# Learning About Loads to Improve Power System Operation and Control

Johanna Mathieu

Department of Electrical Engineering & Computer Science

University of Michigan

# What do we want to learn?

- Electric loads are poorly characterized by power system operators

- Yesterday: Network injections, Demand response actions, Baselines, …

- Other fun problems…

# 1. Index Policies for Demand Response

- Assume:
  - Your goal is maximum curtailment given a fixed budget.
  - You have to pay a load each time it's picked.
- Which load should you pick?
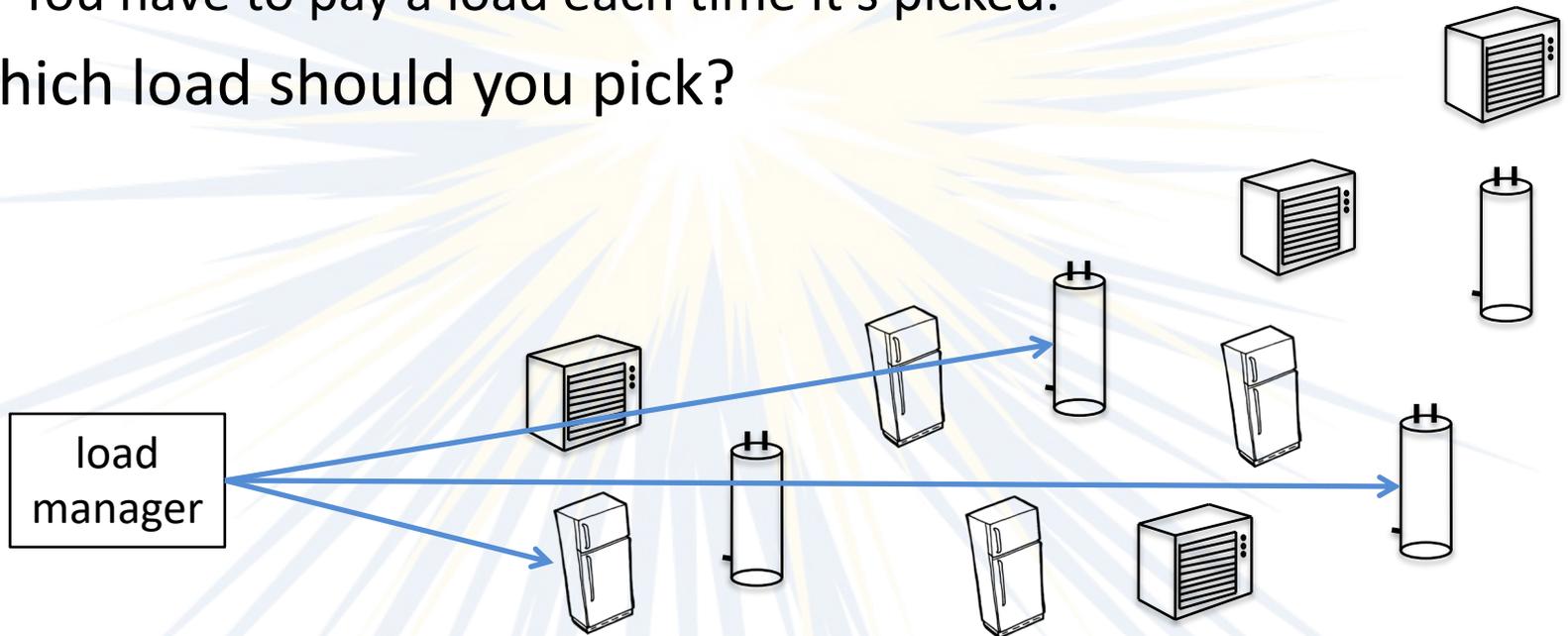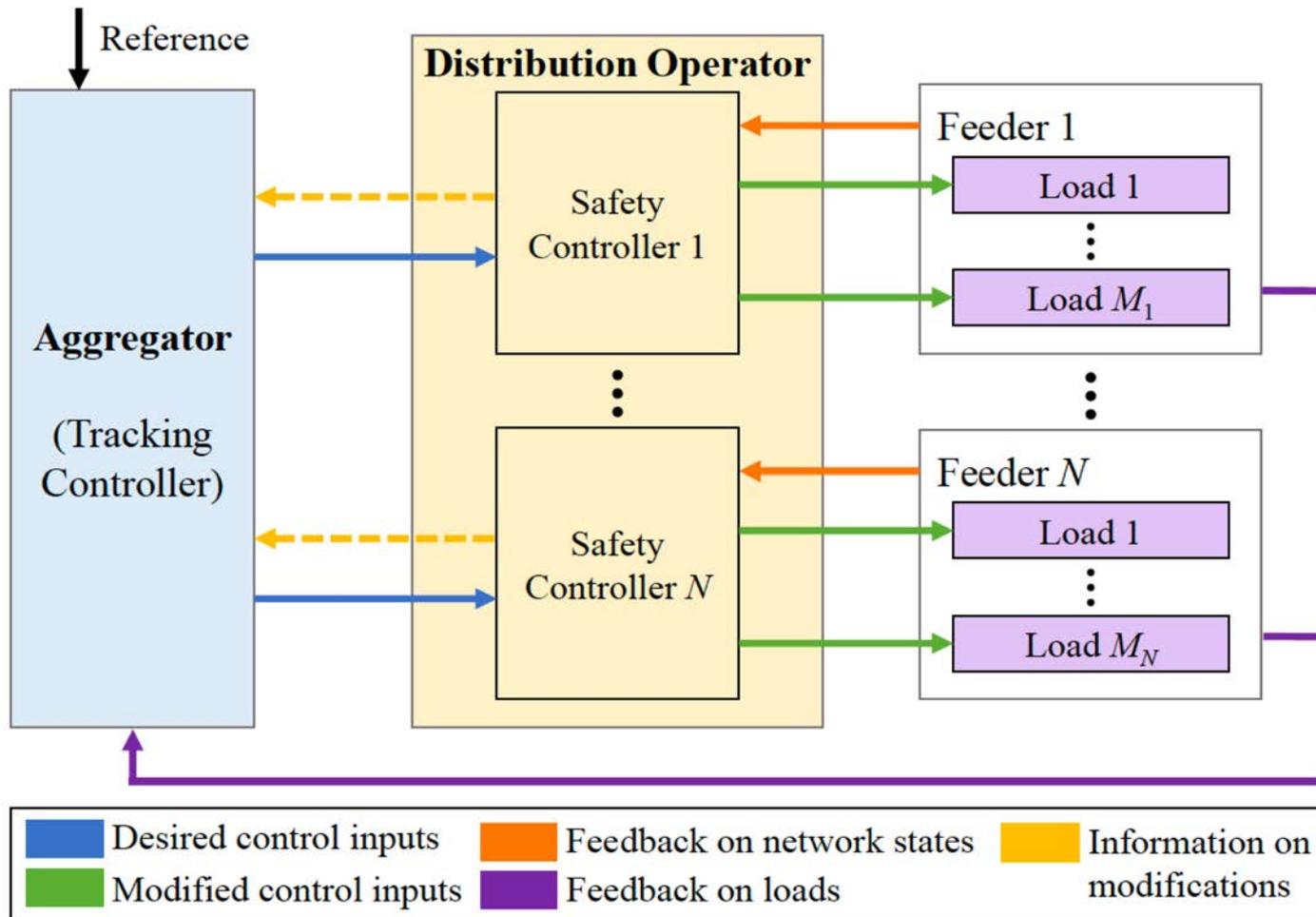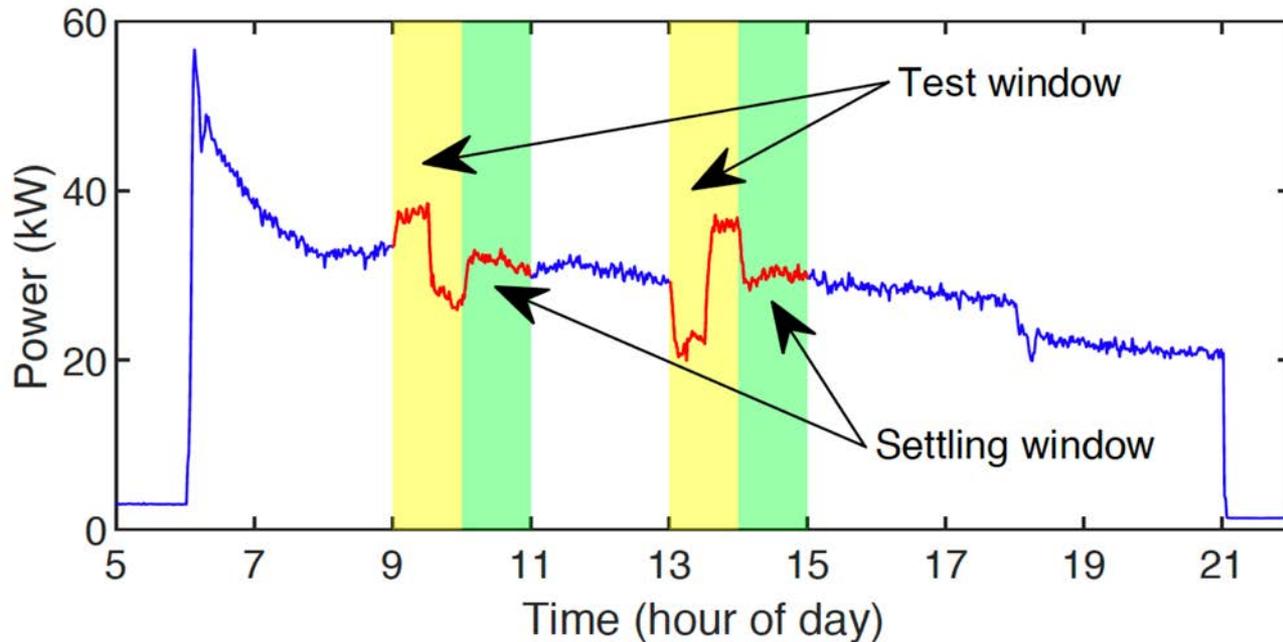
Fig. 1.  Total fan power trace of RAC on an event day (Sep. 26, 2017).

