Learning and Control Applied to Demand Response and Electricity Distribution Networks

by

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A dissertation submitted in partial fulfillment
of the requirements for the degree of
Doctor of Philosophy
(Electrical Engineering: Systems)
in The University of Michigan
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Doctoral Committee:

Assistant Professor Johanna L. Mathieu, Chair
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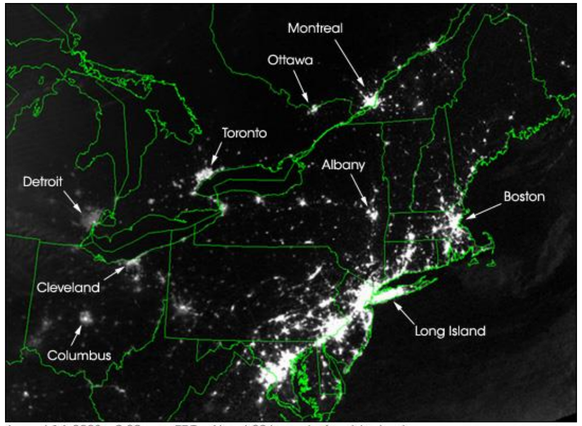
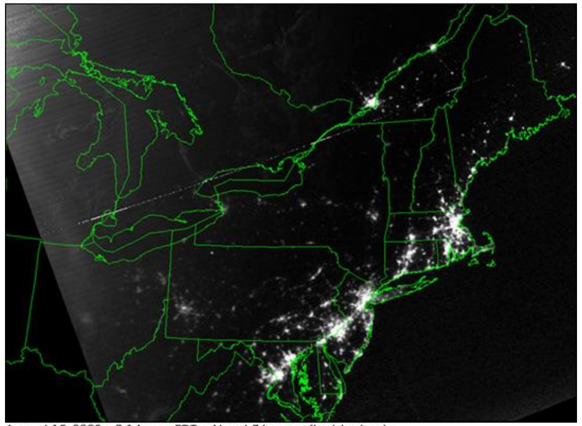
COLLEGE OF ENGINEERING
ELECTRICAL ENGINEERING & COMPUTER SCIENCE
UNIVERSITY OF MICHIGAN

Background

Access to electricity is central to daily life, and it is expected to be reliable, inexpensive, and (increasingly) environmentally friendly.



August 14, 2003 • 9:29 p.m. EDT • About 20 hours before blackout

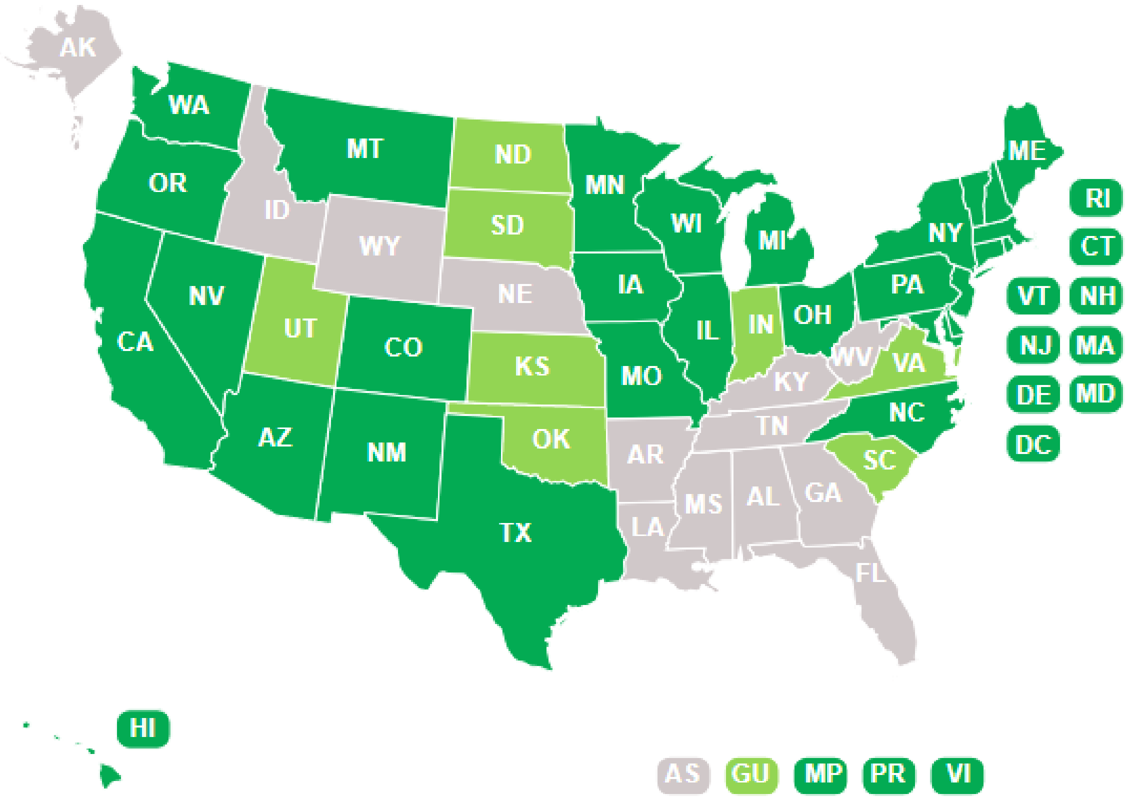


August 15, 2003 • 9:14 p.m. EDT • About 7 hours after blackout

https://earthobservatory.nasa.gov/images/3719/blackout-leaves-american-cities-in-the-dark

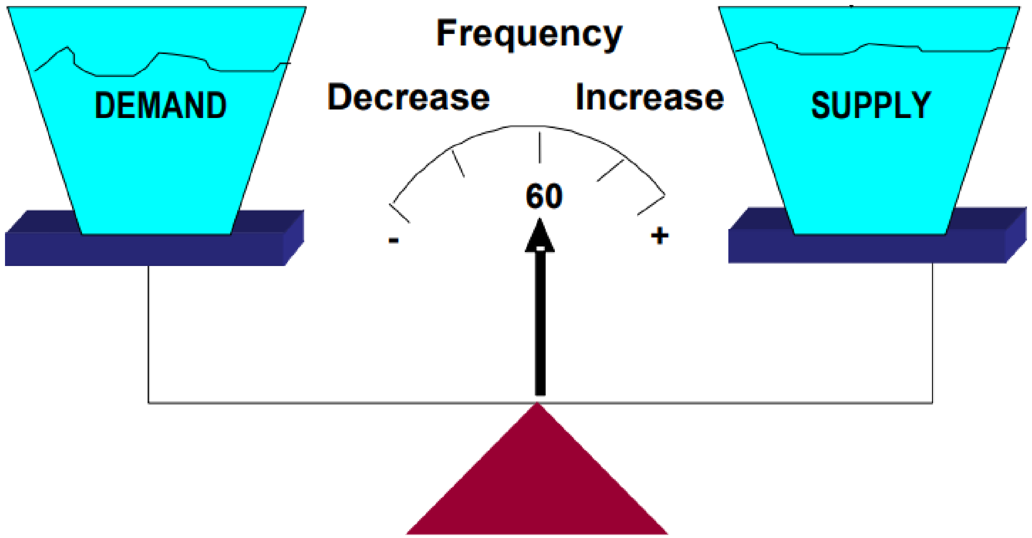
https://news.nationalgeographic.com/energy/2015/08/150817-power-plant-pollution-depends-on-the-weather/

Electricity generation from renewable energy sources is increasing due to concerns over climate change and falling costs of renewable installations.



http://www.ncsl.org/research/energy/renewable-portfolio-standards.aspx

The supply and demand of electrical energy must be balanced in real-time, and frequency regulation is the fastest dispatchable resource.



[NERC, “Balancing and Frequency Control,” 2011]

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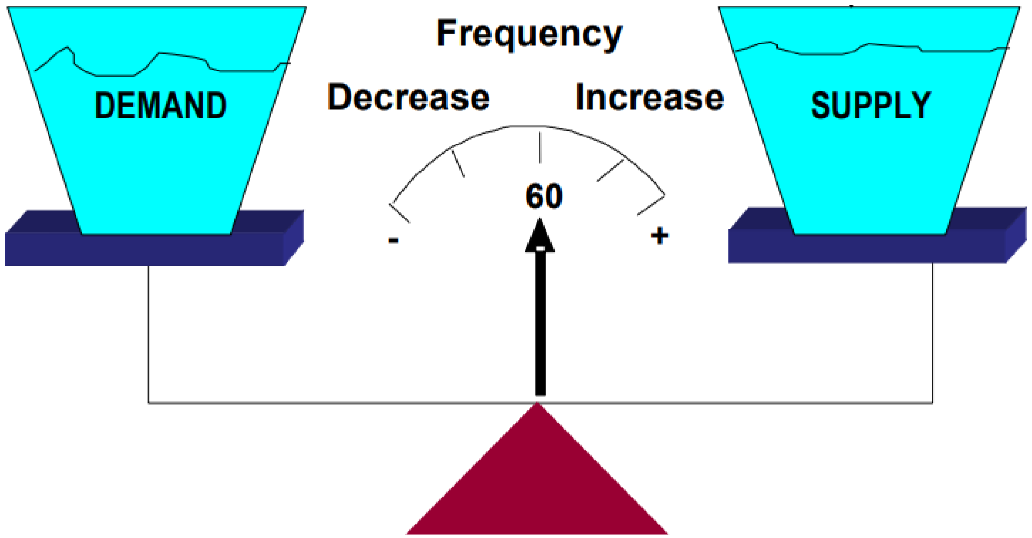

