Practical Issues in Automatic, Residential Demand Response

Gregory S. Ledva

PhD Candidate in Electrical Engineering: Systems

The University of Michigan

Advisor, Johanna Mathieu

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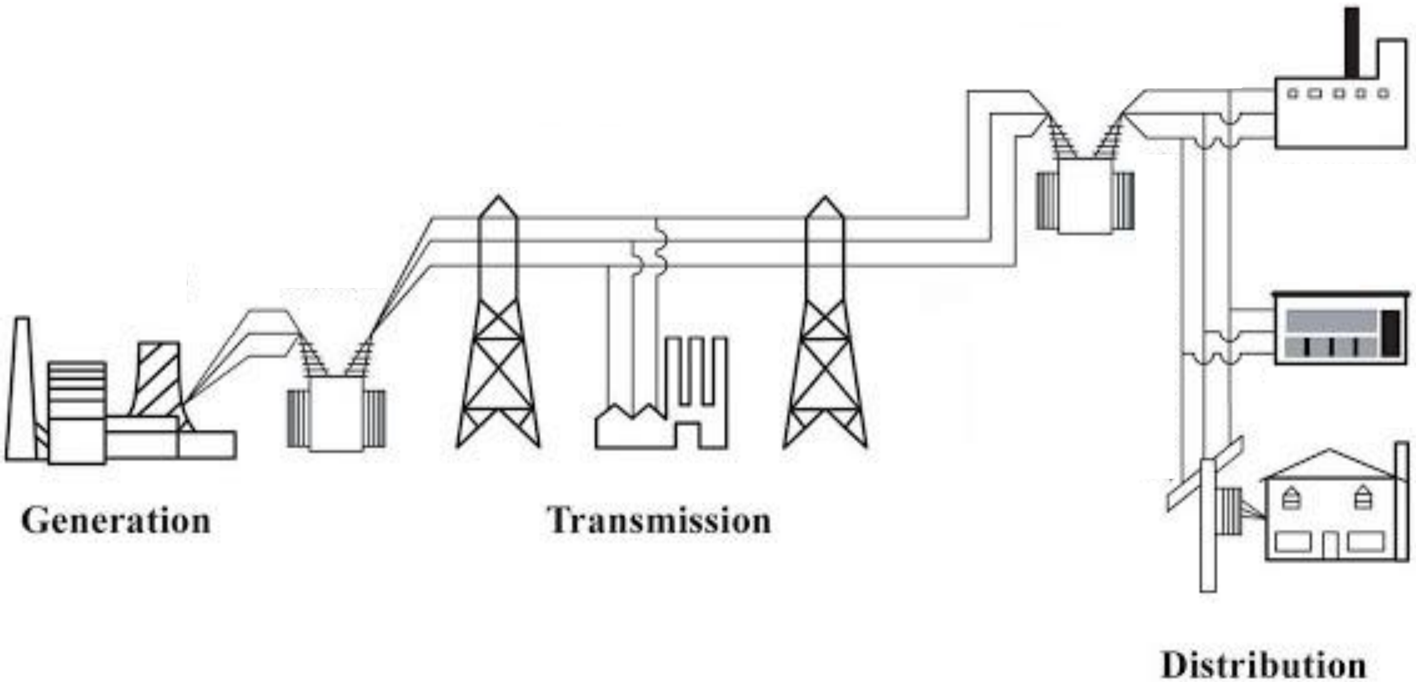
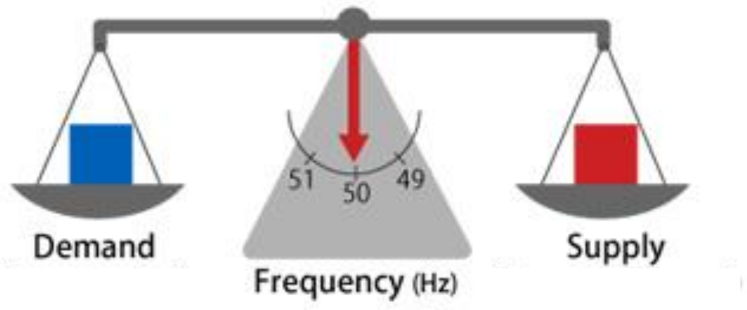
An electric power network is the equipment to transport electrical energy from producers (generators) to consumers (loads).



[http://electrical-engineering-course.blogspot.com/p/module1-what-is-electricity-and.html]

Electricity supply and demand must be balanced in real-time, and a system operator achieves this using frequency regulation.



[TEPCO "Where does excess electricity go?"]

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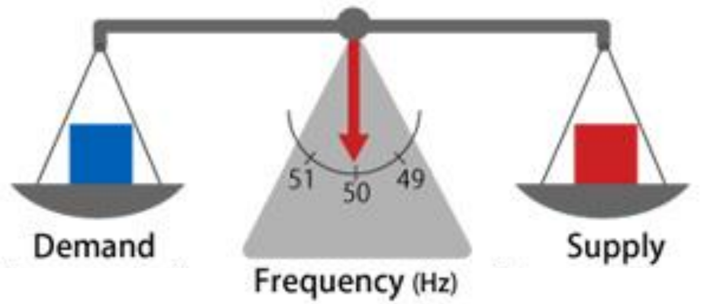
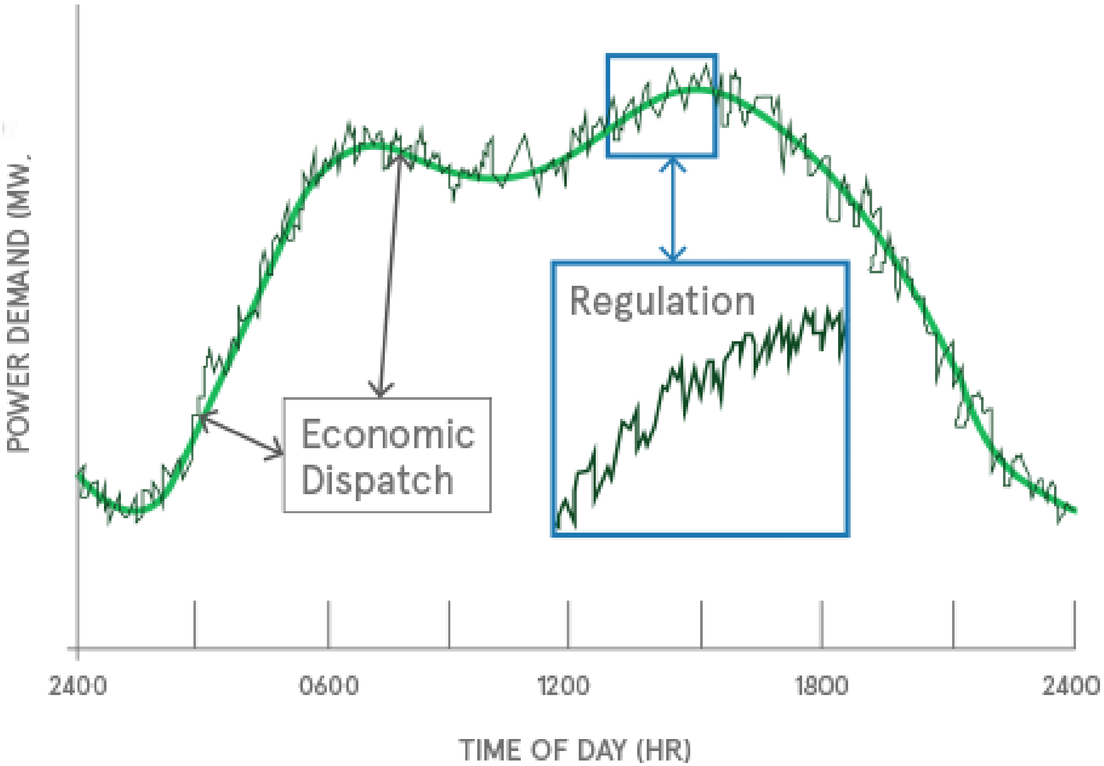


[TEPCO "Where does excess electricity go?"]



[Distributed energy solutions for the 21st century grid. Solar City.]

A trend in demand response research investigates the use of a group (or aggregation) of residential loads for frequency regulation.

"**Demand response is a** tariff or **program established to motivate changes in electric use by end-use customers** in response to changes in the price of electricity over time, or to give incentive payments designed to induce lower electricity use at times of high market prices or when grid reliability is jeopardized."

[U.S. DOE 2006]

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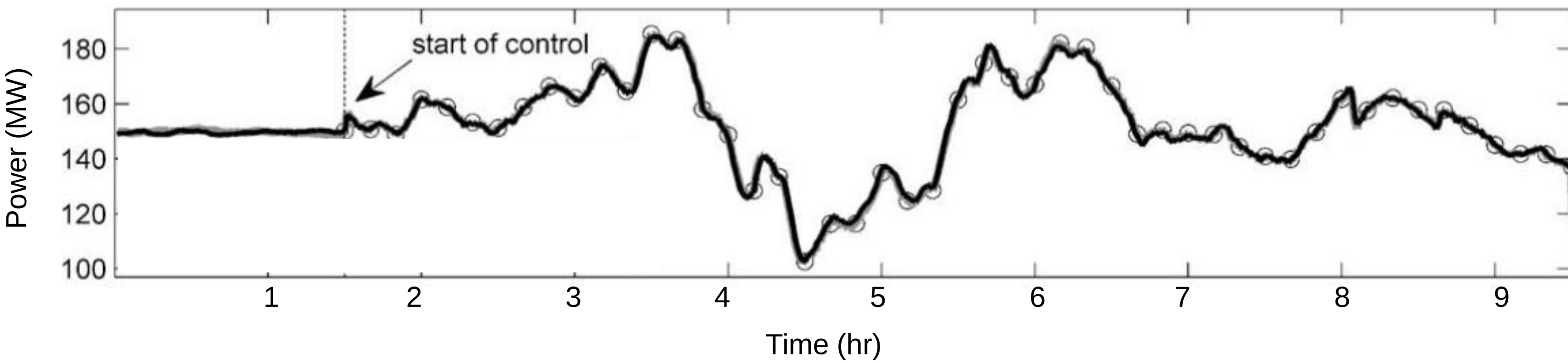

[Callaway 2009]

Increased renewable generation, increasing “smart” infrastructure, and recent regulations have created a favorable environment for residential demand response.

