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Engaging Distributed Flexible Electric Loads in Power System Operation

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Benefits and Challenges of the Modern Electric Grid

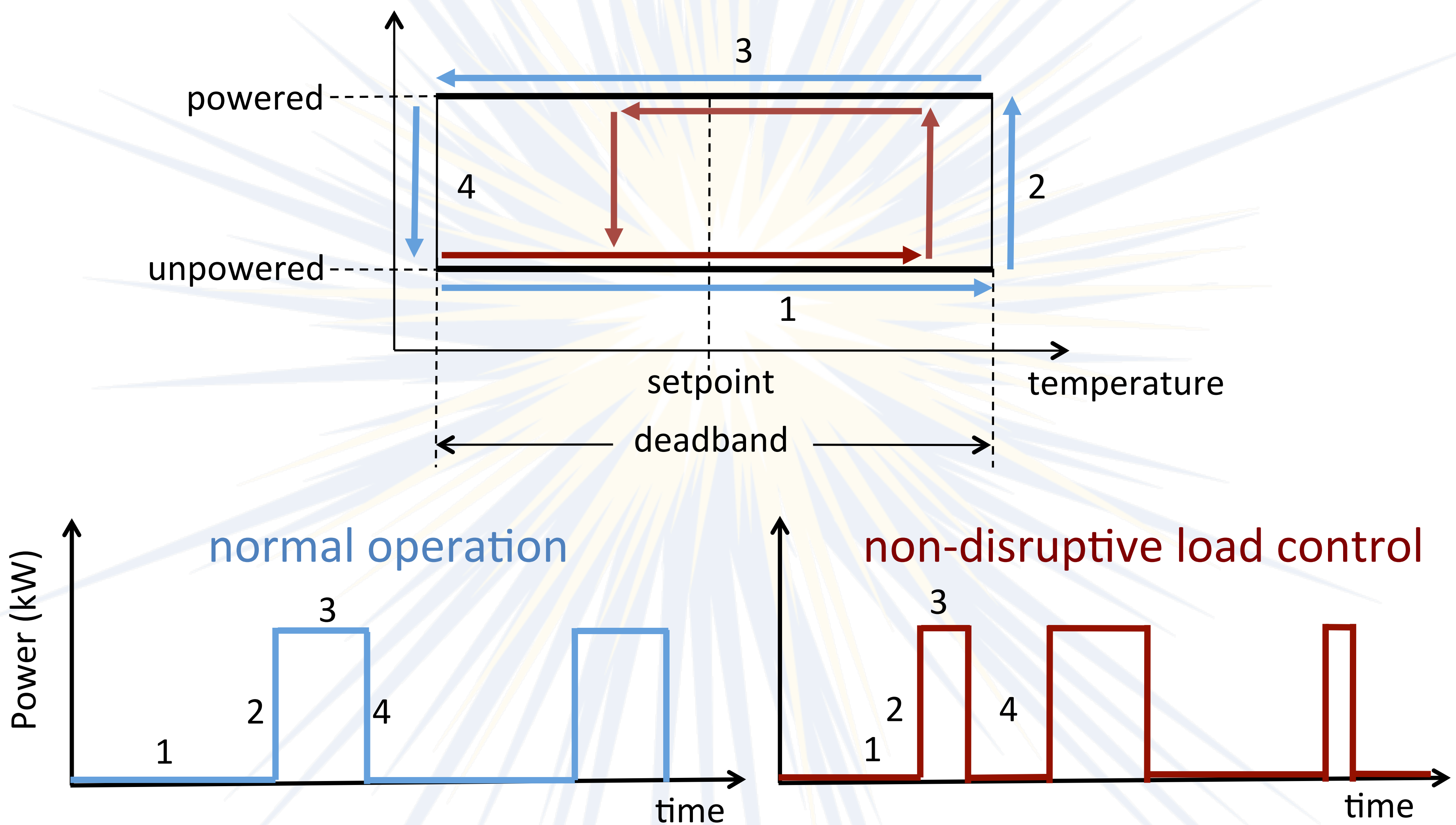
- Grid sensing and communication systems are becoming more prevalent
  - Cost & privacy concerns
  - Need methods to infer grid/load information from existing measurements
- Renewable energy resources are also becoming more prevalent
  - Most (e.g., wind and solar) are intermittent and uncertain
  - Need new sources of power system reserves

Overview

- **Control:** Controlling distributed electric loads to provide power system services with sparse measurements and input/measurement delays
  [Ledva, Vrettos, Mastellone, Andersson & Mathieu, HICSS 2015 & IEEE TPWRS (in review)]
  [Ledva & Mathieu, ACC 2017 (in review)]

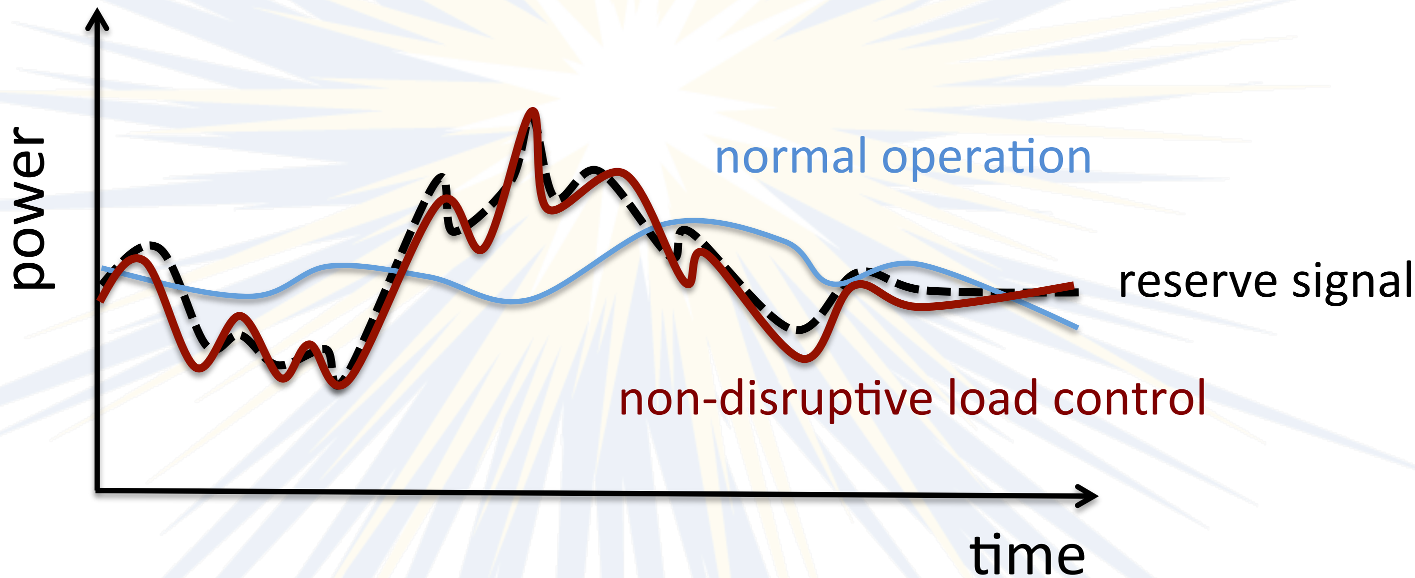
- **Inference:** Energy disaggregation at the feeder to infer the aggregate power of flexible loads
  [Ledva, Balzano, & Mathieu, Allerton 2015]

How can loads provide reserves?
→ your refrigerator is already flexible



Thousands of thermostatically controlled loads (TCLs) can track signals and provide reserves

TCLs: air conditioners, heat pumps, space heaters, electric water heaters, refrigerators



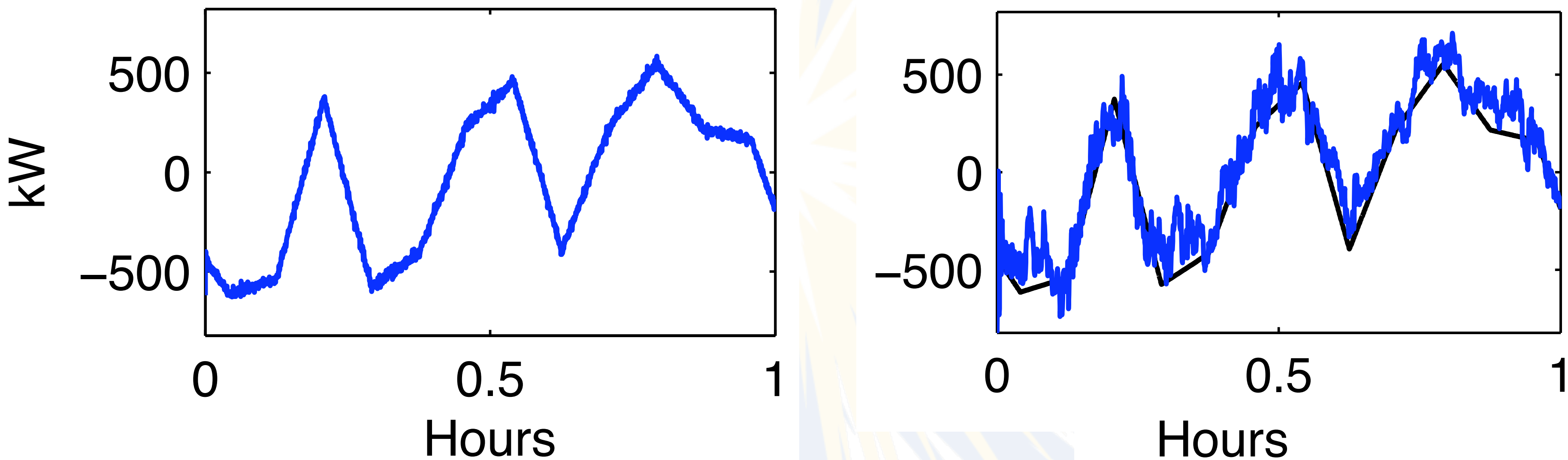
[Mathieu, Koch, and Callaway *IEEE Transactions on Power Systems* 2013]

Simulation results:

1000 ACs tracking 5-minute market signal

Controller gets temperature/state of each load every 2 seconds

Controller infers TCL behavior from power measurements at the substation



→The more the controller knows about the loads, the better it can track a signal

[Mathieu, Koch, and Callaway *IEEE Transactions on Power Systems* 2013]

Data from loads

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- Parameters
  - the make/model of the load?
  - its temperature setpoint/dead-band width?
  - some information about the household?

