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Real-Time Market Participation of Aggregators with Energy Storage

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Outline

- Motivation and problem formulation

- Real-time energy management of energy storage
  - Bidding into day-ahead and real-time energy markets

- Case study in New England
  - Energy storage, solar, wind, commercial load
  - Real-time management of energy storage can reduce costs

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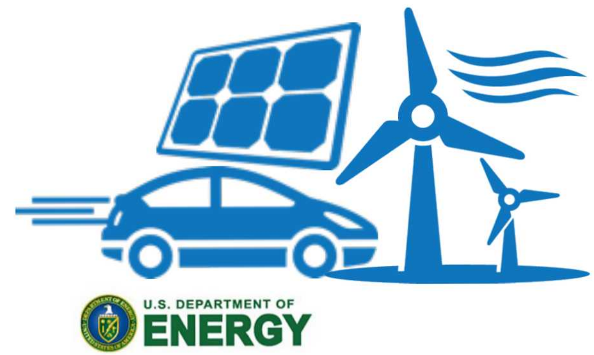
Motivation

Modern energy systems are rapidly changing.

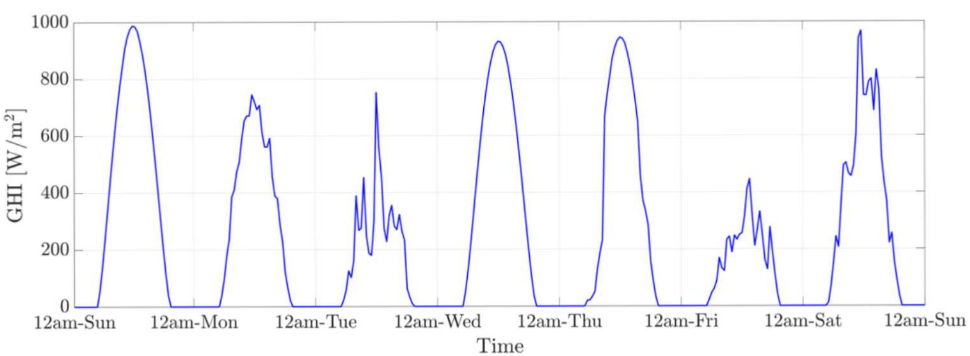
- Changing generation mix
- Highly distributed loads and generation
- Growing need for resilience

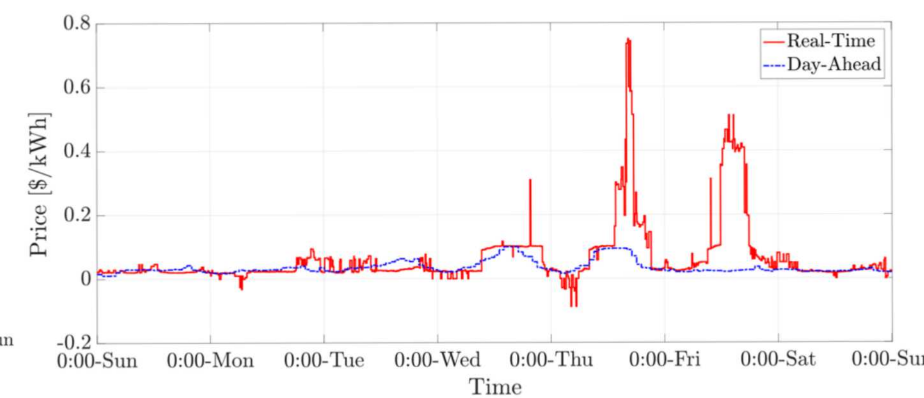


Characterized by large amount of variability and uncertainty

- Loads
- Generation
- Prices

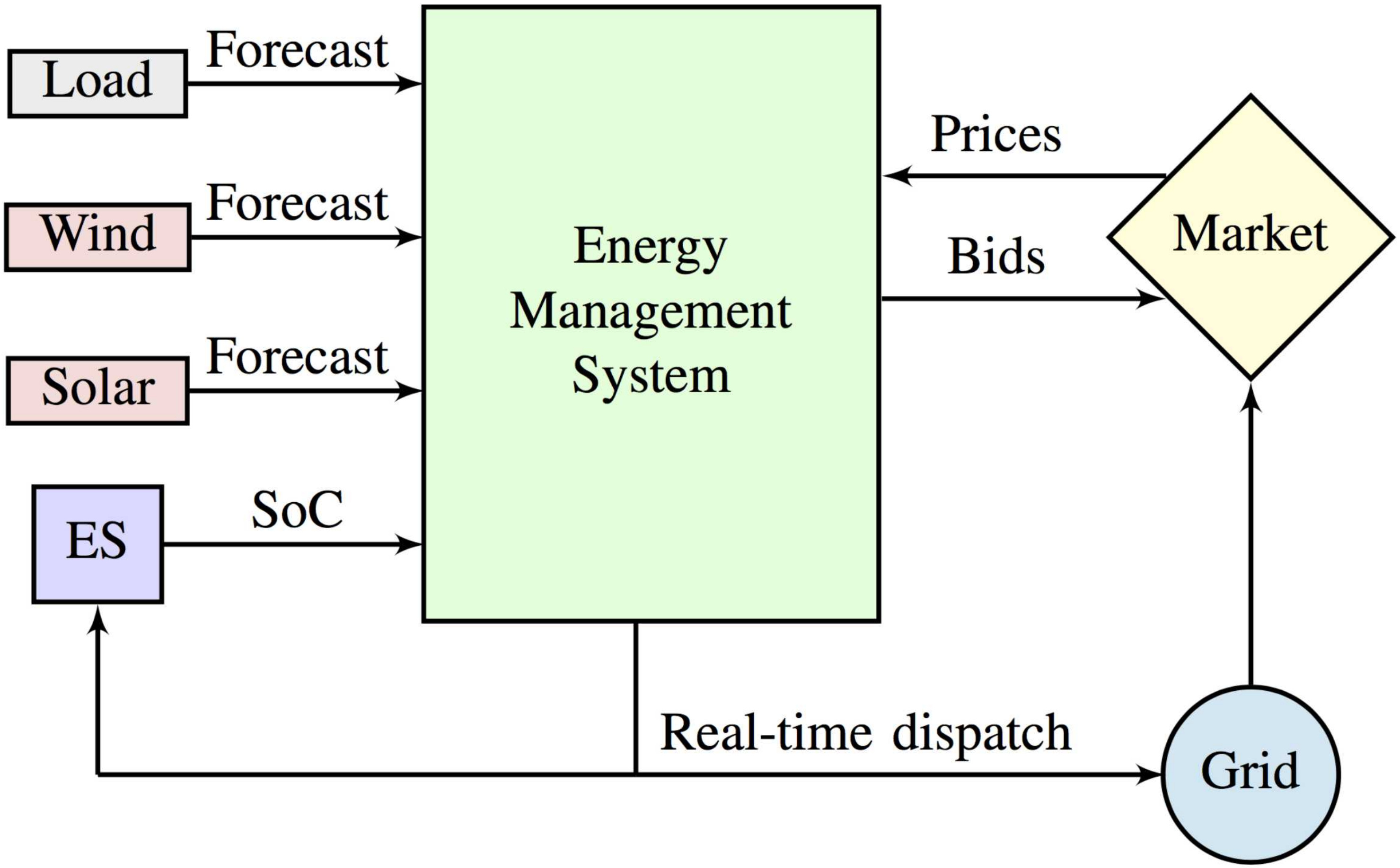
Need to design systems with resources and energy management algorithms to accommodate/take advantage.