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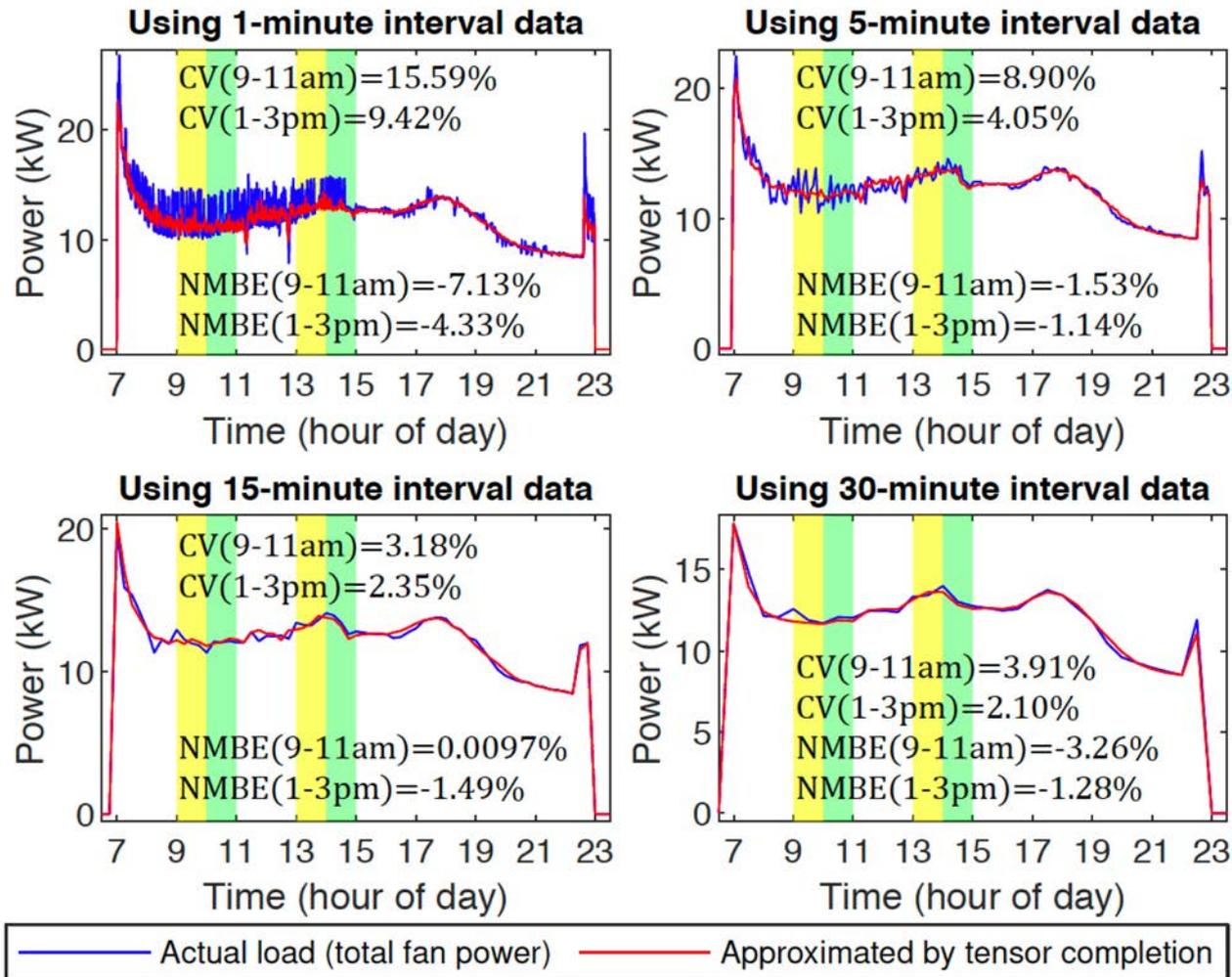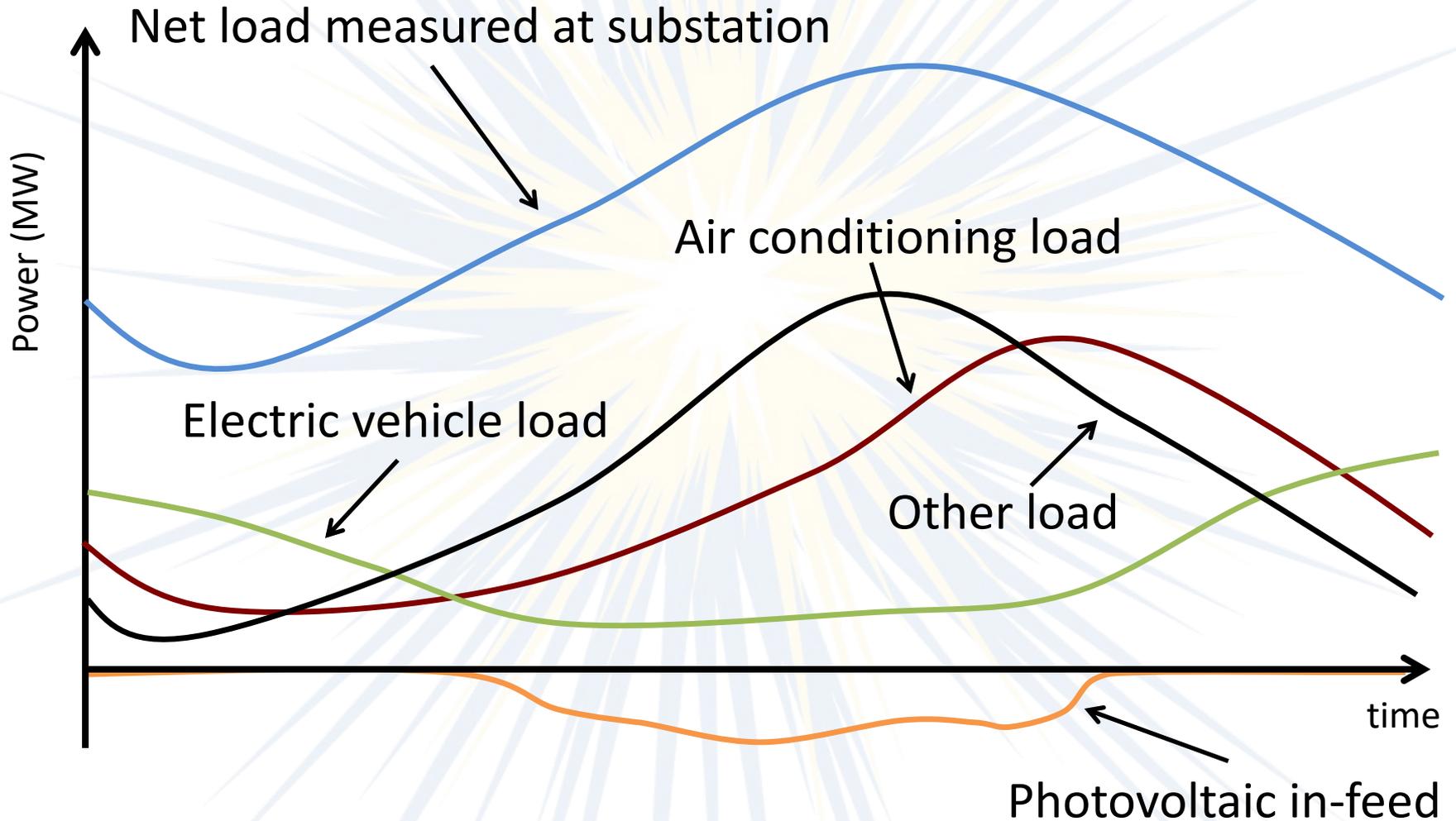


Fig. 6. Actual and estimated total fan power traces based on given data with different temporal frequencies (BBB, Aug. 9, 2017).

11/13/19

6

Net load measured at substation

Air conditioning load

Electric vehicle load

Other load

Photovoltaic in-feed

Power (MW)

time

# Energy Disaggregation
## a.k.a Non-Intrusive Load Monitoring (NILM)



Power (KW)

Stove Burner

Fan Heater

Blender

Oven

Workstation

Time (Min)
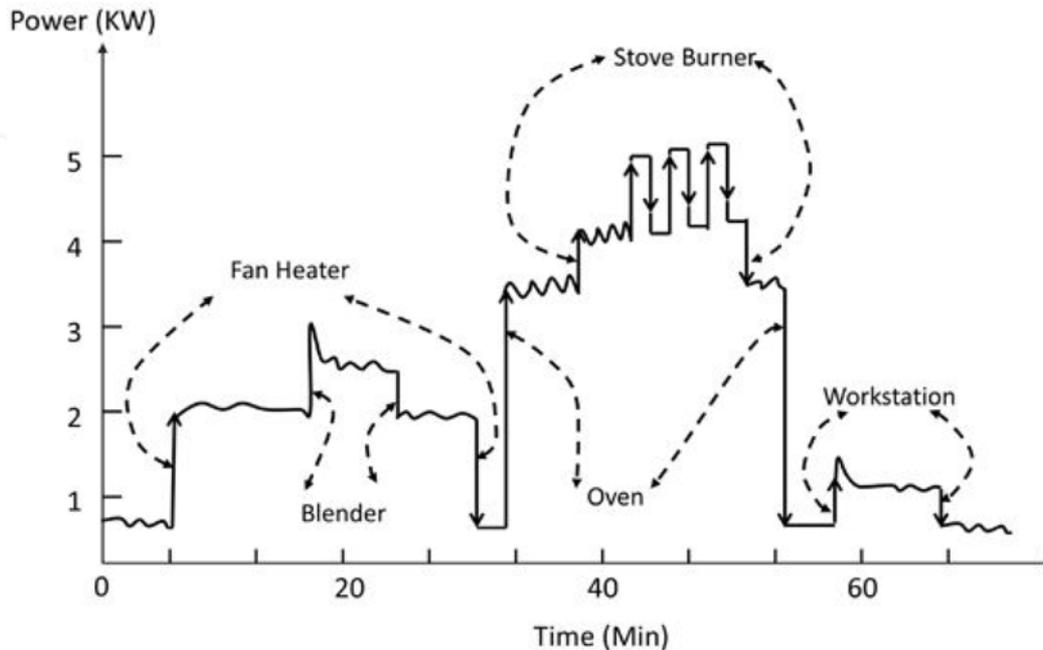
[Hart 2010; Ziefman and Roth 2011; Berges et al. 2009; Dong, Sastry, et al. 2013, 2014; Wytock & Kolter 2013; Kolter and Jaakkola 2012; Kim et al. 2010; …]

Fig from Zoha et al. 2012

Problem: Estimate individual load 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 estimate the power consumption of all loads of a specific type, not individual loads

- 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!

# Why disaggregate feeder load?

## Uses in demand response…

- Load control feedback [noisy aggregate power measurements are assumed in Mathieu et al. 2013; Can Kara et al. 2013; Bušić and Meyn 2016; Callaway 2009; …]
- Load aggregator bidding
- Demand response event signaling (when/how much)

ref → Controller → u → | Load 1 | Load 2 | ⋮ | Load N | → aggregate power
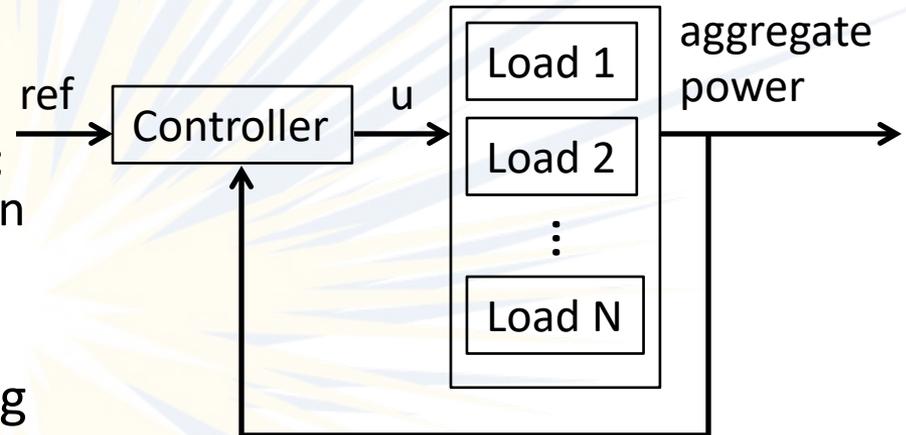
## Beyond demand response…

- Energy efficiency via conservation voltage reduction (disaggregate by ZIP load type)
- Contingency planning (disaggregate motor loads)
- Reserve planning (disaggregate PV production)

# Possible Methods

- Short-term load (component) forecasting
  - Doesn't incorporate real-time feedback
- State estimation
  - Linear techniques require linear system models
  - Nonlinear techniques can be computationally demanding

- Online learning
  - (Typically) data-driven, model-free

- Hybrid approach: Dynamic Fixed Share & 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

- Problem Framework
- Algorithms: Dynamic Mirror Descent (DMD) & Dynamic Fixed Share (DFS)
- Models, Algorithm Modifications
- Case studies
- Connections with Kalman Filtering
- Extension to multiple measurements

Ledva, Balzano, and Mathieu, "Inferring the Behavior of Distributed Energy Resources with Online Learning," Allerton 2015.

Ledva, Balzano, and Mathieu, "Real-time Energy Disaggregation of a Distribution Feeder's Demand using Online Learning," IEEE Transactions on Power Systems, 2018.

