracking is nearly perfect when the capacity limits of the collection are respected**

Validating Capacity Estimates

- Power *deviation* of the collection can track a reference signal
- 120,000 water heaters tracking a scaled version of a real-world grid regulation signal, Bonneville Power Administration’s (BPA) Balancing Reserves Deployed (BRD)
- **Tracking is nearly perfect when the capacity limits of the collection are respected**

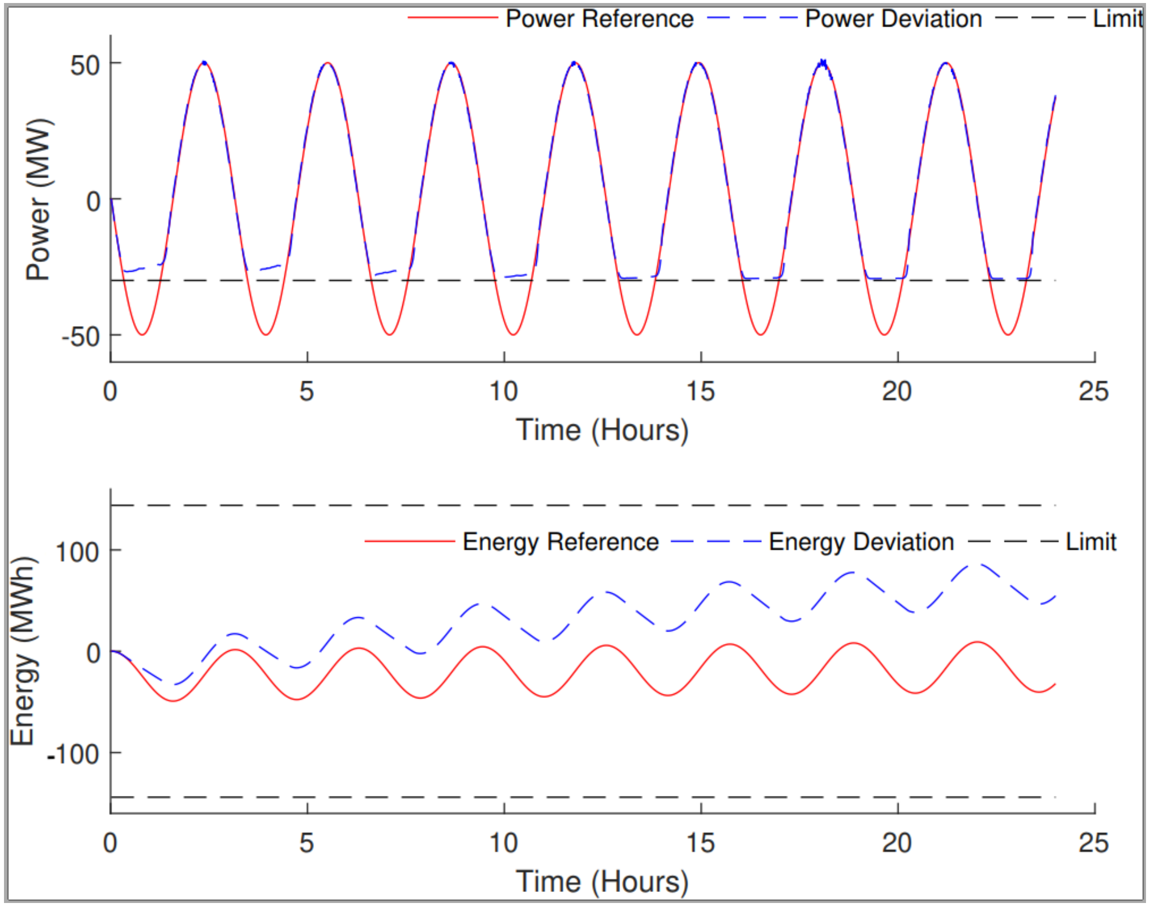


Validating Capacity Estimates