[Ryan Kh 2015]

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[Atkinson 2017]

[Solar Panel Permits]

[Lacoma 2016]

Research objective:

Develop algorithms for providing frequency regulation via automated, residential demand response that take into account practical limitations of the communication and sensing infrastructure

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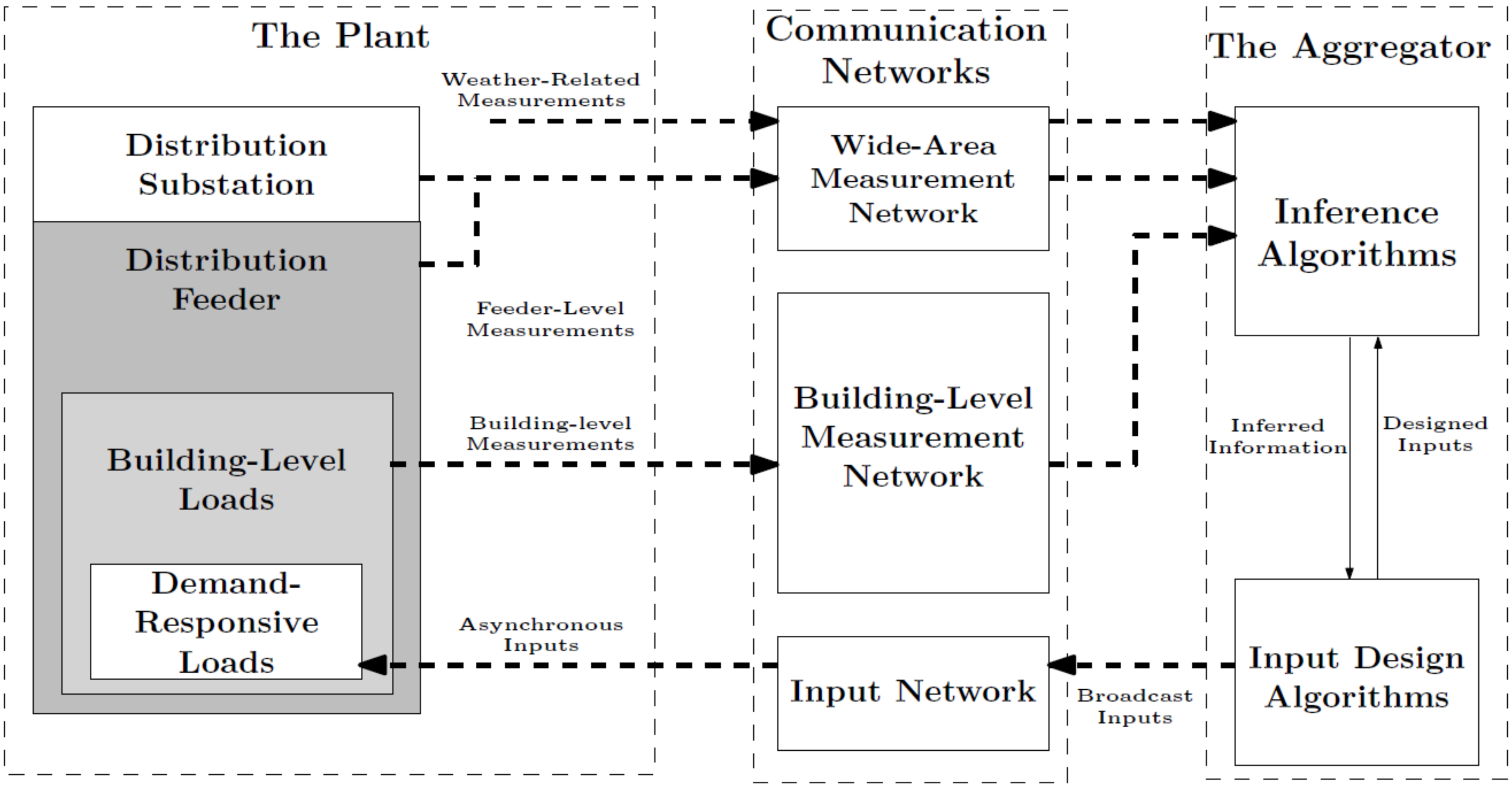
Contents

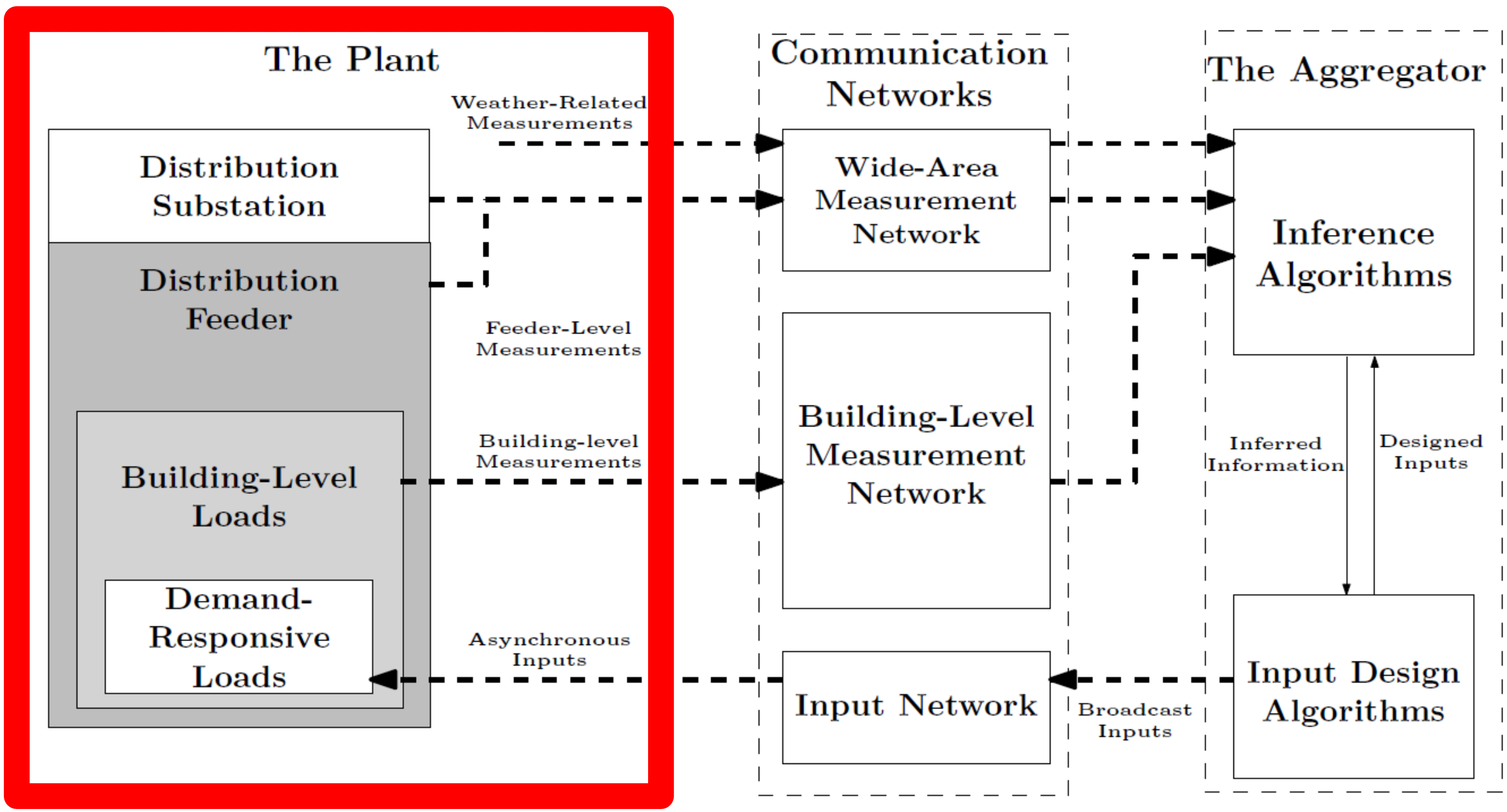
This work focuses on an aggregator that provides frequency regulation using an aggregation of residential, demand-responsive loads.