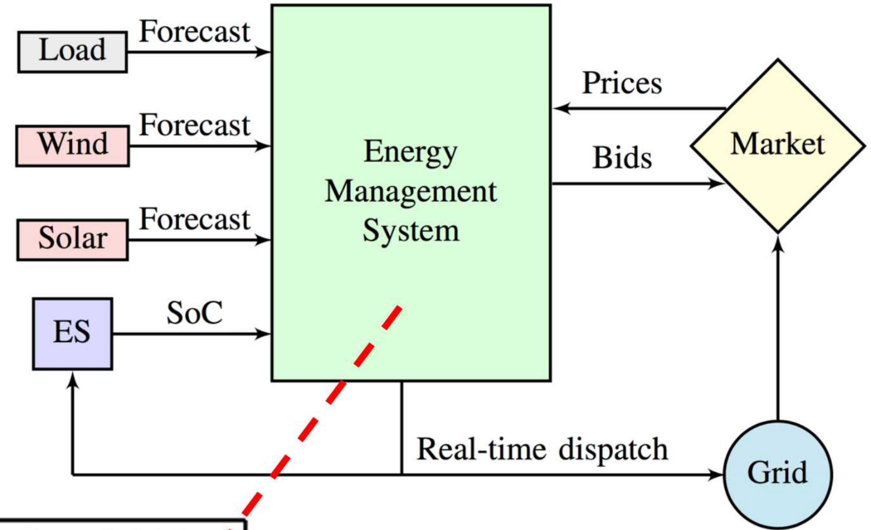
Problem Architecture

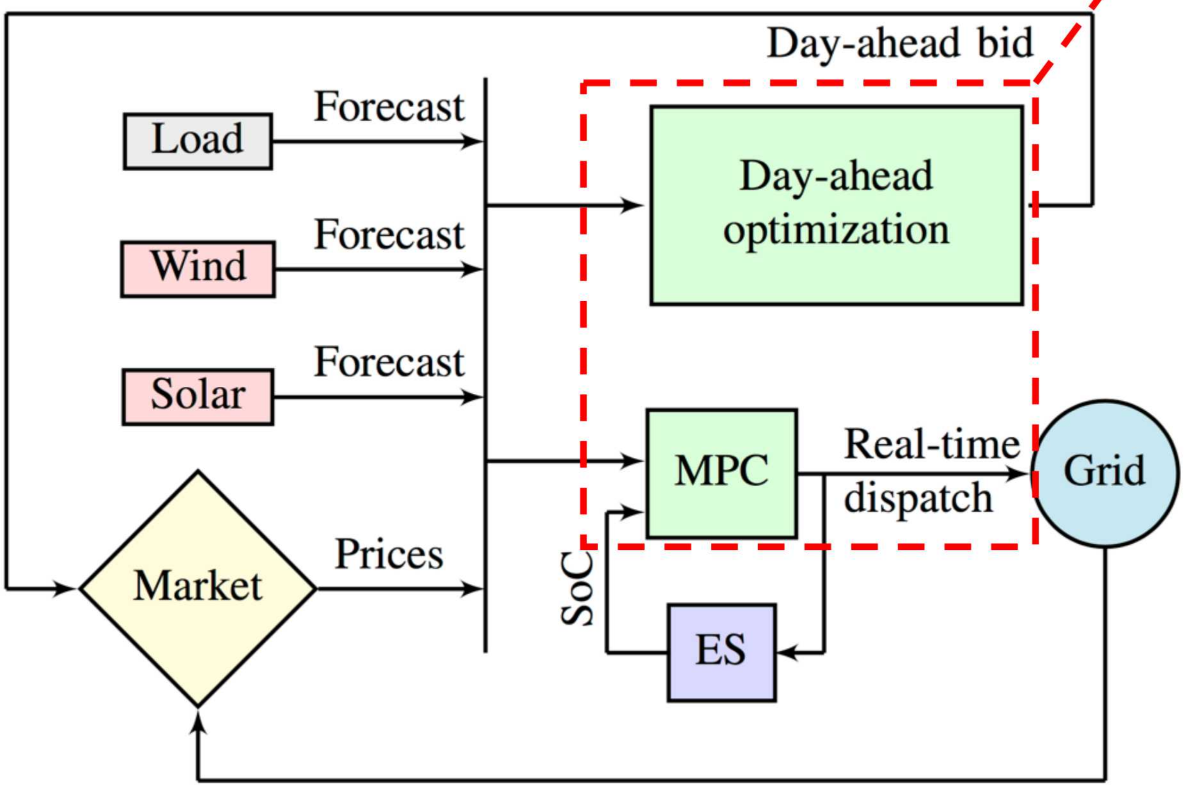
Energy management system for minimizing cost of energy purchased from the grid while balancing net load.



Optimization Formulation

Two-stage optimization:
1) Day-ahead scheduling
2) Real-time dispatch





Assumptions:
1) Price taker

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Ideal Optimization

$$\min_{\hat{p}^c_{t:T}, \hat{p}^d_{t:T}, \hat{p}^g_{t:T}} \sum_{t=1}^{T} (\lambda_t^{\mathrm{DA}} - \lambda_t^{\mathrm{RT}}) \hat{p}_t^g \Delta t,$$

Decision variables

DA energy price

RT energy price

Power purchased from grid

Time step

Ideal Optimization

$$\min_{\hat{p}^c_{t:T}, \hat{p}^d_{t:T}, \hat{p}^g_{t:T}} \sum_{t=1}^{T} (\lambda_t^{\mathrm{DA}} - \lambda_t^{\mathrm{RT}}) \hat{p}_t^g \Delta t,$$

Decision variables: $\hat{p}^c_{t:T}, \hat{p}^d_{t:T}, \hat{p}^g_{t:T}$

DA energy price: λ_t^{DA}

RT energy price: λ_t^{RT}

Power purchased from grid: $\hat{p}_t^g$

Time step: Δt

Subject to

$$\hat{p}_t^c \geq 0$$ Charge power

$$\hat{p}_t^d \geq 0$$ Discharge power

$$\hat{p}_t^c + \hat{p}_t^d \leq p_{\mathrm{ES}}$$ Power rating

Ideal Optimization

DA energy price

RT energy price

Power purchased from grid

Time step

$$\min_{\hat{p}^c_{t:T},\hat{p}^d_{t:T},\hat{p}^g_{t:T}} \sum_{t=1}^{T} (\lambda_t^{\mathrm{DA}} - \lambda_t^{\mathrm{RT}})\hat{p}_t^g \Delta t,$$

Decision variables

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$$\hat{p}_t^c \geq 0$$ Charge power

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$$p_t^{\mathrm{net}} + \hat{p}_t^c - \hat{p}_t^d - \hat{p}_t^g = 0$$ Load balancing

Ideal Optimization

DA energy price · RT energy price · Power purchased from grid · Time step

$$\min_{\hat{p}^c_{t:T},\hat{p}^d_{t:T},\hat{p}^g_{t:T}} \sum_{t=1}^{T} (\lambda_t^{\mathrm{DA}} - \lambda_t^{\mathrm{RT}})\hat{p}_t^g \Delta t,$$

Decision variables

Subject to

$\hat{p}_t^c \geq 0$	Charge power
$\hat{p}_t^d \geq 0$	Discharge power
$\hat{p}_t^c + \hat{p}_t^d \leq p_{\mathrm{ES}}$	Power rating
$p_t^{\mathrm{net}} + \hat{p}_t^c - \hat{p}_t^d - \hat{p}_t^g = 0$	Load balancing
$\delta s_{\mathrm{ES}} \leq \eta_s \hat{s}_t + \eta_c \hat{p}_t^c \Delta t - \hat{p}_t^d \Delta t \leq (1-\delta) s_{\mathrm{ES}}$	Energy capacity
$\eta_s \hat{s}_T + \eta_c \hat{p}_T^c \Delta t - \hat{p}_T^d \Delta t = s_0$	Initial SoC

Desired fraction of unused SoC (δ)

Ideal Optimization

DA energy price

RT energy price

Power purchased from grid

Time step

$$\min_{\hat{p}^c_{t:T}, \hat{p}^d_{t:T}, \hat{p}^g_{t:T}} \sum_{t=1}^{T} (\lambda_t^{\mathrm{DA}} - \lambda_t^{\mathrm{RT}}) \hat{p}_t^g \Delta t,$$

Decision variables

BUT… We have uncertainty in

- energy prices,
- load,
- and generation.