→ Modeling

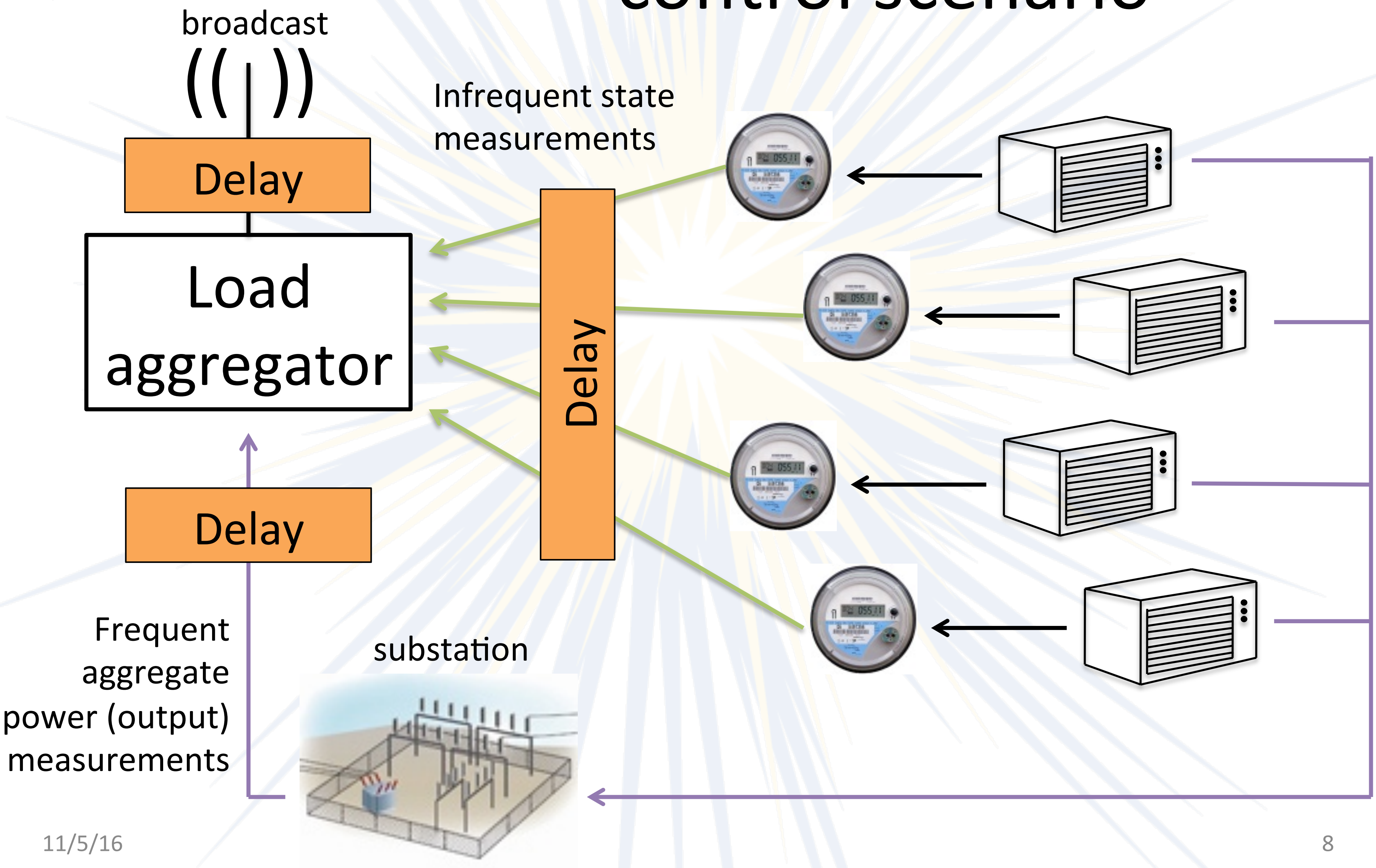
- Real-time data
  - Measurements of the on/off state and/or internal temperature?
  - Household smart meter data? → High quality, infrequent
  - Power measurements from the distribution network? → Low quality, frequent

→ Feedback control

- Recorded data
  - high resolution power measurements of each load?

→ Auditing

Communication and control scenario



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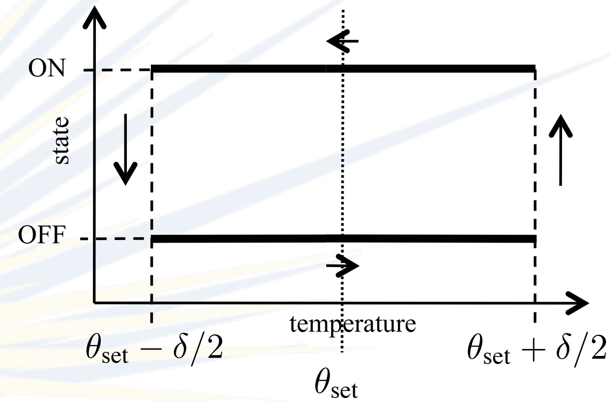
The Challenge

- Design an estimator and controller to enable loads to track a signal *despite delays*
- Assuming…
  - Control inputs & measurements are time-stamped
  - Delay statistics are known
  - State measurements are taken frequently; measurement *histories* are transmitted infrequently
  - Aggregate power measurements are *very* noisy (though the noise is normally distributed, zero-mean, and the standard deviation is known)

Two-state TCL model

Each TCL i is modeled with a stochastic hybrid difference equation:



Temperature of the space

$$\theta_i(k+1) = a_i\theta_i(k) + (1-a_i)(\theta_{\text{a},i} - m_i(k)\theta_{\text{g},i}) + \epsilon_i(k)$$

On/off state

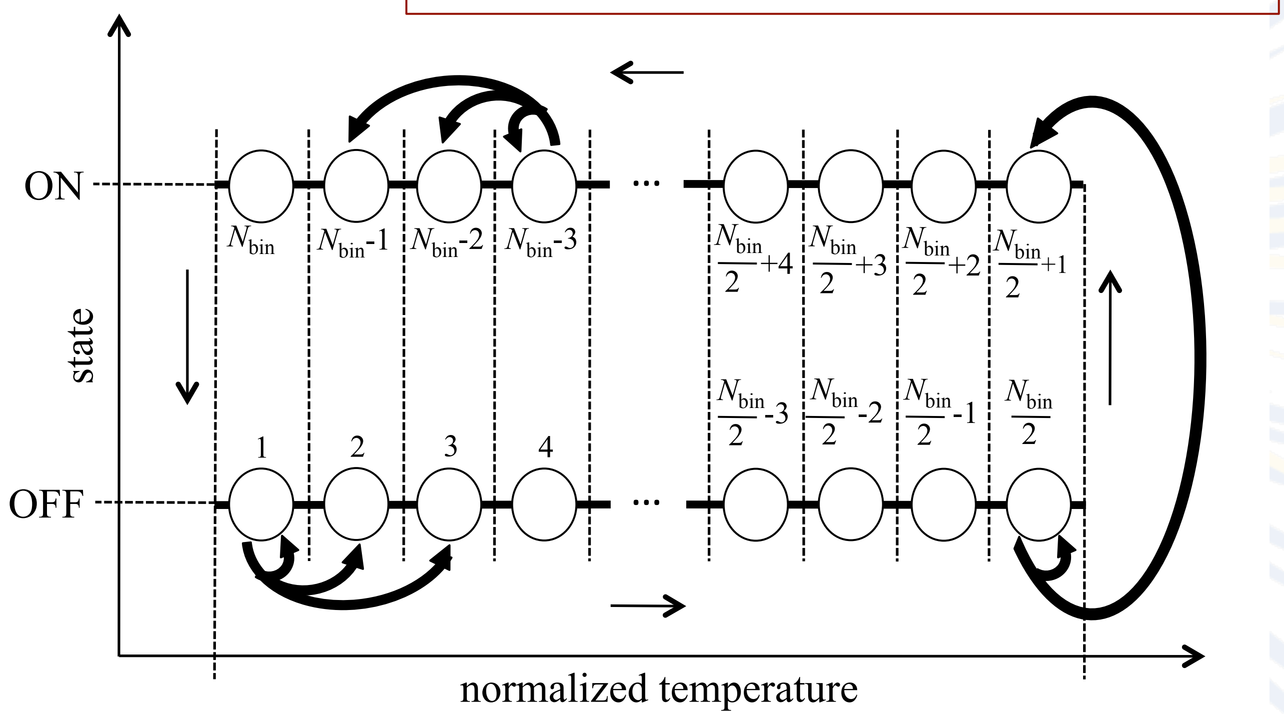
$$m_i(k+1) = \begin{cases} 0, & \theta_i(k+1) < \theta_{\text{set},i} - \delta_i/2 \\ 1, & \theta_i(k+1) > \theta_{\text{set},i} + \delta_i/2 \\ m_i(k), & \text{otherwise} \end{cases}$$

a, thermal parameter
θ_{g}, temperature gain
θ_{a}, ambient temperature
ϵ, noise
θ_{set}, set point
δ, dead-band width

[Chong & Debs 1979; Ihara & Schweppe 1981, Mortensen & Haggerty 1990, Uçak & Çağlar 1998]

Aggregate System Model

$$\boldsymbol{x}(k+1) = \boldsymbol{A}\boldsymbol{x}(k) + \boldsymbol{B}\boldsymbol{u}(k) + \boldsymbol{B}_\omega \boldsymbol{\omega}(k)$$
$$\boldsymbol{y}(k) = \boldsymbol{C}\boldsymbol{x}(k) + \boldsymbol{\nu}(k)$$



Similar models in the literature:

- Lu & Chassin 2004/2005
- Bashash & Fathy 2011/2013
- Kundu & Hiskens 2011
- Zhang et al. 2013

[Mathieu, Koch, and Callaway *IEEE Transactions on Power Systems* 2013]

Estimator Designs

- Based on Kalman Filtering
  - Estimator 1: Parallel filter estimator
    - One Kalman Filter per load
    - Each time a measurement arrives, filter it
    - Synthesize aggregate estimate from individual estimates
  - Estimator 2: Single Kalman Filter Using Aggregate State Predictions
    - Use state measurement histories to estimate *individual* load parameters (two-state model)
    - Use individual load models to predict current state
    - Use predictions as “measurements” in Kalman Filter

Controller Design

- Based on Model Predictive Control
  - Use knowledge of delay distributions and past control inputs