Contents

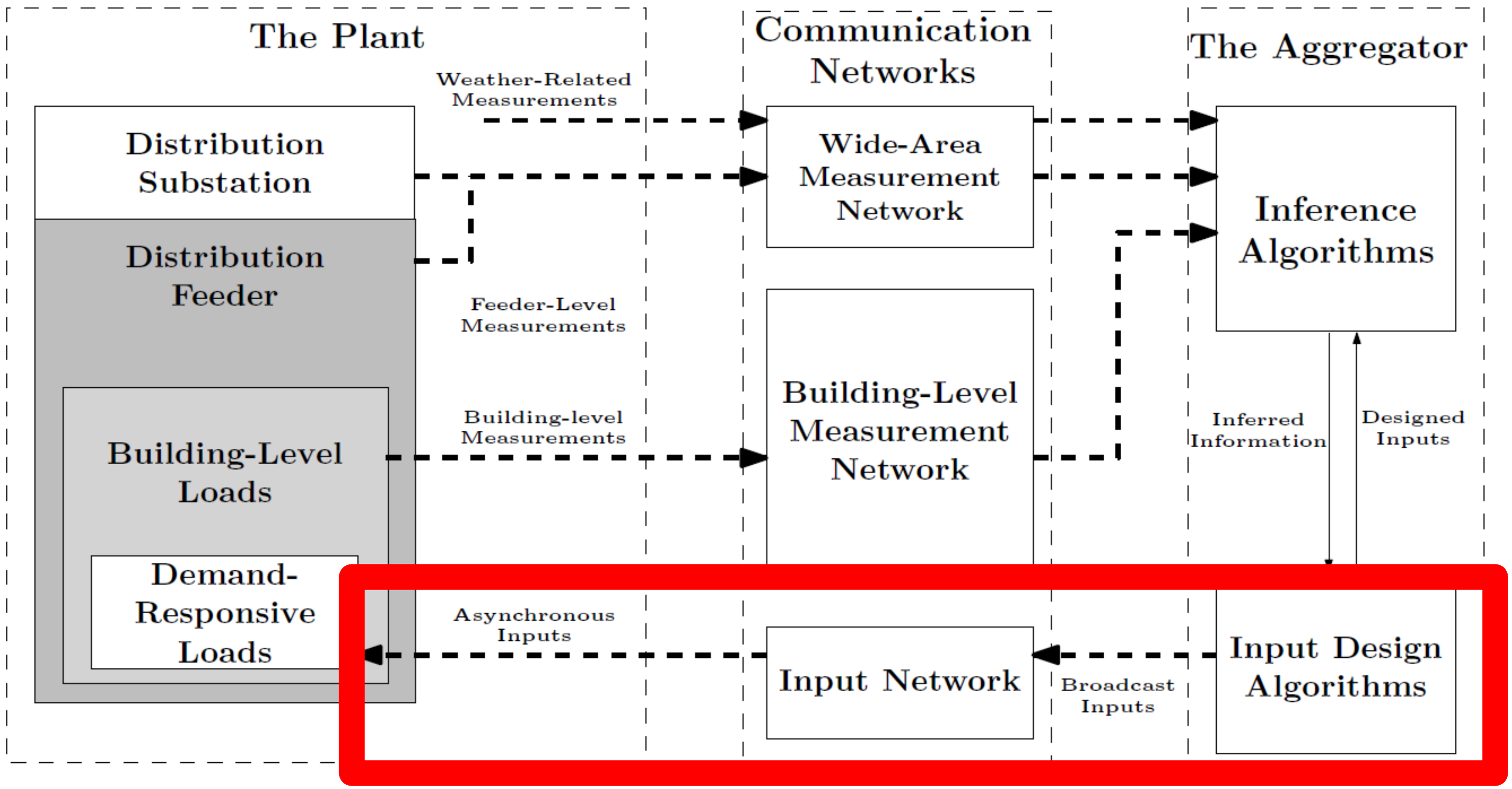
1) Developed controllers and state estimators to account for and mitigate the effects of communication network imperfections.

The plant consisted of demand-responsive loads; added noise to aggregate power measurements



4) Developed an algorithm to disaggregate feeder demand measurements into components in real-time.

Frequency of communication was included; measurement delays were not



Does not include computation of inputs to manipulate the demand-responsive loads

Contents

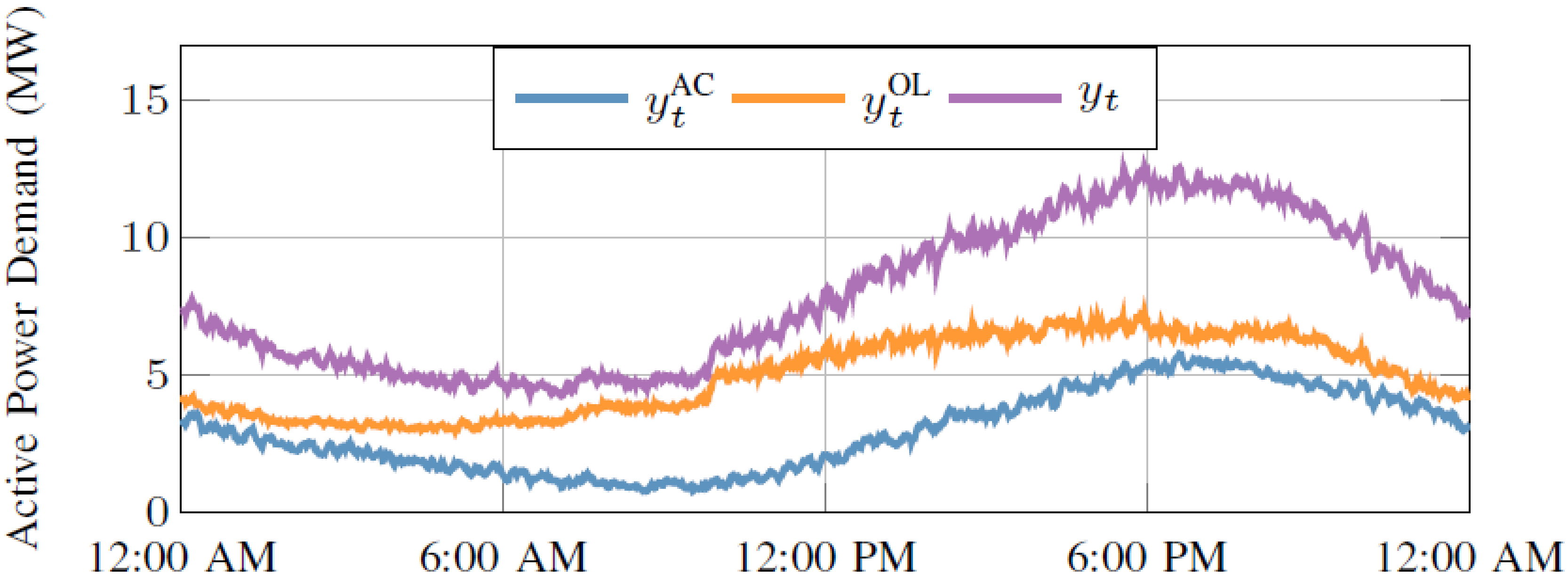
It is often assumed that aggregate demand-responsive load measurements are available, but obtaining these is an open question.

- Previous works assumed that aggregate demand measurements were available
  - For example, [Kara 2013], [Mathieu 2013], and [Soudjani 2015]

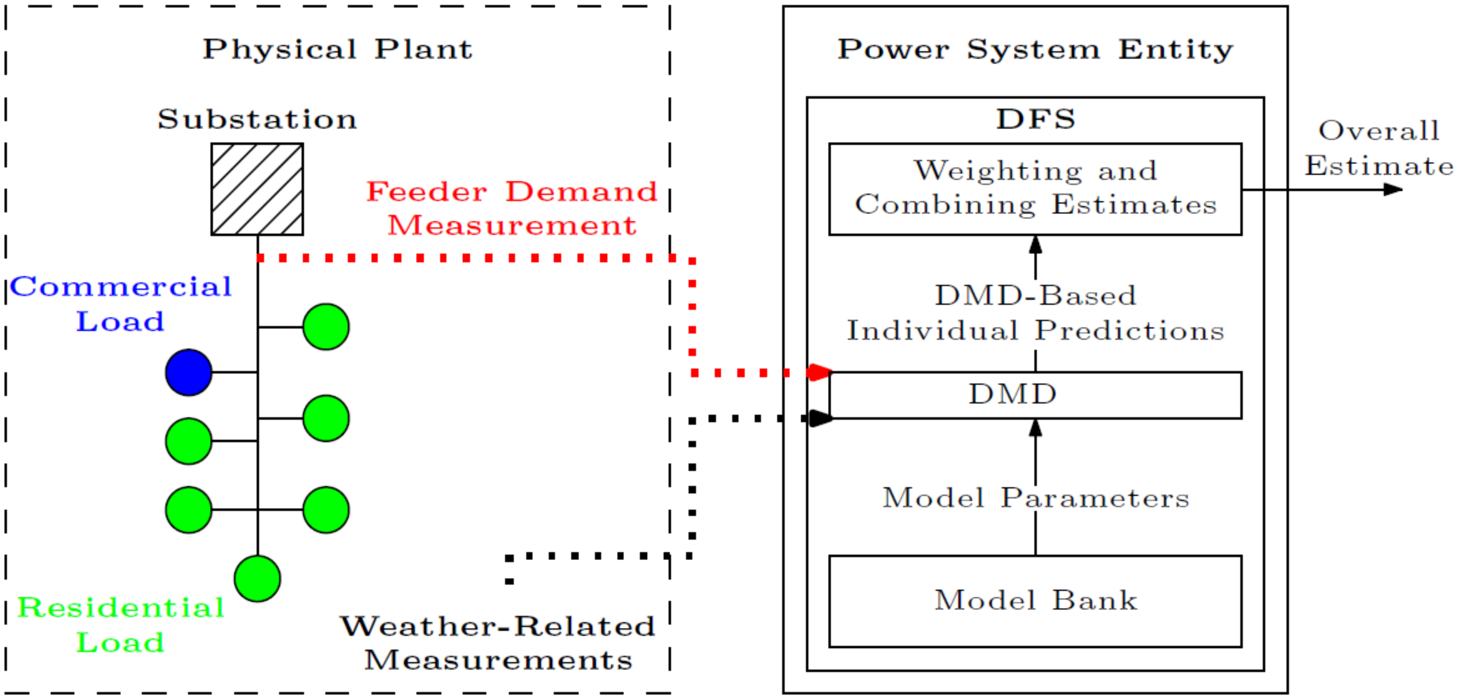
- Could use “bottom up” approach using sensors
  - ✗ Sub-metered devices needed
  - ✗ Fast communication required
  - ✗ Expensive

- Could use “top down” approach using energy disaggregation
  - Building-level energy disaggregation is long-studied [Hart 1992]
  - ✓ Work within capabilities of distribution network sensors
  - ✓ Work within capabilities of smart meters
  - ✓ Less expensive

Goal: separate measurements of the demand served by a distribution feeder into components as the measurements arrive.