Also have different time scales for DA and RT markets. Therefore, consider a two-stage, stochastic approach with forecasts and probabilistic constraint:

$$\mathbb{P}\{\hat{p}_t^{\mathrm{net}} + \hat{p}_t^c - \hat{p}_t^d - \hat{p}_t^g \leq 0\} \geq \alpha$$

Net load

Power charged

Power discharged

Power purchased from grid

Desired probability

Real-Time Algorithm

PROCEDURE: Each day

- **Stage 1 (DA):**
  - Receive/compute hourly DA net load and price forecasts
  - Solve DA scheduling optimization
  - Bid resulting supply/demand into DA market
- **Stage 2 (RT):**
  - **For** each time step:
    - Measure/receive SoC, net load, RT price
    - Receive/compute RT net load and price forecasts
    - Solve RT dispatch optimization
    - Implement charge/dispatch command
  - **End for**

END PROCEDURE

Repeat procedure each day.

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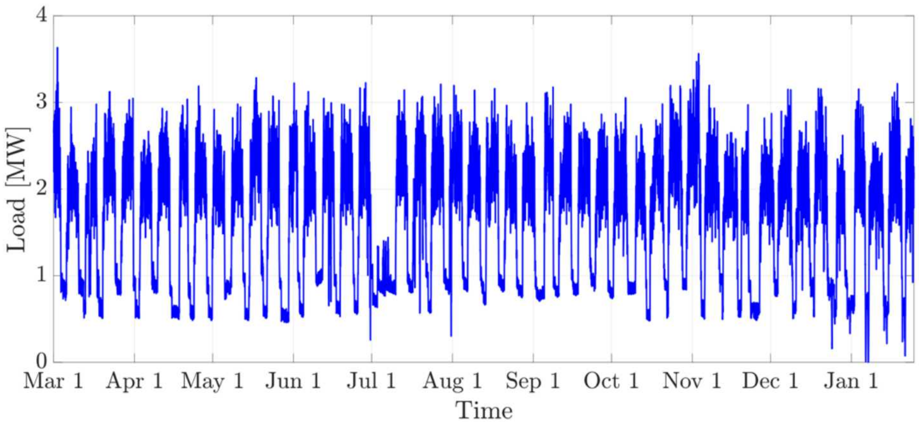
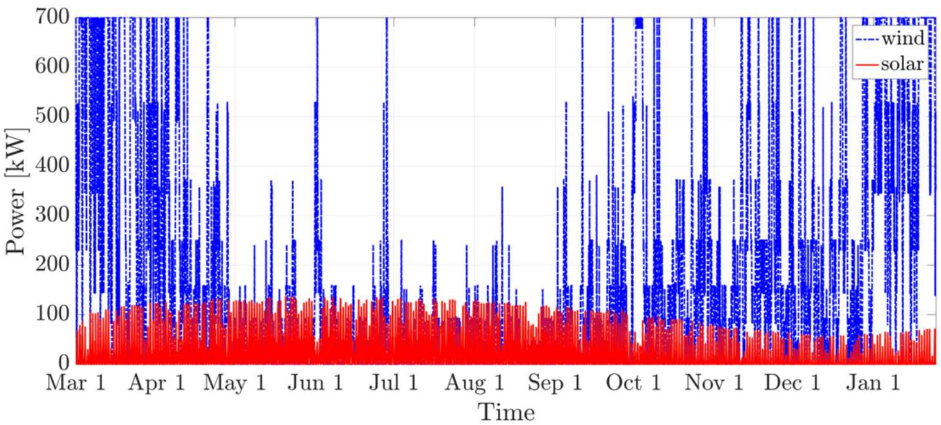
Data for March 1 to January 24

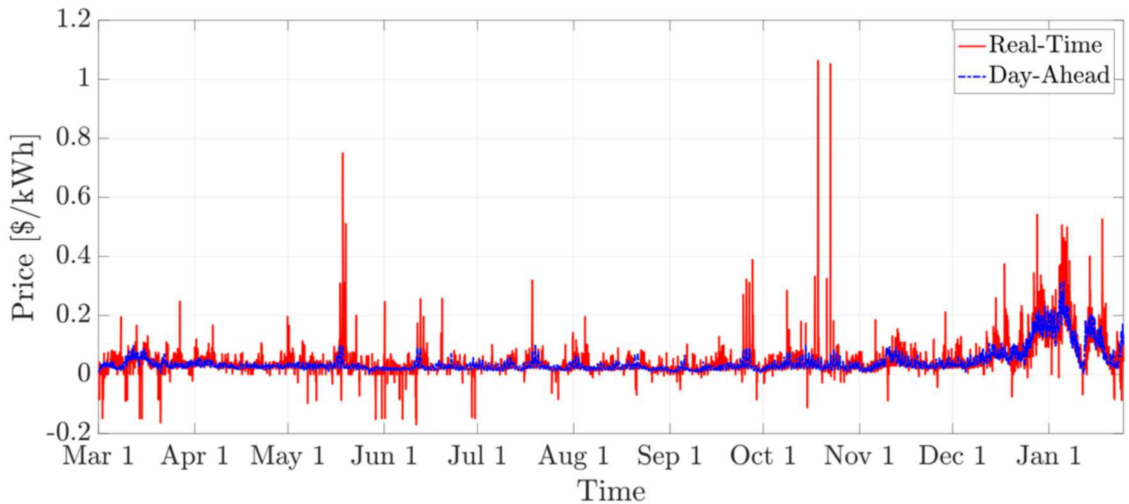


Load from Mar 1, 2017 to Jan 24, 2018.



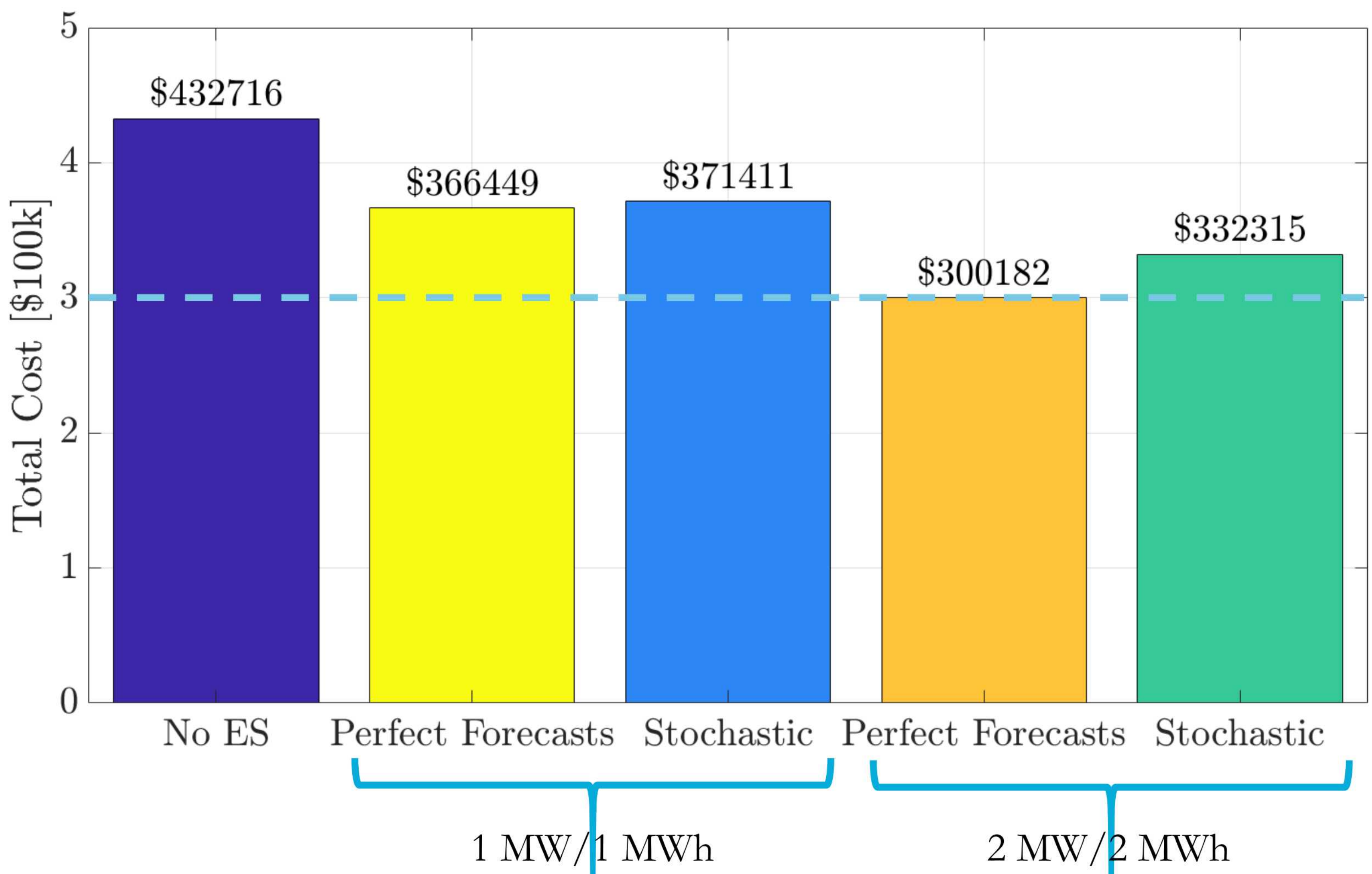
Renewable Generation from Mar 1, 2015 to Jan 24, 2016.