First control sequence: $u_1, u_2, \boxed{u_3}, \ldots, u_n$

Second control sequence: $u_2, \boxed{u_3}, \ldots, u_{n+1}$

Third control sequence: $\boxed{u_3}, u_4, \ldots, u_{n+1}$

$\mathcal{U}_k$

Input estimate: $\widehat{u}_k = \mathcal{U}_k \mathcal{P}$

Control Formulation

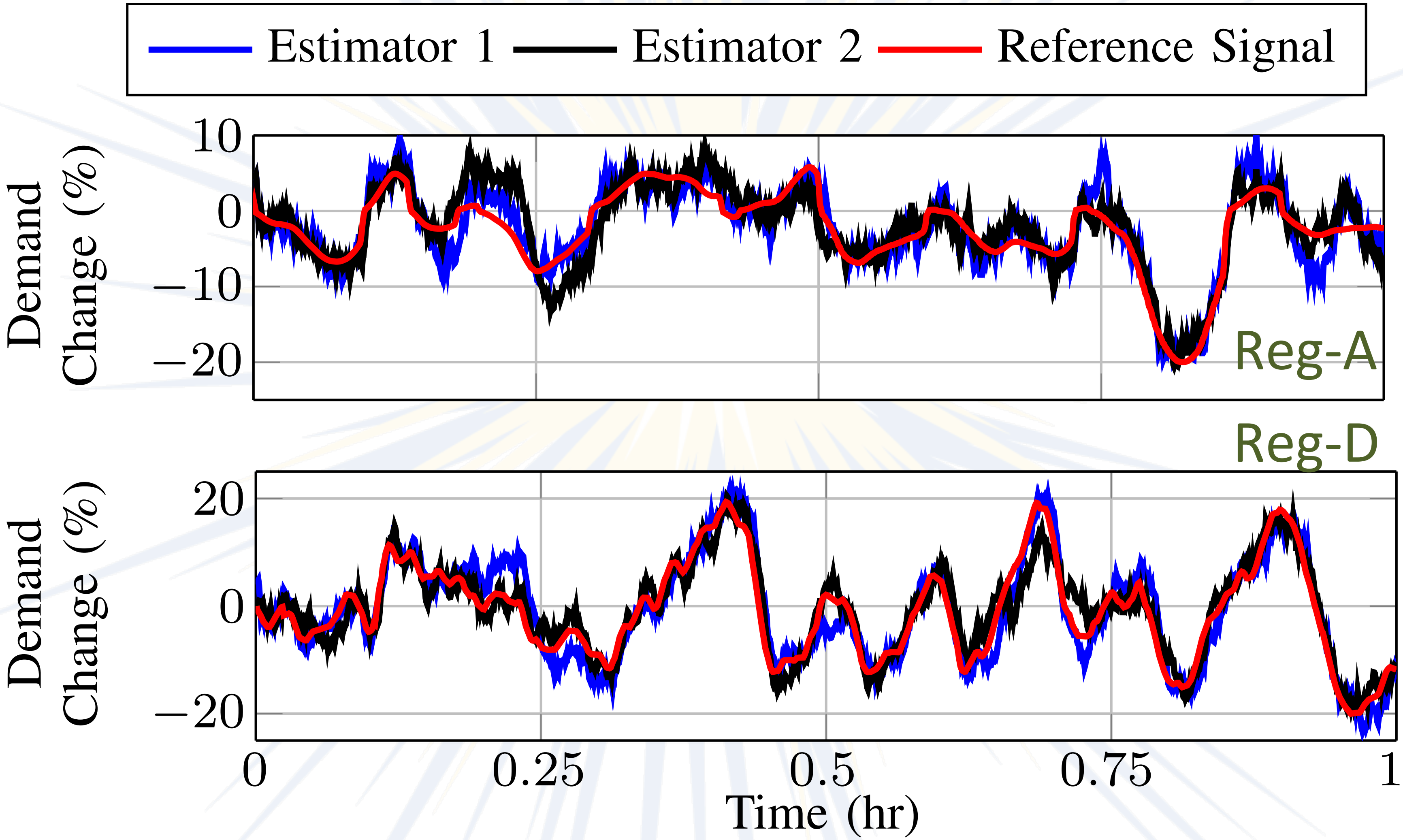
$$\underset{u,\delta}{\text{minimize}} \sum_{k=t}^{t+N^{\text{mpc}}-1} \Bigg[\underbrace{c^y \left(y_k^{\text{err}}\right)^2}_{\text{Tracking error}} + \underbrace{c^\delta (\delta_k^- + \delta_k^+)}_{\text{State constraint deviations}} + \underbrace{\sum_{m=k-N^{\text{mpc}}+1}^{k} c^u (u_{k|m}^\top u_{k|m})}_{\text{Control effort}} \Bigg]$$

$$\begin{aligned}
\text{s.t.} \quad x_{k+1} &= A\,x_k + B\,\widehat{u}_k \\
\widehat{u}_k &= \mathcal{U}_k \mathcal{P} \\
y_k^{\text{err}} &= y_k^{P,\text{ref}} - C^{\text{P}} x_k \\
u_{k|m}^i &\le x_k^i & i \in \{1, \ldots, N^{\text{x}}/2\} \\
-u_{k|m}^i &\le x_k^{N^{\text{x}}+1-i} & i \in \{1, \ldots, N^{\text{x}}/2\} \\
0 - \delta_k^- \le x_k &\le 1 + \delta_k^+ \\
0 &\le \delta_k^-, \delta_k^+ .
\end{aligned}$$

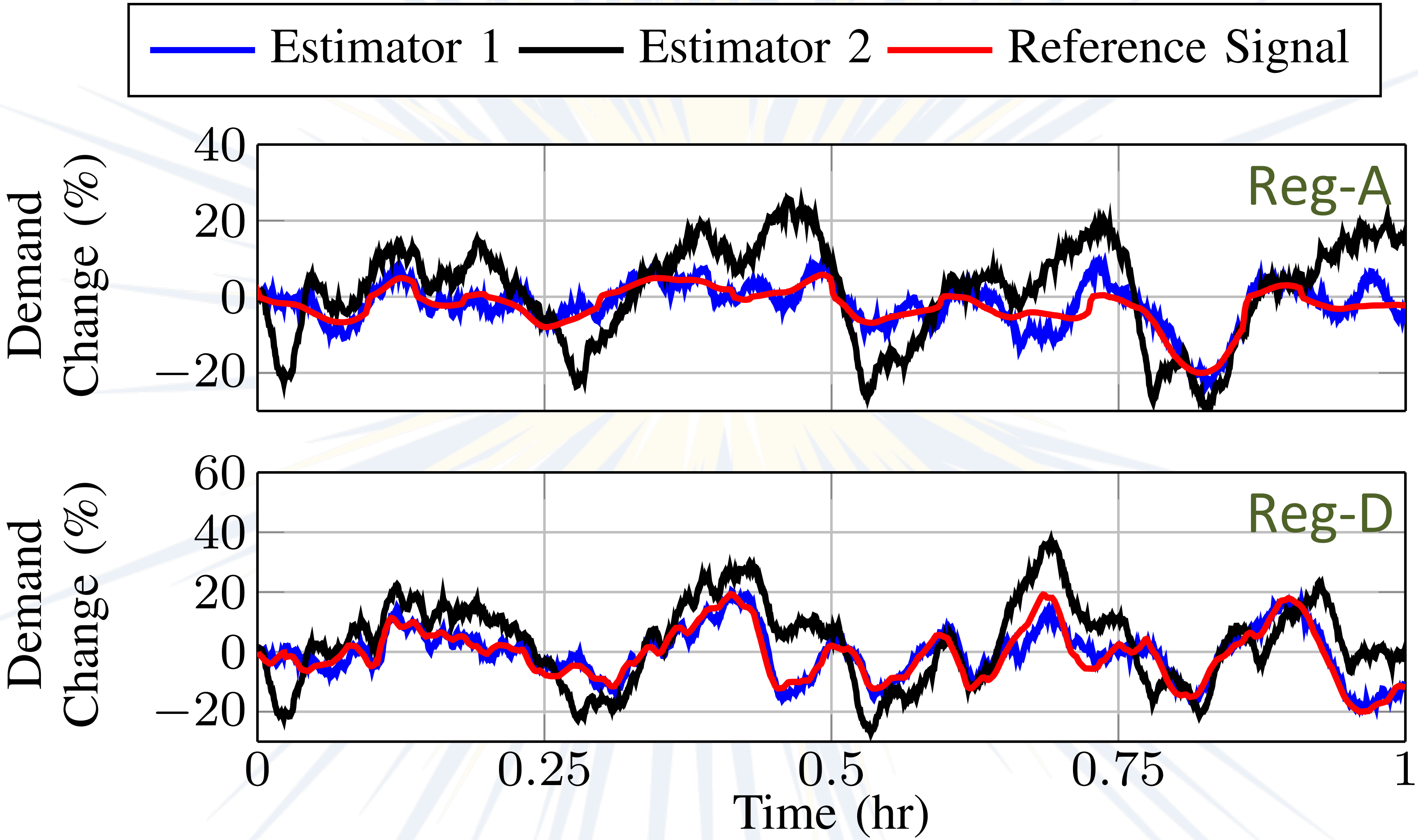
Case Studies

- PJM Regulation Signals, Reg-A & Reg-D
- Average input delay of 20 seconds
- (Delayed) state histories arrive every 15 minutes