# Problem Framework
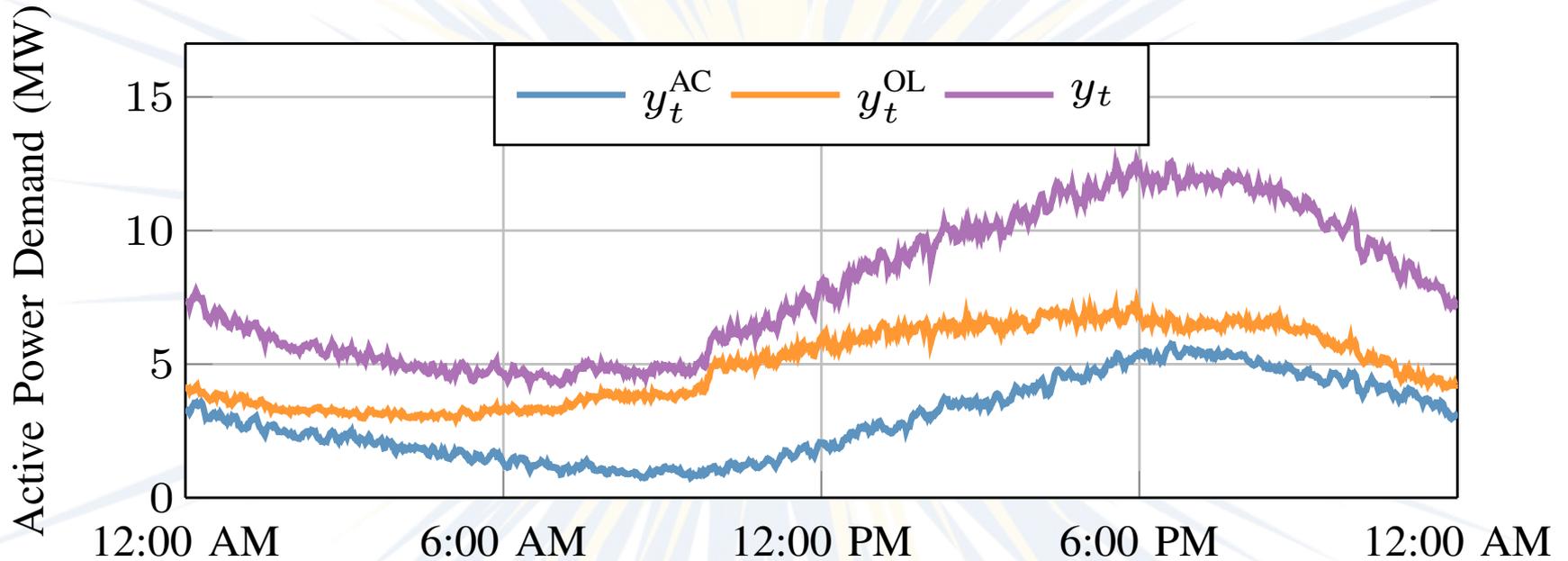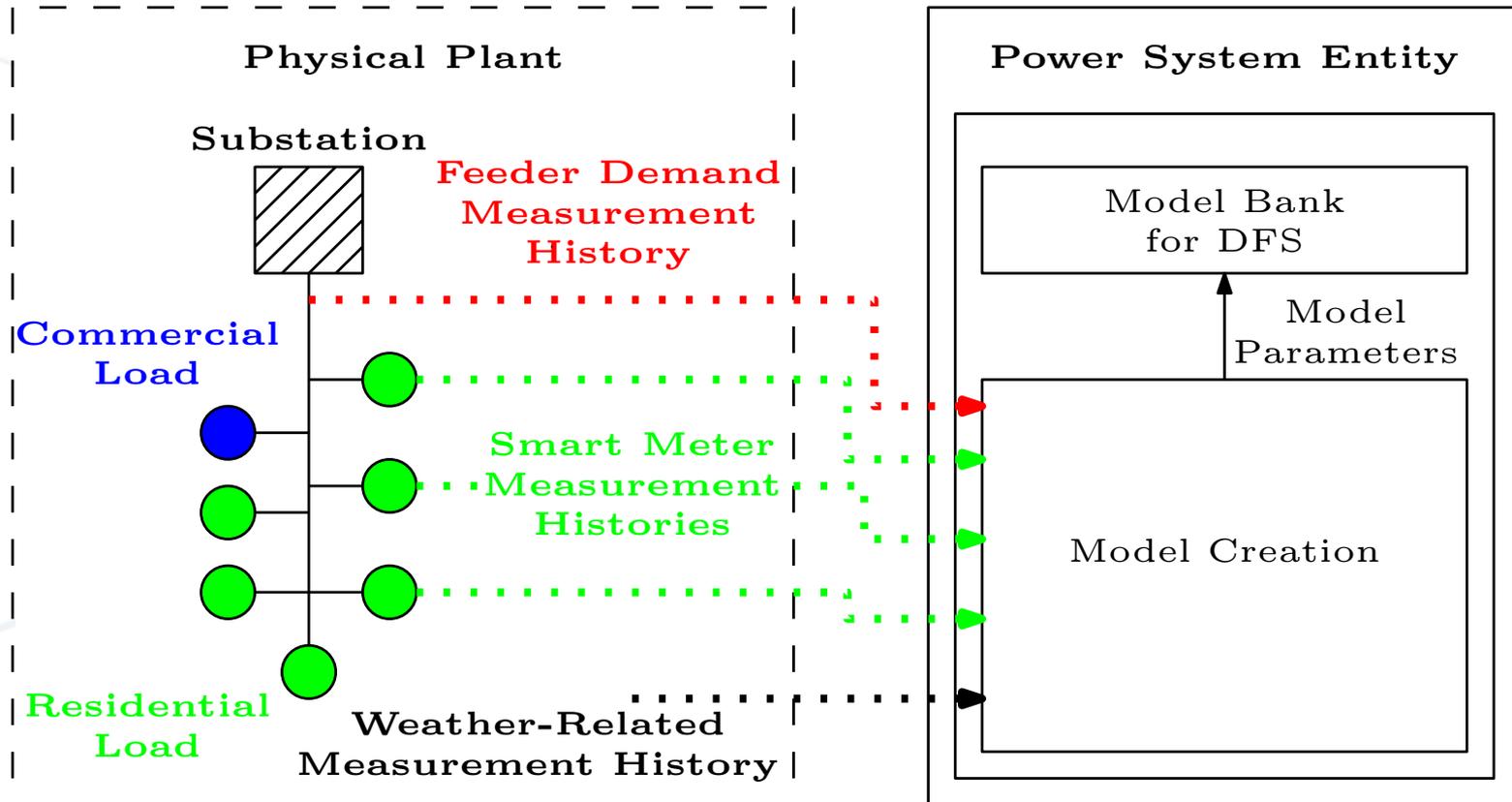
# Problem Framework: Real-time Estimation

# Dynamic Mirror Descent
[Hall & Willet 2015]
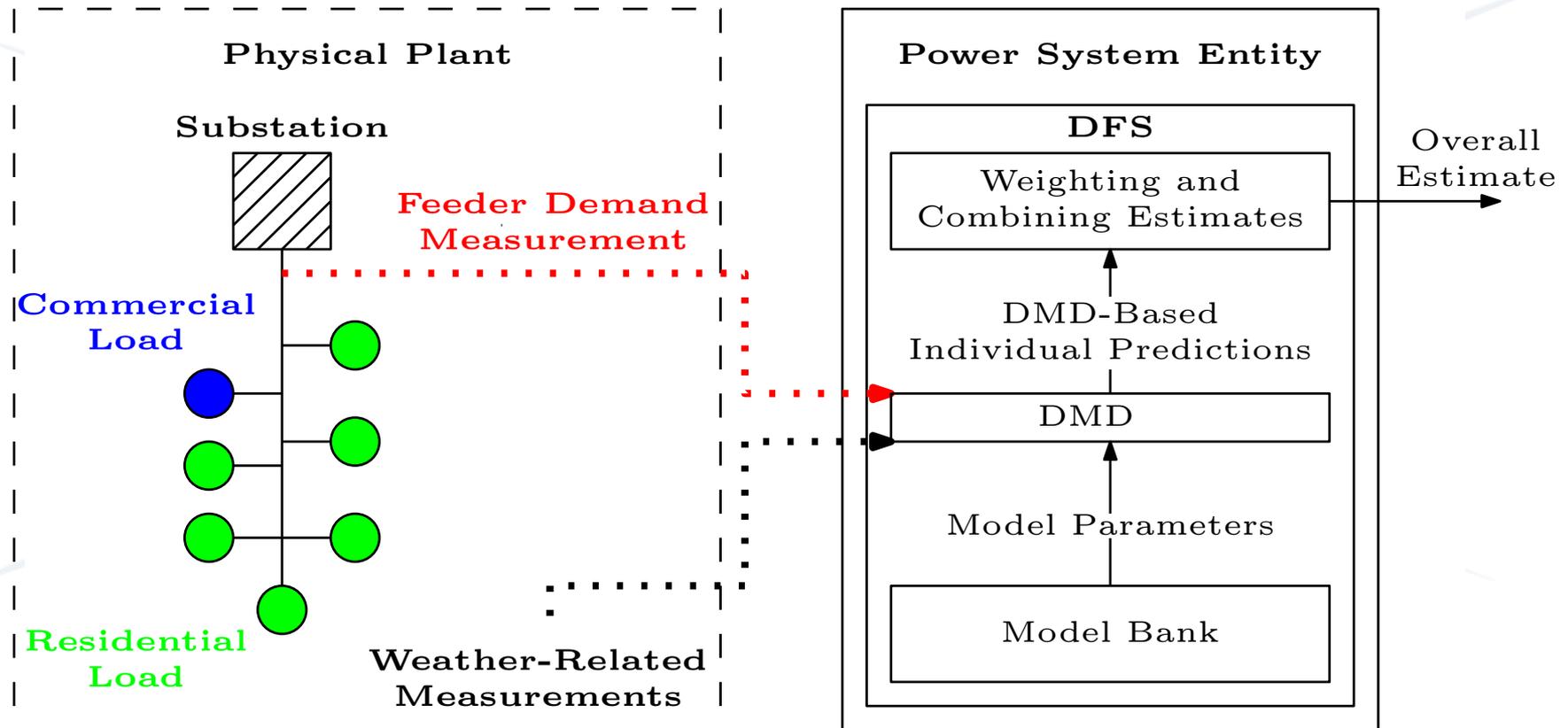
For each model $m$ we compute

1.  an observation-based update

$$\widetilde{\theta}_t^m = \underset{\theta \in \Theta}{\arg\min}\ \eta^{\mathrm{s}} \left\langle \nabla \ell_t(\widehat{\theta}_t^m),\ \theta \right\rangle + D\left(\theta \| \widehat{\theta}_t^m\right)$$

where $\ell_t(\widehat{\theta}_t^m)$ is a convex loss function and $D$ is a Bregman divergence function

2.  a model-based update

$$\widehat{\theta}_{t+1}^m = \Phi^m(\widetilde{\theta}_t^m)$$

# Dynamic Fixed Share
## [Hall & Willet 2015]

3. Next, we update the weight of each model

$$w_{t+1}^m = \frac{\lambda}{N^{\mathrm{mdl}}} + (1 - \lambda) \frac{w_t^m \exp\left(-\eta^r \, \ell_t\left(\widehat{\theta}_t^m\right)\right)}{\sum_{j=1}^{N^{\mathrm{mdl}}} w_t^j \exp\left(-\eta^r \, \ell_t\left(\widehat{\theta}_t^j\right)\right)}$$

4. and compute the overall estimate.

$$\widehat{\theta}_{t+1} = \sum_{m \in \mathcal{M}^{\mathrm{mdl}}} w_{t+1}^m \, \widehat{\theta}_{t+1}^m$$