- 15-minute commercial load in MA
- 30-minute solar GHI near Boston
- 30-minute wind speed near Boston
- Hourly DA and 5-minute RT Locational Marginal Prices (LMPs) for Brighton pricing node near Boston from ISO New England



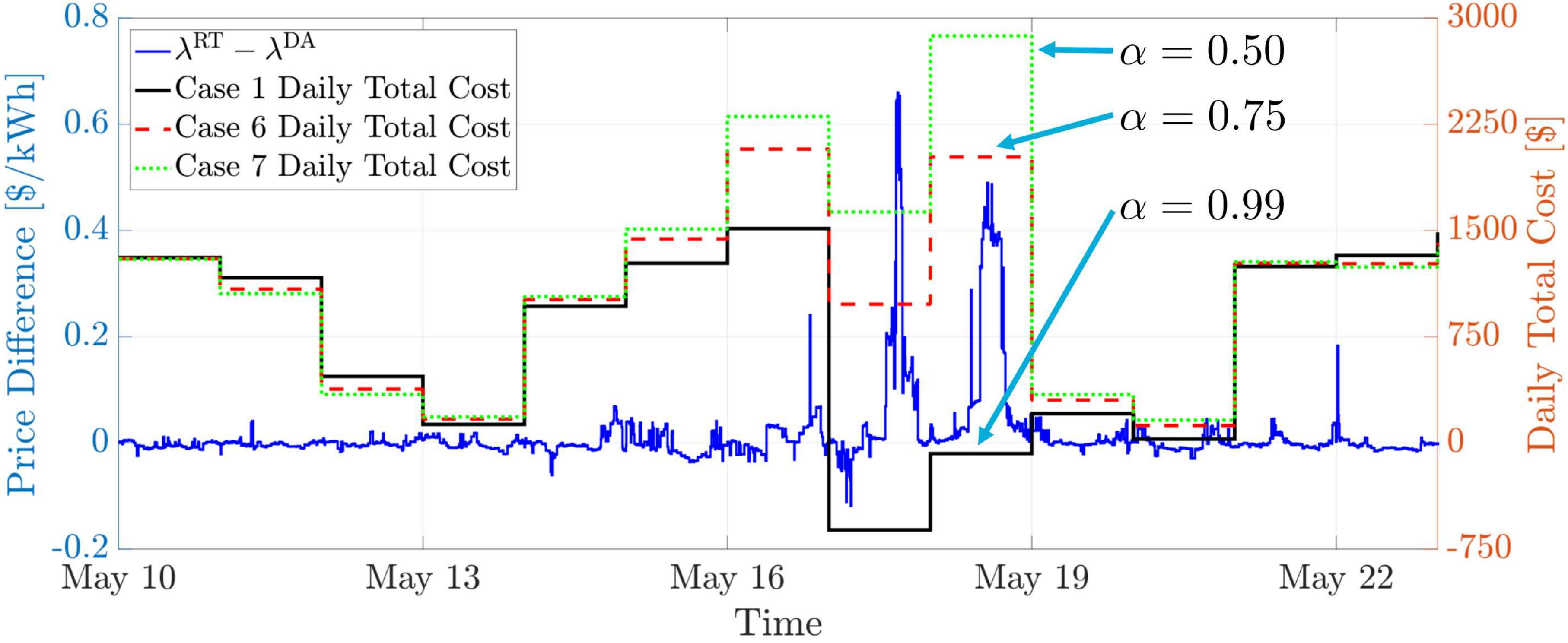
Prices from Mar 1, 2017 to Jan 24, 2018.

Total cumulative cost from 3/1/2017 – 1/24/2018



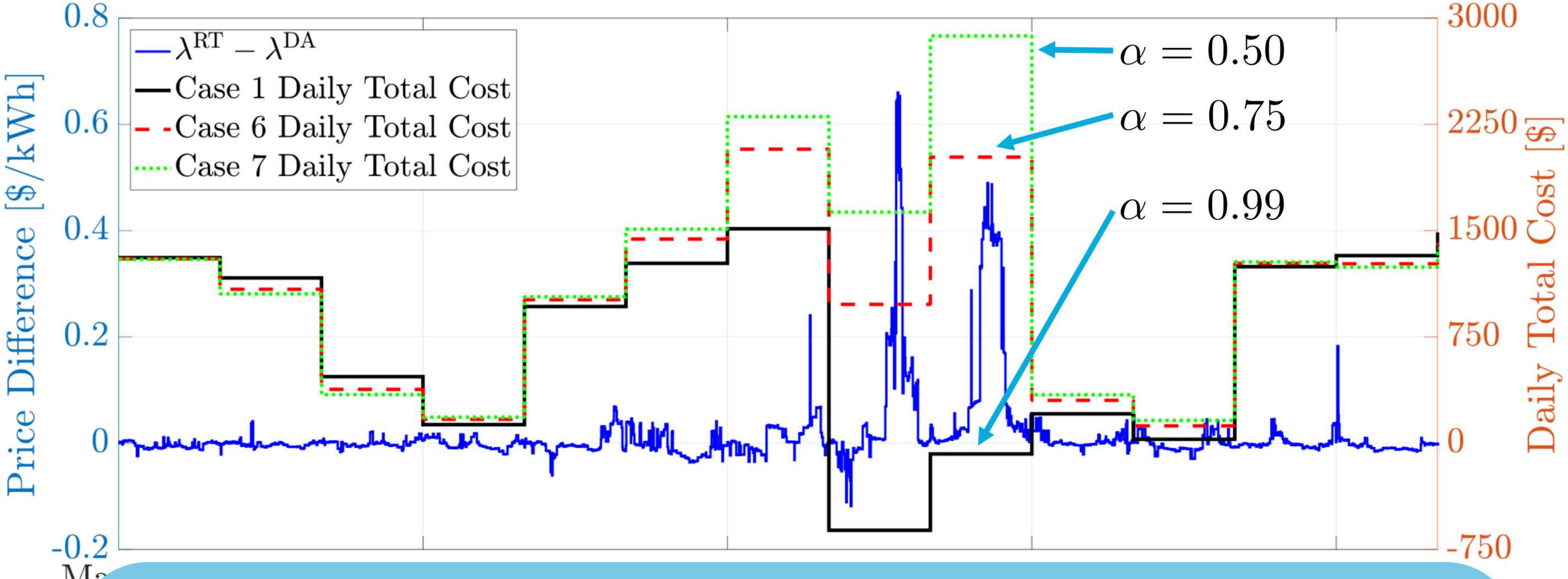
- Using ES reduces cost **>15%** (1MW/1MWh) or **>30%** (2MW/2MWh)
- Simple (suboptimal) algorithm with naïve forecasts performs well (>23% cost reduction)

Case Study: Probabilistic Constraint



Significantly different daily total cost due to significant DA/RT price difference.