- This reference signal exceeds the ‘discharge’ power limit of the collection

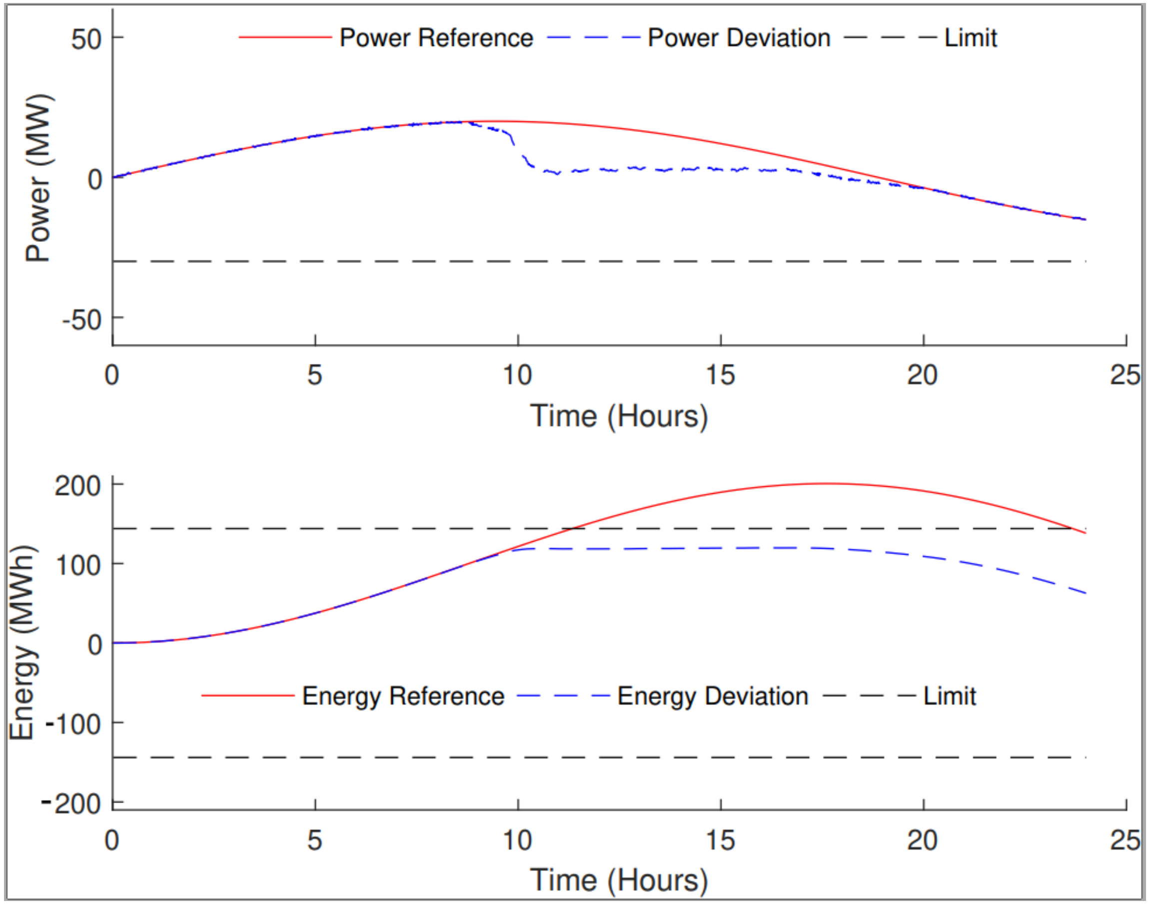
- Tracking fails at or near the boundary because nearly all the water heaters have already turned off

- **Tracking fails when the capacity limits are violated**



Validating Capacity Estimates

- This reference signal exceeds the energy limit of the collection
- Tracking fails near the energy limit because local control is working as intended, i.e., QoS is guaranteed for each water heater
- **Tracking fails when the capacity limits are violated**