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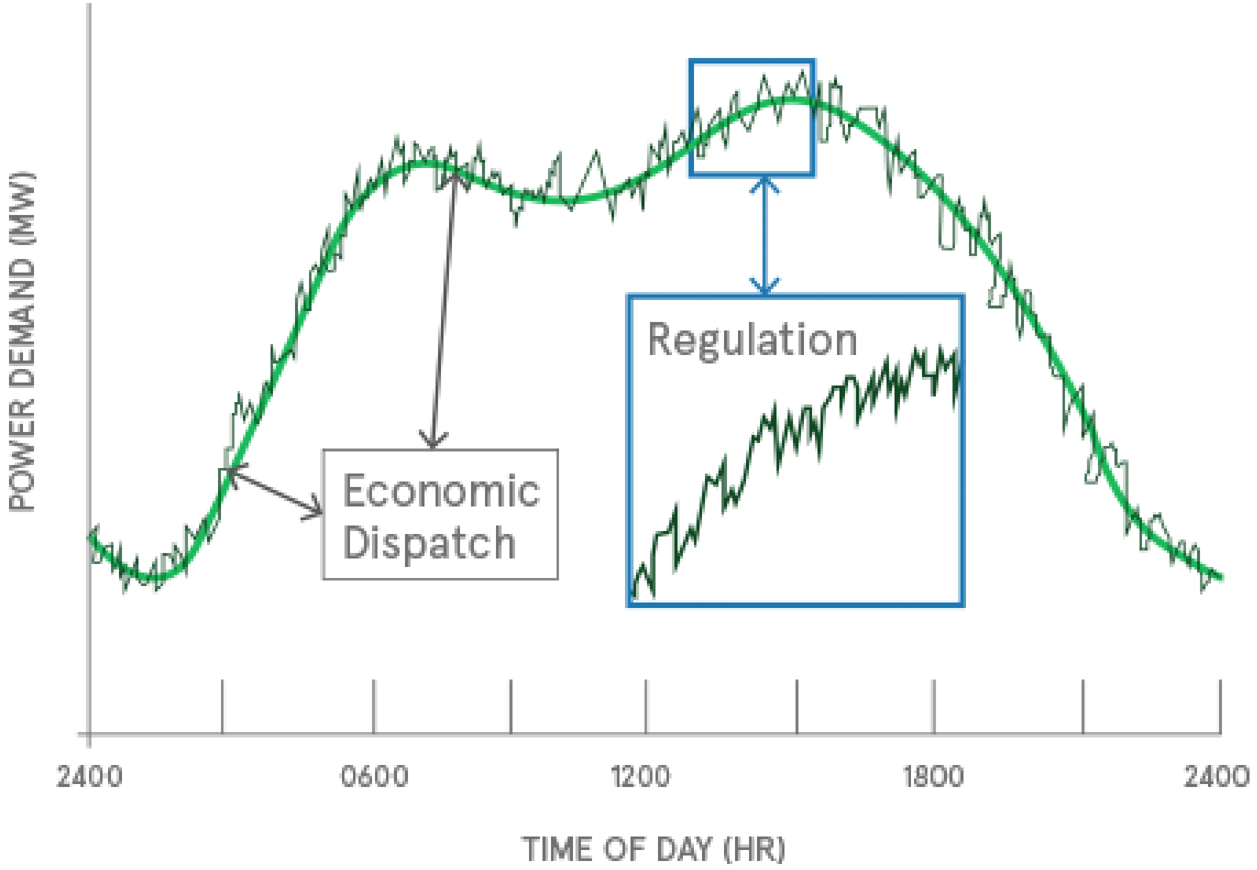
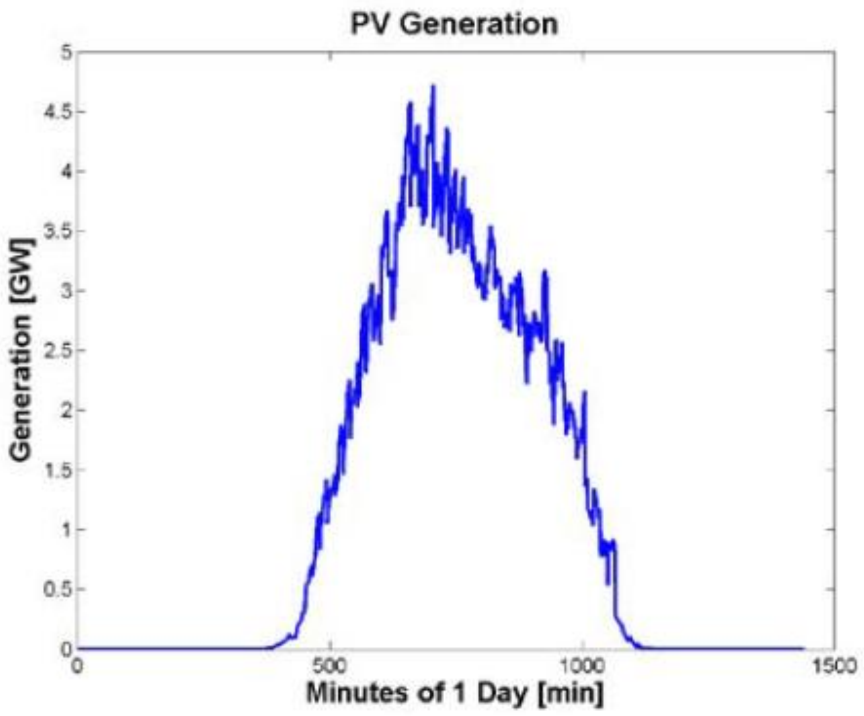
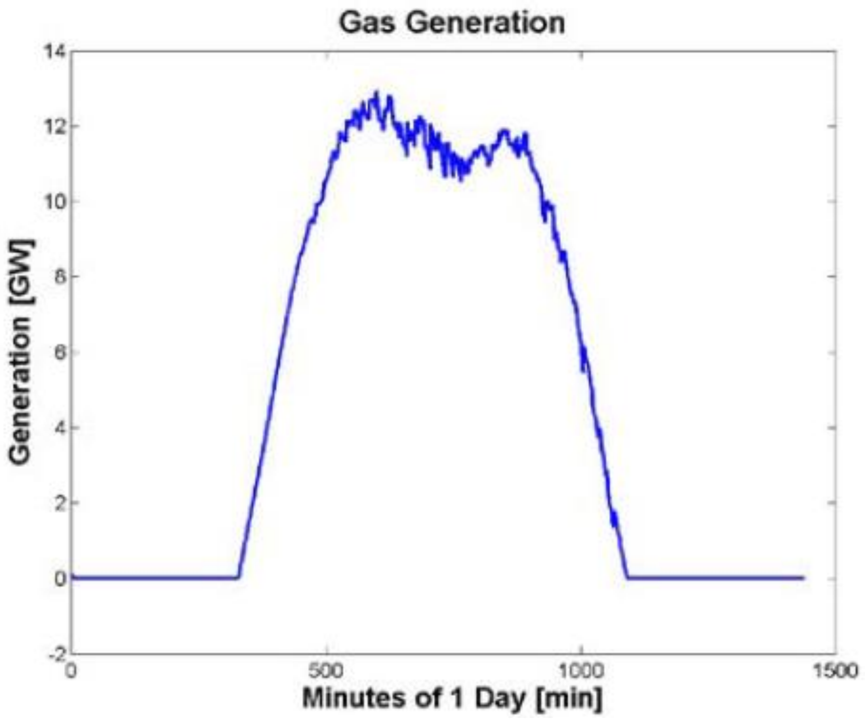


http://universityofindependence.com/distributed-energy-solutions/

Additional generation from renewable energy sources increases the need for real-time energy balancing, which can increase costs.





[Bhat "Effects of PV on conventional generation,“ 2014.]

A modern trend in demand response research coordinates the demand of residential loads to follow a desired power trajectory.

"**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, "Benefits of Demand Response and Recommendations …," 2006]

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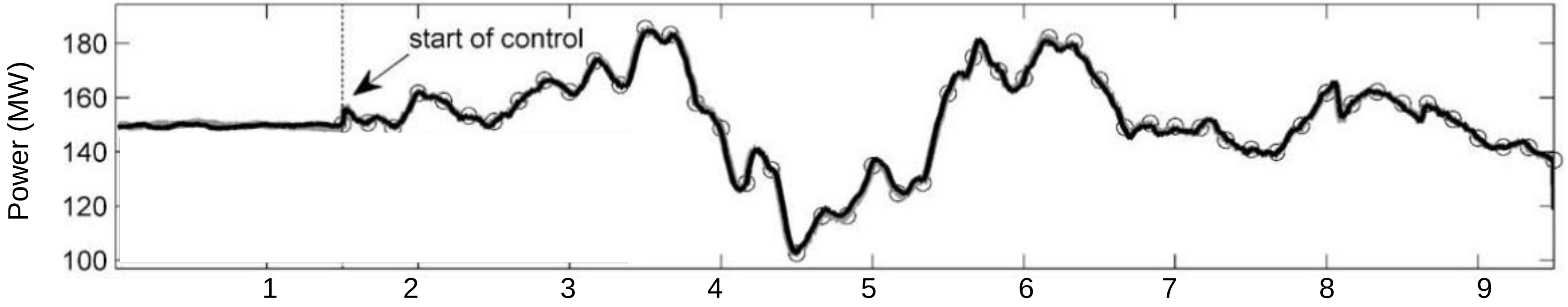

[Callaway, "Tapping the energy storage potential in electric loads to deliver load following …," 2009.]

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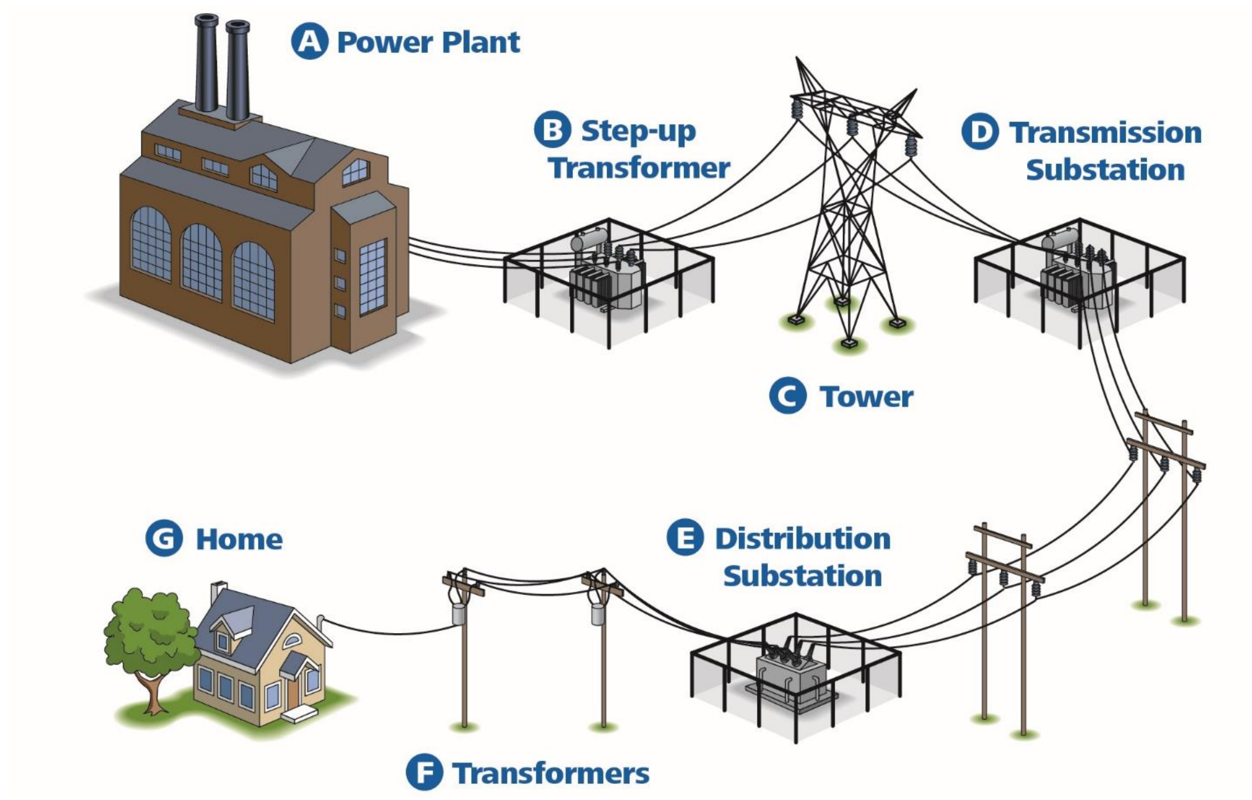
} Feeder-Level Energy Disaggregation

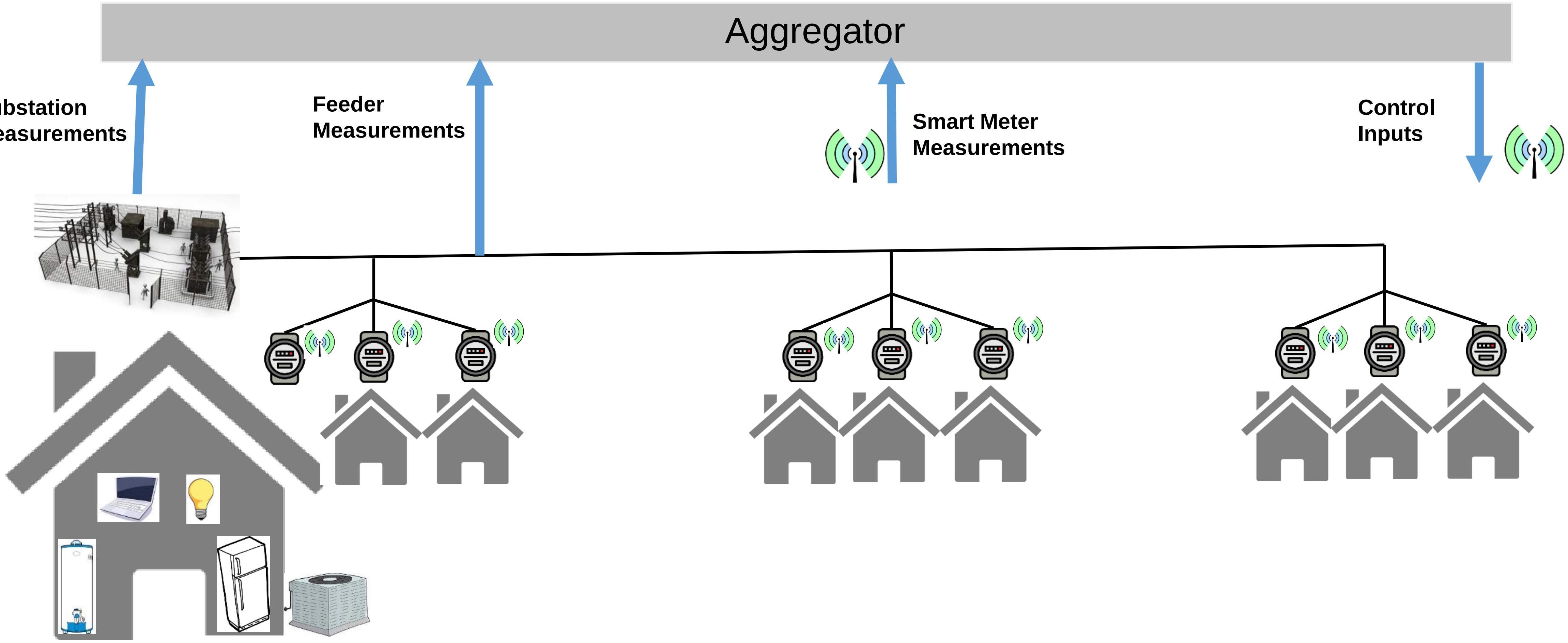
Conclusions

An electric power system contains several sub-systems, and the work in this dissertation focuses on the distribution system.



https://www.delmarva.com/SafetyCommunity/Education/Pages/EnergyBasics/Infrastructure101.aspx

The framework of this work consists of an aggregator that controls a set of loads connected to a distribution feeder using a variety of measurements.