Case Study: Probabilistic Constraint



SO…

Larger α is better *in this case*.

- Bidding more than necessary in DA market is advantageous because RT prices often/more significantly higher than DA prices
- If prices are confidently known day-before, α could be made time-varying, and DA bid could be as large/small as allowable by ISO.

Conclusions

- Grid conditions are changing - need flexible and controllable resources and effective energy management systems.

- Energy storage can effectively reduce costs for entities participating in markets (even without sophisticated algorithms/forecasts)

- Case study:
  - Energy storage system reduced operating cost
  - Simple (suboptimal) stochastic approach performs well
  - Conservative bidding in the day-ahead market was advantageous
  - Only considered energy arbitrage; could further reduce costs by participating in freq. regulation markets

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Thank you.

Extra slides

Energy Storage as Flexible Resource

Grid-scale energy storage can enable significant cost savings to industry while improving infrastructure reliability and efficiency

Mitigate $79B/yr in commercial losses from outages

Reduce $2T in required T&D upgrades

Reduce commercial and industrial electrical bills through demand charge management. 7.5 million U.S. customers are enrolled in dynamic pricing (EIA 2015)

Balance the variability of 825 GW of new renewable generation while improving grid reliability and efficiency.

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Energy Storage as Flexible Resource

Grid-scale energy storage can enable significant cost savings to industry while improving infrastructure reliability and efficiency

ULTIMATELY…

Can act as a controllable, flexible resource (source and sink) that can accommodate variability and uncertainty in load, generation, and prices.

Reduce commercial and industrial electrical bills through demand charge management. 7.5 million U.S. customers are enrolled in dynamic pricing (EIA 2015)

Balance the variability of 825 GW of new renewable generation while improving grid reliability and efficiency.

U.S. DEPARTMENT OF ENERGY

Two-Stage Optimization

Day-Ahead Scheduling

$$\min_{\tilde{p}^c_{1:24},\tilde{p}^d_{1:24},\tilde{p}^g_{1:24}} \sum_{h=1}^{24} \underbrace{\mathbb{E}[\hat{\lambda}^{\mathrm{DA}}_h - \hat{\lambda}^{\mathrm{RT}}_h]}_{\text{Expected value}} \tilde{p}^g_h$$

Real-Time Dispatch

$$\min_{\hat{p}^c_{t:T},\hat{p}^d_{t:T},\hat{p}^g_{t:T}} \sum_{t=1}^{T} \mathbb{E}[\hat{\lambda}^{\mathrm{RT}}_t]\hat{p}^g_t \Delta t$$

Subject to the probabilistic constraint

$$\mathbb{P}\{\hat{p}^{\mathrm{net}}_t + \hat{p}^c_t - \hat{p}^d_t - \hat{p}^g_t \leq 0\} \geq \alpha$$

- $\hat{p}^{\mathrm{net}}_t$: Net load
- $\hat{p}^c_t$: Power charged
- $\hat{p}^d_t$: Power discharged
- $\hat{p}^g_t$: Power purchased from grid
- α: Desired probability

Two-Stage Optimization

Day-Ahead Scheduling

$$\min_{\tilde{p}^c_{1:24},\tilde{p}^d_{1:24},\tilde{p}^g_{1:24}} \sum_{h=1}^{24} \underbrace{\mathbb{E}[\hat{\lambda}^{\mathrm{DA}}_h - \hat{\lambda}^{\mathrm{RT}}_h]}_{\text{Expected value}} \tilde{p}^g_h$$

Real-Time Dispatch

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Subject to the probabilistic constraint

$$\mathbb{P}\{\hat{p}^{\mathrm{net}}_t + \hat{p}^c_t - \hat{p}^d_t - \hat{p}^g_t \leq 0\} \geq \alpha$$

If normally distributed forecast errors, probabilistic constraint can be written as deterministic linear inequality constraint. Optimization problems become linear programs.

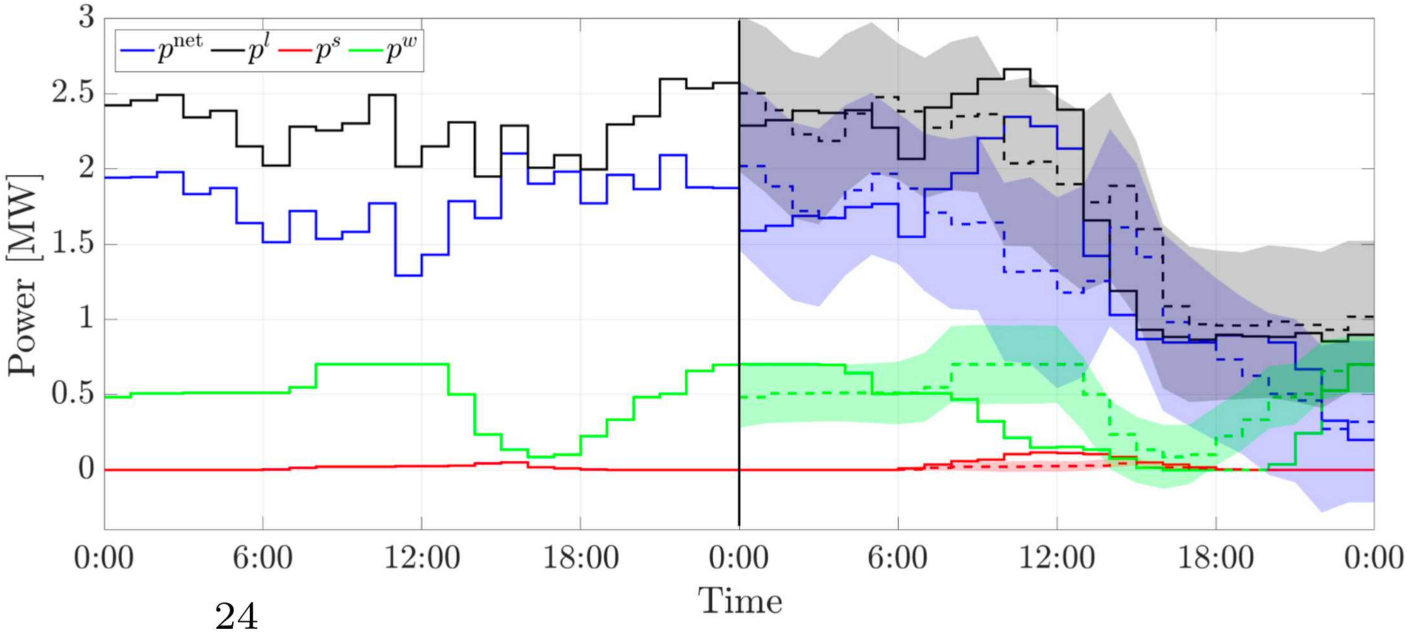
Parameters

Parameter	Description	Value	Units
ρ	Air density	1.2	kg/m^3
$\underline{v}$	Wind turbine cut-in speed	4	m/s
$\overline{v}$	Wind turbine cut-out speed	25	m/s
v^*	Wind turbine rated speed	10	m/s
η_w	Wind conversion efficiency	0.45	-
η_{PV}	PV panel efficiency	0.15	-
η_{conv}	PV conversion efficiency	0.90	-
η_s	ES storage efficiency	1.00	-
η_c	ES charging efficiency	0.85	-
A_{PV}	Total area of solar panels	1000	m^2
A_{wind}	Total swept area of turbine blades	1357	m^2
p_{ES}	ES power rating	1000	kW
s_{ES}	ES energy capacity	1000	kWh
s_0	Daily initial SoC	$s_{\text{ES}}/2$	kWh
δ	Desired fraction of unused SoC	0.1	-
Δt	Real-time optimization time step	5	minutes
T	Real-time optimization horizon	48	-
α	Load balancing probability	0.99	-