Net Present Value Analysis

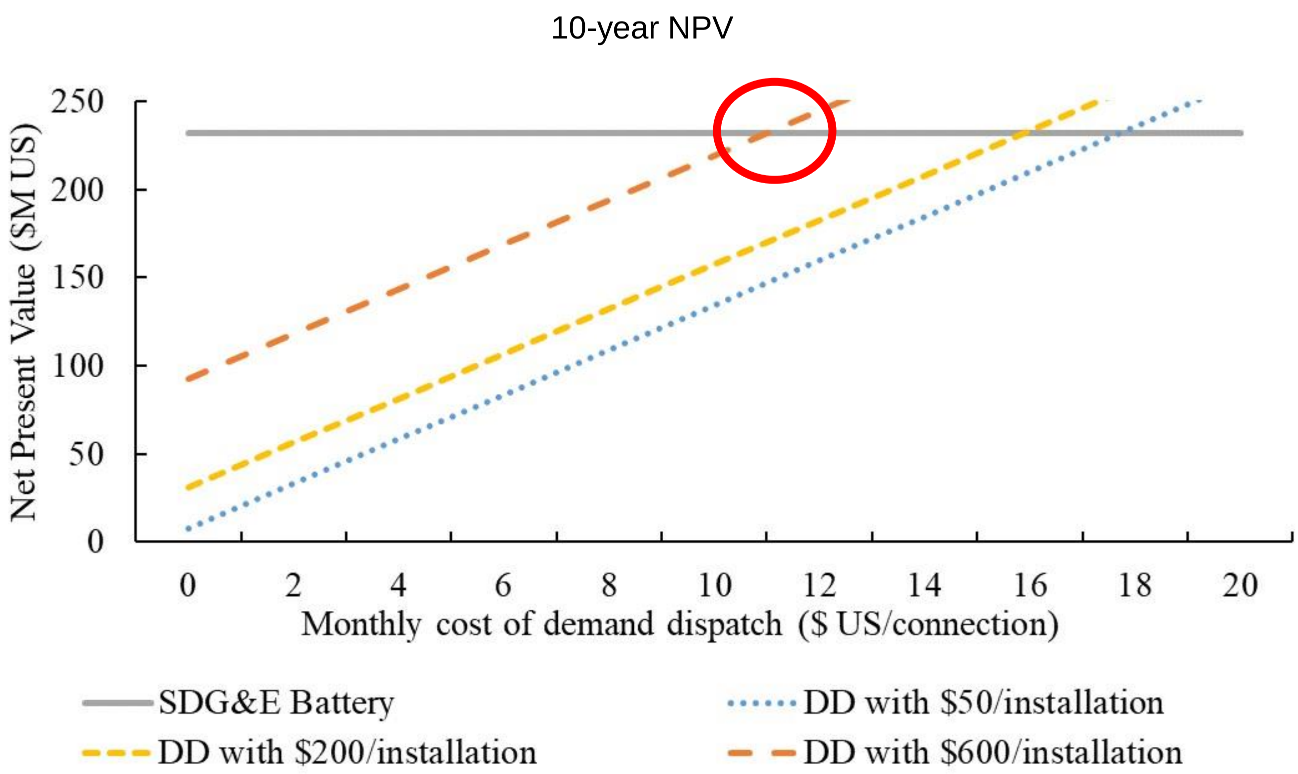
- The NPV of a 30 MW, 120 MWh battery is estimated using data from Lazard [7] and NREL [8], including:
  - Capital costs for battery modules and interconnection equipment
  - Recurring costs for O&M, cycling losses, cell replacement

	Scenario		
Time Horizon	**Best**	**Expected**	**Worst**
10 years	$149 M	$232 M	$329 M
20 years	$241 M	$398 M	$493 M