# Models

The chart shows Active Power Demand (MW) over a 24-hour period from 12:00 AM to 12:00 AM, with three curves: $y_t^{\text{AC}}$, $y_t^{\text{OL}}$, and $y_t$.
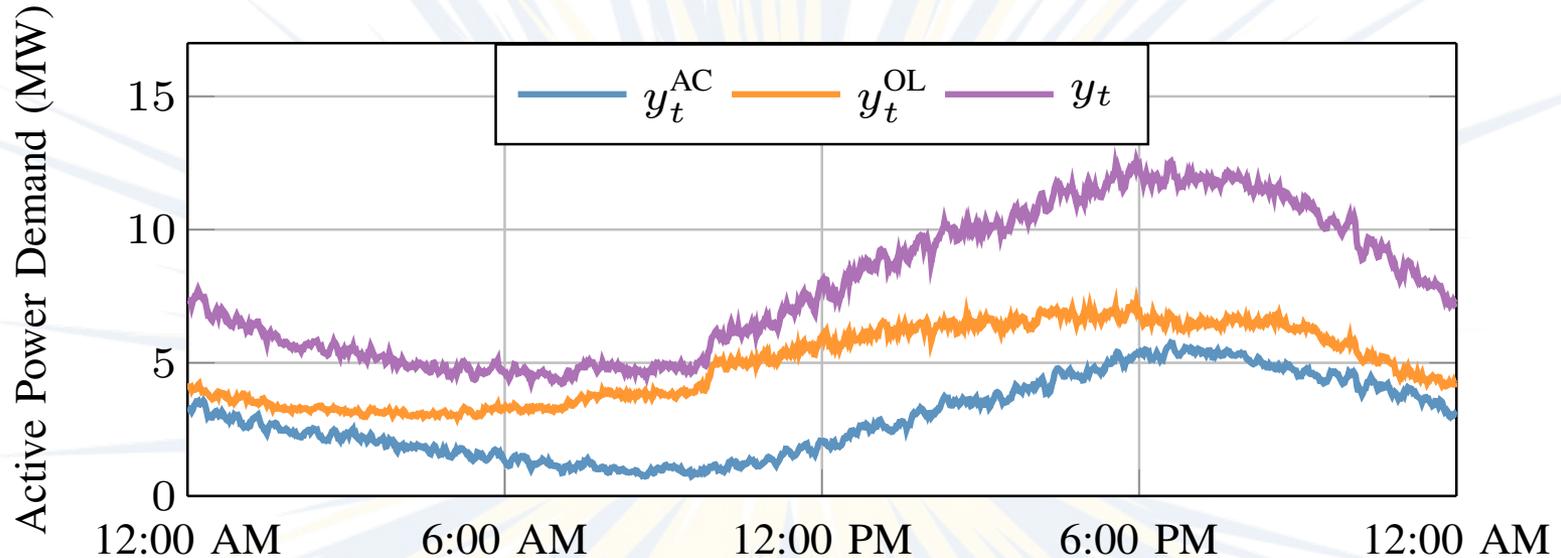
- 29 aggregate air conditioning load (AC) models
- 6 "other load" (OL) model
- 1 AC model + 1 OL model = 1 total load model
  → 174 total load models

# "Other load" Models

- (Smoothed) load on previous days (Mon-Fri)
- Multiple linear regression (MLR) model using time-of-week, outdoor temperature, and previous total demand measurement
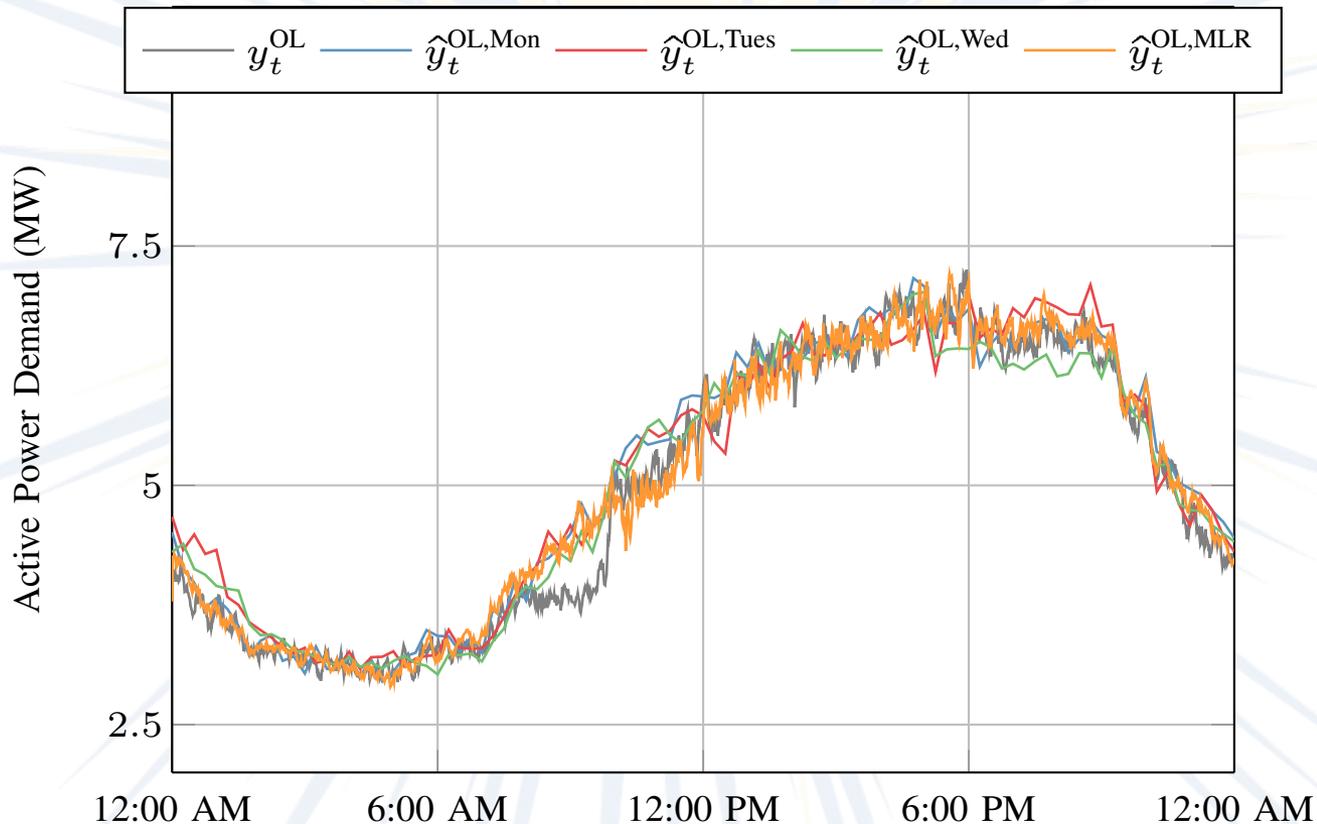
# AC Models

- Multiple linear regression (MLR) model using time-of-week and current/past outdoor temperatures

- Linear time-invariant (LTI) system models corresponding to different outdoor temperatures

- Linear time-varying (LTV) system models

$$\widehat{x}_{t+1}^{\text{LTI},m} = A^{\text{LTI},m} \, \widehat{x}_t^{\text{LTI},m}$$

$$\widehat{y}_t^{\text{AC,LTI},m} = C^{\text{LTI},m} \, \widehat{x}_t^{\text{LTI},m}$$
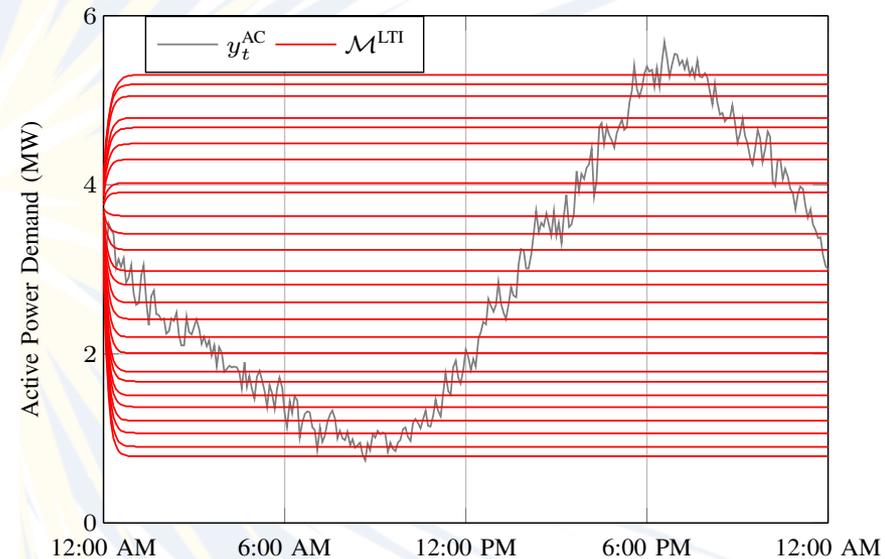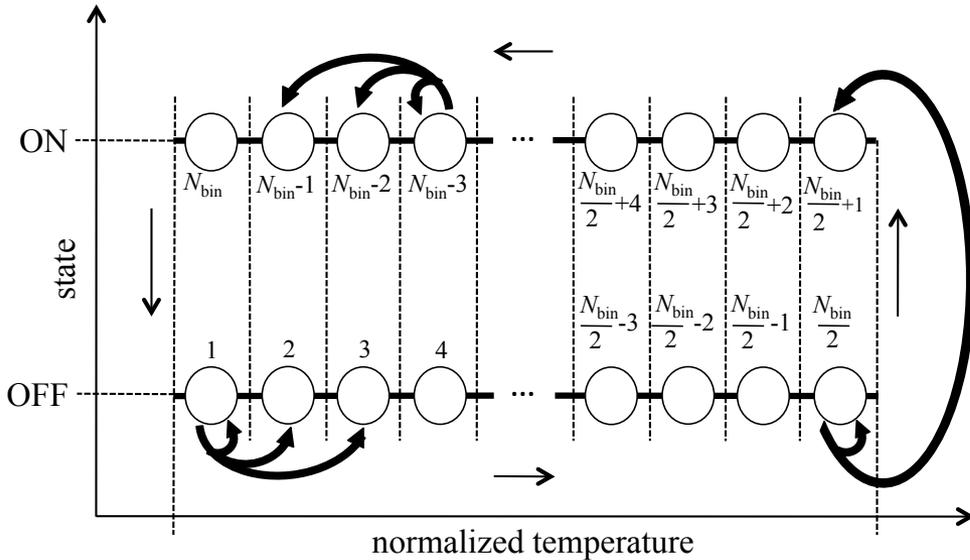
# LTV AC Models
## [Mathieu et al. 2015]

$$\widehat{x}_{t+1}^{\text{LTV1}} = A_t^{\text{LTV1}} \, \widehat{x}_t^{\text{LTV1}}$$

$$\widehat{y}_t^{\text{AC,LTV1}} = C_t^{\text{LTV1}} \, \widehat{x}_t^{\text{LTV1}}$$

Two variants identify $A_t$ using delayed temperature measurements vs. a moving average of past temperature measurements
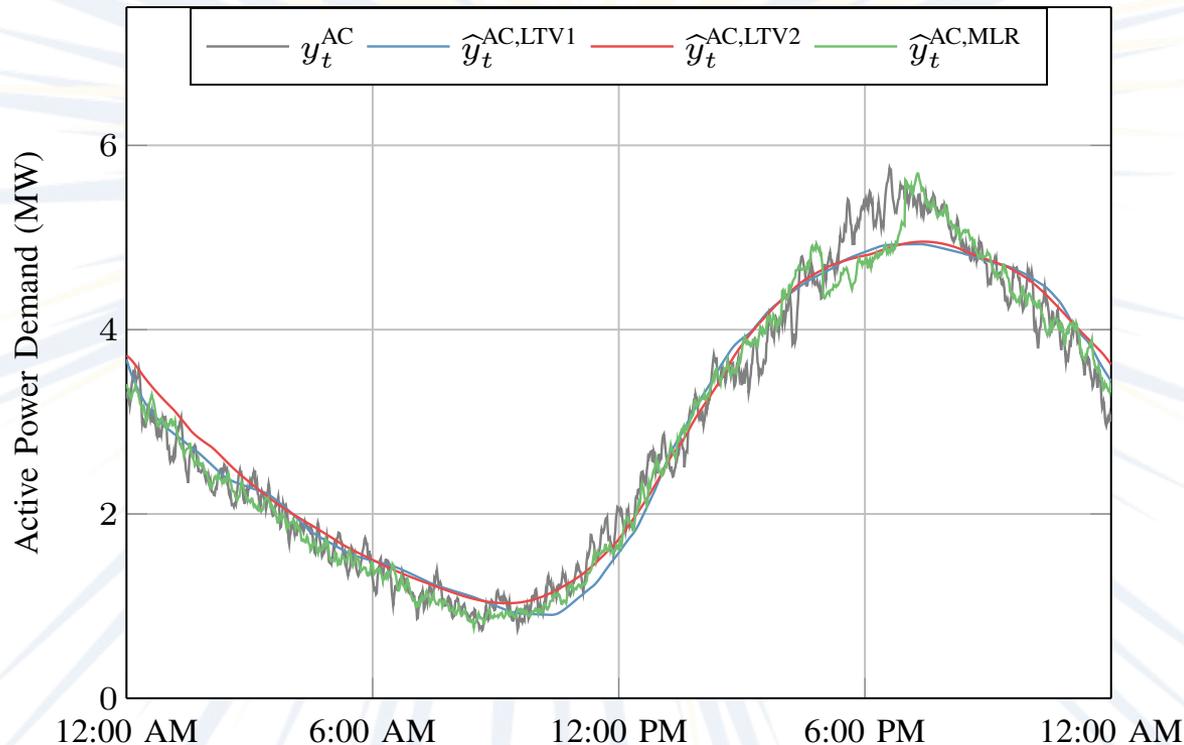
# Algorithm Modifications

- The models have different structures, dynamic states, and/or parameters. It is difficult to define a common "state" $\theta_t$.