1 MW
1MWh

4 hour window

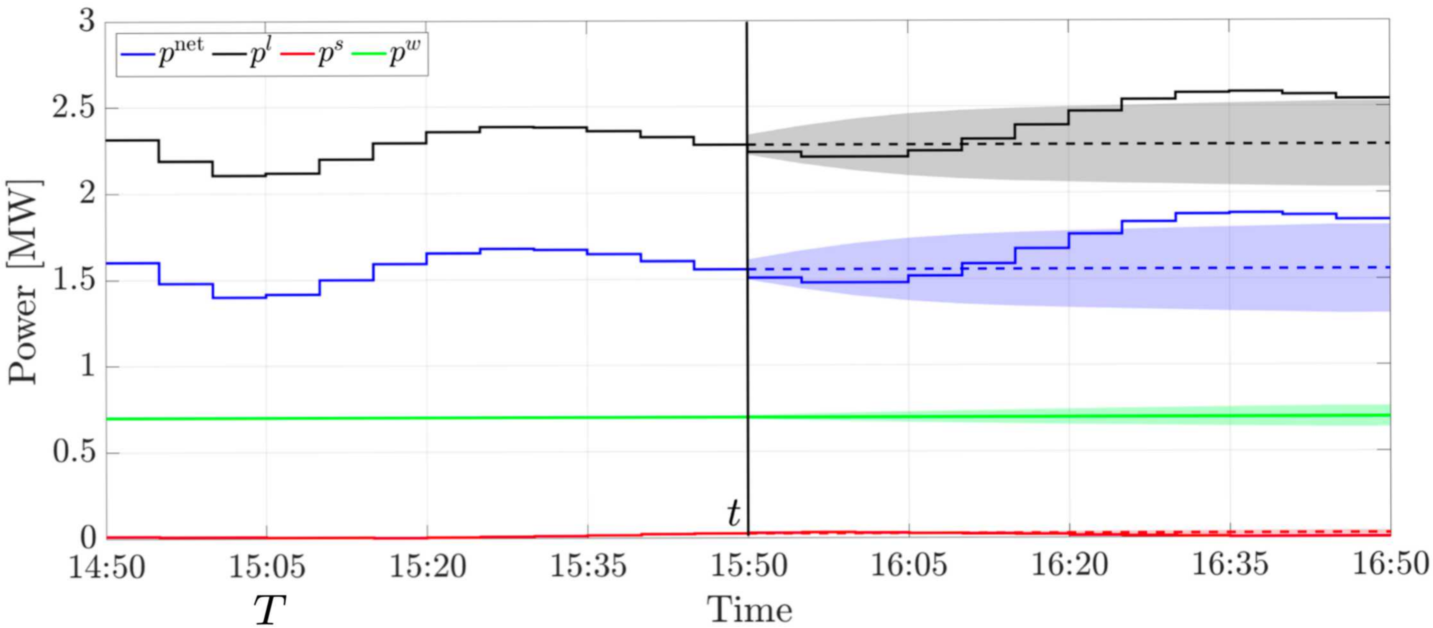
Case Study: Day-Ahead Forecasts



$$\min_{\tilde{p}^c_{1:24},\tilde{p}^d_{1:24},\tilde{p}^g_{1:24}} \sum_{h=1}^{24} \mathbb{E}[\lambda_h^{\text{DA}} - \lambda_h^{\text{RT}}]\tilde{p}_h^g$$

- Hourly load forecast = load in same hour from previous week
- Hourly solar/wind generation forecast = average value in same hour from previous day
- Hourly day-ahead price forecast = day-ahead price in same hour from previous day
- Hourly-averaged real-time price forecast = average real-time price in same hour from previous day

Case Study: Real-Time Forecasts

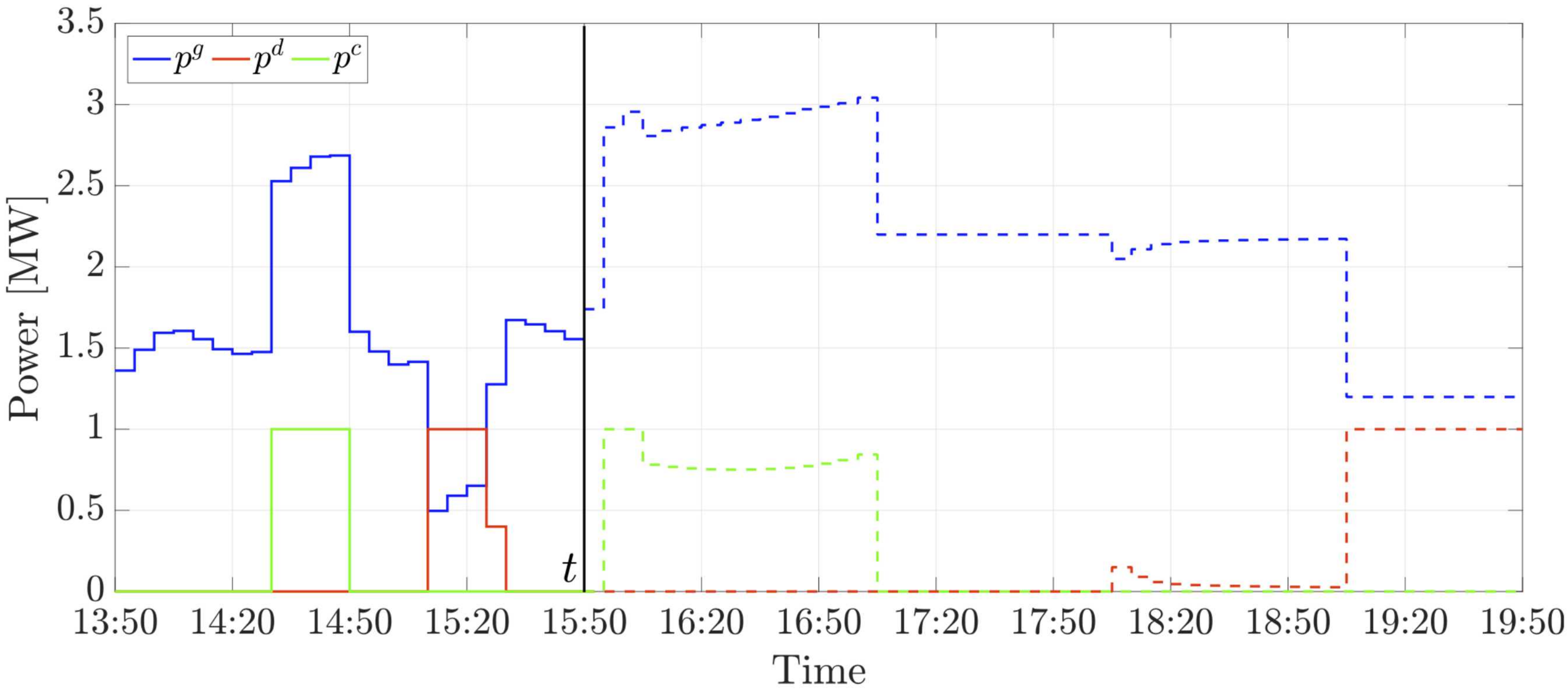


$$\min_{\hat{p}^c_{t:T}, \hat{p}^d_{t:T}, \hat{p}^g_{t:T}} \quad \sum_{t=1}^{T} \mathbb{E}[\lambda_t^{\mathrm{RT}}] \hat{p}_t^g \Delta t$$

- Real-time load/solar/wind forecast = load/solar/wind from previous 5-minutes
- Real-time price forecast = price from previous 5-minutes and cleared day-ahead prices, i.e.,

$$\hat{\lambda}^{\mathrm{RT}}_{t:T} = \{\lambda^{\mathrm{RT}}_{t-1}, \lambda^{\mathrm{DA}}_{t+1}, \lambda^{\mathrm{DA}}_{t+2}, \ldots, \lambda^{\mathrm{DA}}_{T-1}\}$$