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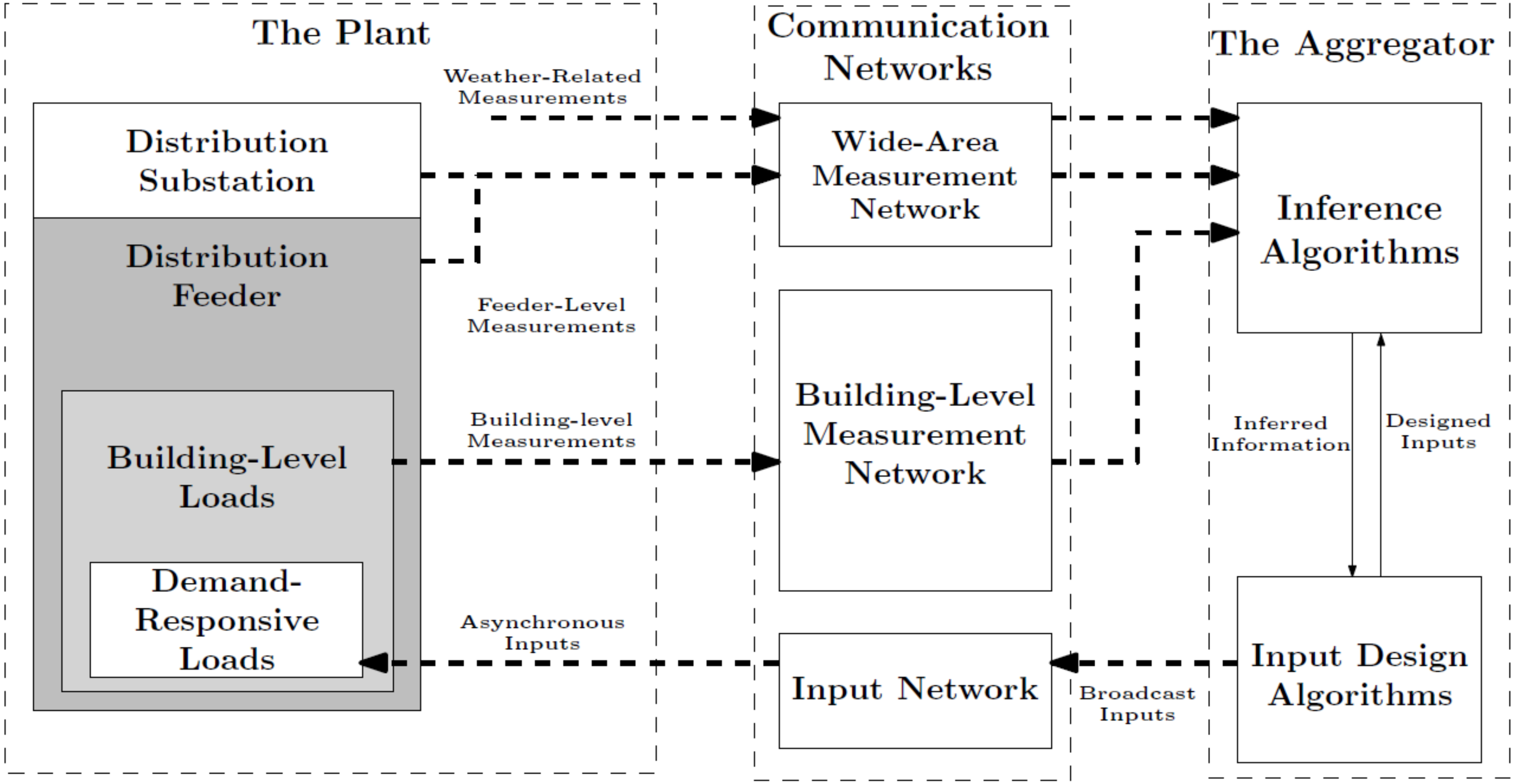
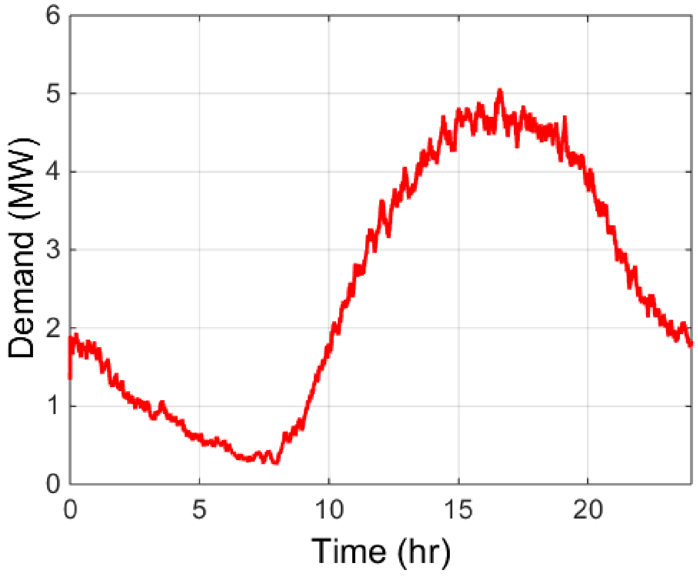


An aggregator seeks to control the demand-responsive loads to follow a frequency regulation signal determined from a capacity bid into the market.



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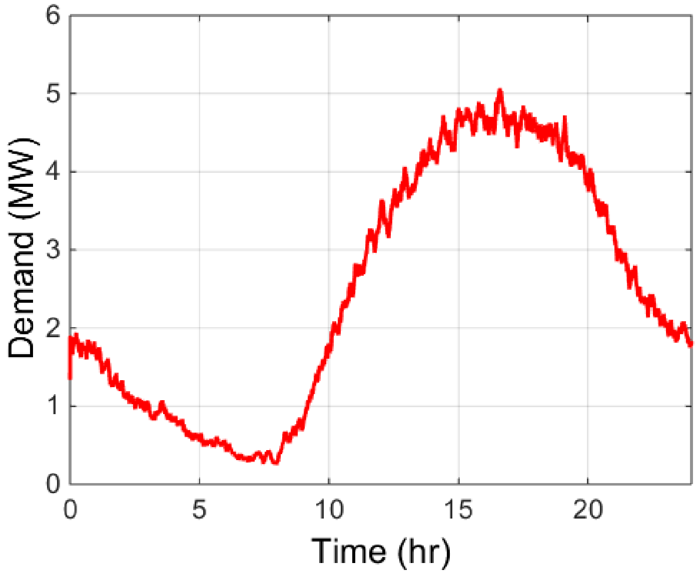

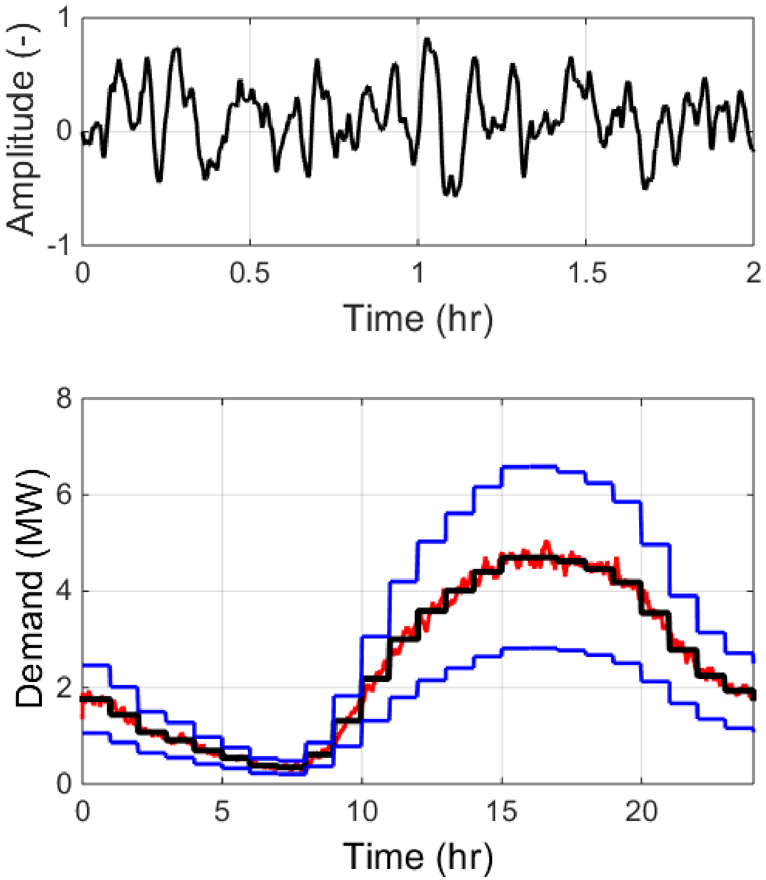

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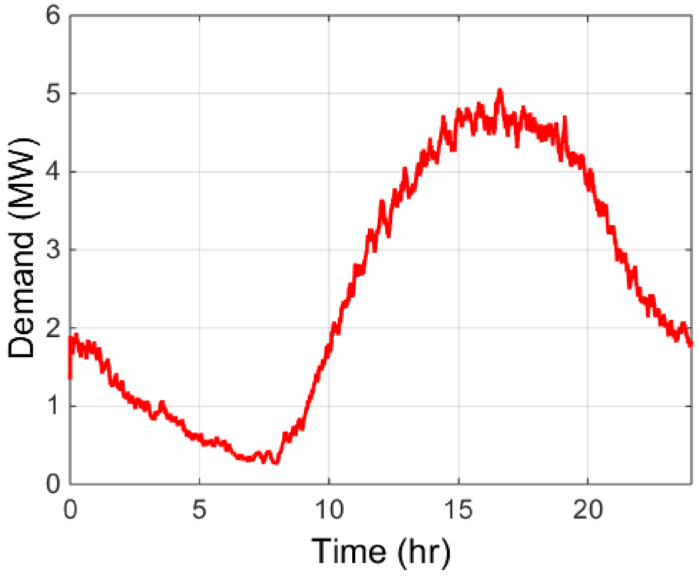