- Two versions
  - Update Method 1: updates the output
  - Update Method 2: updates the state (i.e., for the LTI/LTV models, update the state, i.e., $\theta_t = x_t$)

# Update Method 1

Adjust the output (demand estimates), rather than the state.

$$\widetilde{\theta}_t^m = \arg\min_{\theta \in \Theta} \eta^{\mathrm{s}} \left\langle \nabla\ell_t(\widehat{\theta}_t^m),\ \theta \right\rangle + D\left(\theta\|\widehat{\theta}_t^m\right)$$
$$\widehat{\theta}_{t+1}^m = \Phi^m(\widetilde{\theta}_t^m)$$
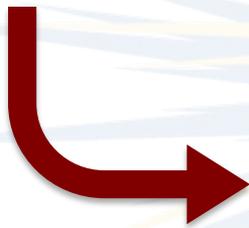
$$\widehat{\kappa}_{t+1} = \arg\min_{\theta \in \Theta} \eta^{\mathrm{s}} \left\langle \nabla\ell_t(\widehat{\theta}_t),\ \theta \right\rangle + D\left(\theta\|\widehat{\kappa}_t\right)$$
$$\breve{\theta}_{t+1} = \Phi(\breve{\theta}_t)$$
$$\widehat{\theta}_{t+1} = \breve{\theta}_{t+1} + \widehat{\kappa}_{t+1}.$$

Then, with $\ell_t(\widehat{\theta}_t) = \frac{1}{2}\|C_t\widehat{\theta}_t - y_t\|_2^2$ and $D(\theta\|\widehat{\kappa}_t) = \frac{1}{2}\|\theta - \widehat{\kappa}_t\|_2^2$ we can derive a closed form update:

$$\widehat{\kappa}_{t+1} = \widehat{\kappa}_t + \eta^{\mathrm{s}} C_t^T \left(y_t - C_t\widehat{\theta}_t\right)$$

# Case studies: Plant

- Residential load and weather data from Pecan Street Dataport (Austin, TX)

- Commercial load data from Pacific Gas & Electric Company; weather data from NOAA (Bay Area, CA)

- GridLab-D feeder used to size the load

Total load measurement

"Other load" prediction →〔 − 〕

AC load pseudo-measurement

u = 0 → | Time-varying Kalman Filter (using LTV model) |
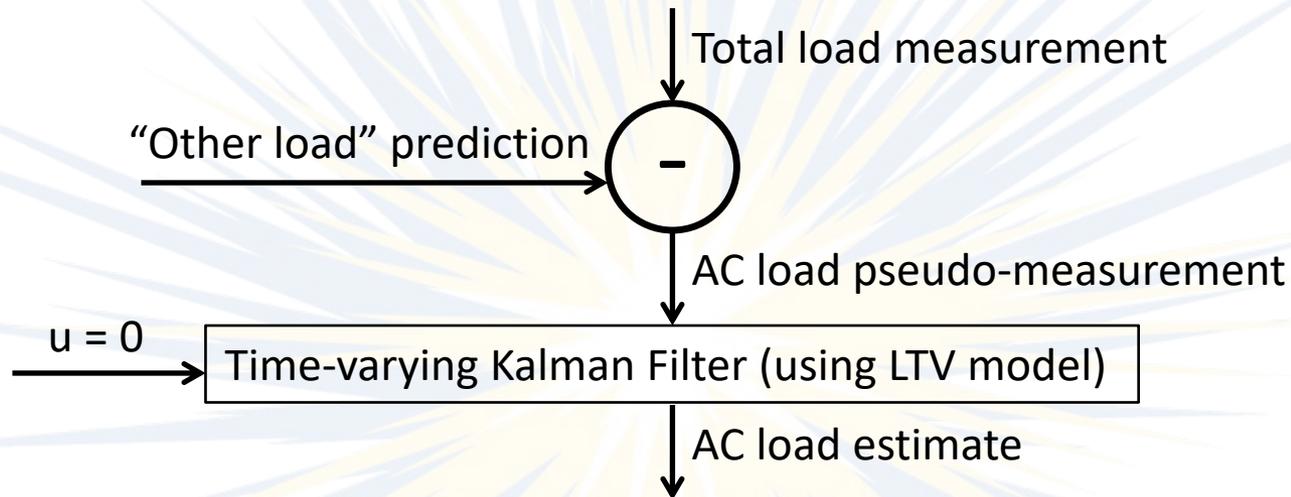
AC load estimate

- Each "other load" model + LTV AC model combination is used to compute one AC load estimate.
- We obtain the estimates from all Kalman filters and compute the a posteriori best (BKF) and average (AKF) results.

# Example results

## AC load RMSE

- DFS/DMD   151 kW
- BKF         177 kW
- AKF         214 kW



Model weights



Total load



Other load



AC load
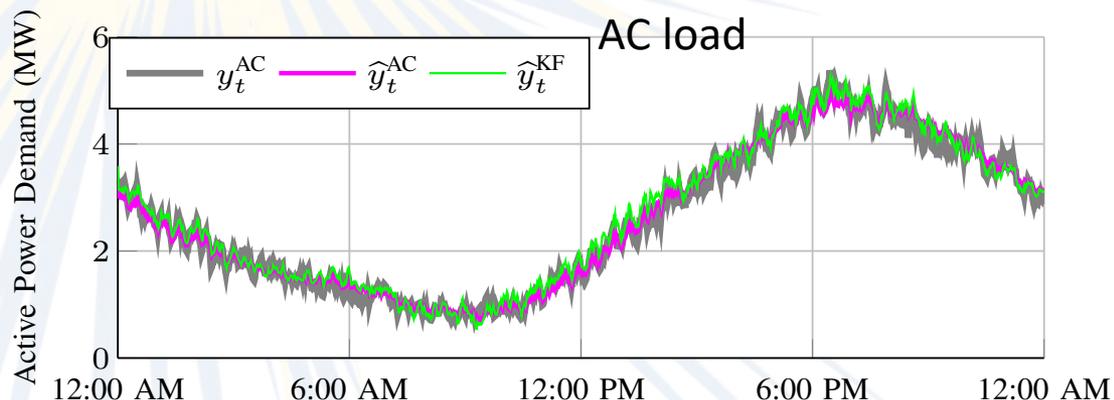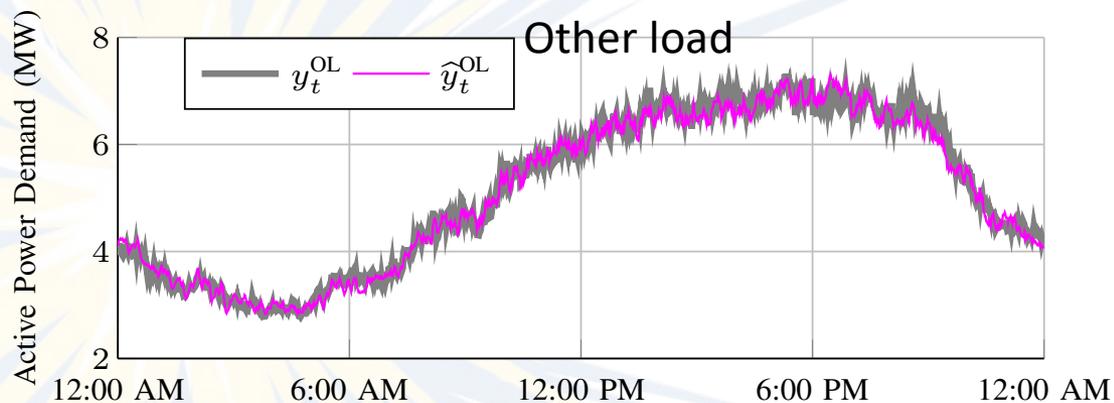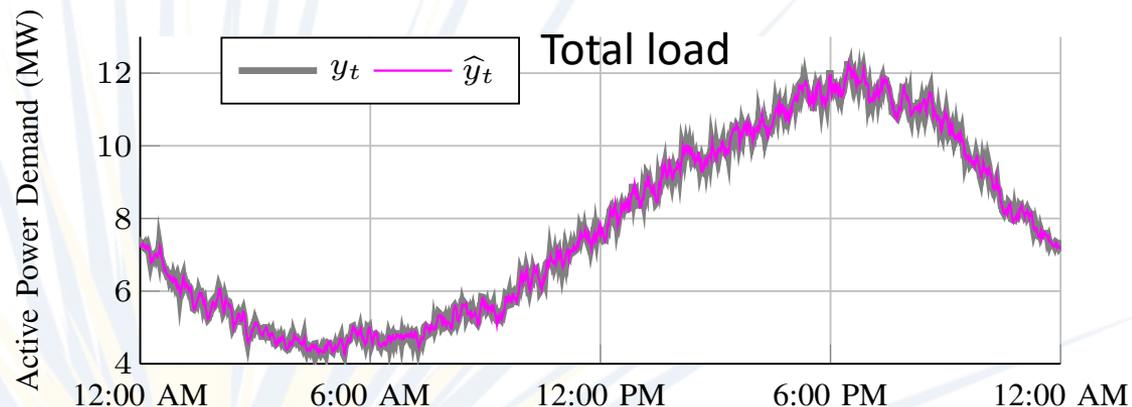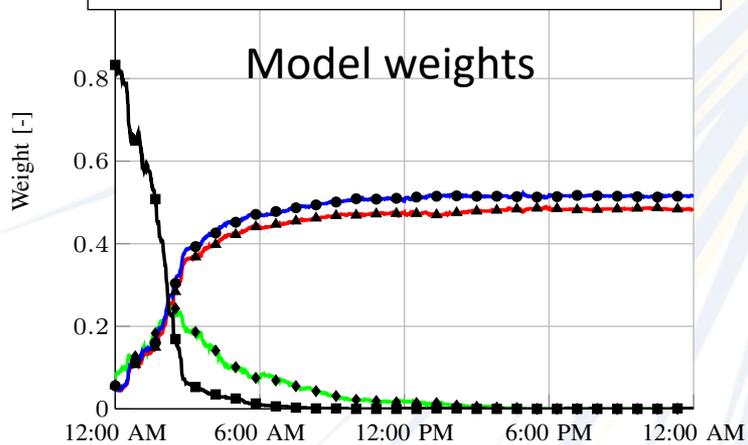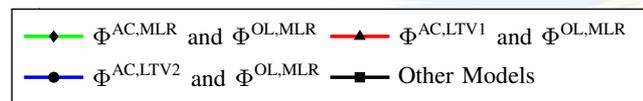
# Comparison across model sets & update methods