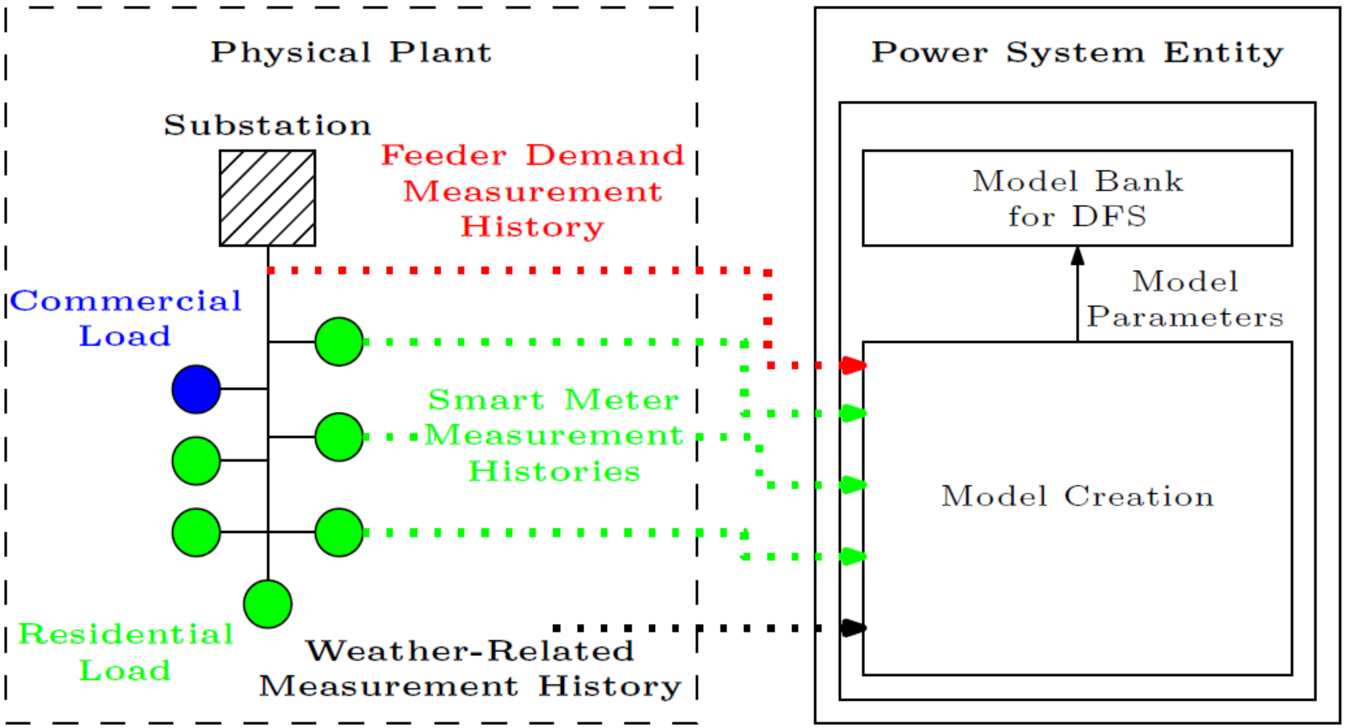


Energy disaggregation is performed on real-time demand measurements using Dynamic Fixed Share (DFS), an online learning algorithm.



(a) Real-time estimation mode

Dynamic Fixed Share incorporates predictions from models that are generated from historical building- and device-level data.



(b) Offline model generation mode

Dynamic Mirror Descent (DMD) iteratively updates an estimate based on a new measurement, then advances the estimate in time.

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

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

DMD was developed in [Hall 2015]

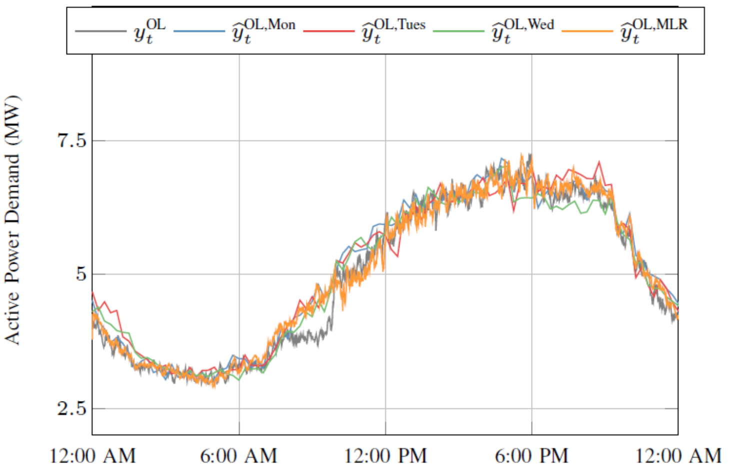
Dynamic Fixed Share combines estimates from separate Dynamic Mirror Descent algorithms, each using separate models, into an overall estimate.

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

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

Dynamic Fixed Share was developed in [Hall 2015] and uses the Fixed Share Algorithm [Herbster 1998]

The models used are based on linear regression, linear time-invariant systems, and linear time-varying systems.



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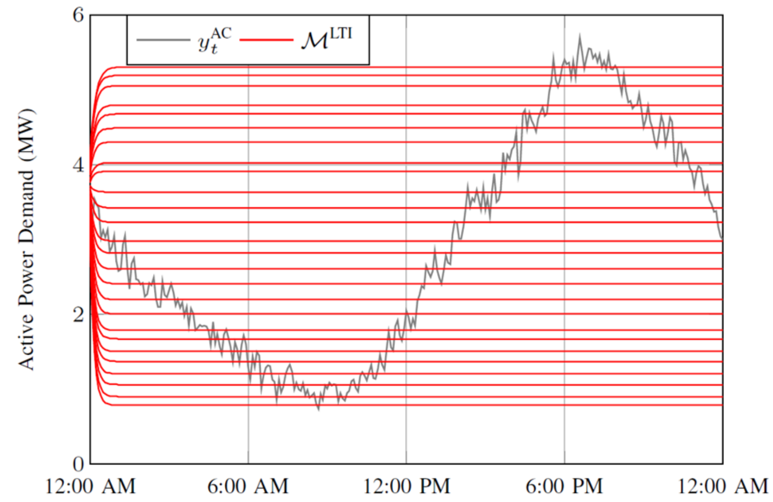
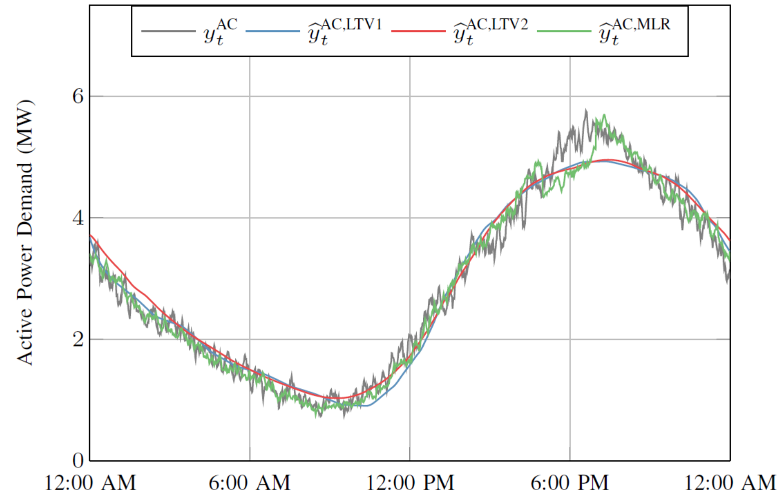