Case Study: Solution Snapshot



Data for August 6-12

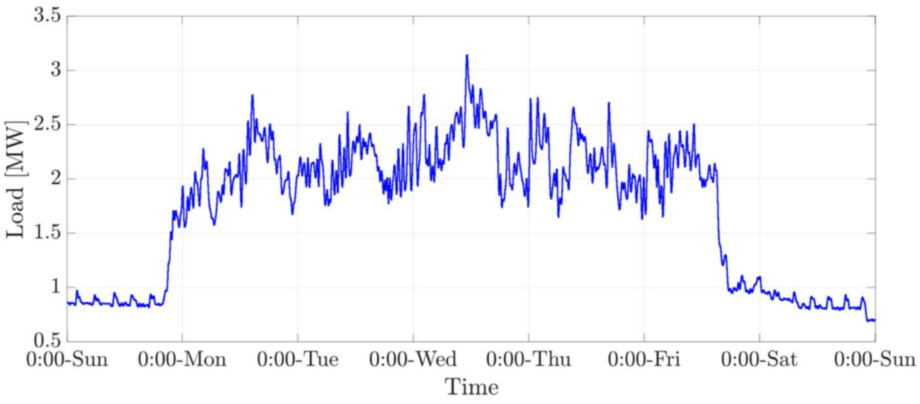


Fig. 22. Load for the week of August 6-12, 2017.

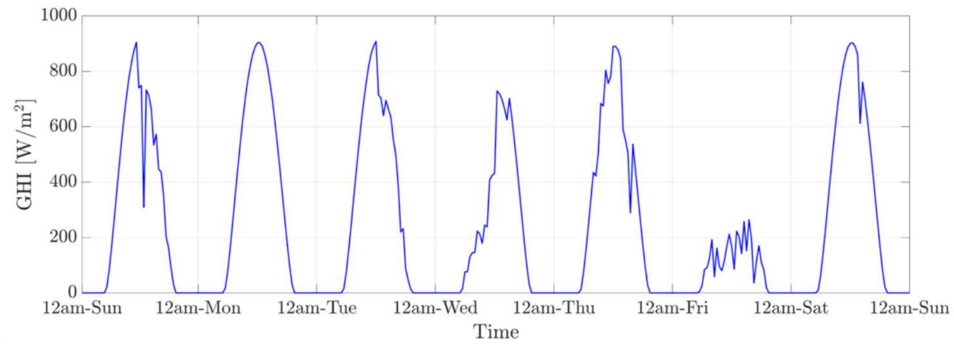


Fig. 23. GHI for the week of August 6-12, 2015.

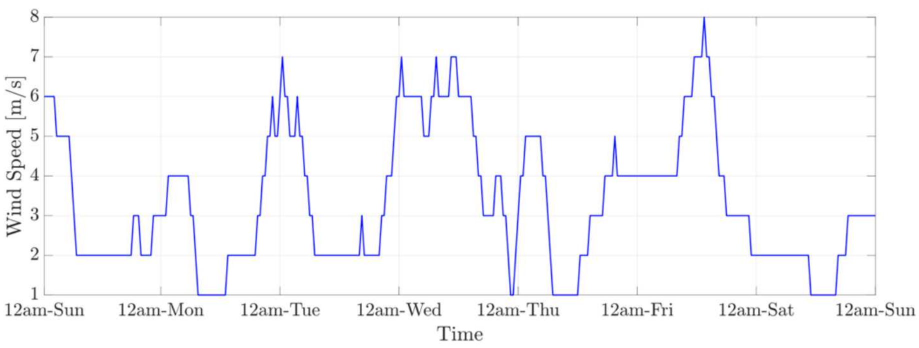


Fig. 24. Wind speed for the week of August 6-12, 2015.

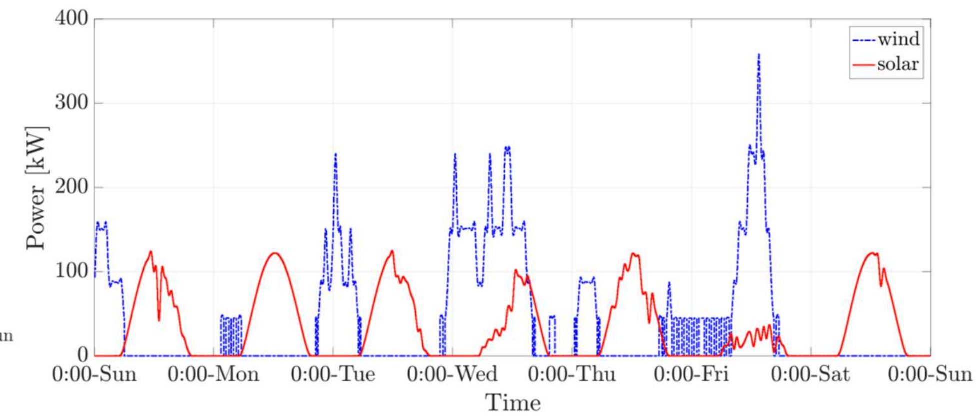


Fig. 25. Renewable Generation for the week of August 6-12, 2015.

Data for August 6-12

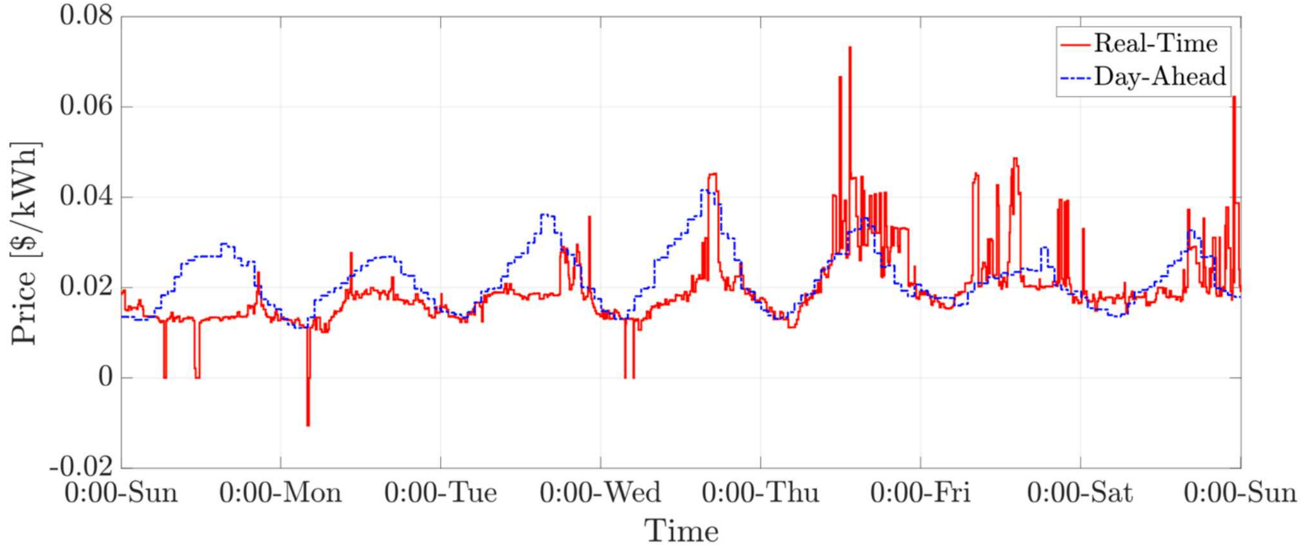


Fig. 26. Prices for the week of August 6-12, 2017.