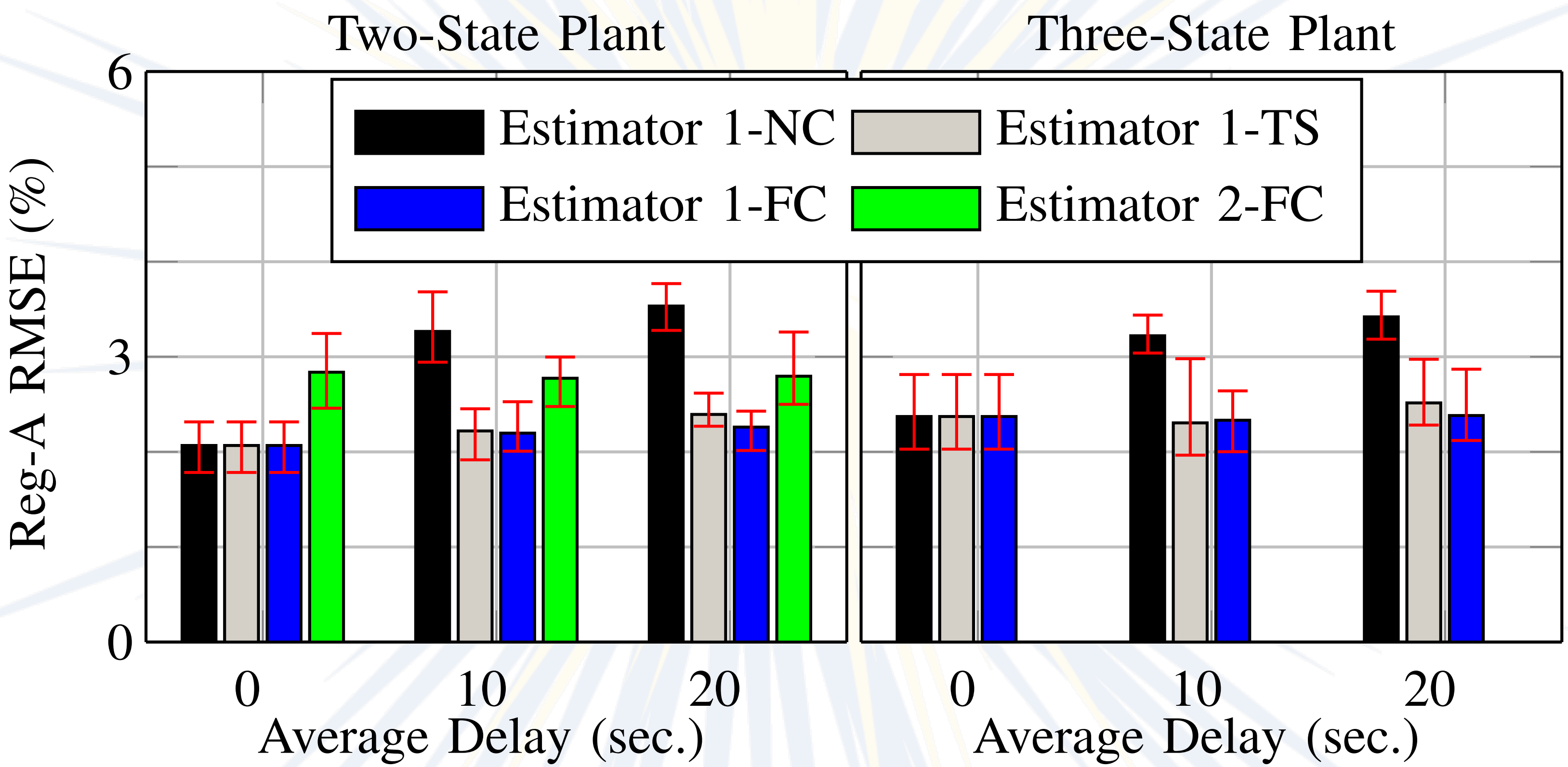
Results: Tracking



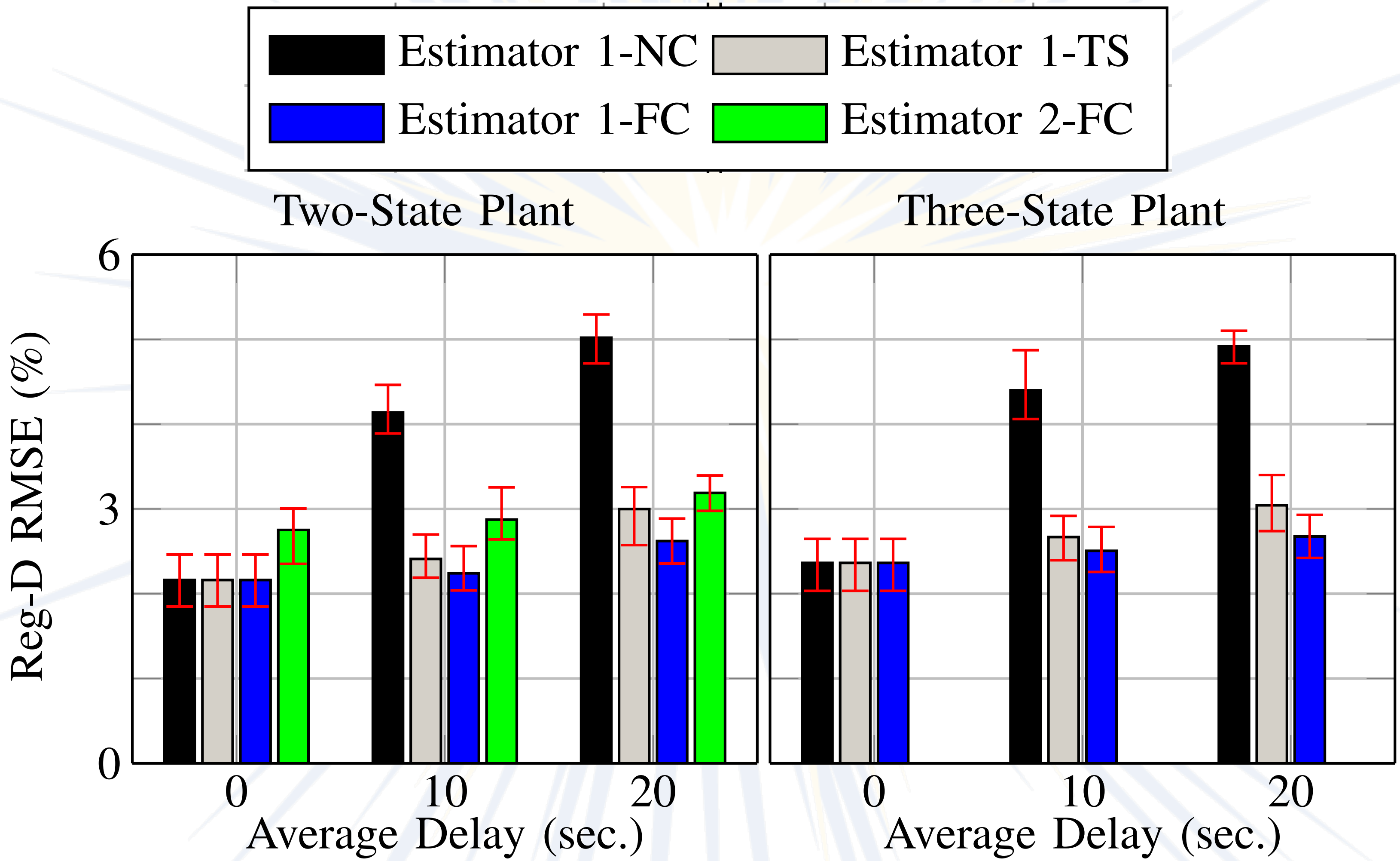
Results: Model Mismatch



Control Results: Reg-A



Control Results: Reg-D



Controller Reformulation

Original Model

$$x_{k+1} = A\,x_k + B\,u_k$$
$$y_k = C\,x_k.$$

Modal Model

$$\begin{bmatrix} 1 \\ \widetilde{x}_{k+1} \end{bmatrix} = \overbrace{\begin{bmatrix} 1 & 0 \\ 0 & \widetilde{A} \end{bmatrix}}^{A^*} \overbrace{\begin{bmatrix} 1 \\ \widetilde{x}_k \end{bmatrix}}^{x_k^*} + \overbrace{\begin{bmatrix} 0 \\ \widetilde{B} \end{bmatrix}}^{B^*} u_k$$
$$y_k = \underbrace{\begin{bmatrix} y_{\mathrm{ss}} & \widetilde{C} \end{bmatrix}}_{C^*} \begin{bmatrix} 1 \\ \widetilde{x}_k \end{bmatrix}$$

Reduced-Order Model

$$\widetilde{x}_{k+1} = \widetilde{A}\,\widetilde{x}_k + \widetilde{B} u_k$$
$$\widetilde{y}_k = \widetilde{C}\,\widetilde{x}_k.$$

Controller Reformulation

The linear controller uses constant gains generated from an output-regulating Linear Quadratic Regulator (LQR) with reference feedforward.

Linear Controller $u_t^{\text{seq}} = -K_\infty^{\text{x}}\, \overline{x}_t - K_\infty^{\text{w}}\, w_t + K_\infty^{\text{y}}\, y_t^{\text{des}}$

LQR Formulation $$\min_u \sum_{k=t}^{\infty} \begin{bmatrix} \widetilde{\overline{x}}_k \\ w_k \end{bmatrix}^T \begin{bmatrix} \widetilde{\overline{C}}^T q^{\text{y}} \widetilde{\overline{C}} & 0 \\ 0 & q^{\text{w}} \end{bmatrix} \begin{bmatrix} \widetilde{\overline{x}}_k \\ w_k \end{bmatrix} + (u_k^{\text{seq}})^T R\, u_k^{\text{seq}}$$

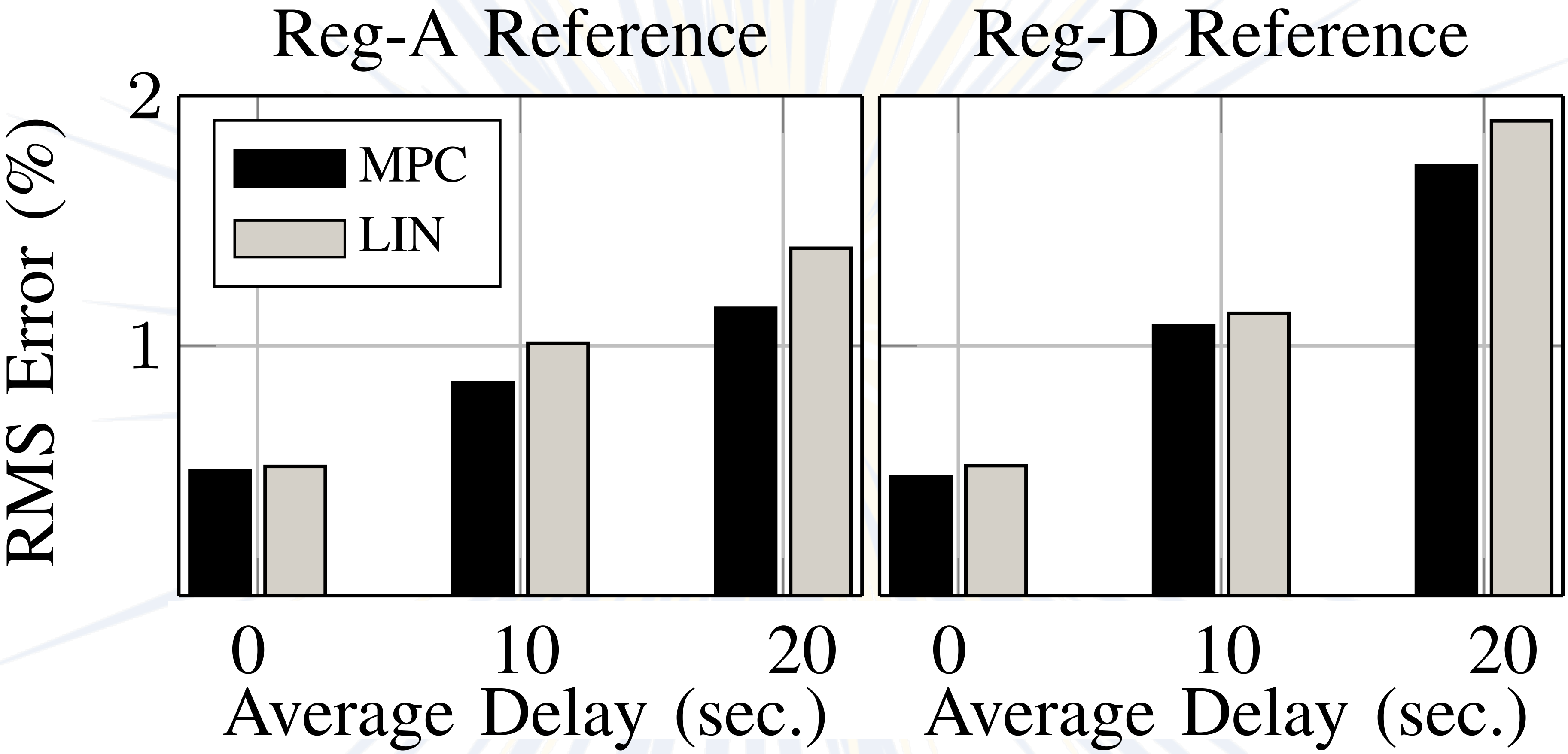
$$\text{s.t.} \quad \begin{bmatrix} \widetilde{\overline{x}}_{k+1} \\ w_{k+1} \end{bmatrix} = \begin{bmatrix} \widetilde{\overline{A}} & 0 \\ \widetilde{\overline{C}} & 0 \end{bmatrix} \begin{bmatrix} \widetilde{\overline{x}}_k \\ w_k \end{bmatrix} + \begin{bmatrix} \widetilde{\overline{B}} \\ 0 \end{bmatrix} u_k^{\text{seq}}$$