Update Method 1: update output
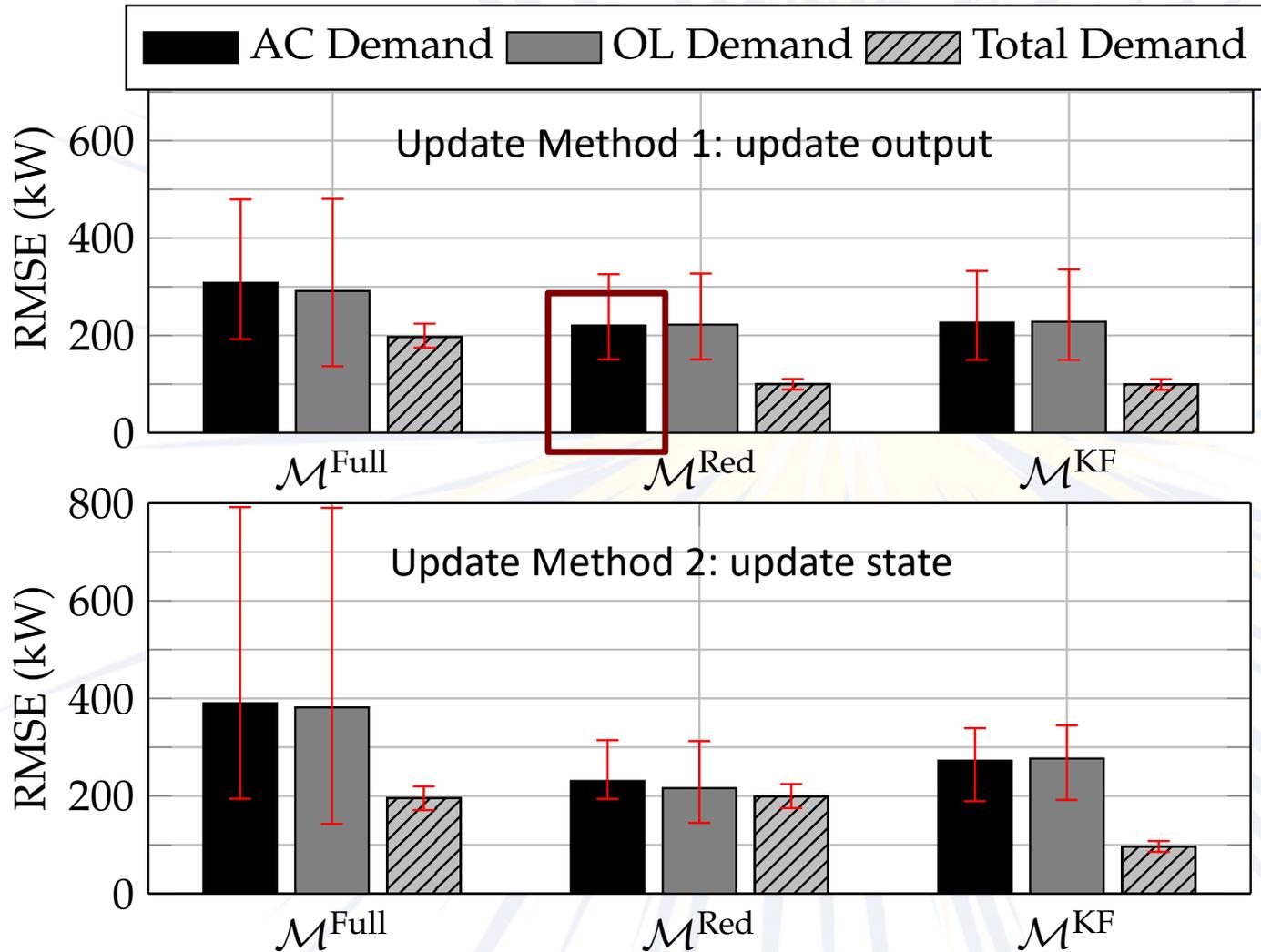
a posteriori BKF RMSE
- Mean 195 kW
- Min 148 kW
- Max 319 kW

AKF RMSE
- Mean 259 kW
- Min 173 kW
- Max 358 kW

Update Method 2: update state

# Sensitivity to parameter selections



faster transitions in weights →
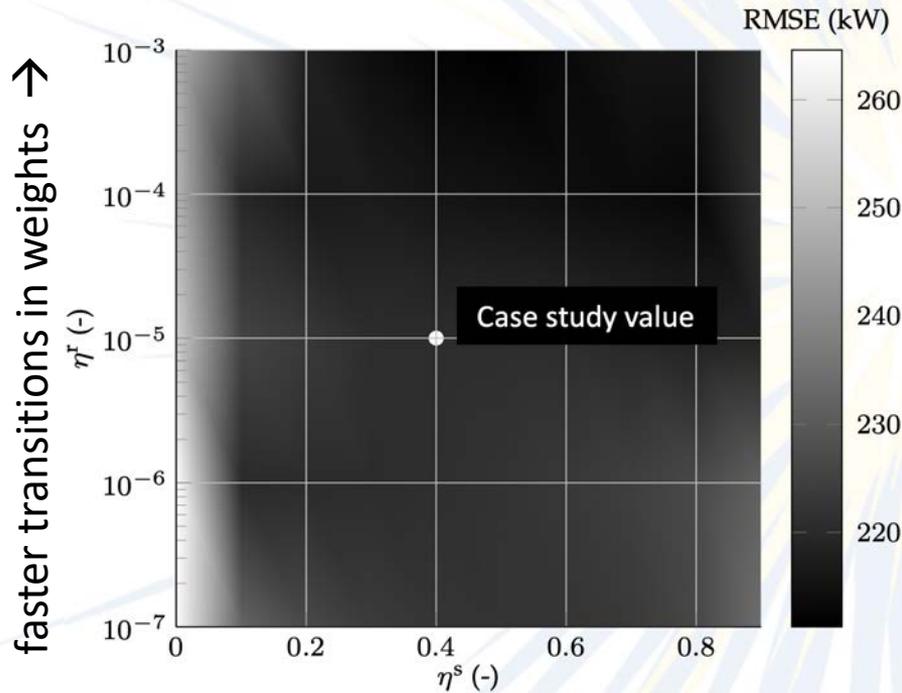
larger adjustments to estimates
based on prediction error →
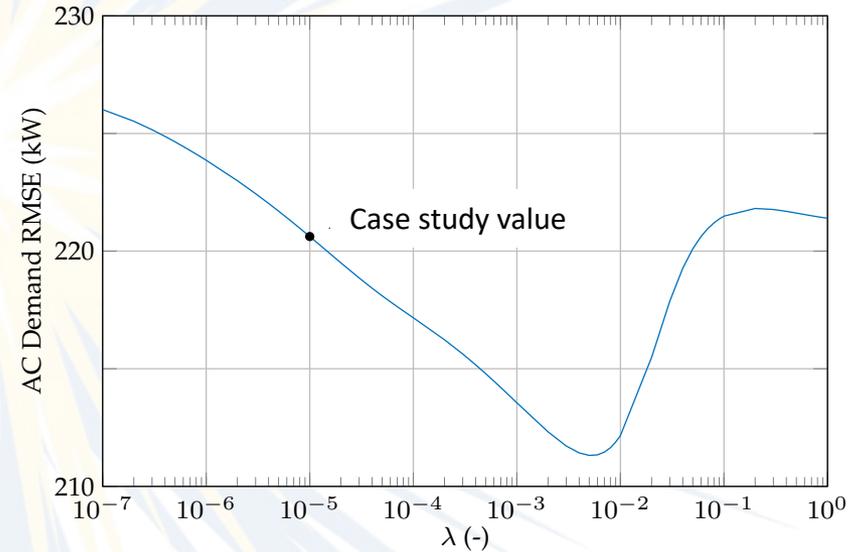
estimate closer to the average of all models →
← a single model can dominate

- In a Kalman Filter we assume the model form and use/choose the process and measurement noise covariance

- In DMD the model can take any form and we choose the loss and divergence functions. What should we pick?

Ledva, Du, Balzano, and Mathieu, "Disaggregating Load by Type from Distribution System Measurements in Real Time," In: Energy Markets and Responsive Grids, 2018.

Ledva, Balzano, and Mathieu, "Exploring Connections Between a Multiple Model Kalman Filter and Dynamic Fixed Share with Applications to Demand Response," IEEE CCTA 2018.

If we make the same assumption as we make for a Kalman filter (linear model, normally distributed errors, etc.), and we choose the following loss and divergence functions

$$\ell_k(\widehat{x}_k) = \frac{1}{2}\left(C_k\widehat{x}_k - y_k\right)^T \left(\widehat{P}_k^{\mathrm{y}}\right)^{-1} \left(C_k\widehat{x}_k - y_k\right),$$

$$D\left(x\|\widehat{x}_k\right) = \frac{1}{2}\left(x - \widehat{x}_k\right)^T \widehat{P}_k^{-1} \left(x - \widehat{x}_k\right)$$

where $\widehat{P}_k$ and $\widehat{P}_k^{\mathrm{y}}$ are symmetric positive-definite covariance matrices corresponding to the state and output estimation error, then the DMD updates are identical to those of the Kalman filter.

# Including error statistics

Use the Kalman Filter covariance update equations and compare three options for obtaining the process and measurement noise covariance

| Method | Covariance | Total Demand | | | AC Demand | | | OL Demand | | |
|--------|-----------|------|------|------|------|------|------|------|------|------|
| | | Min | Mean | Max | Min | Mean | Max | Min | Mean | Max |
| UM 1 | Identity | 88.9 | 100.0 | 110.5 | 151.0 | 220.6 | 325.8 | 150.8 | 222.3 | 327.2 |
| UM 1 | Historical | 98.4 | 114.8 | 123.2 | 155.0 | 252.2 | 371.5 | 150.2 | 250.1 | 372.5 |
| UM 1 | Real-Time | 146.6 | 154.3 | 168.4 | 120.2 | 125.3 | 131.8 | 104.8 | 114.5 | 130.5 |
| UM 2 | Identity | 175.4 | 199.1 | 224.8 | 194.2 | 230.9 | 314.5 | 145.0 | 216.2 | 312.7 |
| UM 2 | Historical | 100.5 | 119.5 | 126.1 | 192.0 | 259.8 | 311.5 | 190.6 | 265.5 | 320.2 |
| UM 2 | Real-Time | 120.8 | 125.2 | 129.1 | 104.0 | 116.5 | 140.1 | 96.6 | 109.4 | 131.9 |
| BKF | Historical | - | - | - | 148.4 | 195.3 | 318.9 | - | - | - |
| AKF | Historical | - | - | - | 173.1 | 259.4 | 357.5 | - | - | - |

UM 1: Update Method 1 (output), UM 2: Update Method 2 (state)

# DFS and Multiple Model Kalman Filtering

- We can also construct DFS to produce identical updates to a Multiple Model Kalman Filter (MMKF).

- A number of heuristics have been developed for MMKFs; these can be adapted for DFS.
  - Setting a minimum weight
  - Exponential decay used to update weights
  - Sliding window used to update weights

# Multiple Measurements
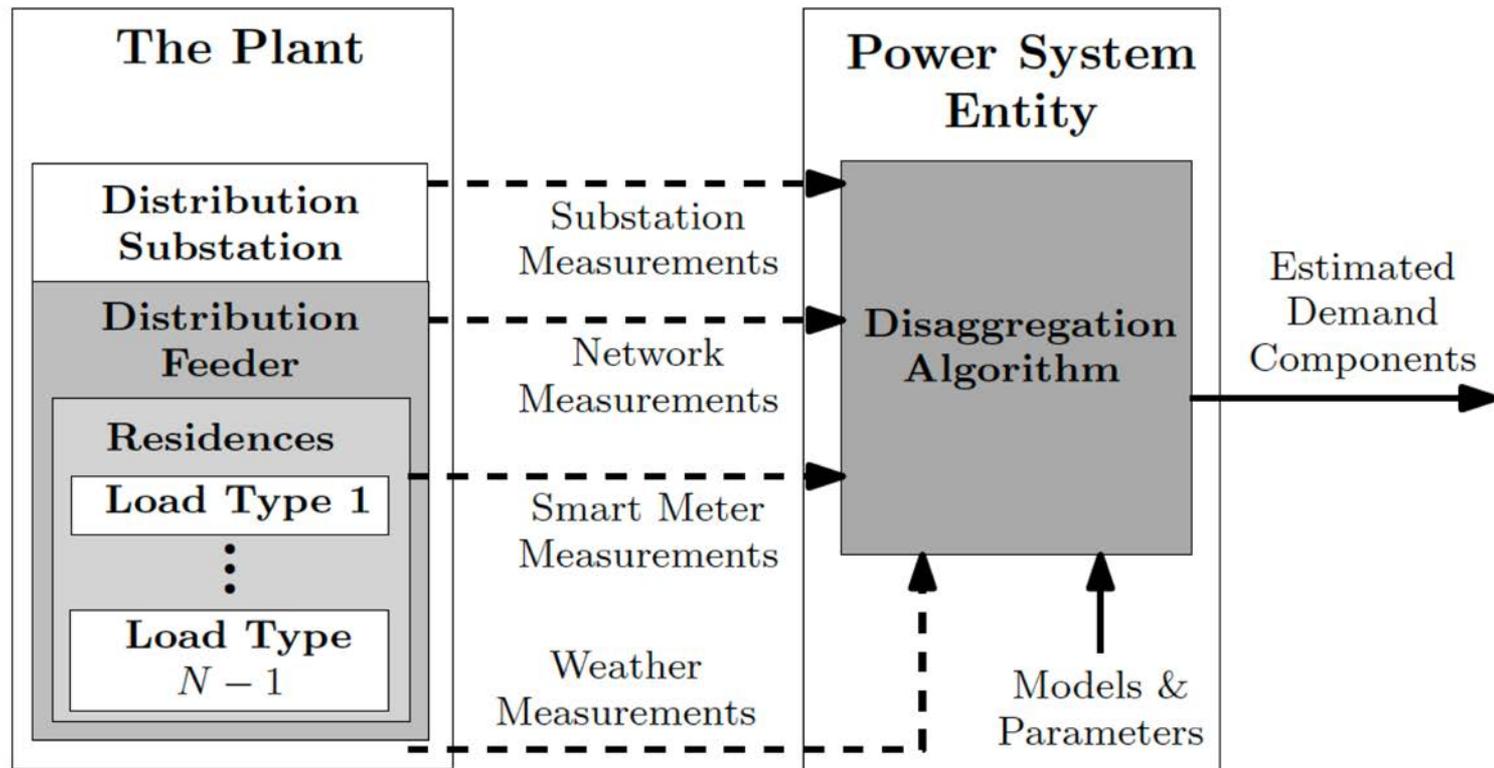


Ledva and Mathieu, "Separating Feeder Demand into Components Using Substation, Feeder, and Smart Meter Measurements," in review.