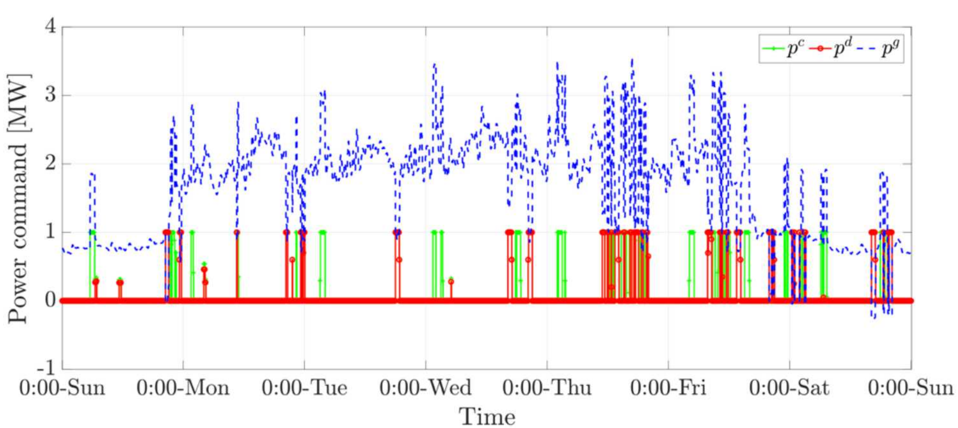


Fig. 27. Commands for the week of August 6-12.

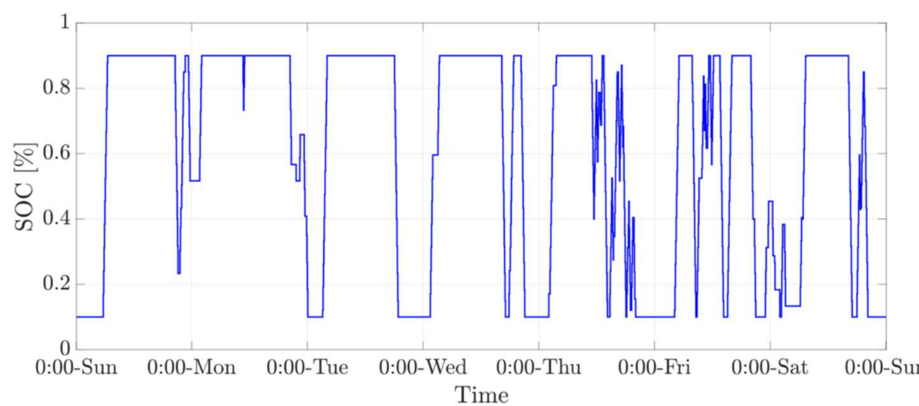


Fig. 28. SoC for the week of August 6-12.

Histograms of net load forecasting errors

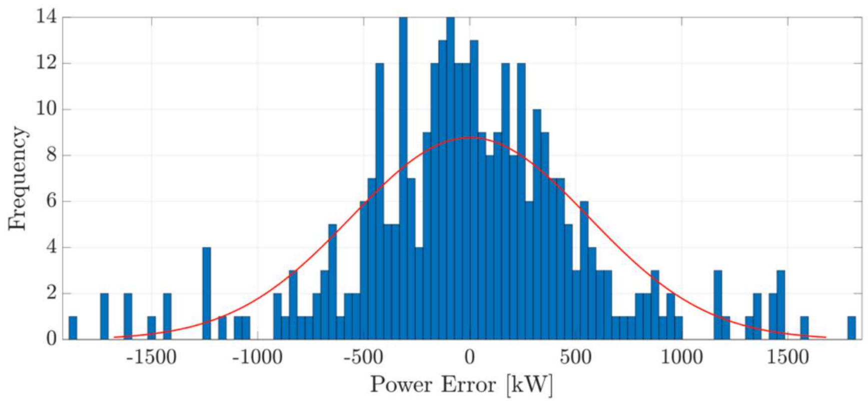


Fig. 43. Histogram of the Day-Ahead net load forecasting error for the hour of 12AM to 1AM. The normal distribution fit is shown in red.

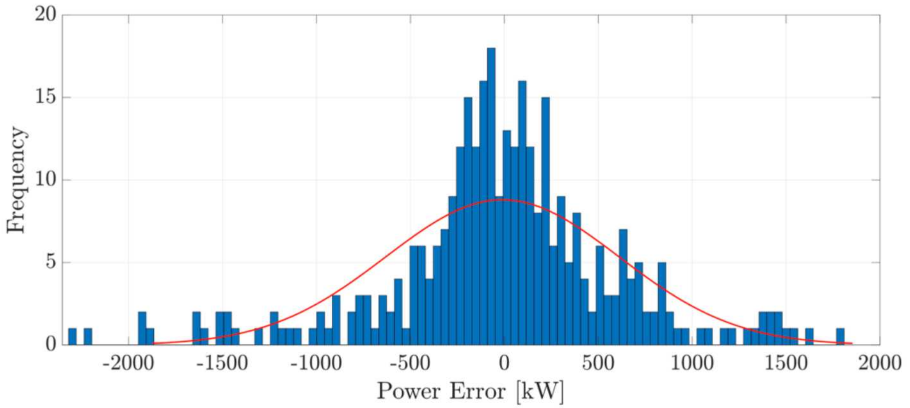


Fig. 44. Histogram of the Day-Ahead net load forecasting error for the hour of 12PM to 1PM. The normal distribution fit is shown in red.

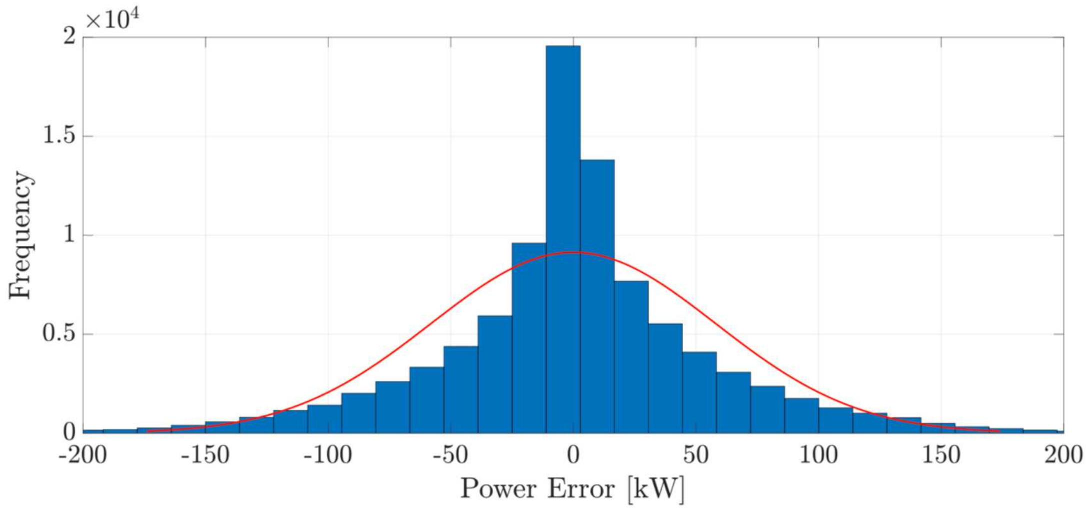


Fig. 45. Histogram of the Real-Time net load forecasting error for next five-minute interval. The normal distribution fit is shown in red.

Why Do We Need Storage?

Storage can provide many grid services:

- Resiliency and reliability
- Transmission and Distribution (T&D) upgrade deferral
- More efficient operation of the generation fleet
- Balance the variability of renewable generation
- Behind the meter savings for commercial and industrial customers
- Ancillary services (frequency regulation, spinning reserve, black start, etc.)
- Peaker plant replacement
- Voltage support

Energy Storage Analytics

Equitable Regulatory Environment Thrust Area

Goals: Lower barriers to widespread deployment of energy storage by identifying new and existing value streams, quantifying the impact of policy on deployment, and developing new control strategies

Objectives:

- Project case studies
- Tools for storage valuation
- Identify new value streams
- Control strategies to maximize revenue/grid benefit
- Assess policy impact on storage
- Develop policy recommendations