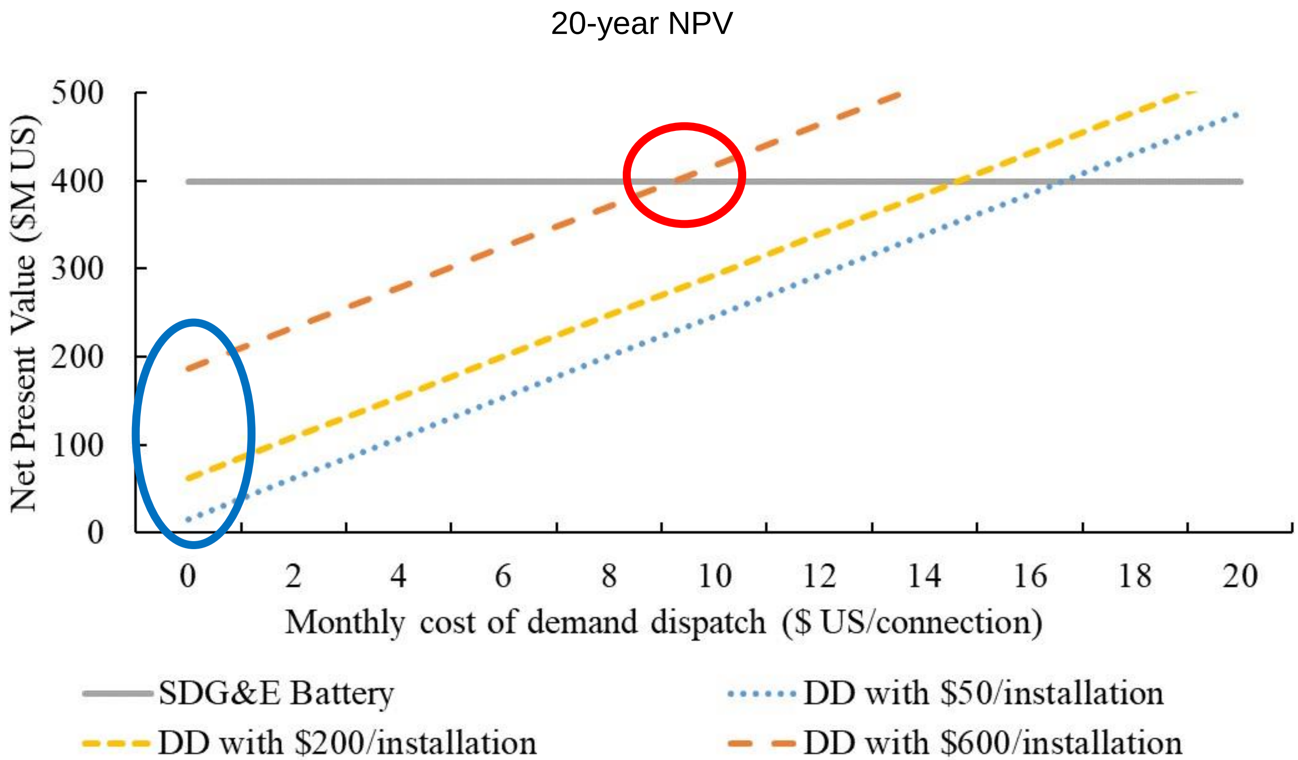
Net Present Value Analysis

- The NPV of equipping 120,000 water heaters for demand dispatch was estimated using data from [6] and [9], including:
  - Capital costs for hardware installation
  - Recurring costs for customer payments, accessing communication networks