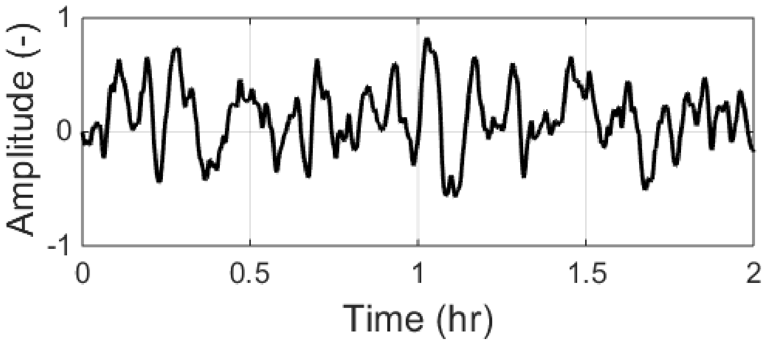

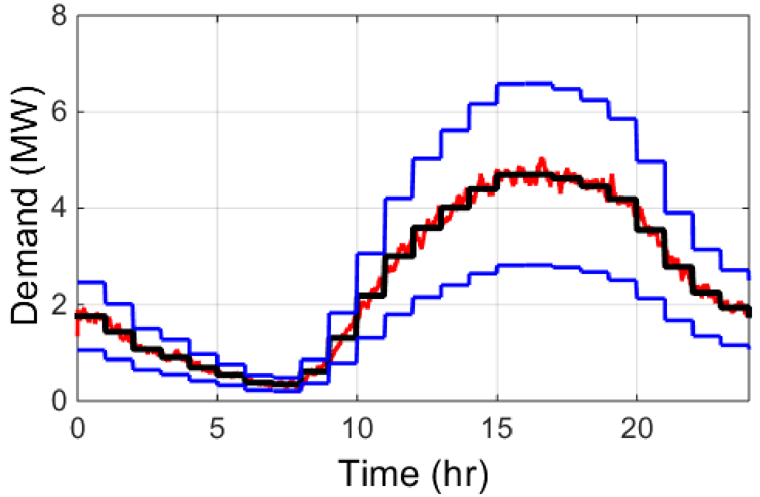

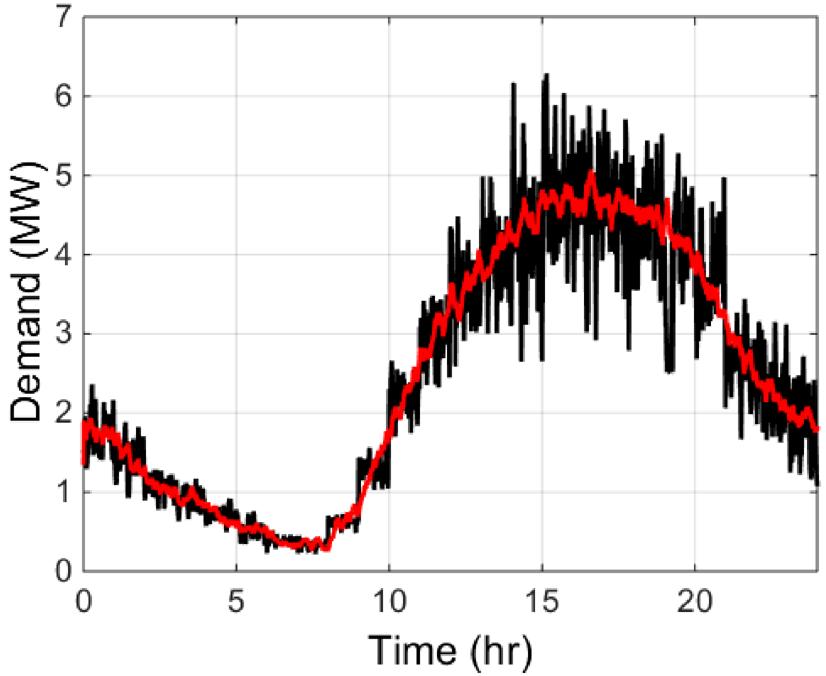

<u>**Research objective:**</u> to show that advanced algorithms can leverage **existing infrastructure** to make energy balancing with loads feasible in the near-term, which improves the reliability, economics, and environmental impact of the power grid.

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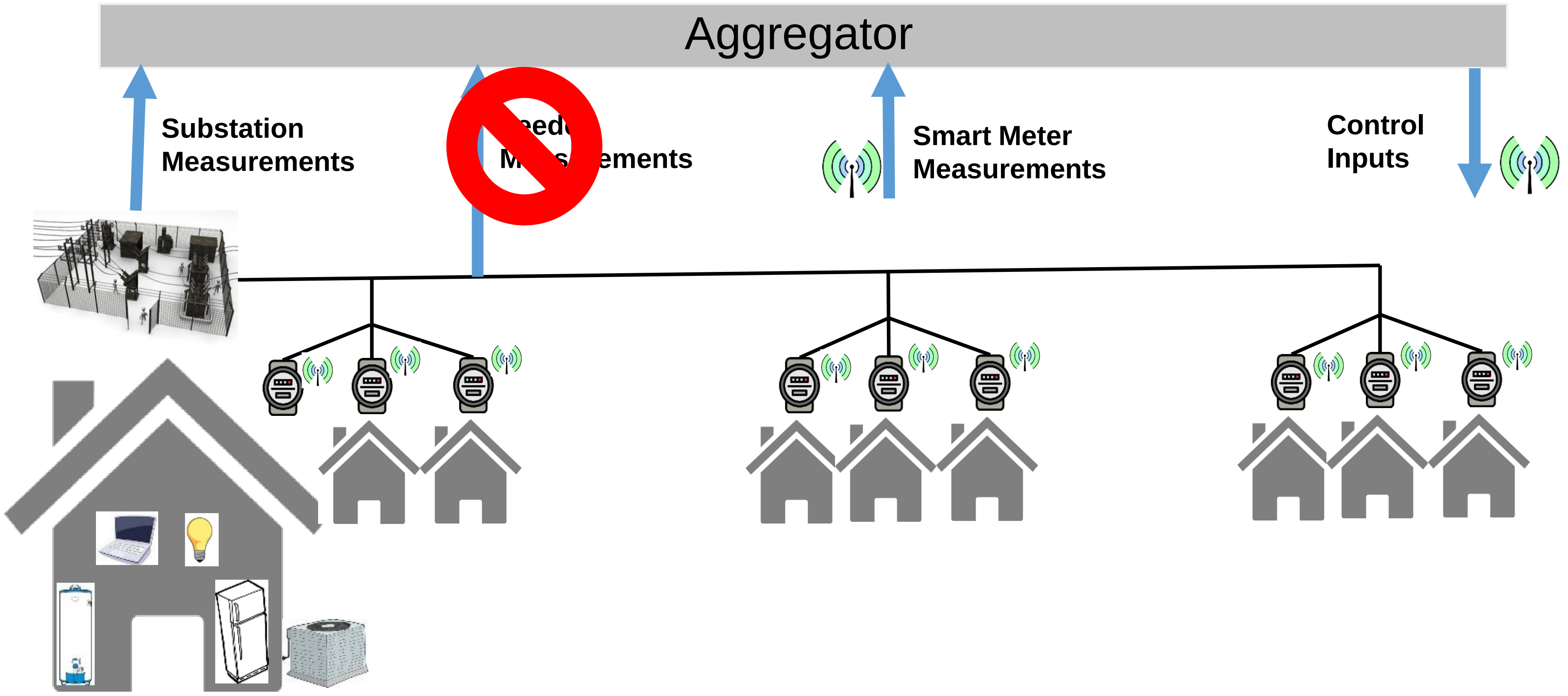
Chapter II develops control and estimation algorithms that address measurement and input delays while respecting smart meter limits.



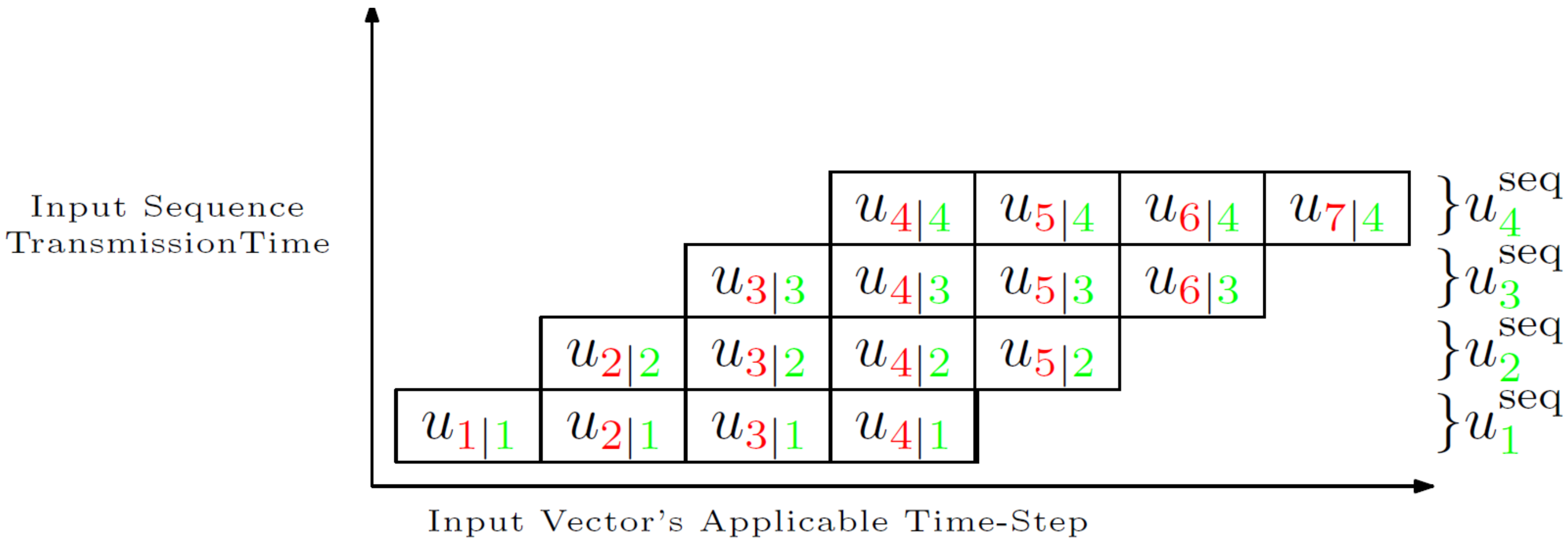
Within demand response literature, several works investigate unavailable or intermittent load measurements, but addressing delays is an open question.

- Communication infrastructure may exist and have significant delays (e.g., 70 seconds)
  - [Eto, “The Demand Response Spinning Reserve Demonstration …,” 2012]
- Smart meters have significant communication limitations
  - [Armel, “Is disaggregation the holy grail …,” 2013]
- Existing work investigates unavailable demand-responsive load measurements:
  - [Mathieu, “State estimation and control…,” 2013]
  - [Borsche, “Minimizing communication cost …,” 2013]
  - [Vrettos, “Control of thermostatic loads…,” 2014]
  - [Ghaffari, “PDE-based modeling …,” 2015]
- Existing work also investigates the impact of delays but does not compensate for them
  - [Hao, “Frequency Regulation from Flexible Loads …,” 2014]

The main contribution is to adapt networked control and estimation algorithms, which address delays, for residential demand response

- Networked control algorithms:
  - Address communication imperfections
  - Usually apply to a centralized (i.e., not distributed) system.
- The adaptations:
  - Address state measurements that consist of thousands of load measurements
  - Address intermittently available smart meter measurements
  - Address inputs actuated at loads that depend on the realized delays

At each time-step, the controller transmits an input sequence and allow demand-responsive loads to select an input based on the realized delays.