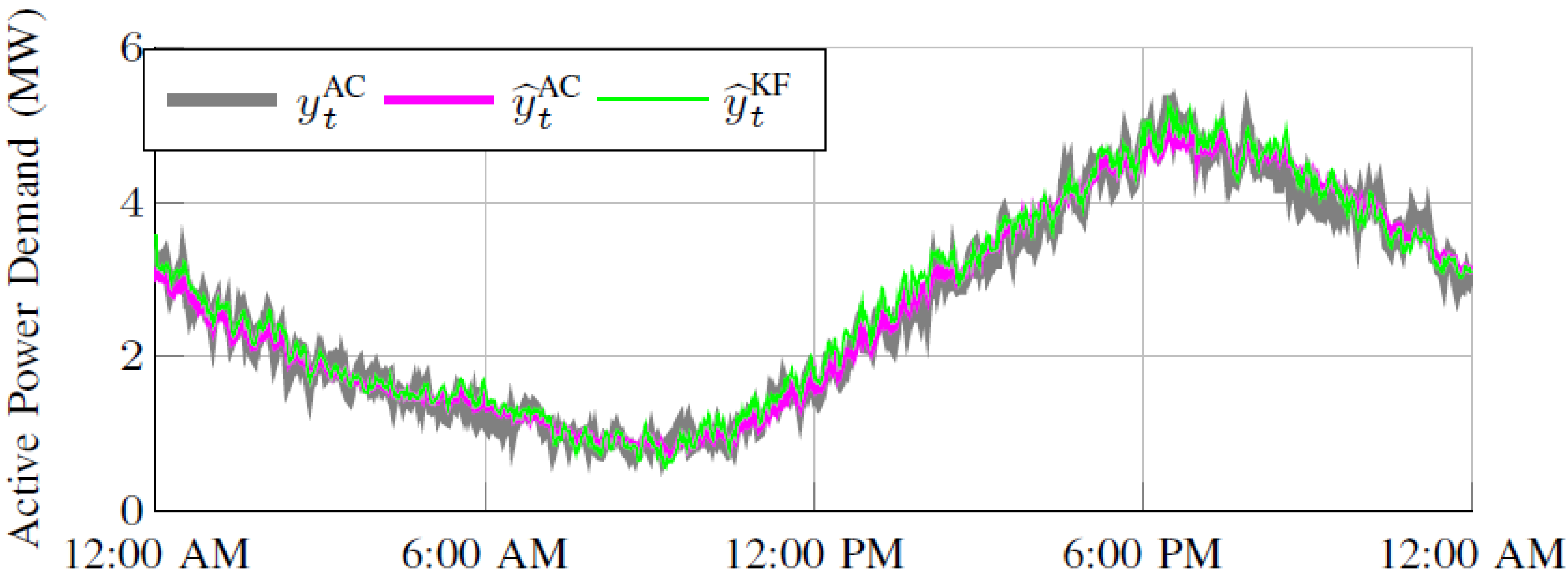


Michigan Power & Energy Laboratory

The simulation setup uses real-world data at the device level, allowing the true AC and OL demand to be known.

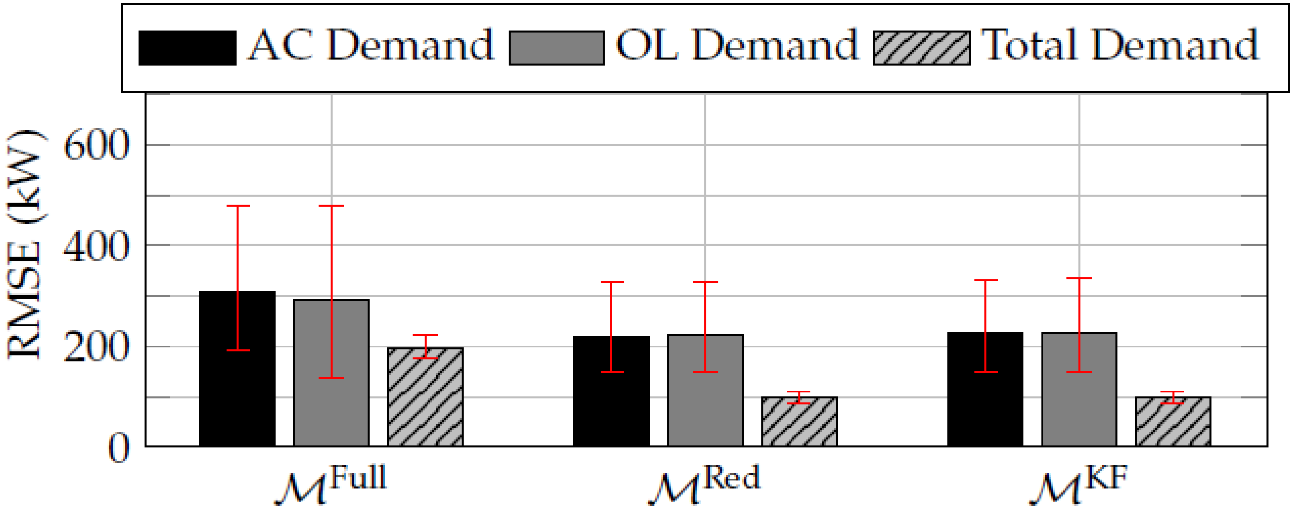
- Demand data sources
  - Feeder model from GridLAB-D feeder taxonomy [Schneider 2009]
  - Commercial building data from PG&E
  - Residential building and device data from Pecan Street [Pecan Street 2017]
- 10 separate “testing” days
- One minute time-steps
- Three model sets
  - $\mathcal{M}^{\mathrm{Full}}$: all model combinations
  - $\mathcal{M}^{\mathrm{Red}}$: model combinations excluding the LTI AC models
  - $\mathcal{M}^{\mathrm{KF}}$: model combinations using all OL models and only the LTV AC models
- Benchmark Algorithms
  - Best Kalman filter: best (ex post) filter from the set of models $\mathcal{M}^{\mathrm{KF}}$
  - Average Kalman filter: average of all filters from the set of models $\mathcal{M}^{\mathrm{KF}}$

Running Dynamic Fixed Share with $\mathfrak{M}^{Red}$ effectively estimates the AC demand in real-time.



(c) AC Demand

RMS Error values across the case studies show that model selection is important in algorithm performance.

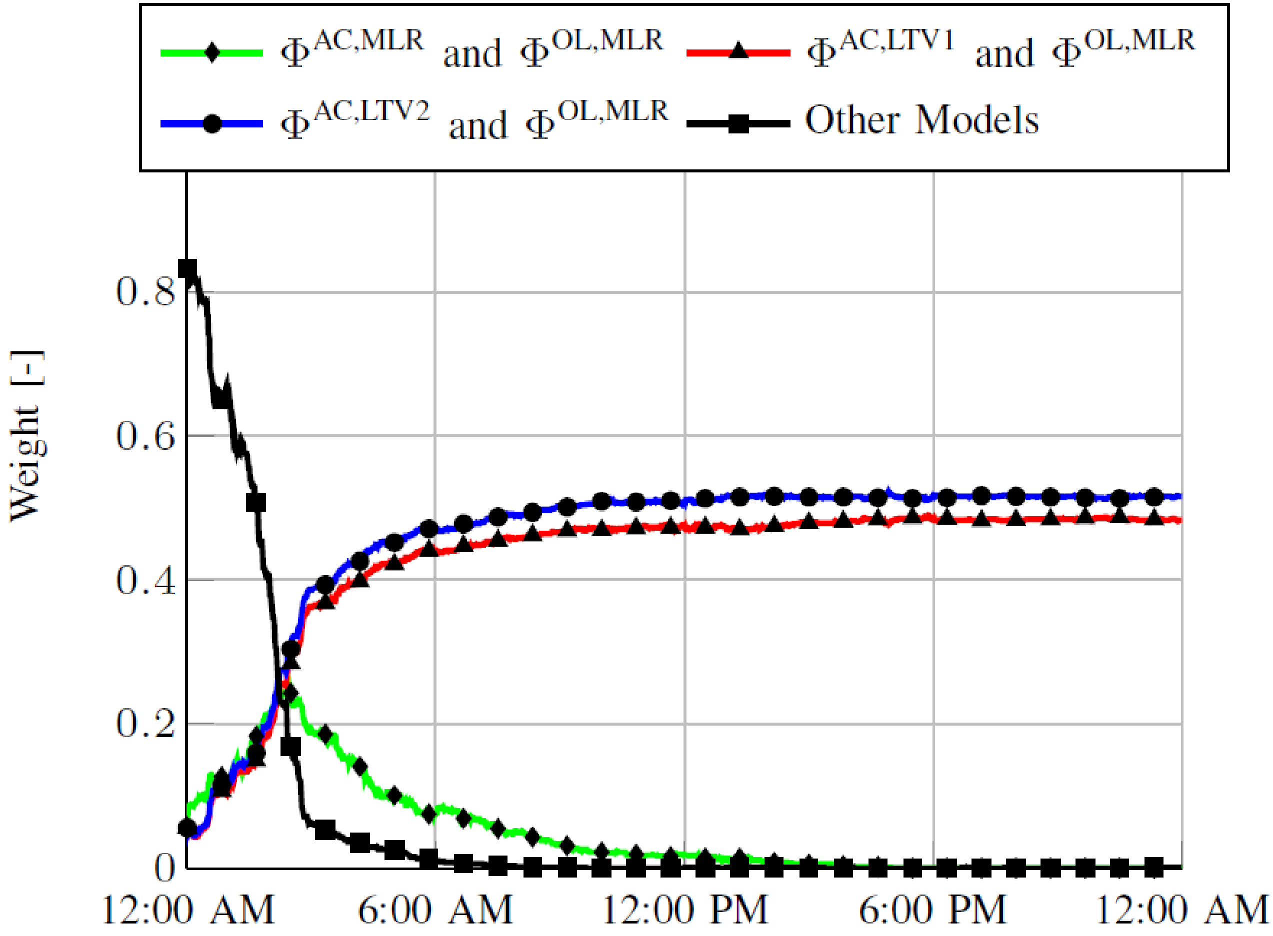


RMSE of the AC demand

Best Kalman Filter:
min = 148.4 kW
mean = 195.3 kW
max = 318.9 kW

Average Kalman Filter:
min = 173.1 kW
mean = 259.4 kW
max = 357.5 kW

Time series of model weights indicating the most accurate (available) model is a combination of two candidate models.



This work applies DFS to a feeder-level energy disaggregation problem, separating the feeder demand into two components.