Net Present Value Analysis



Net Present Value Analysis



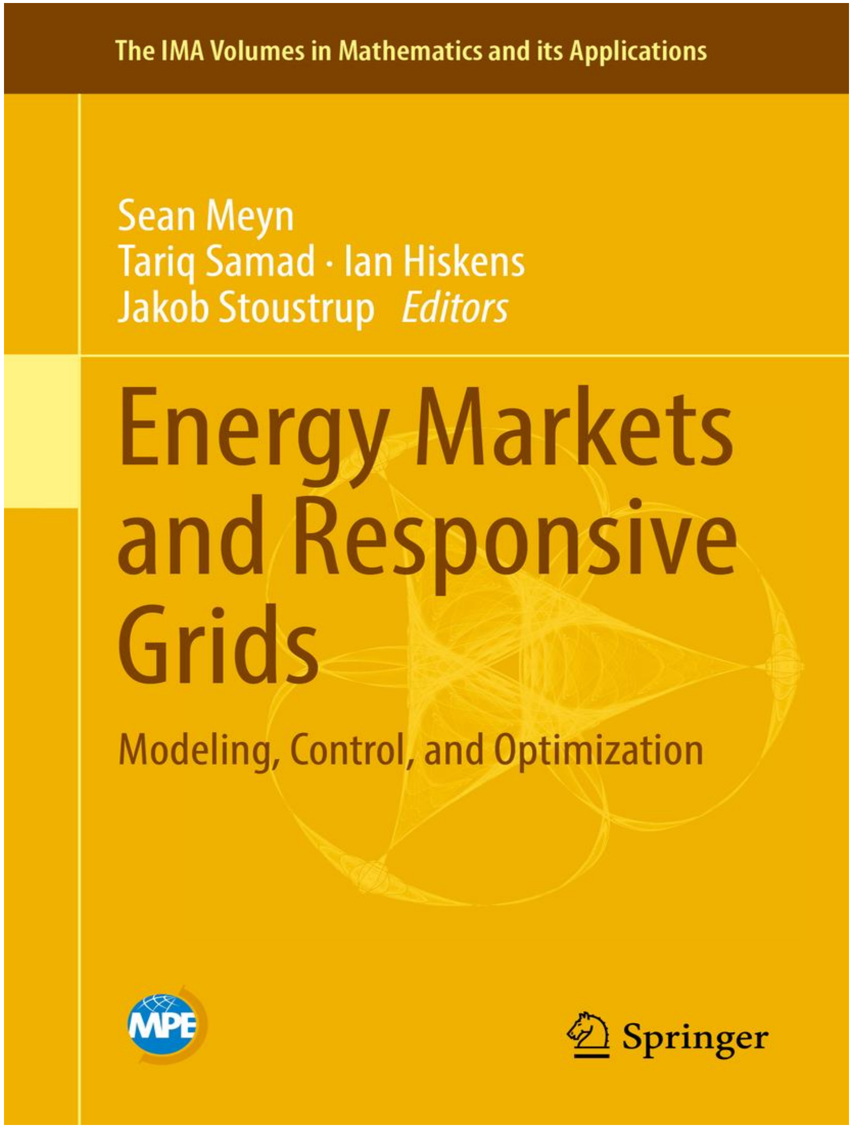
If monthly costs are below $10, it may be cheaper to give away 120,000 'smart' water heaters!

Summary/Conclusion

- Demand Dispatch is not “load shedding” for contingencies, though it can support them.
- It is not “load shedding” for pure economics, though it can be.
- It does not violate Quality of Service (QoS).
- It can closely match the performance of a Battery System, but at significantly less cost.
- It allows loads to be responsive to market conditions—something that has been elusive in the organized markets. (“Prices to devices”)
- Clearly, batteries will play an important role in the smart grid of the future, however, utilities should first consider retro-fitting flexible loads to create virtual energy storage resources

Reinventing Control and Economics in the Power Grid
Six-hour short course within the EDF Workshop: *Thematic Semester on Statistics for Energy Markets Modelling, Forecasting for Renewable Energy Production and Statistical Inference*
http://www.thematicsemester.com/

New project with EDF – **Open Access TCL simulator** for testing VES algorithms (stay tuned)



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