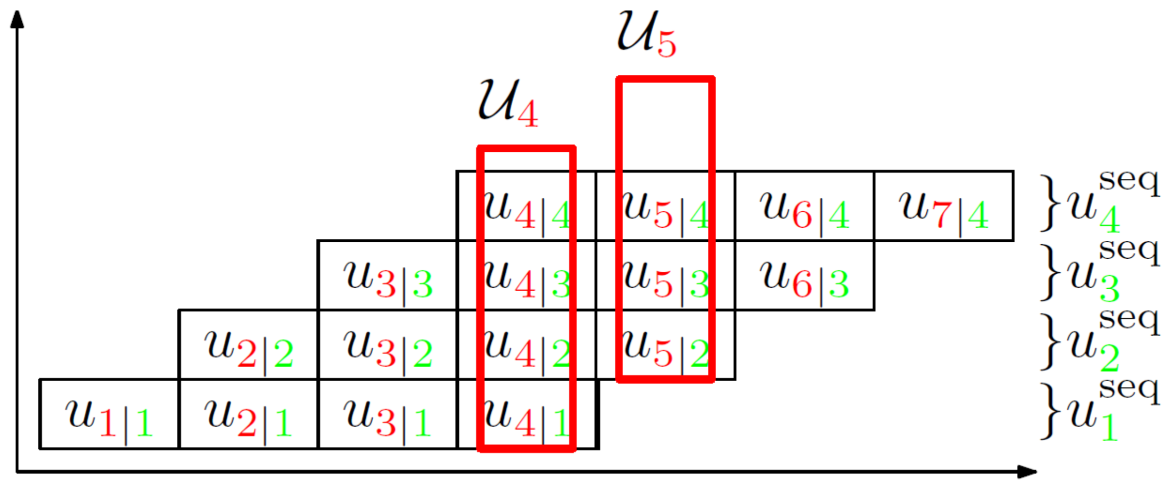


The controller is formulated as a quadratic program similar to a finite-horizon, tracking LQR with state and input constraints.

$$\min_{u} \quad \sum_{k=t}^{t+N} \left[c^{y}\,(\text{tracking error})^2 + c^{u}(\text{input effort})^2 \right]$$

$$\begin{aligned}
\text{s.t. } x_{k+1} &= A\,x_k + B\,\widehat{u}_k \\
y_k &= C\,x_k \\
\widehat{u}_k &= \mathcal{U}_k \mathcal{P} \\
&\quad \text{input constraints} \\
&\quad \text{state constraints}
\end{aligned}$$

The controller computes an expected input using knowledge of the input delay distribution and using the previously transmitted inputs.



$$\hat{u}_k = \overbrace{\begin{bmatrix} u_{k|k} & u_{k|k-1} & u_{k|k-2} & \cdots & u_{k|k-N} \end{bmatrix}}^{\mathcal{U}_k} \overbrace{\begin{bmatrix} p_k \\ p_{k-1} \\ p_{k-2} \\ \vdots \\ p_{k-N} \end{bmatrix}}^{\mathcal{P}}$$

Results indicate that allowing input selection logic at loads and including the input delay distribution in input computation reduces the effects of delays.

- A controller was developed that accounts for input delays in a distributed plant
- Two estimators were developed that address intermittent smart meter measurement availability and measurement delays
- It is possible to accurately follow a frequency regulation signal while experiencing substantial delays

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Chapters III, IV, and V develop controllers, models, and estimators for demand response scenarios.

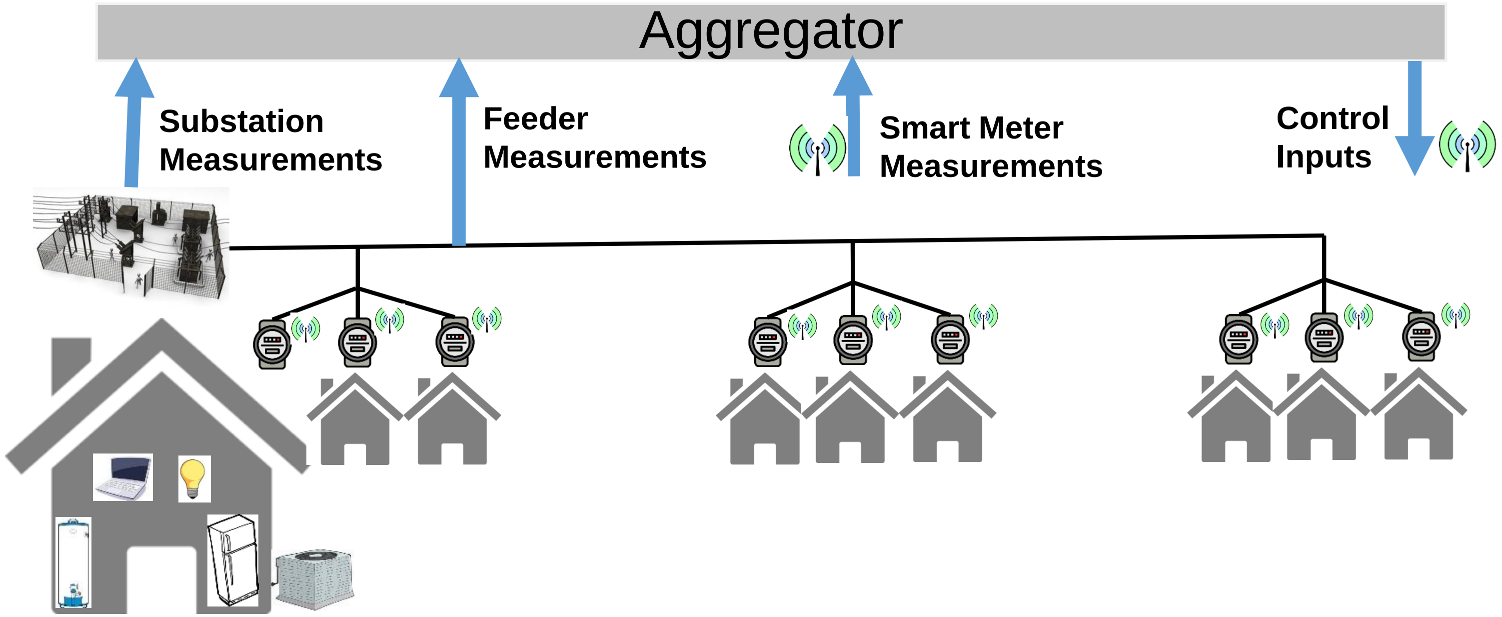
Chapter III: Simplifies the controller in Chapter II to a linear feedback law that mitigates the effects of input delays at reduced computational complexity.

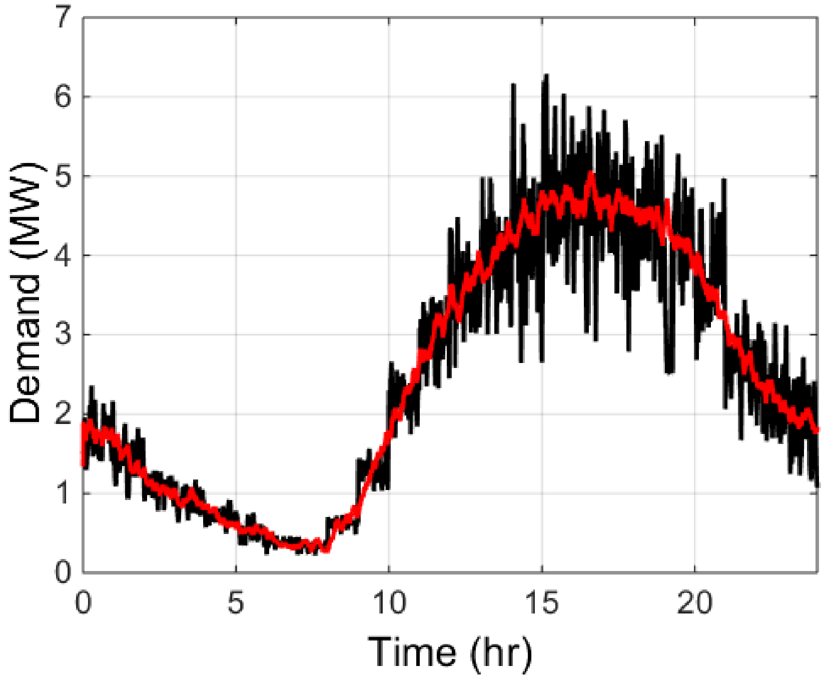
Chapter IV: Adapts existing aggregate models to a more realistic scenario, uses aspects of this scenario to modify the models and improve the models' prediction accuracy, and benchmarks their performance against one another.

Chapter V: Establishes connections and similarities between Kalman filter and online learning methods, which can both be used in demand response estimators.

An open question in Chapters II-V is how to determine the real-time aggregate demand-responsive load within existing sensing capabilities.

- It is common in literature to assume a feedback signal is known:
  - E.g., [Mathieu, “State estimation and control…,” 2013], [Vrettos, “Control of thermostatic loads…,” 2014], [Ghaffari, “PDE-based modeling …,” 2015]





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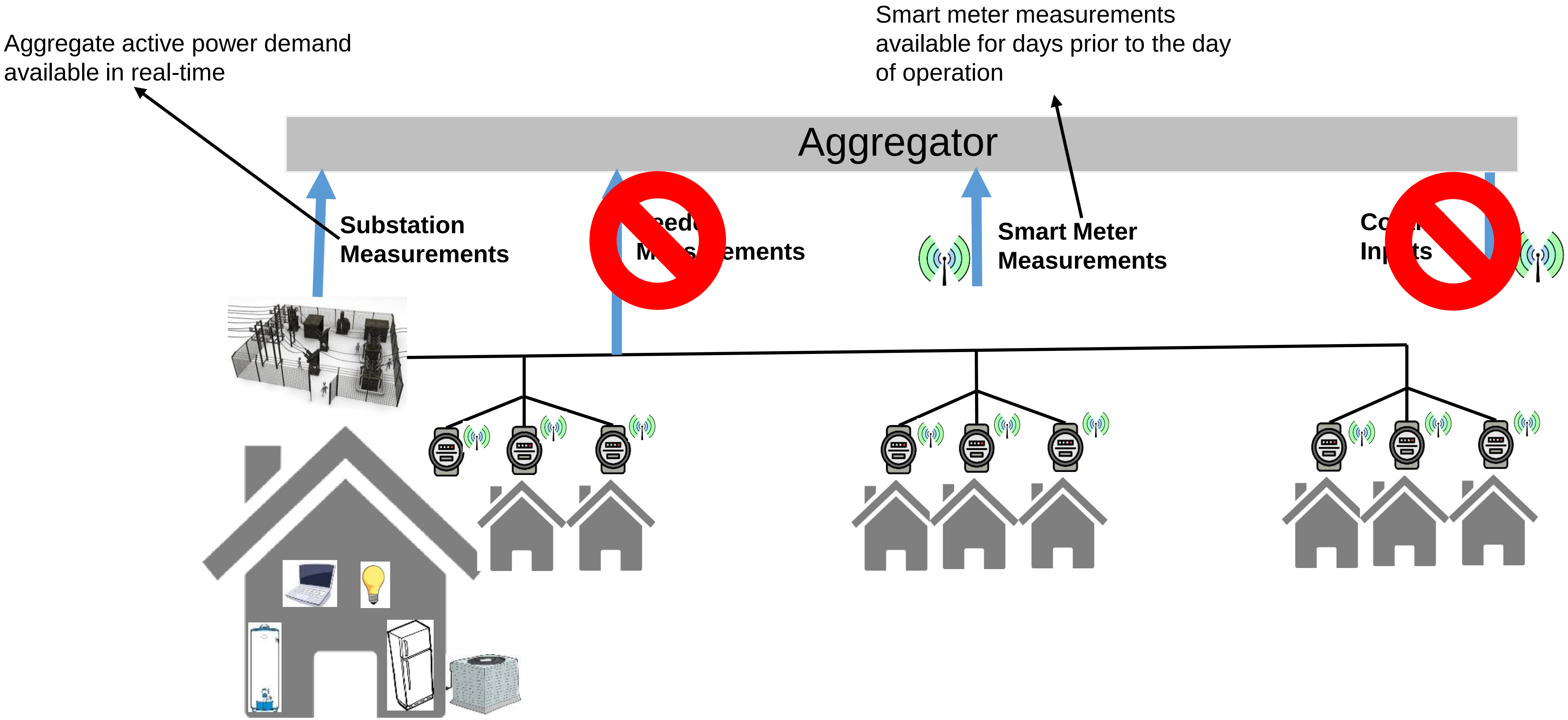
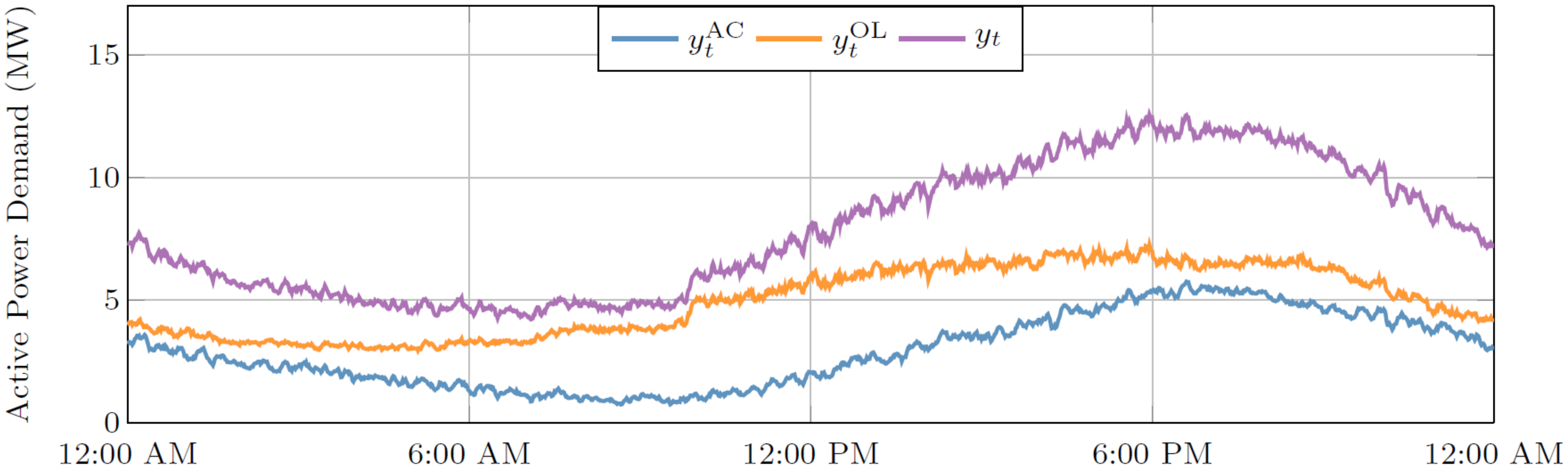
Chapter VI seeks to determine the real-time aggregate air conditioning demand using historical smart meter measurements and real-time active power measurements.