# Possible Measurements

## POSSIBLE REAL-TIME MEASUREMENTS

| Measurement Type | Frequency |
|---|---|
| **Substation Measurements** | |
| Active and reactive power flow into the feeder | 1 minute |
| Complex current flowing into the feeder | 1 minute |
| Complex voltage at the feeder head | 1 minute |
| **Network Measurements** | |
| Active and reactive power flow within the feeder | 1 minute |
| Complex voltage within the feeder | 1 minute |
| **Smart Meter Measurements** | |
| Active and reactive power flowing into the residence | 10-60 minutes |
| Current magnitude flowing into the residence | 10-60 minutes |
| Voltage magnitude at the residence | 10-60 minutes |
| Voltage and current phase difference at the residence | 10-60 minutes |
| **Weather Measurements** | |
| Outdoor temperature | 1 minute |

# Approach

- Dynamic Mirror Descent ← more or less the same

- Sensor Fusion← combining different types of measurements available at different timescales

- Output equations corresponding to each type of measurement ← the hard part!
  - Real and reactive power flow from a node
  - Voltage magnitude differences
  - Voltage angle differences
  - Smart meter measurements (real/reactive power consumption)

## Feeder Portions
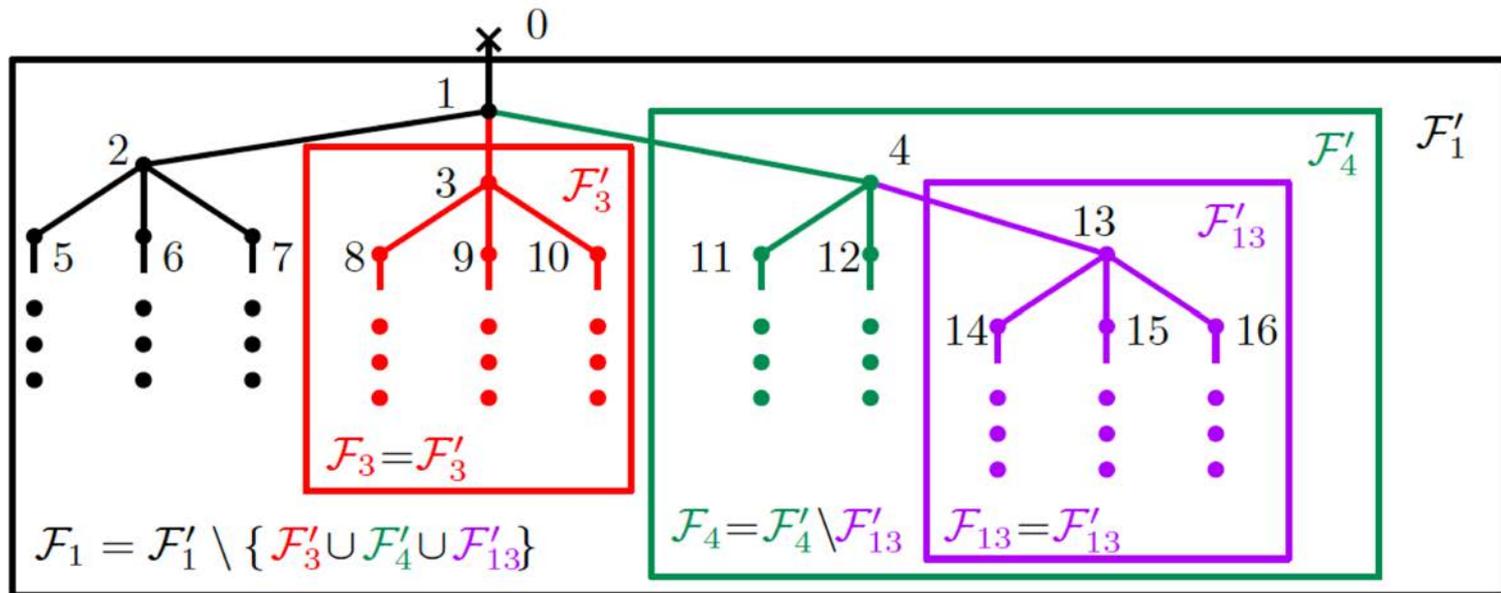


## Output Equation

$$y = C\theta \quad \text{where} \quad \theta \triangleq \begin{bmatrix} P_{\mathcal{F}_{m_1}}^{\mathrm{T}} & \cdots & P_{\mathcal{F}_{m_M}}^{\mathrm{T}} & Q_{\mathcal{F}_{m_1}}^{\mathrm{T}} & \cdots & Q_{\mathcal{F}_{m_M}}^{\mathrm{T}} \end{bmatrix}^{\mathrm{T}},$$

$y$ are the measurements and $C$ depends on the measurement type

Michigan Power & Energy Laboratory

CASE STUDY REAL-TIME MEASUREMENT SCENARIO DEFINITIONS

| Scenario | Models | Real-Time Measurements | Purpose |
|---|---|---|---|
| 1 | $\mathcal{M}^{nc}$ | None | Evaluate the prediction accuracy of $\mathcal{M}^{nc}$ |
| 2 | $\mathcal{M}^{c}$ | Substation complex current | Evaluate the prediction accuracy of $\mathcal{M}^{c}$ |
| 3 | $\mathcal{M}^{nc}$ | Substation active power | Benchmark these results against those in [10], [11], which use a similar measurement scenario |
| 4 | $\mathcal{M}^{c}$, $\mathcal{M}^{nc}$ | Substation apparent power; substation complex current | Evaluate the disaggregation accuracy with reactive power measurements |
| 5 | $\mathcal{M}^{c}$ | Scenario 4 measurements; voltage phasors at nodes 650 and 671 | Evaluate the disaggregation accuracy with additional voltage phasor measurements. |

J. Mathieu, University of Michigan
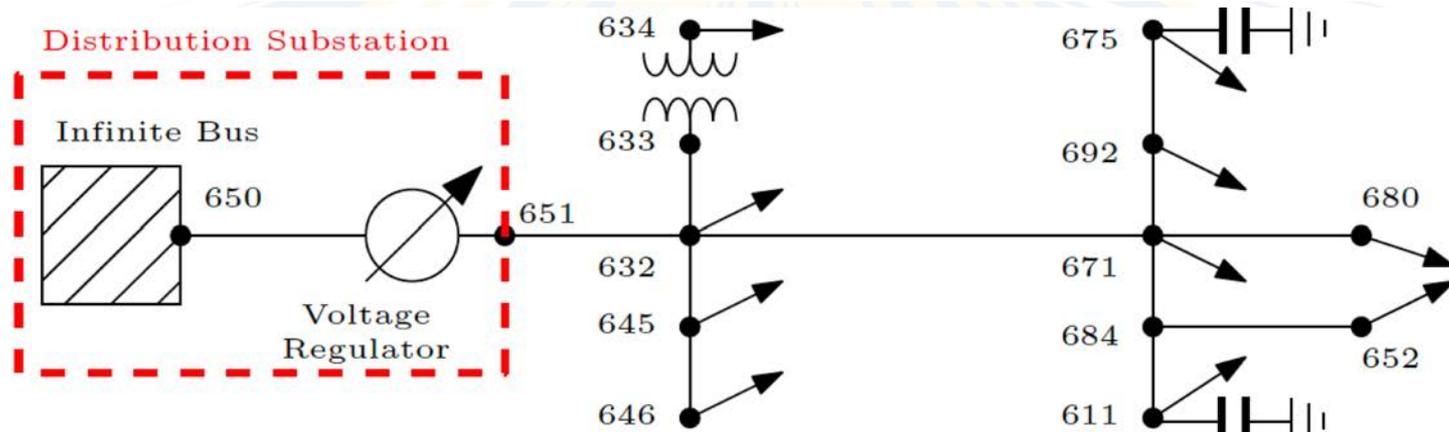
# Example Results

Red = Scenario 1 (no real-time measurements)

Blue = Scenario 2 (substation complex current measurement)



(a) AC Demand Time Series

(b) OL Demand Time Series

(c) NW Demand Time Series

# Value of Additional Measurements

## DEMAND COMPONENT RMSE (KW/KVAR/KVA) IN DIFFERENT CASES

| Scenario | Models | AC-P | AC-Q | AC-S | OL-P | OL-Q | OL-S | NW-P | NW-Q | NW-S |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | | | Demand Component | | | | | |
| 1 | $\mathcal{M}^{nc}$ | 181.4 | 45.4 | 187.0 | 179.2 | 52.7 | 186.8 | 50.0 | 157.0 | 165.4 |
| 2 | $\mathcal{M}^{c}$ | 64.1 | 16.0 | 66.1 | 68.0 | 20.0 | 70.9 | 5.6 | 8.2 | 9.9 |
| 3 | $\mathcal{M}^{nc}$ | 129.6 | - | - | 114.0 | - | - | 23.0 | - | - |
| 3-60 | $\mathcal{M}^{nc}$ | 77.5 | - | - | 63.0 | - | - | 16.8 | - | - |
| 3-30 | $\mathcal{M}^{nc}$ | 69.6 | - | - | 55.7 | - | - | 13.8 | - | - |
| 3-15 | $\mathcal{M}^{nc}$ | 61.1 | - | - | 47.0 | - | - | 10.9 | - | - |
| 4 | $\mathcal{M}^{nc}$ | 103.5 | 25.9 | 106.7 | 97.0 | 33.1 | 102.5 | 8.7 | 21.4 | 23.1 |
| 4 | $\mathcal{M}^{c}$ | 64.1 | 16.0 | 66.1 | 64.8 | 19.6 | 67.7 | 5.7 | 8.2 | 10.0 |
| 4-60 | $\mathcal{M}^{c}$ | 46.9 | 11.7 | 48.3 | 48.7 | 15.6 | 51.1 | 5.6 | 7.7 | 9.5 |
| 4-30 | $\mathcal{M}^{c}$ | 45.7 | 11.4 | 47.1 | 47.5 | 14.9 | 49.8 | 5.2 | 7.1 | 8.8 |
| 4-15 | $\mathcal{M}^{c}$ | 41.2 | 10.3 | 42.4 | 43.1 | 13.4 | 45.2 | 5.0 | 6.4 | 8.1 |
| 5 | $\mathcal{M}^{c}$ | 61.7 | 15.4 | 63.6 | 62.2 | 20.2 | 65.4 | 6.1 | 13.6 | 15.1 |