Feedforward Gain $K_\infty^{\text{y}} = \left(\widetilde{\overline{C}} \{ zI - \widetilde{\overline{A}} + \widetilde{\overline{B}} \widetilde{K}_\infty^{\text{x}} \}^{-1} \widetilde{\overline{B}} \right)^{-\dagger}$

Case Studies

- PJM Regulation Signals, Reg-A & Reg-D
- Average input delay of 20 seconds
- Full state feedback, no measurement delay
- Three-state models used for the plant

Results Summary



→ LIN is 100 times faster than MPC

Key takeaways

- Communication network limitations necessitate controller/estimator designs that cope with delays, bandwidth limitations, etc.

- Delays make loads less capable of providing fast services, but we can mitigate these impacts through delay-aware control and estimation.

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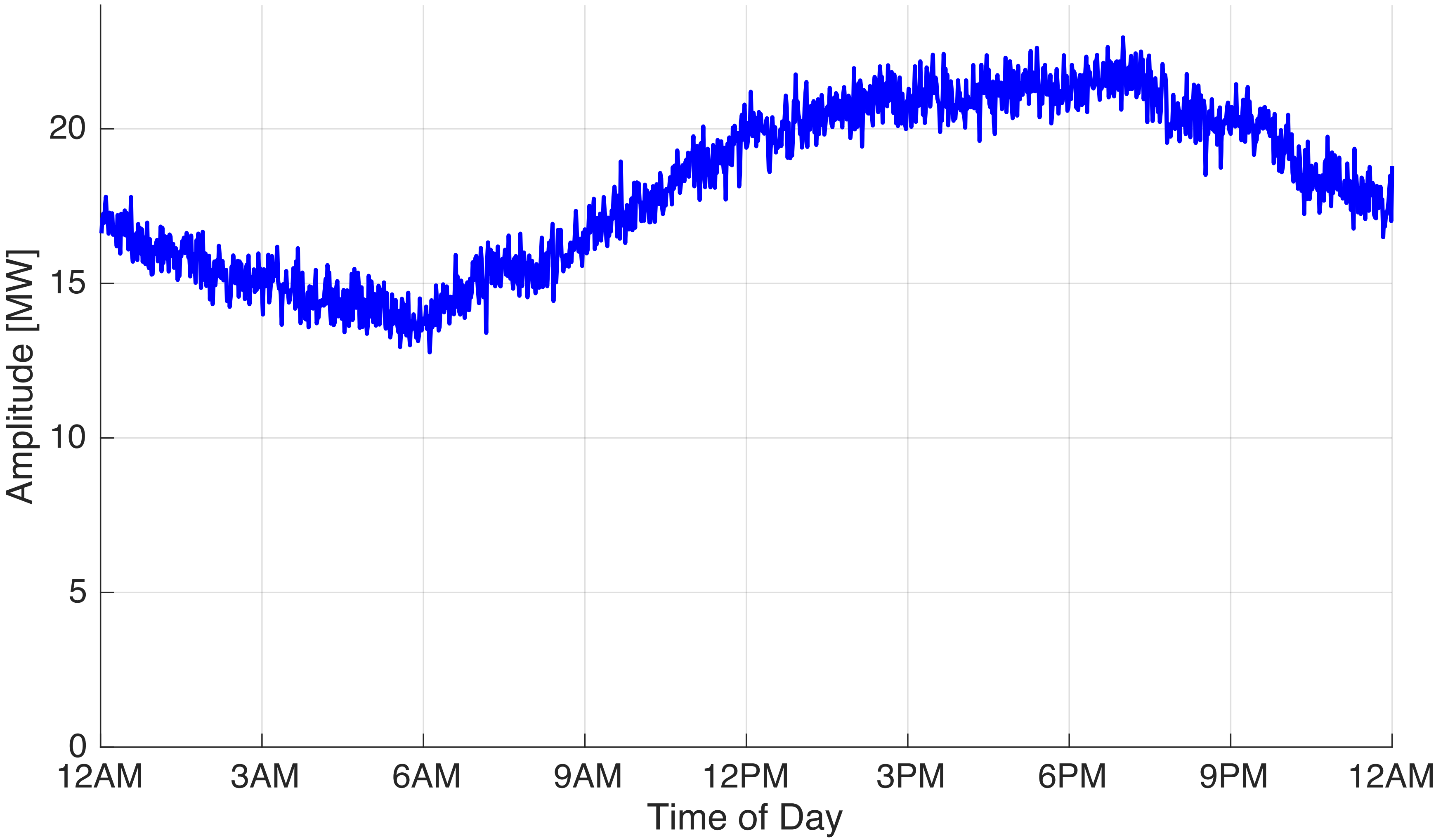
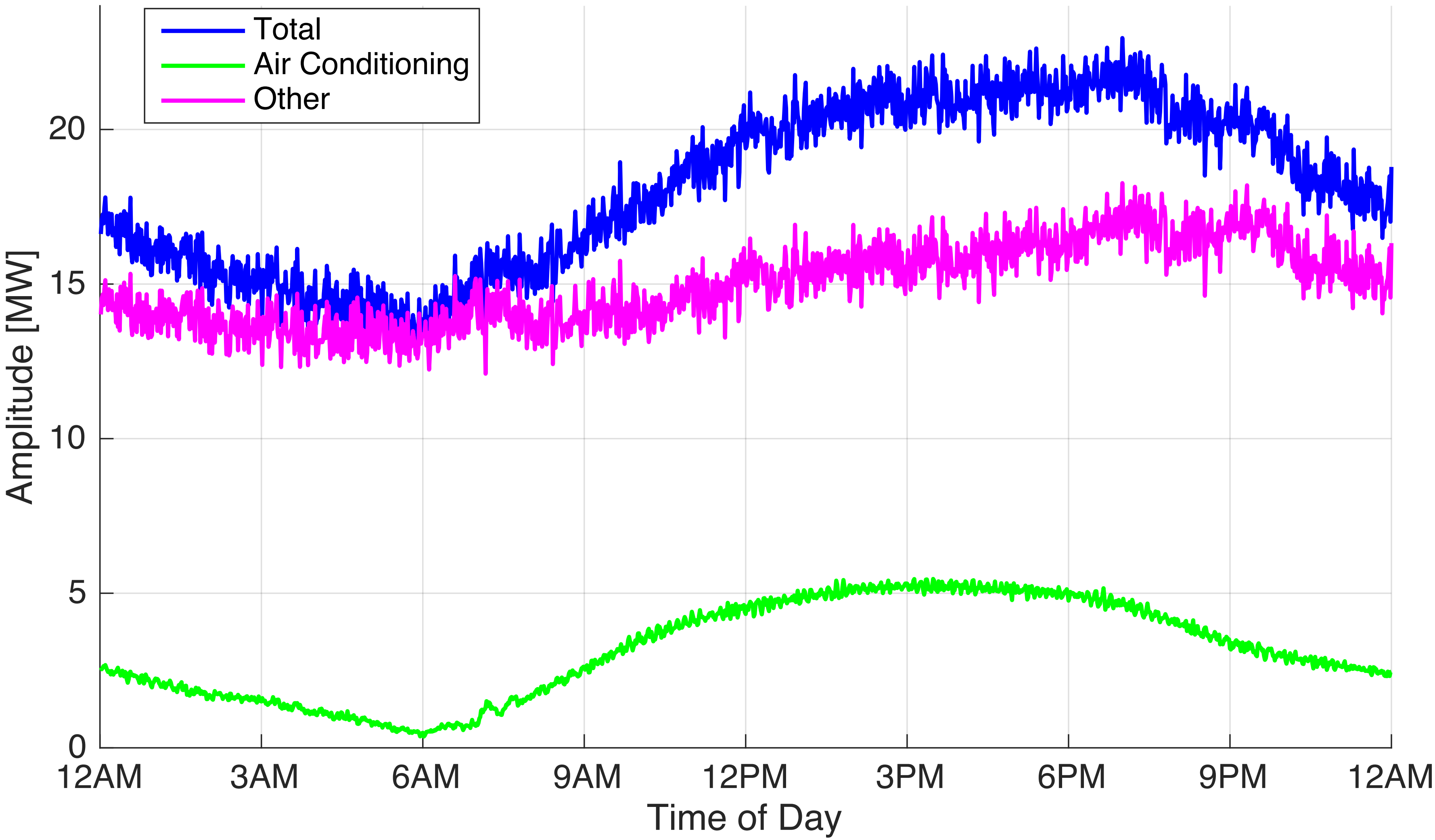
Load Served by a Substation

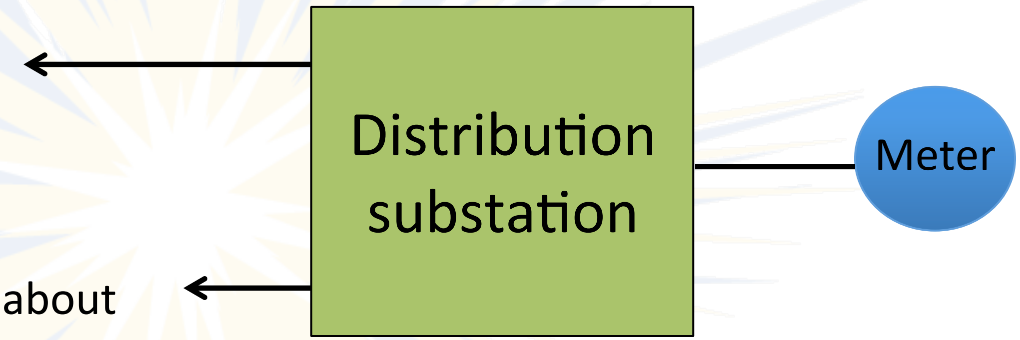


Load Served by a Substation



Disaggregating substation load data

Power consumption of all the loads/generators we care about (e.g., Air Conditioning)



Power consumption of all the loads/generators we DON'T care about ("Other loads")

In this talk, we use measurements of real power only.