A disaggregation algorithm takes measurements of the total active power on a distribution feeder and seeks to separate it into two demand components.



The main contributions of Chapter VI are to frame the feeder-level energy disaggregation problem and to adapt Dynamic Fixed Share to perform disaggregation.

- Frame the feeder-level energy disaggregation problem
  - Draws on aspects of building-level energy disaggregation
  - Draws on aspects of load forecasting

- Adapt Dynamic Mirror Descent (DMD) and Dynamic Fixed Share (DFS) for feeder-level energy disaggregation
  - DMD and DFS are online learning algorithms
  - Previously developed in [Hall, "Online convex optimization in dynamic environments," 2015]
  - Adapt DFS to use models with a variety of structures simultaneously

Feeder-level energy disaggregation differs from building-level disaggregation in the scale of the problem, and it differs from load forecasting in the timescale of the predictions.

- Building-level energy disaggregation
  - Separates the measured demand of a building into the demand of component loads
    - [Hart, “Nonintrusive appliance load monitoring,” 1992]
  - Disaggregate into 10-100 loads
    - [Armel, “Is disaggregation the holy grail …,” 2013]
  - Data sampling rates range from 1 hour intervals to over 1 MHz
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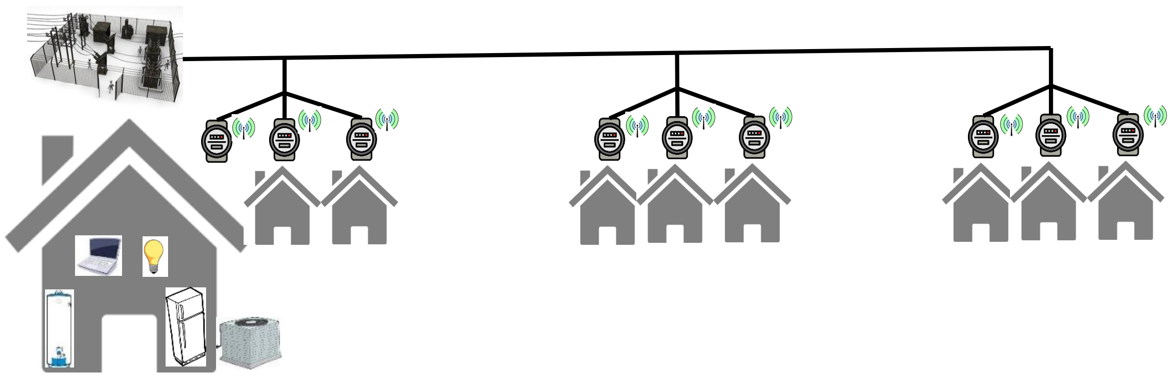
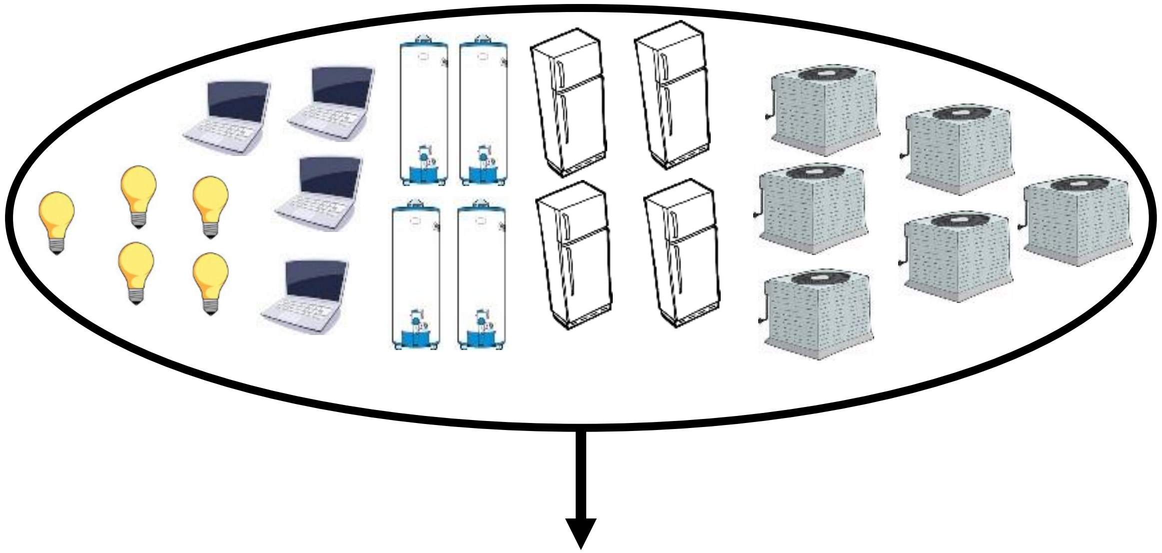
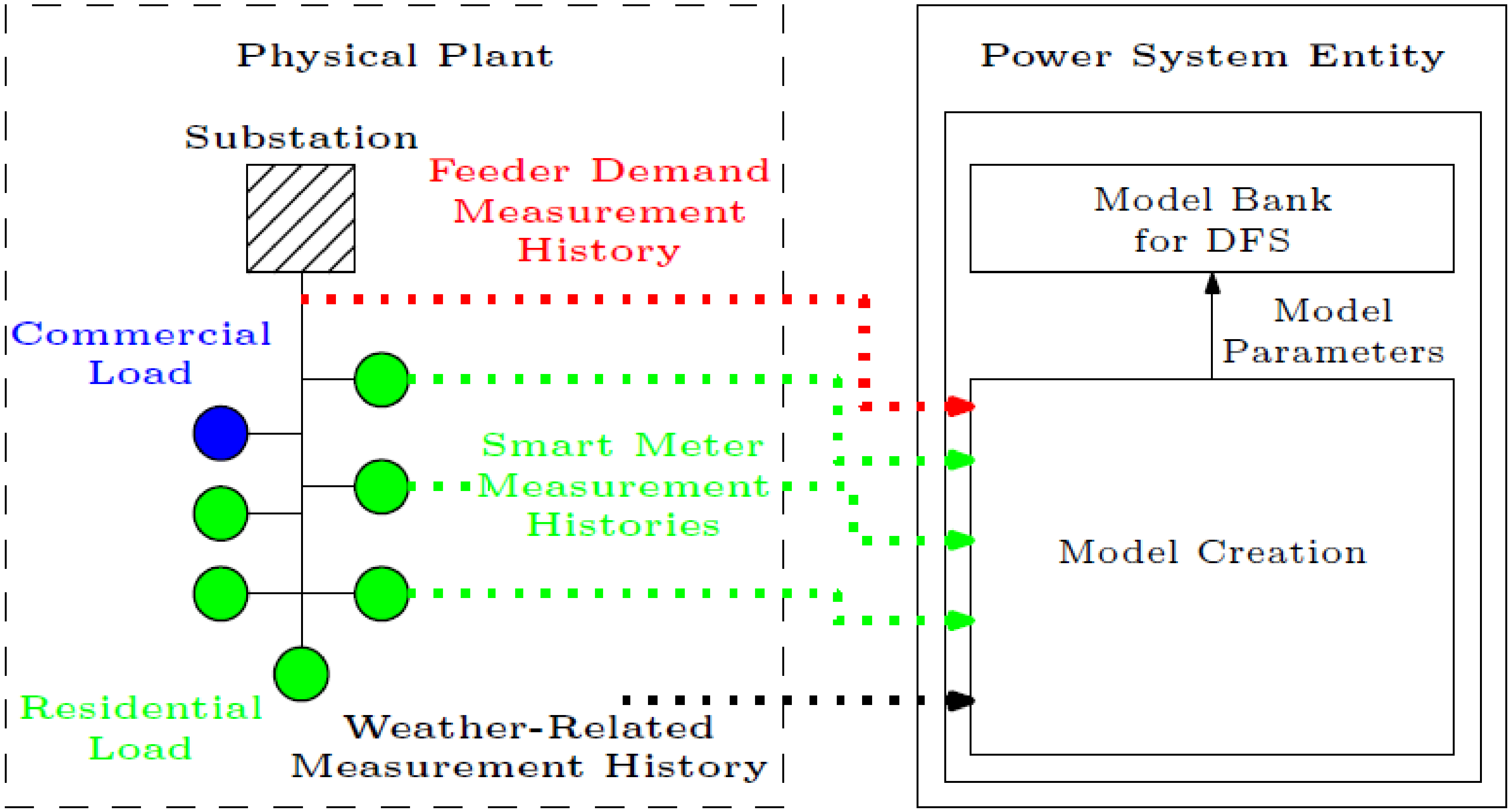
  - Usually solved offline
- Load forecasting
  - Predicts the expected aggregate demand for a given area
  - Deals with aggregations of thousands to millions of loads
    - [Hong, "Probabilistic electric load forecasting…," 2016]
  - Intraday forecasts use data rates of 15-60 min
    - [Hong, "Short Term Electric Load Forecasting," 2010]
  - Timescales range from sub-hourly to years
    - [Hong, "Short Term Electric Load Forecasting," 2010]

The distribution network is not modeled, and the network consists of air conditioning demand and the other load demand connected to a measured point.