# Value of Additional Measurements

## DEMAND COMPONENT RMSE (KW/KVAR/KVA) IN DIFFERENT CASES

| Scenario | Models | Demand Component | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | AC-P | AC-Q | AC-S | OL-P | OL-Q | OL-S | NW-P | NW-Q | NW-S |
| 1 | $\mathcal{M}^{nc}$ | 181.4 | 45.4 | 187.0 | 179.2 | 52.7 | 186.8 | 50.0 | 157.0 | 165.4 |
| 2 | $\mathcal{M}^{c}$ | 64.1 | 16.0 | 66.1 | 68.0 | 20.0 | 70.9 | 5.6 | 8.2 | 9.9 |
| 3 | $\mathcal{M}^{nc}$ | 129.6 | - | - | 114.0 | - | - | 23.0 | - | - |
| 3-60 | $\mathcal{M}^{nc}$ | 77.5 | - | - | 63.0 | - | - | 16.8 | - | - |
| 3-30 | $\mathcal{M}^{nc}$ | 69.6 | - | - | 55.7 | - | - | 13.8 | - | - |
| 3-15 | $\mathcal{M}^{nc}$ | 61.1 | - | - | 47.0 | - | - | 10.9 | - | - |
| 4 | $\mathcal{M}^{nc}$ | 103.5 | 25.9 | 106.7 | 97.0 | 33.1 | 102.5 | 8.7 | 21.4 | 23.1 |
| 4 | $\mathcal{M}^{c}$ | 64.1 | 16.0 | 66.1 | 64.8 | 19.6 | 67.7 | 5.7 | 8.2 | 10.0 |
| 4-60 | $\mathcal{M}^{c}$ | 46.9 | 11.7 | 48.3 | 48.7 | 15.6 | 51.1 | 5.6 | 7.7 | 9.5 |
| 4-30 | $\mathcal{M}^{c}$ | 45.7 | 11.4 | 47.1 | 47.5 | 14.9 | 49.8 | 5.2 | 7.1 | 8.8 |
| 4-15 | $\mathcal{M}^{c}$ | 41.2 | 10.3 | 42.4 | 43.1 | 13.4 | 45.2 | 5.0 | 6.4 | 8.1 |
| 5 | $\mathcal{M}^{c}$ | 61.7 | 15.4 | 63.6 | 62.2 | 20.2 | 65.4 | 6.1 | 13.6 | 15.1 |

No real-time measurements vs. complex current at substation

# Value of Additional Measurements

## Demand Component RMSE (kW/kVar/kVA) in Different Cases

| Scenario | Models | AC-P | AC-Q | AC-S | OL-P | OL-Q | OL-S | NW-P | NW-Q | NW-S |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | $M^{nc}$ | 181.4 | 45.4 | 187.0 | 179.2 | 52.7 | 186.8 | 50.0 | 157.0 | 165.4 |
| 2 | $M^{c}$ | 64.1 | 16.0 | 66.1 | 68.0 | 20.0 | 70.9 | 5.6 | 8.2 | 9.9 |
| 3 | $M^{nc}$ | 129.6 | - | - | 114.0 | - | - | 23.0 | - | - |
| 3-60 | $M^{nc}$ | 77.5 | - | - | 63.0 | - | - | 16.8 | - | - |
| 3-30 | $M^{nc}$ | 69.6 | - | - | 55.7 | - | - | 13.8 | - | - |
| 3-15 | $M^{nc}$ | 61.1 | - | - | 47.0 | - | - | 10.9 | - | - |
| 4 | $M^{nc}$ | 103.5 | 25.9 | 106.7 | 97.0 | 33.1 | 102.5 | 8.7 | 21.4 | 23.1 |
| 4 | $M^{c}$ | 64.1 | 16.0 | 66.1 | 64.8 | 19.6 | 67.7 | 5.7 | 8.2 | 10.0 |
| 4-60 | $M^{c}$ | 46.9 | 11.7 | 48.3 | 48.7 | 15.6 | 51.1 | 5.6 | 7.7 | 9.5 |
| 4-30 | $M^{c}$ | 45.7 | 11.4 | 47.1 | 47.5 | 14.9 | 49.8 | 5.2 | 7.1 | 8.8 |
| 4-15 | $M^{c}$ | 41.2 | 10.3 | 42.4 | 43.1 | 13.4 | 45.2 | 5.0 | 6.4 | 8.1 |
| 5 | $M^{c}$ | 61.7 | 15.4 | 63.6 | 62.2 | 20.2 | 65.4 | 6.1 | 13.6 | 15.1 |

Complex current vs. real power at substation

# Value of Additional Measurements

## DEMAND COMPONENT RMSE (KW/KVAR/KVA) IN DIFFERENT CASES

| Scenario | Models | AC-P | AC-Q | AC-S | OL-P | OL-Q | OL-S | NW-P | NW-Q | NW-S |
|----------|--------|------|------|------|------|------|------|------|------|------|
| | | | | | Demand Component | | | | | |
| 1 | $\mathcal{M}^{nc}$ | 181.4 | 45.4 | 187.0 | 179.2 | 52.7 | 186.8 | 50.0 | 157.0 | 165.4 |
| 2 | $\mathcal{M}^{c}$ | 64.1 | 16.0 | 66.1 | 68.0 | 20.0 | 70.9 | 5.6 | 8.2 | 9.9 |
| 3 | $\mathcal{M}^{nc}$ | 129.6 | - | - | 114.0 | - | - | 23.0 | - | - |
| 3-60 | $\mathcal{M}^{nc}$ | 77.5 | - | - | 63.0 | - | - | 16.8 | - | - |
| 3-30 | $\mathcal{M}^{nc}$ | 69.6 | - | - | 55.7 | - | - | 13.8 | - | - |
| 3-15 | $\mathcal{M}^{nc}$ | 61.1 | - | - | 47.0 | - | - | 10.9 | - | - |
| 4 | $\mathcal{M}^{nc}$ | 103.5 | 25.9 | 106.7 | 97.0 | 33.1 | 102.5 | 8.7 | 21.4 | 23.1 |
| 4 | $\mathcal{M}^{c}$ | 64.1 | 16.0 | 66.1 | 64.8 | 19.6 | 67.7 | 5.7 | 8.2 | 10.0 |
| 4-60 | $\mathcal{M}^{c}$ | 46.9 | 11.7 | 48.3 | 48.7 | 15.6 | 51.1 | 5.6 | 7.7 | 9.5 |
| 4-30 | $\mathcal{M}^{c}$ | 45.7 | 11.4 | 47.1 | 47.5 | 14.9 | 49.8 | 5.2 | 7.1 | 8.8 |
| 4-15 | $\mathcal{M}^{c}$ | 41.2 | 10.3 | 42.4 | 43.1 | 13.4 | 45.2 | 5.0 | 6.4 | 8.1 |
| 5 | $\mathcal{M}^{c}$ | 61.7 | 15.4 | 63.6 | 62.2 | 20.2 | 65.4 | 6.1 | 13.6 | 15.1 |

Value of smart meter measurements (no complex current)

# Value of Additional Measurements

## DEMAND COMPONENT RMSE (KW/KVAR/KVA) IN DIFFERENT CASES

| Scenario | Models | AC-P | AC-Q | AC-S | OL-P | OL-Q | OL-S | NW-P | NW-Q | NW-S |
|----------|--------|------|------|------|------|------|------|------|------|------|
| 1 | $\mathcal{M}^{nc}$ | 181.4 | 45.4 | 187.0 | 179.2 | 52.7 | 186.8 | 50.0 | 157.0 | 165.4 |
| 2 | $\mathcal{M}^{c}$ | 64.1 | 16.0 | 66.1 | 68.0 | 20.0 | 70.9 | 5.6 | 8.2 | 9.9 |
| 3 | $\mathcal{M}^{nc}$ | 129.6 | - | - | 114.0 | - | - | 23.0 | - | - |
| 3-60 | $\mathcal{M}^{nc}$ | 77.5 | - | - | 63.0 | - | - | 16.8 | - | - |
| 3-30 | $\mathcal{M}^{nc}$ | 69.6 | - | - | 55.7 | - | - | 13.8 | - | - |
| 3-15 | $\mathcal{M}^{nc}$ | 61.1 | - | - | 47.0 | - | - | 10.9 | - | - |
| 4 | $\mathcal{M}^{nc}$ | 103.5 | 25.9 | 106.7 | 97.0 | 33.1 | 102.5 | 8.7 | 21.4 | 23.1 |
| 4 | $\mathcal{M}^{c}$ | 64.1 | 16.0 | 66.1 | 64.8 | 19.6 | 67.7 | 5.7 | 8.2 | 10.0 |
| 4-60 | $\mathcal{M}^{c}$ | 46.9 | 11.7 | 48.3 | 48.7 | 15.6 | 51.1 | 5.6 | 7.7 | 9.5 |
| 4-30 | $\mathcal{M}^{c}$ | 45.7 | 11.4 | 47.1 | 47.5 | 14.9 | 49.8 | 5.2 | 7.1 | 8.8 |
| 4-15 | $\mathcal{M}^{c}$ | 41.2 | 10.3 | 42.4 | 43.1 | 13.4 | 45.2 | 5.0 | 6.4 | 8.1 |
| 5 | $\mathcal{M}^{c}$ | 61.7 | 15.4 | 63.6 | 62.2 | 20.2 | 65.4 | 6.1 | 13.6 | 15.1 |

Value of smart meter measurements (with complex current)

# Value of Additional Measurements

## DEMAND COMPONENT RMSE (KW/KVAR/KVA) IN DIFFERENT CASES

| Scenario | Models | Demand Component | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | AC-P | AC-Q | AC-S | OL-P | OL-Q | OL-S | NW-P | NW-Q | NW-S |
| 1 | $\mathcal{M}^{nc}$ | 181.4 | 45.4 | 187.0 | 179.2 | 52.7 | 186.8 | 50.0 | 157.0 | 165.4 |
| 2 | $\mathcal{M}^{c}$ | 64.1 | 16.0 | 66.1 | 68.0 | 20.0 | 70.9 | 5.6 | 8.2 | 9.9 |
| 3 | $\mathcal{M}^{nc}$ | 129.6 | - | - | 114.0 | - | - | 23.0 | - | - |
| 3-60 | $\mathcal{M}^{nc}$ | 77.5 | - | - | 63.0 | - | - | 16.8 | - | - |
| 3-30 | $\mathcal{M}^{nc}$ | 69.6 | - | - | 55.7 | - | - | 13.8 | - | - |
| 3-15 | $\mathcal{M}^{nc}$ | 61.1 | - | - | 47.0 | - | - | 10.9 | - | - |
| 4 | $\mathcal{M}^{nc}$ | 103.5 | 25.9 | 106.7 | 97.0 | 33.1 | 102.5 | 8.7 | 21.4 | 23.1 |
| 4 | $\mathcal{M}^{c}$ | 64.1 | 16.0 | 66.1 | 64.8 | 19.6 | 67.7 | 5.7 | 8.2 | 10.0 |
| 4-60 | $\mathcal{M}^{c}$ | 46.9 | 11.7 | 48.3 | 48.7 | 15.6 | 51.1 | 5.6 | 7.7 | 9.5 |
| 4-30 | $\mathcal{M}^{c}$ | 45.7 | 11.4 | 47.1 | 47.5 | 14.9 | 49.8 | 5.2 | 7.1 | 8.8 |
| 4-15 | $\mathcal{M}^{c}$ | 41.2 | 10.3 | 42.4 | 43.1 | 13.4 | 45.2 | 5.0 | 6.4 | 8.1 |
| 5 | $\mathcal{M}^{c}$ | 61.7 | 15.4 | 63.6 | 62.2 | 20.2 | 65.4 | 6.1 | 13.6 | 15.1 |

Value of including complex voltage measurements

# Conclusions

- Dynamic Mirror Descent (DMD) and Dynamic Fixed Share (DFS) enables us to solve the feeder energy disaggregation problem leveraging dynamical models of arbitrary form

- Empirical results are often comparable to the a posteriori best Kalman filter (obtained from the same models)

- We can leverage ideas from Kalman filtering to inform our choice of DFS functions/parameters and heuristics

- The approach extends to cases with multiple measurements

Contact: jlmath@umich.edu

# Backup

J. Mathieu, University of Michigan

# 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 $T$