We could consider additional measurements (reactive power, voltage, etc.) from multiple meters at different points in the distribution network.

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Why disaggregate the substation load?

Uses in demand response...

- Load coordination feedback
- Load aggregator bidding
- Demand response event signaling (when/how much)

Beyond demand response...

- Energy efficiency via conservation voltage reduction
  - Disaggregate by load type
- Contingency planning
  - Disaggregate motor loads
- Reserve planning
  - Disaggregate PV production

Connections to other problems

- Non-intrusive load monitoring (NILM) [Hart 2010; Ziefman and Roth 2011; Berges et al. 2009; Zoha et al. 2012; Dong, Sastry, et al. 2014; …]
- Energy disaggregation [Wytock & Kolter 2013; Kolter and Jaakkola 2012; Dong, Satsry, et al. 2013; Kim et al. 2010 …]

Problem: Infer individual load behavior from a single power measurement (usually) sampled at high frequency (10kHz-1MHz) from the household main

Solution approaches: offline algorithms including change detection, supervised learning, unsupervised learning

Key differences

- We assume measurements at the substation, not the household
- We infer aggregate load (e.g., all air conditioning load), not individual load behavior
- We solve the problem online, not offline
- We use lower frequency measurements (e.g., taken every second to minute)
- In some cases, we may get to be "intrusive," but not in this talk!

Possible Methods

- State estimation
  - Linear techniques require linear system models
  - Nonlinear techniques can be computationally demanding
- Online learning
  - Data-driven, model-free
- Hybrid approach: Dynamic Mirror Descent [Hall & Willet 2015]
  - Admits dynamic models of arbitrary forms
  - Optimization-based method to choose a weighted combination of the estimates of a collection of models

Outline

- Dynamic Mirror Descent
- Problem setting: Plant data/models
- Algorithm Models
- Results
- Next steps

Dynamic Mirror Descent

- Mirror Descent: online algorithm to estimate a fixed state
- Dynamic Mirror Descent: online algorithm to estimate a dynamic state using a *collection of models* [Hall & Willet, "Online Convex Optimization in Dynamic Environments," IEEE Journal of Selected Topics in Signal Processing 2015]

1. Compute the error between the model predictions and the measured data (i.e., loss function $\ell_t(\widehat{\theta}_t^i, y_t)$)
2. Update the state in the direction of the negative gradient of the loss function

$$\widetilde{\theta}_t^i = \arg\min_{\theta \in \Theta} \eta_t \left\langle \nabla \ell_t(\widehat{\theta}_t^i, y_t),\ \theta \right\rangle + D\left(\theta \| \widehat{\theta}_t^i\right)$$

Dynamic Mirror Descent

3. Use the estimated states to evaluate the models for the next time step

$$\widehat{\theta}^i_{t+1} = \Phi^i_t(\widetilde{\theta}^i_t)$$

4. Compute a weighted version of the estimates

$$\widehat{\theta}_{t+1} = \sum_{i=1}^{N^{\text{mdl}}} w^i_{t+1} \widehat{\theta}^i_{t+1}.$$

5. Update the model weights

$$w^i_{t+1} = \frac{\lambda}{N^{\text{mdl}}} + (1-\lambda) \frac{w^i_t \exp\left(-\eta^r \ell_t\left(\widehat{\theta}^i_t, y_t\right)\right)}{\sum_{j=1}^{N^{\text{mdl}}} w^j_t \exp\left(-\eta^r \ell_t\left(\widehat{\theta}^j_t, y_t\right)\right)}$$

Algorithmic guarantees

- Regret: performance with respect to a comparator $\boldsymbol{\theta}_T$

$$R_T(\boldsymbol{\theta}_T) \triangleq \sum_{t=1}^{T} \ell_t(\widehat{\theta}_t) - \sum_{t=1}^{T} \ell_t(\theta_t).$$

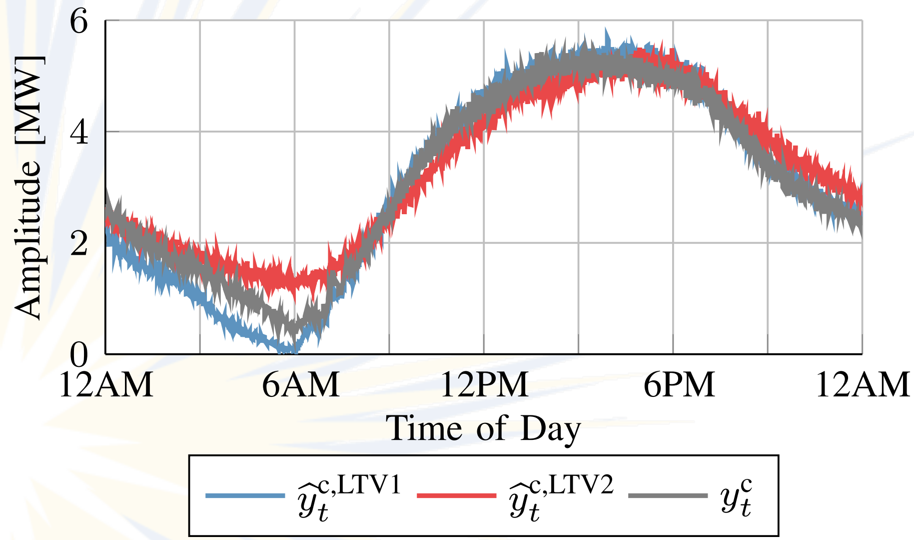
- Often the comparator is the performance of a batch algorithm
- Hall and Willet derive bounds on the regret and show that for many classes of comparators regret scales sublinearly in T

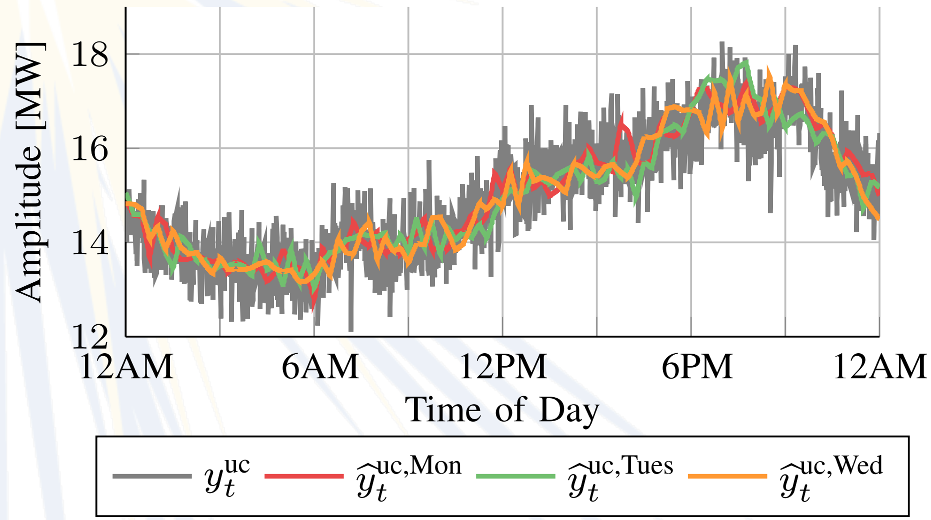
Plant Data/Models

- Air conditioners:
  - Three-state (hybrid) TCL models
- Other loads:
  - Data from Pecan Street Inc. Dataport

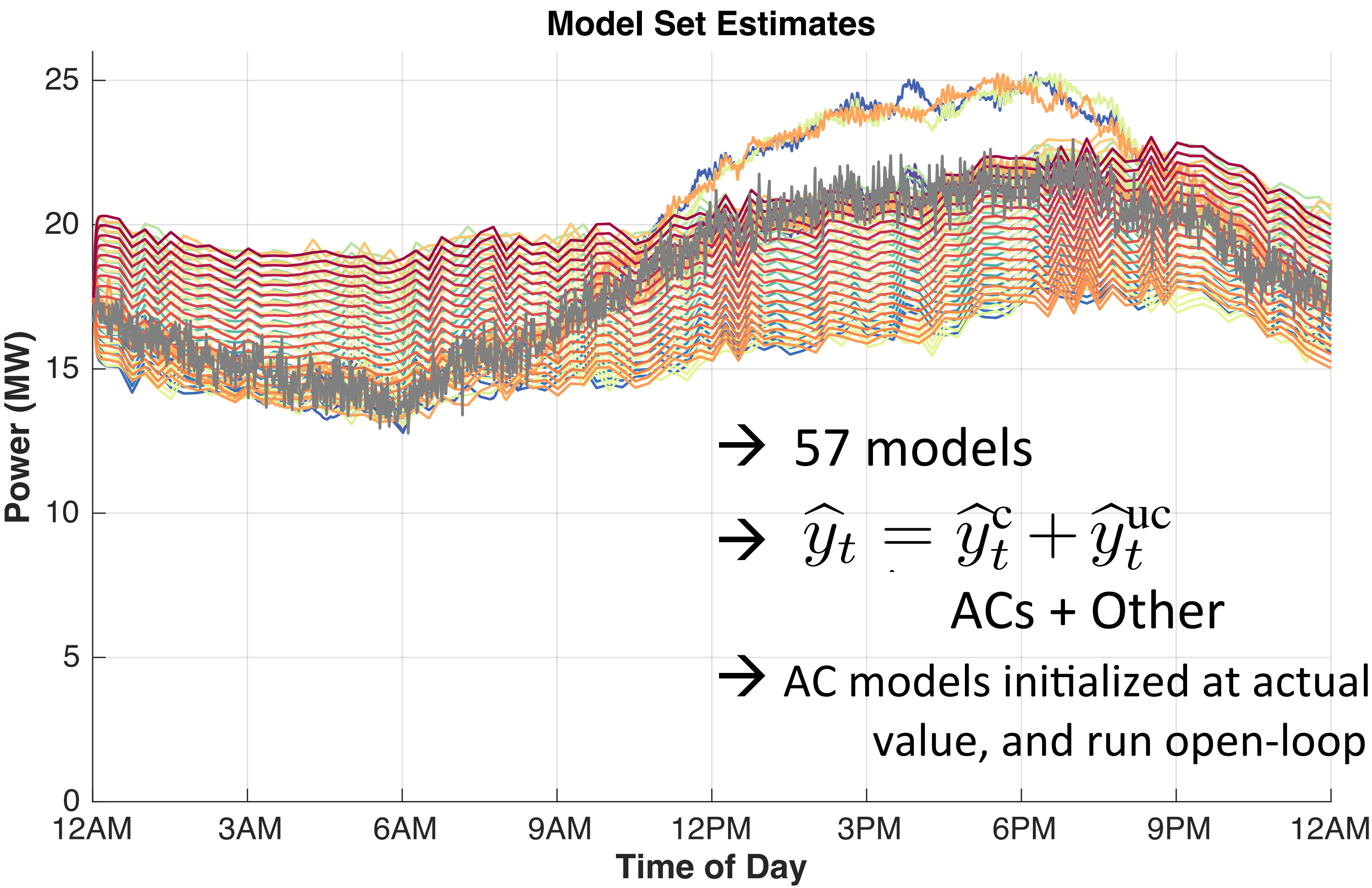
Algorithm Models

- Air conditioners:
  - Two-state (hybrid) TCL models
  - Linear time-invariant aggregate system model
  - Linear time-varying aggregate system model
- Other loads:
  - Smoothed data from previous days