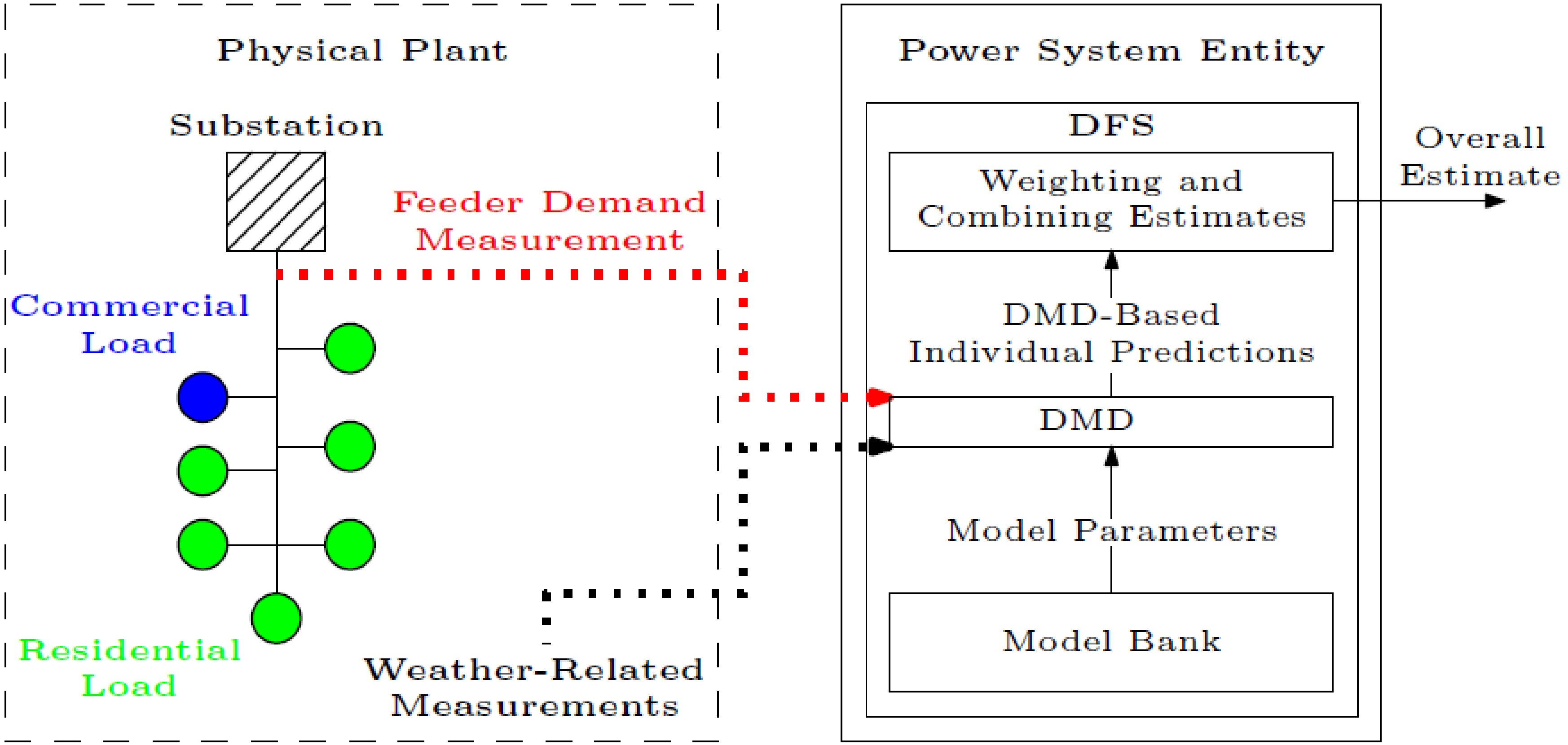




Historical feeder, smart meter, and weather measurements are available to compute model parameters, where the models are used within an online learning algorithm.



In real-time operation, the model parameters are used to predict the AC and OL demand at the next time-step, and feeder demand measurements adjust these predictions.



DMD computes a state estimate at each time-step using a measurement-based update and a model-based update that predicts the state value at the next time-step.

$$\theta_t = \begin{bmatrix} y_t^{\mathrm{AC}} & y_t^{\mathrm{OL}} \end{bmatrix}^{\mathrm{T}}$$

[Hall, "Online convex optimization in dynamic environments," 2015]

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$$\theta_t = \begin{bmatrix} y_t^{\mathrm{AC}} & y_t^{\mathrm{OL}} \end{bmatrix}^{\mathrm{T}}$$

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

$$\ell_t(\hat{\theta}_t) = \frac{1}{2} \left\| (\hat{P}_t^{\mathrm{y}})^{-\frac{1}{2}} (C_t \hat{\theta}_t - y_t) \right\|_2^2$$

[Hall, "Online convex optimization in dynamic environments," 2015]

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

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

$$\ell_t(\widehat{\theta}_t) = \frac{1}{2}\left\| (\widehat{P}_t^{\mathrm{y}})^{-\frac{1}{2}} (C_t \widehat{\theta}_t - y_t) \right\|_2^2$$

[Hall, "Online convex optimization in dynamic environments," 2015]

DMD is modified to decouple the measurement-based adjustment from the model-based update, allowing a variety of model types to be used simultaneously.

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

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

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

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

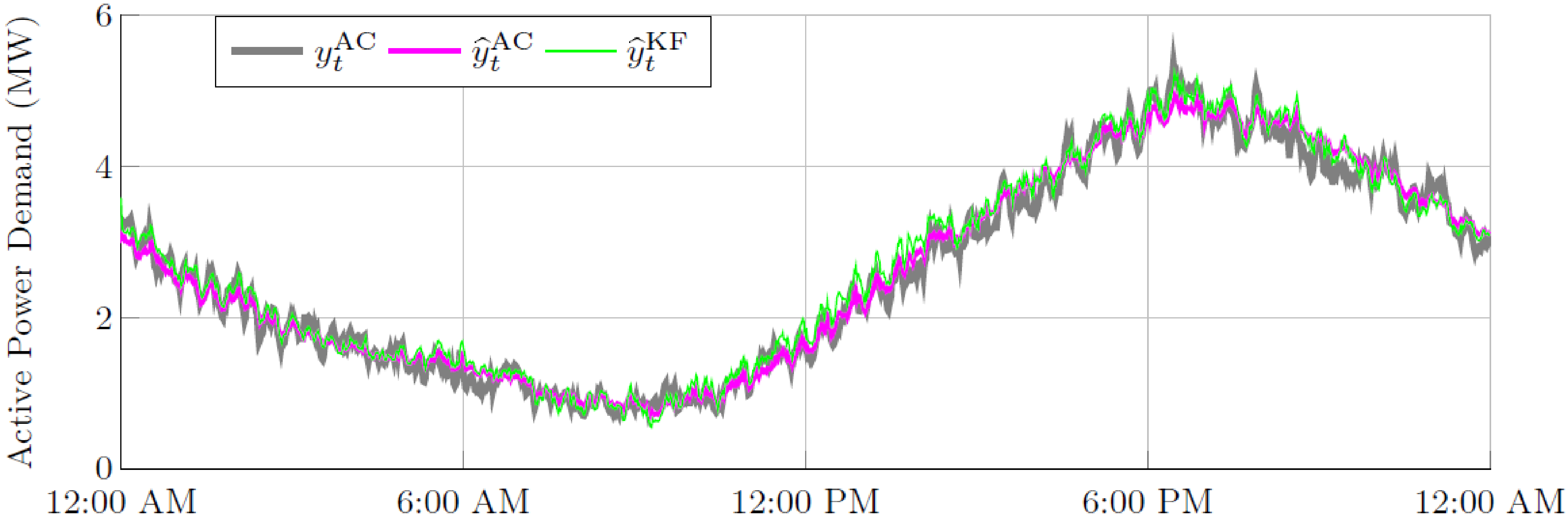
$$\breve{\theta}_{t+1} = \Phi(\breve{\theta}_t)$$

DFS combines estimates/predictions from a number of "experts", DMD implementations in this case, into an overall estimate/prediction using the expert's historical accuracy.

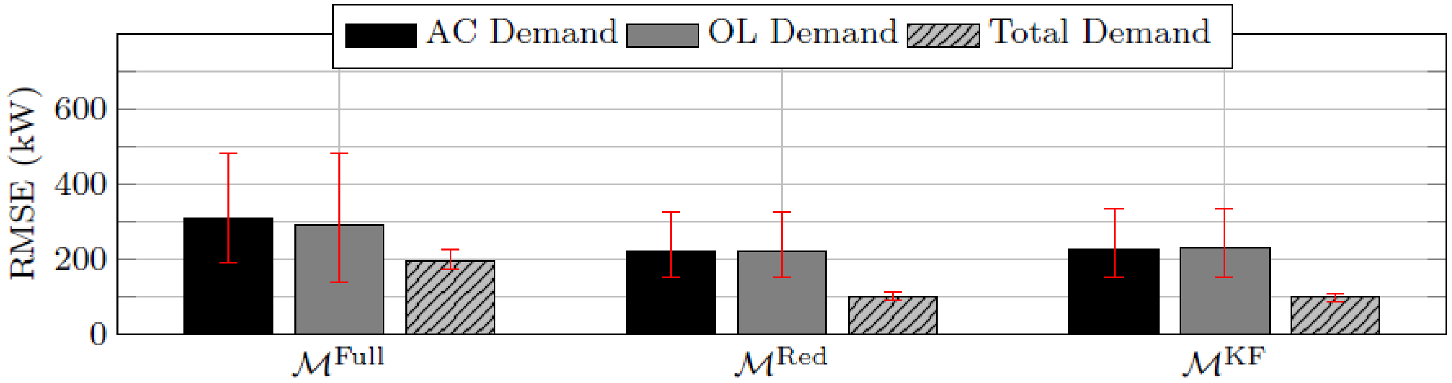
$$\widehat{\theta}_{t+1} = \sum_{m \in \mathcal{M}^{\mathrm{mdl}}} w_{t+1}^{m} \, \widehat{\theta}_{t+1}^{m}$$

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

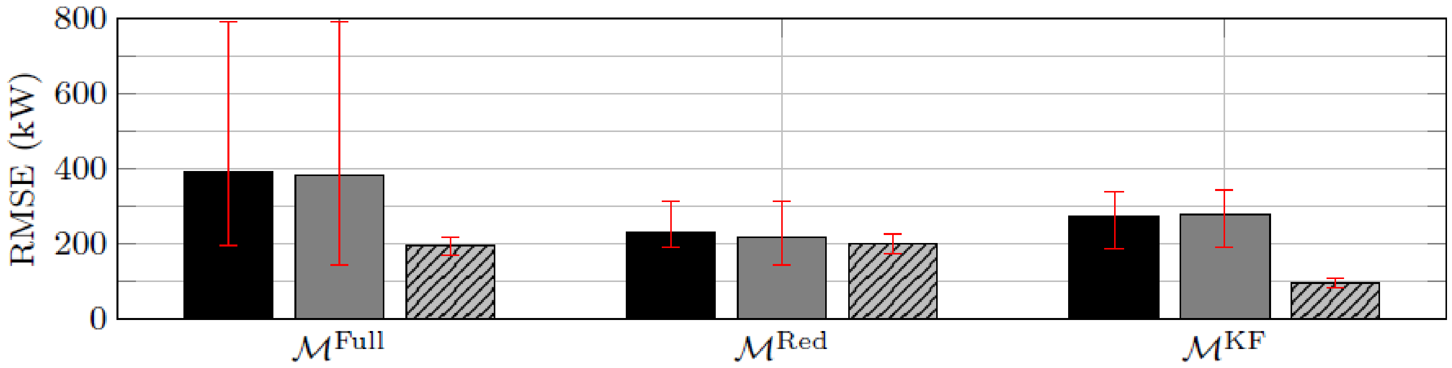
Results indicate that we can disaggregate the AC demand in real-time using measurements of the total load connected to a distribution feeder.



The accuracy of disaggregation depends on the models used within DFS, the update method used within the algorithm, and on the covariance data used (not shown).



(a) Update Method 1



(b) Update Method 2

Chapter VI framed the feeder-level energy disaggregation problem and modified existing online learning algorithms DMD/DFS to be applicable to the problem.