Conclusions

- DFS can effectively perform the disaggregation problem
- Models within DFS strongly influence performance
- DFS achieved lower AC demand RMSE than AKF on average
- DFS achieves higher AC demand RMSE than BKF on average

Additional Results

- Further parameter tuning may improve results
- DMD can be constructed to produce Kalman filter updates
- Estimation error covariances greatly influence the performance of DFS

Future Work

- Incorporate additional feeder measurements (e.g., reactive power)

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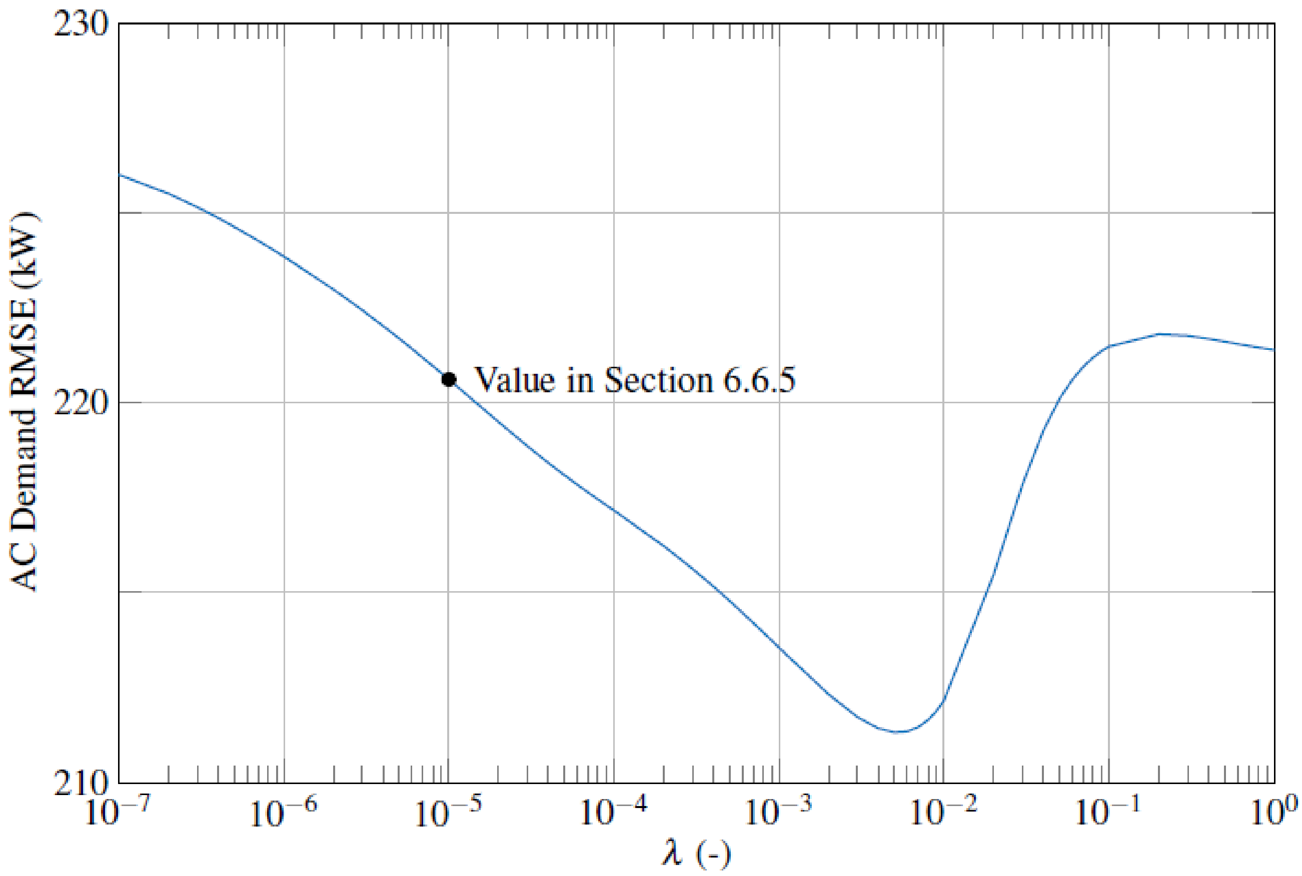
Parameter tuning

TABLE I
PARAMETER η^{s} USED IN THE DFS SCENARIOS IN SECTION VII-D

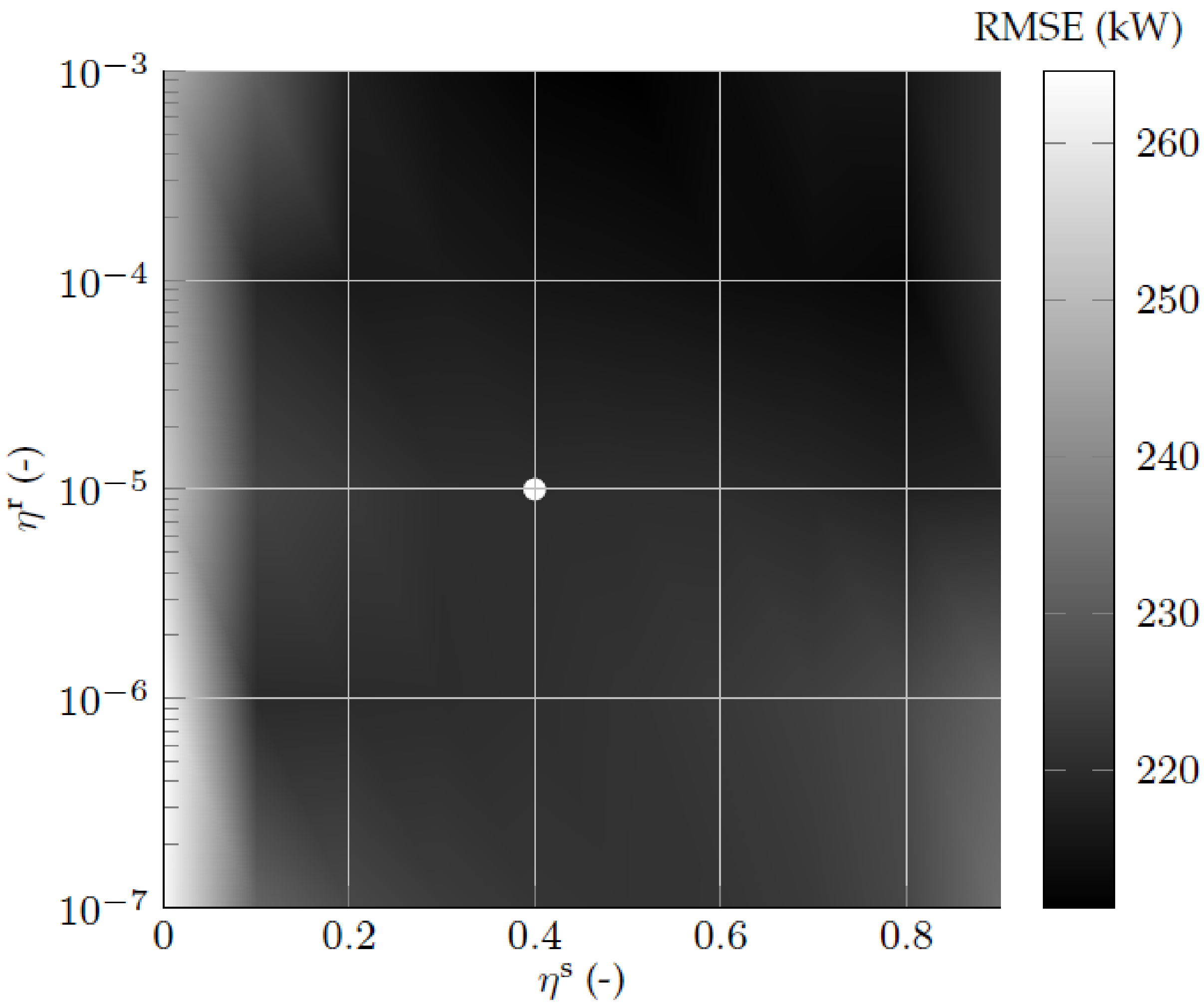
Model Set	$\mathcal{M}^{\text{Full}}$	$\mathcal{M}^{\text{Full}}$	$\mathcal{M}^{\text{Red}}$	$\mathcal{M}^{\text{Red}}$	$\mathcal{M}^{\text{KF}}$	$\mathcal{M}^{\text{KF}}$
Update Method	1	2	1	2	1	2
η^{s}	0.013	0.015	0.4	0.013	0.4	0.5

$$\lambda = \eta^{r} = 1.0 \times 10^{-5}$$

A parameter sweep of λ indicates that tuning the parameter based on similar, historical days may improve performance.



Modifying the $\boldsymbol{\eta}^s$ and $\boldsymbol{\eta}^r$ parameters influences the AC demand RMSE by adjusting the model weight transitions and measurement-based adjustments.