Algorithm Models



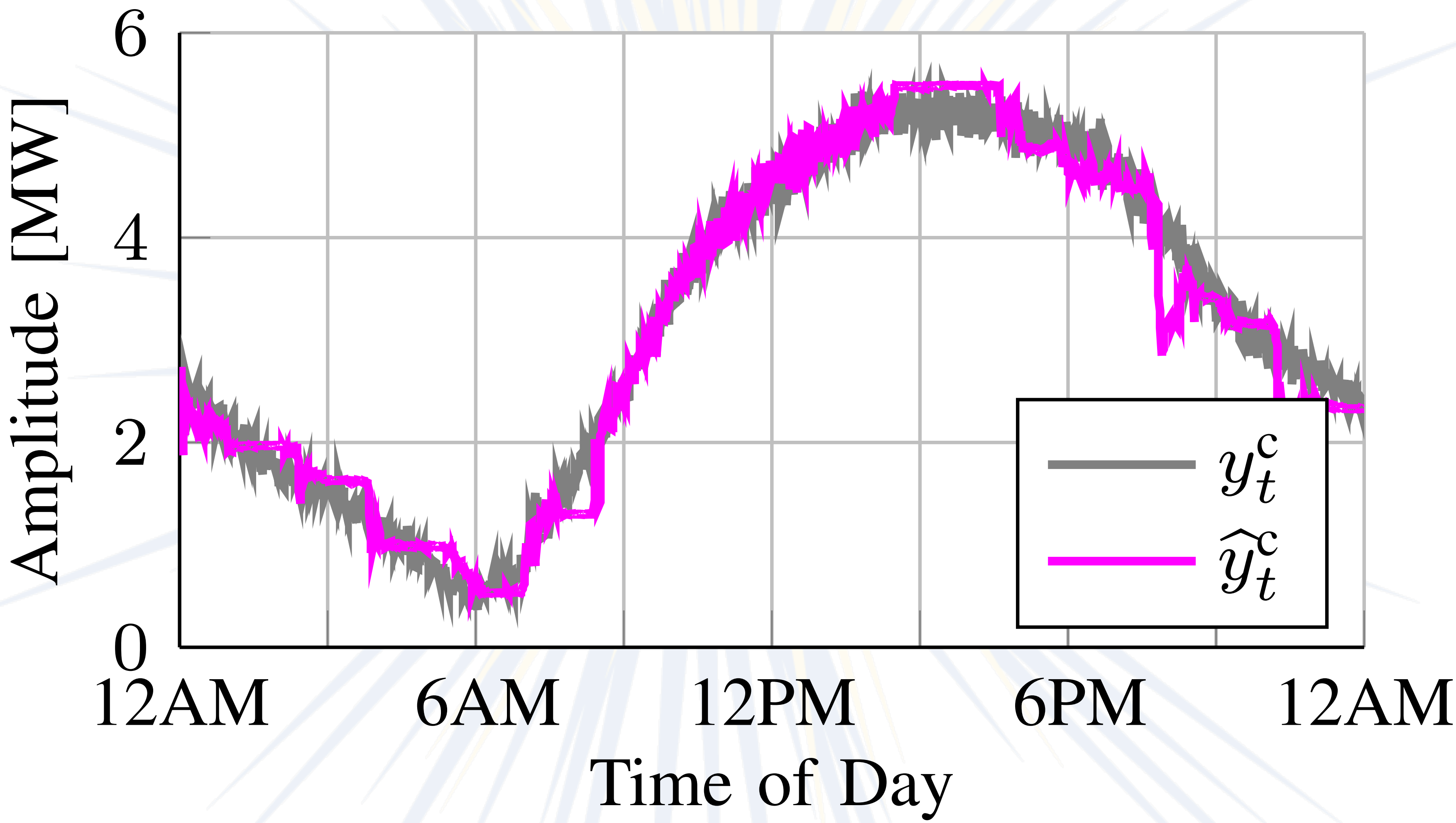
→ 57 models

→ $\widehat{y}_t = \widehat{y}_t^{c} + \widehat{y}_t^{uc}$

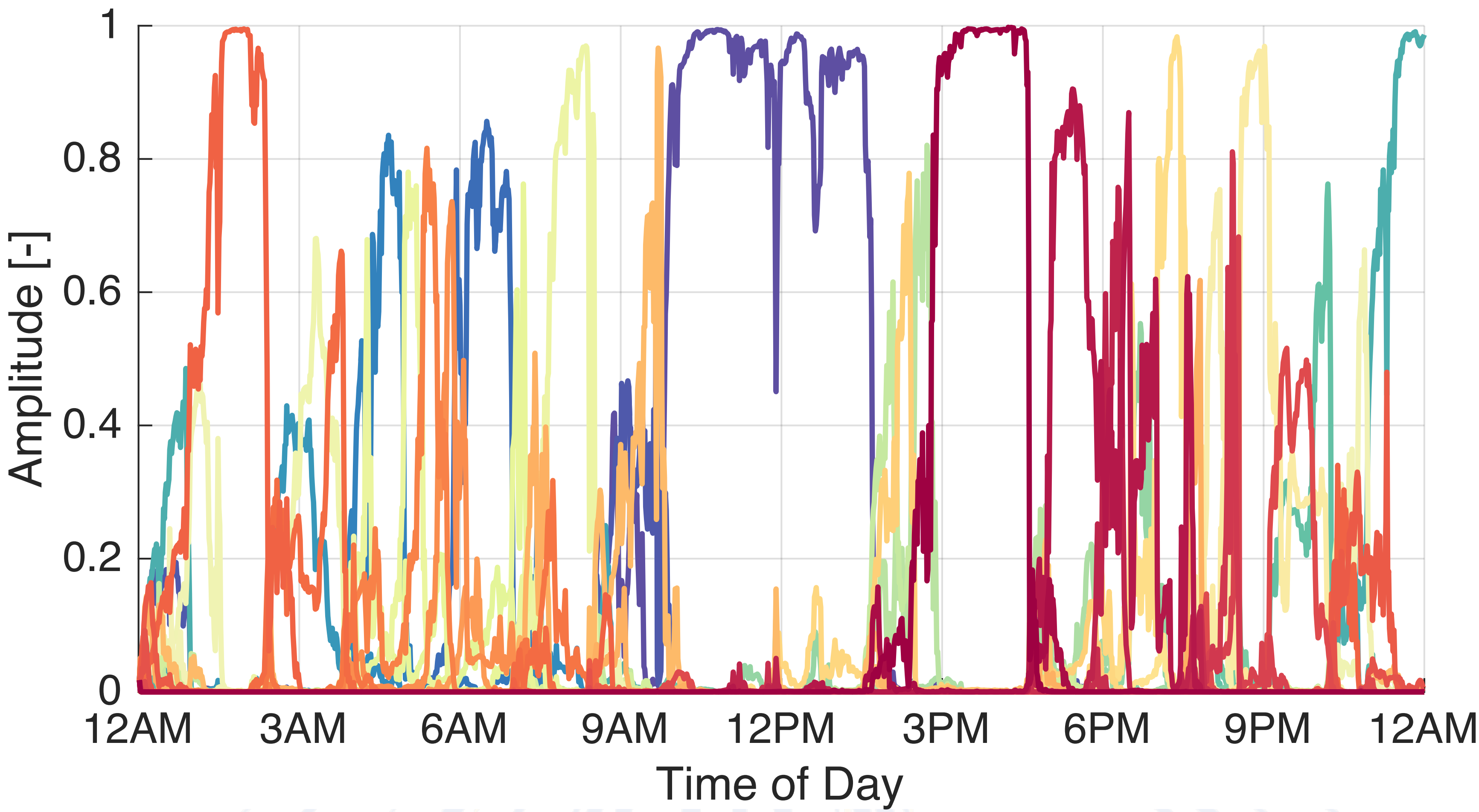
ACs + Other

→ AC models initialized at actual value, and run open-loop

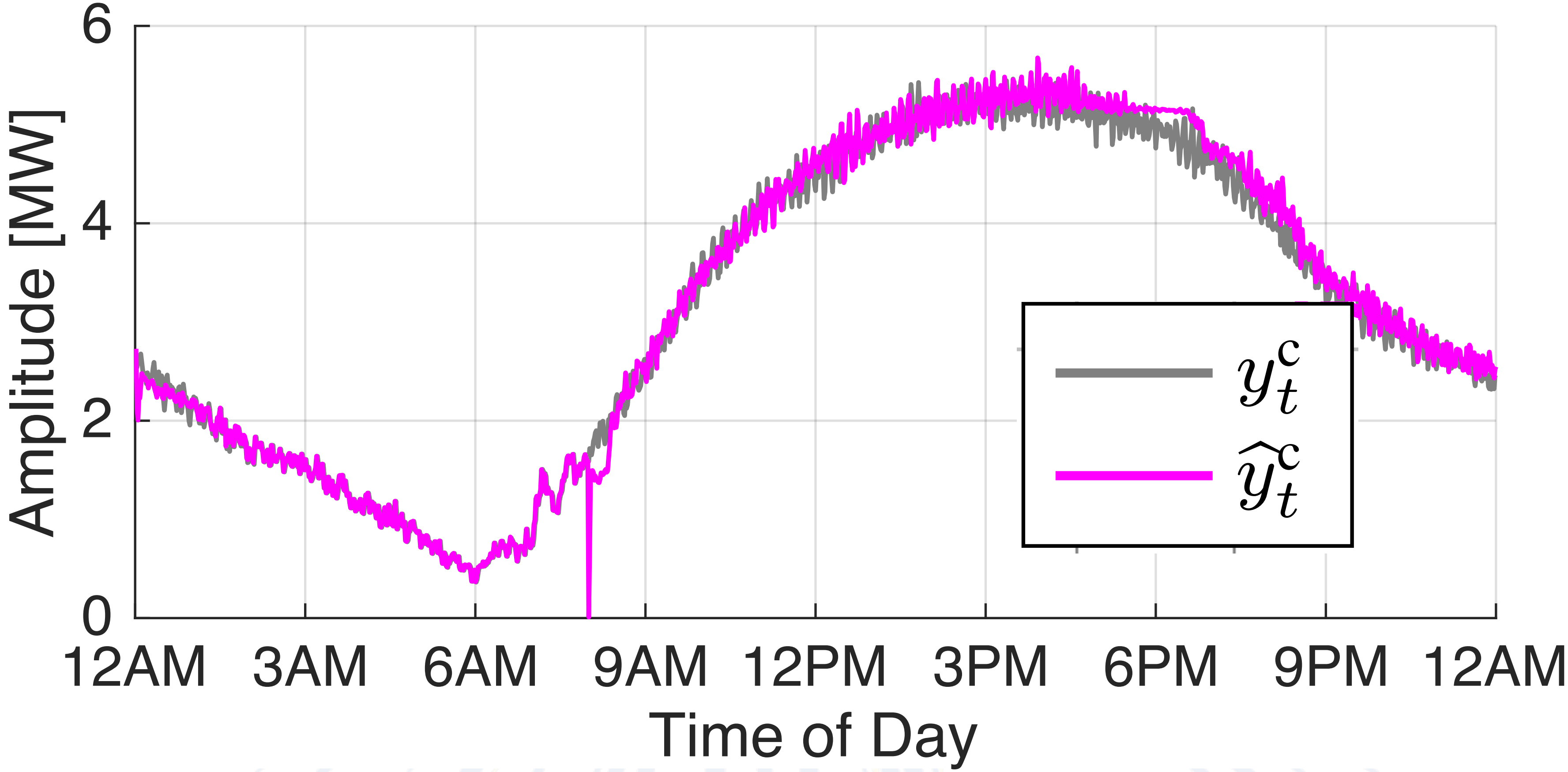
Prediction Results



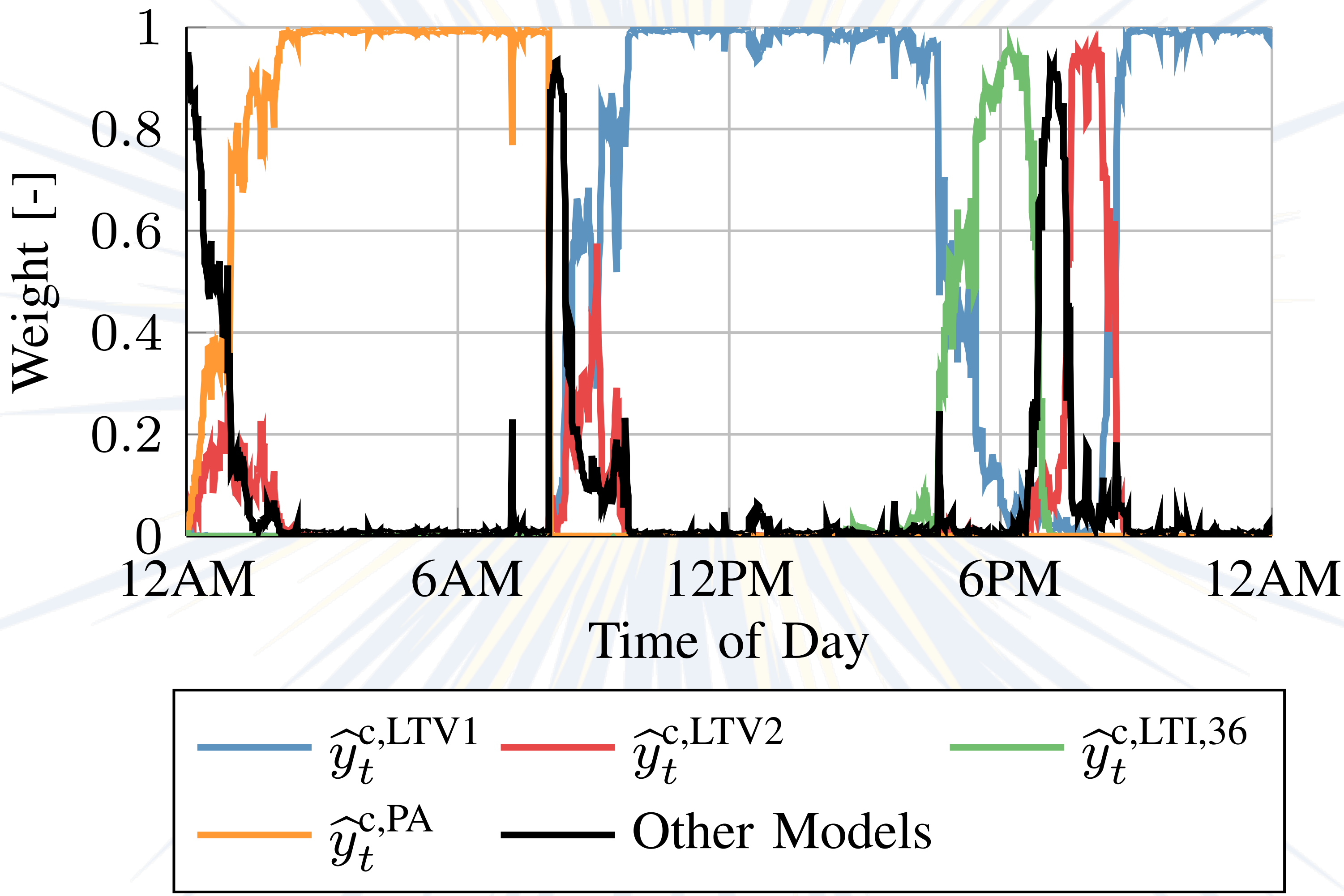
Weightings:
each color is a different model



Prediction Results: Better Models

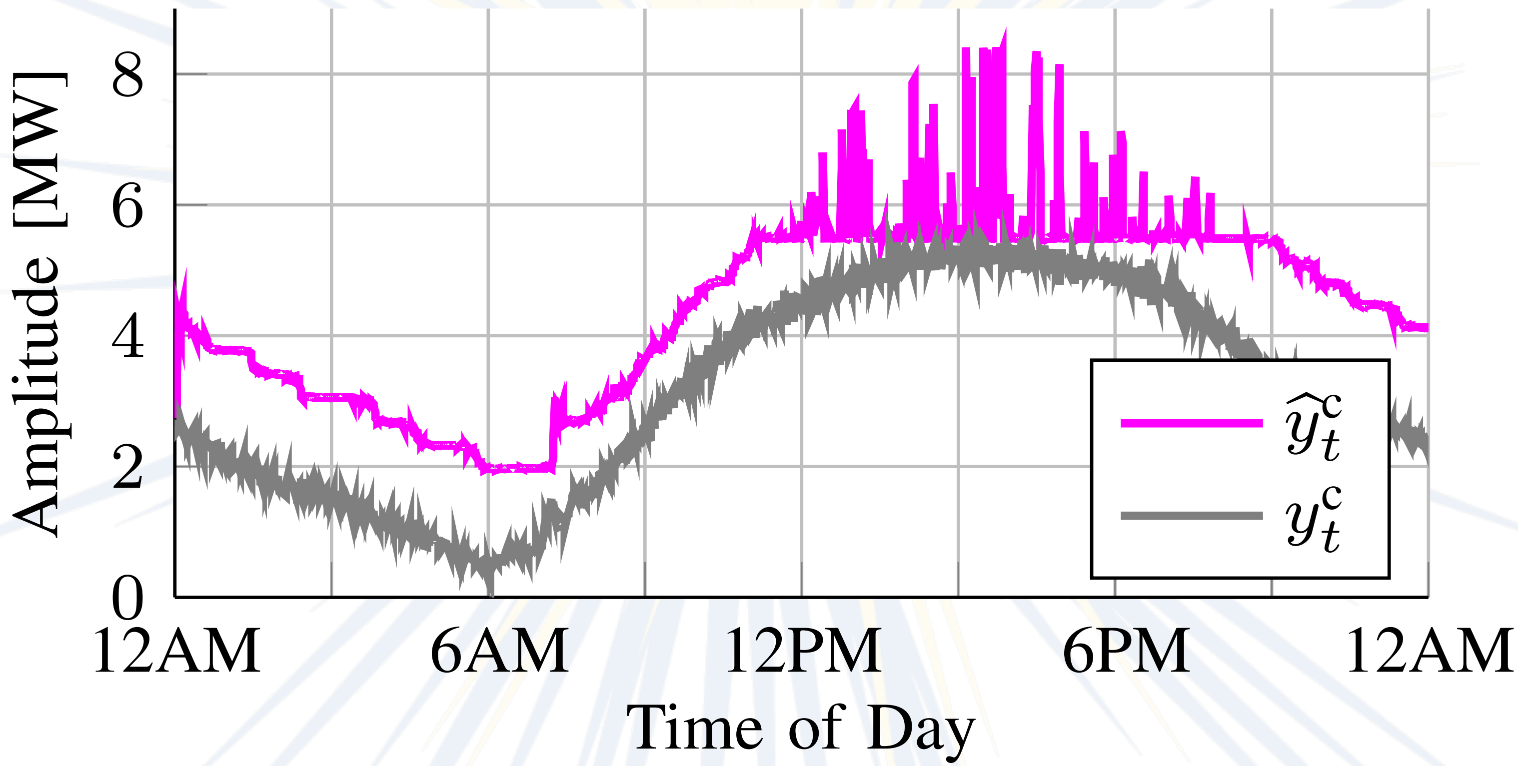


Weightings: Better Models



Prediction Results: Bad Models

- All "other load models" are too low.



Results: Summary

Case	**RMS Error (kW)**
Benchmark: Use current outdoor temperature, LTI models, and interpolation to predict	738
DMD Case 1: Includes every combination of aggregate air conditioner model and "other load model"	264
DMD Case 2: Case 1 models plus a smoothed version of the actual "other loads"	211
DMD Case 3: Case 2 models plus more accurate models of the aggregate air conditioning load over time periods where the other models are less accurate	175
DMD Case 4: Includes "other load models" that underestimate the "other load"	1392

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Next steps

- Investigate more realistic settings
- Develop better load models
- Improve the algorithm, e.g., alternative weighting functions
- Incorporate additional measurements (reactive power, voltage) into the approach

Key findings

- Dynamic Mirror Descent (DMD) enables us to solve the substation disaggregation problem leveraging dynamical models of arbitrary form
- DMD can work well (on simple examples); however, it is easy to find instances where it does not work well

Conclusions

- Need new sources of power system reserves
  - Coordination of distributed electric loads using delay-aware control/estimation
- Need methods to infer electric load behavior from existing measurements
  - Dynamic mirror descent applied to distribution substation measurements

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