- A modified version of DMD was developed that allows regression models and dynamic models to be used in DFS simultaneously.
- Results investigated:
  - The impact of model accuracy on DFS
  - The impact of the update method on disaggregation accuracy
  - The impact of covariance accuracy on disaggregation accuracy (not shown)
- Future work
  - Disaggregation while transmitting inputs
  - Disaggregation with additional sensing capabilities

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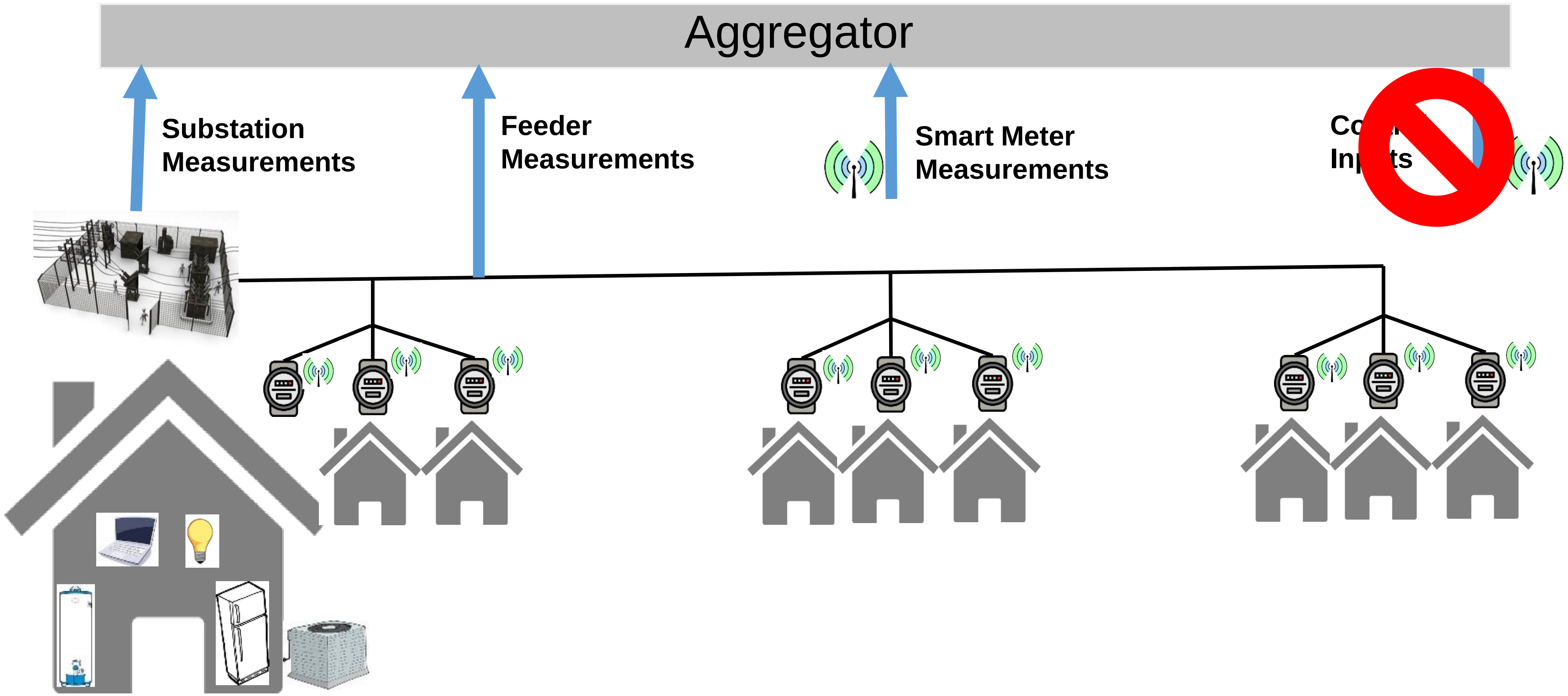
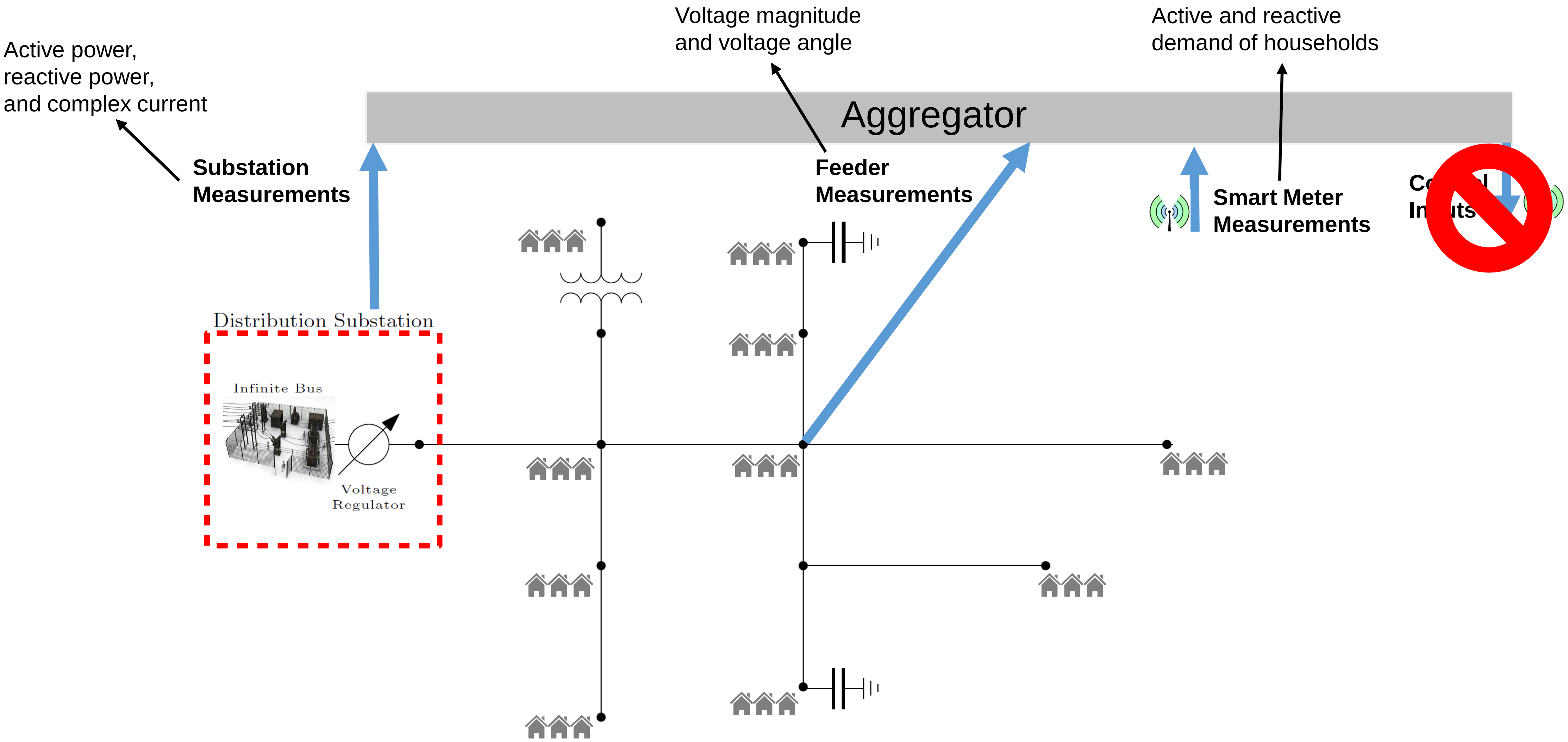
Chapter VII extends the work in the prior chapter to investigate the added value of additional sensing capabilities while explicitly modeling the distribution feeder.



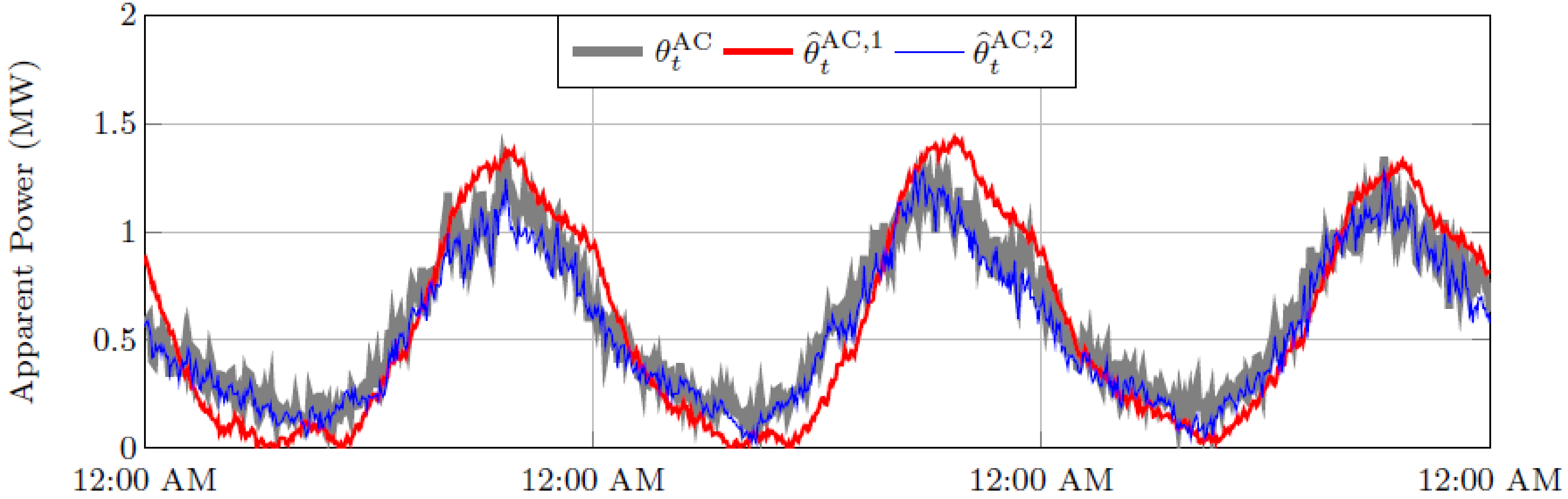
The main contributions of Chapter VII are to formulate a more general feeder-level disaggregation algorithm and to develop models of three demand components.

- The disaggregation algorithm is modified to use active power, reactive power, complex voltage, and smart meter measurements.
- Models of the AC, OL, and network (NW) load are developed that use complex current measurements to compute predictions.
- The value of additional measurements is assessed based on the improved accuracy of the disaggregation algorithm.

Chapter VII models the distribution network explicitly, and it uses a variety of measurements that are available on different timescales.



Including complex current measurements within the input features of the regression models significantly improves prediction accuracy.



(a) AC Demand Time Series

Additional measurements are included in the measurement-based update of (modified) DMD by changing the output matrix and the output error covariance.

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

$$\theta_t = \begin{bmatrix} P_t^{\mathrm{AC}} & P_t^{\mathrm{OL}} & P_t^{\mathrm{NW}} & Q_t^{\mathrm{AC}} & Q_t^{\mathrm{OL}} & Q_t^{\mathrm{NW}} \end{bmatrix}^{\mathrm{T}}$$

Results indicate that including additional substation measurements improves disaggregation accuracy, as does smart meter measurements at increasing frequency.

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	$\mathcal{M}^{c}$	61.5	15.4	63.4	61.9	20.1	65.2	6.1	13.5	14.9

Chapter VII successfully developed methods to incorporate additional measurements into the feeder-level energy disaggregation problem.

- The output equation of a variant of DMD was modified to incorporate a variety of measurements
- Models were developed that incorporate real-time measurements from the distribution feeder

- Results indicate that
  - Substation measurements can improve model accuracy
  - Reactive power and smart meter measurements can improve disaggregation accuracy

- Future work should
  - Incorporate coupling between phases in the distribution system
  - Incorporate control inputs into the problem framework
  - Investigate methods to determine network parameters

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Questions?