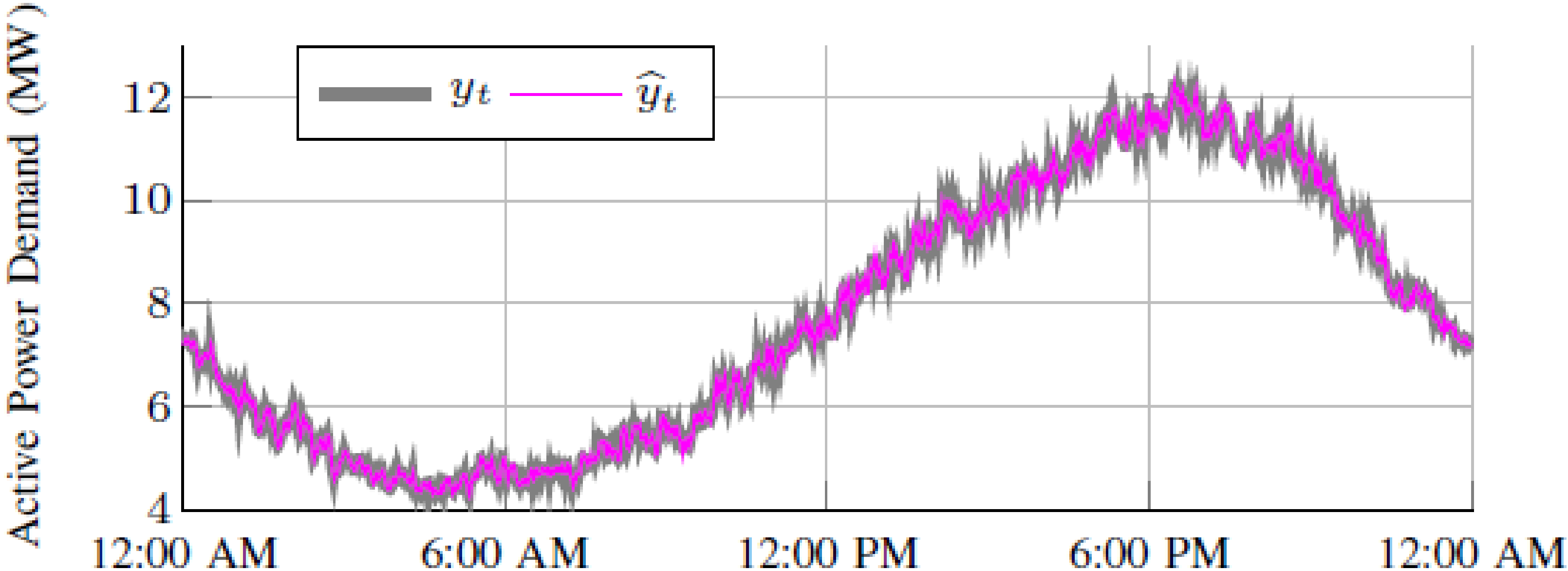
Update Method 2

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

$$\breve{\theta}_{t+1} = \Phi(\breve{\theta}_t)$$

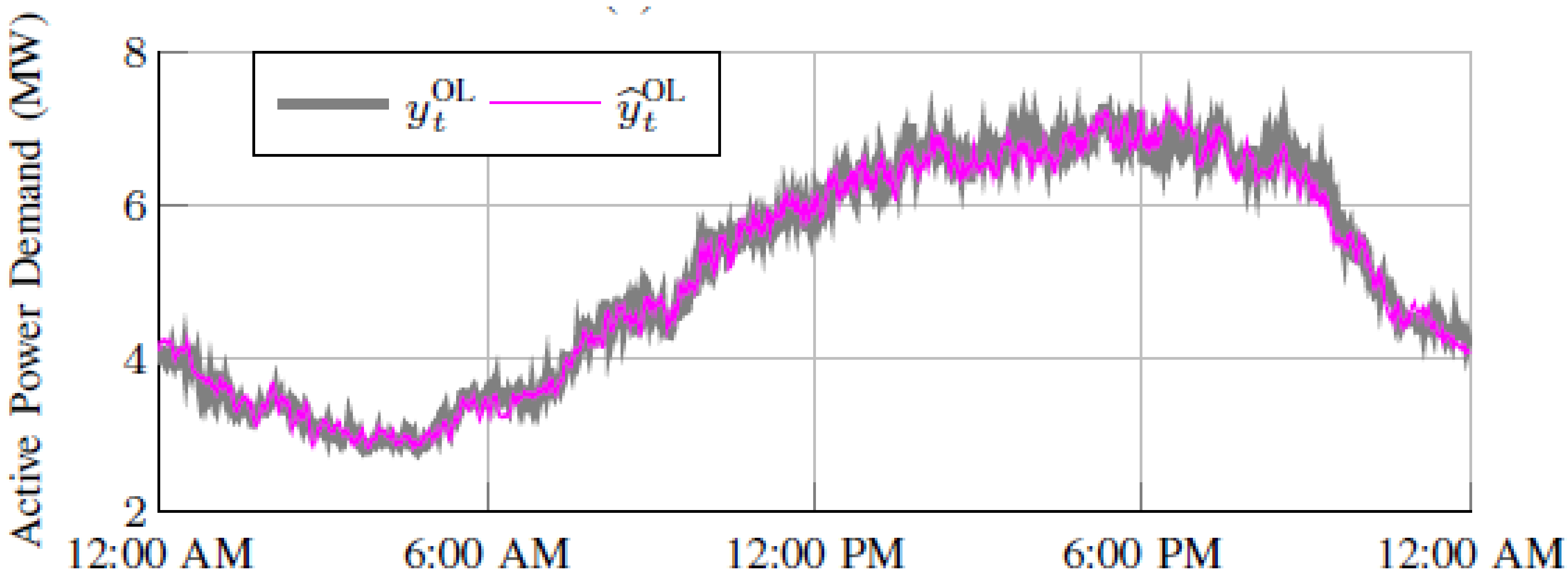
$$\widehat{\theta}_{t+1} = \breve{\theta}_{t+1} + \widehat{\kappa}_{t+1}$$

Total demand estimate time series



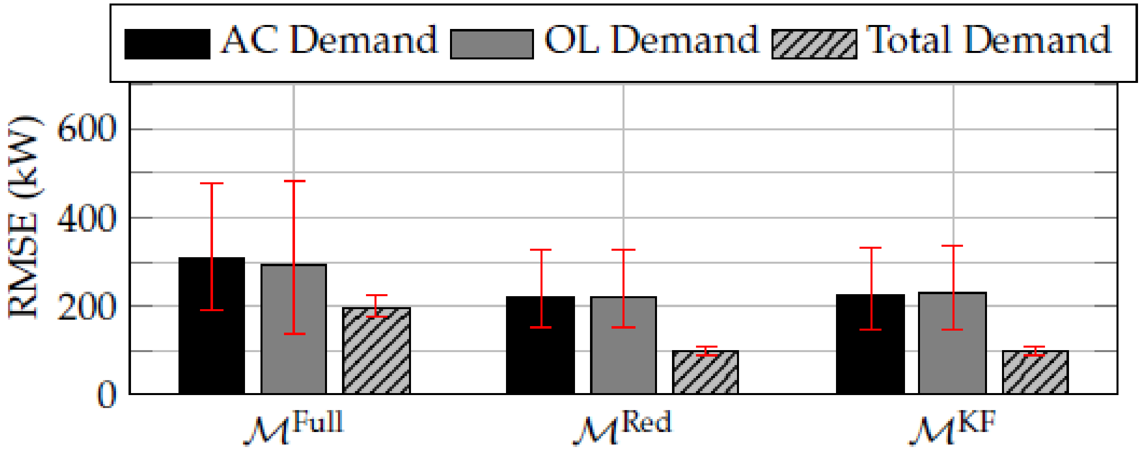
(a) Total Demand

OL demand estimate time series

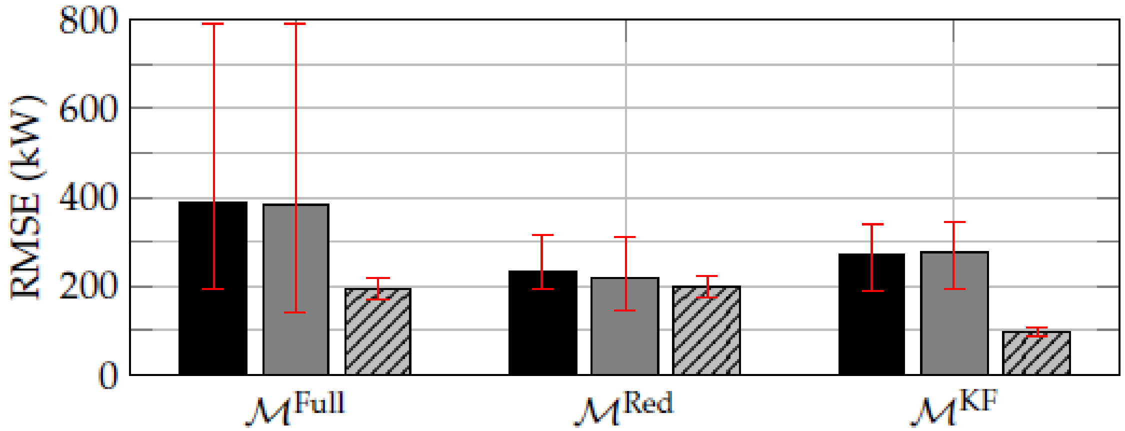


(b) OL Demand

Additional results about update methods



(a) Update Method 1

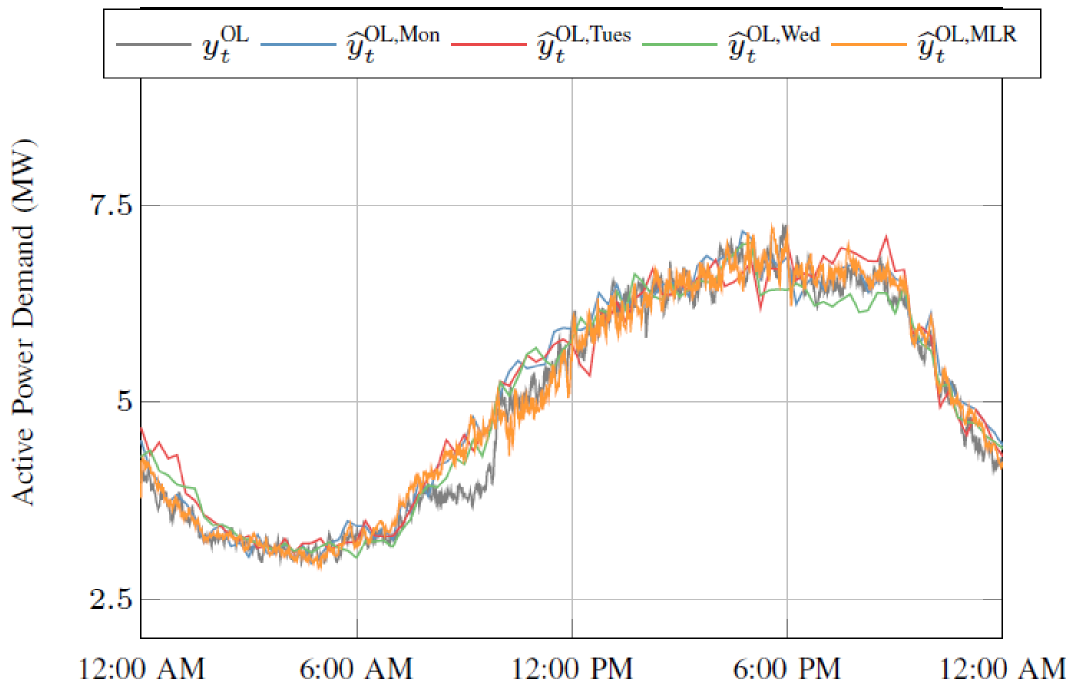


(b) Update Method 2

The models used are based on linear regression, linear time-invariant systems, and linear time-varying systems.

$$\widehat{y}_t^{\text{OL,TOD}} = \alpha_k^{\text{OL,TOD}}$$

$$\begin{aligned}\widehat{y}_t^{\text{OL,MLR}} &= \widehat{y}_t^{\text{OL,res}} + \widehat{y}_t^{\text{OL,com}} \\ &= \beta^{\text{OL,res}} x_t^{\text{OL,res}} + \gamma^{\text{OL,com}} x_t^{\text{OL,com}}\end{aligned}$$

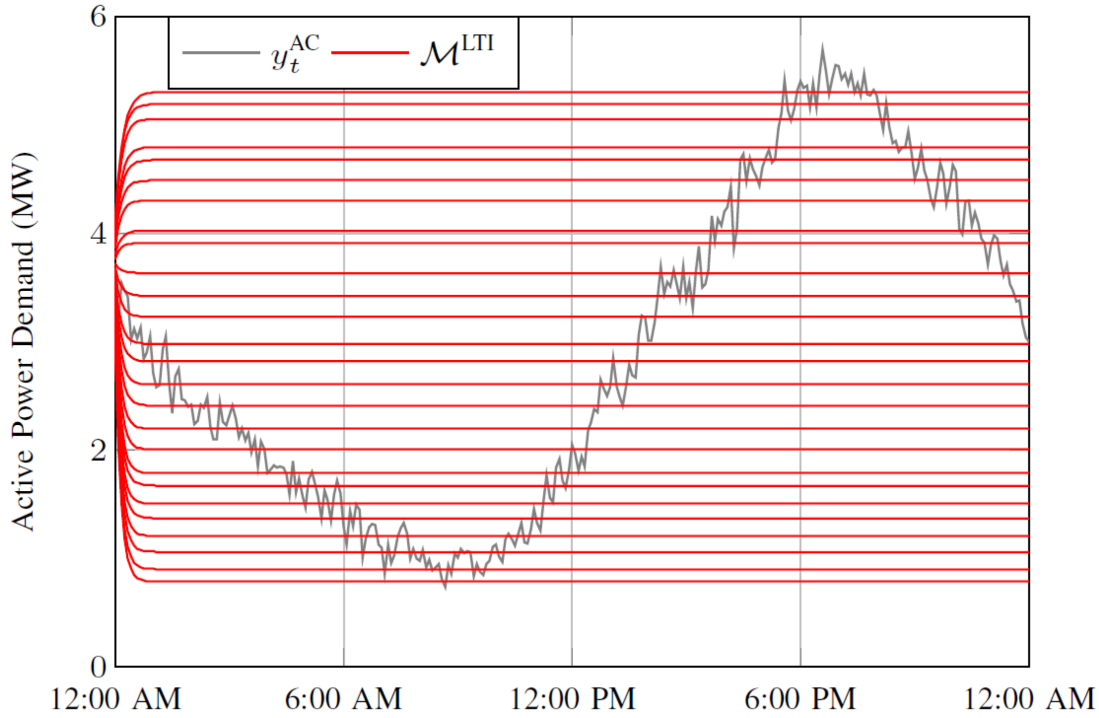


The commercial regression model is based on [Mathieu 2010]

The models used are based on linear regression, linear time-invariant systems, and linear time-varying systems.

$$\hat{x}_{t+1}^{\mathrm{LTI},m} = A^{\mathrm{LTI},m}\,\hat{x}_{t}^{\mathrm{LTI},m}$$
$$\hat{y}_{t}^{\mathrm{AC,LTI},m} = C^{\mathrm{LTI},m}\,\hat{x}_{t}^{\mathrm{LTI},m}$$

$$m \in \mathcal{M}^{\mathrm{LTI}} = \{1, \ldots, N^{\mathrm{LTI}}\}$$

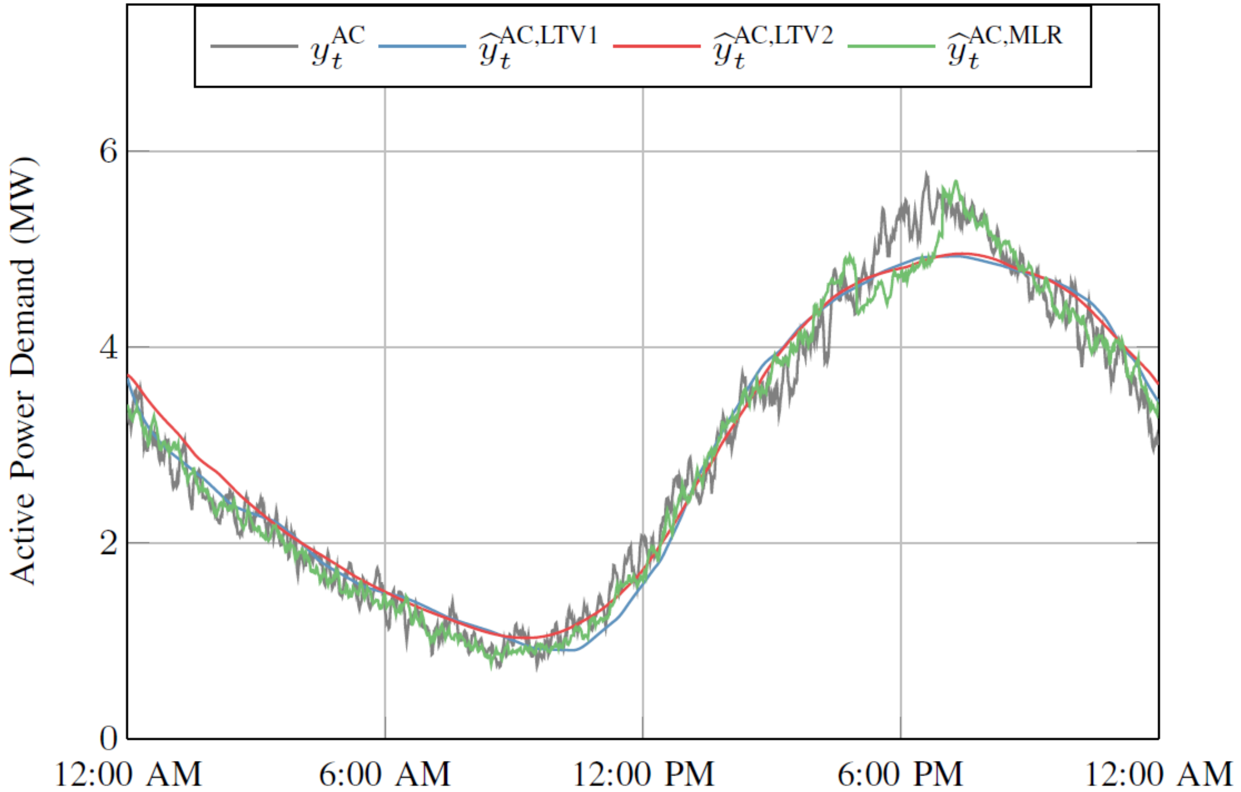


Each model based on [Kalsi 2012, Mathieu 2013] and set based on [Mathieu 2015]

The models used are based on linear regression, linear time-invariant systems, and linear time-varying systems.

$$\widehat{x}_{t+1}^{\mathrm{LTV1}} = A_t^{\mathrm{LTV1}}\ \widehat{x}_t^{\mathrm{LTV1}}$$
$$\widehat{y}_t^{\mathrm{AC,LTV1}} = C_t^{\mathrm{LTV1}}\ \widehat{x}_t^{\mathrm{LTV1}}$$

$$x_t^{\mathrm{AC,MLR}} = \left[(x_t^{\mathrm{TOW}})^{\mathrm{T}} \quad T_{t-\tau^1}^{\mathrm{TX}} \quad (T_{t-\tau^1}^{\mathrm{TX}})^2 \quad (T_{t-\tau^1}^{\mathrm{TX}})^3 \quad (T_{t-\tau^1}^{\mathrm{TX}})^4 \right]^{\mathrm{T}}$$



Dynamic Mirror Descent updates can be made identical to those of a Kalman filter by appropriately choosing the loss and divergence functions.

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

$$\begin{aligned} D(\theta\|\widehat{\theta}_t) =& \frac{1}{2}\left\| (\widehat{P}_t)^{-\frac{1}{2}}(\theta - \widehat{\theta}_t) \right\|_2^2 \\ \ell_t(\widehat{\theta}_t) =& \frac{1}{2}\left\| (\widehat{P}_t^{\mathrm{y}})^{-\frac{1}{2}}(C\widehat{\theta}_t - y_t) \right\|_2^2 \end{aligned}$$

$$\widetilde{\theta}_t = \widehat{\theta}_t + \widehat{P}_t C_t^T \left[C_t \widehat{P}_t C_t^T + R_t \right]^{-1} \left(y_t - C_t \widehat{\theta}_t \right)$$