Practical Issues in Automatic, Residential Demand Response

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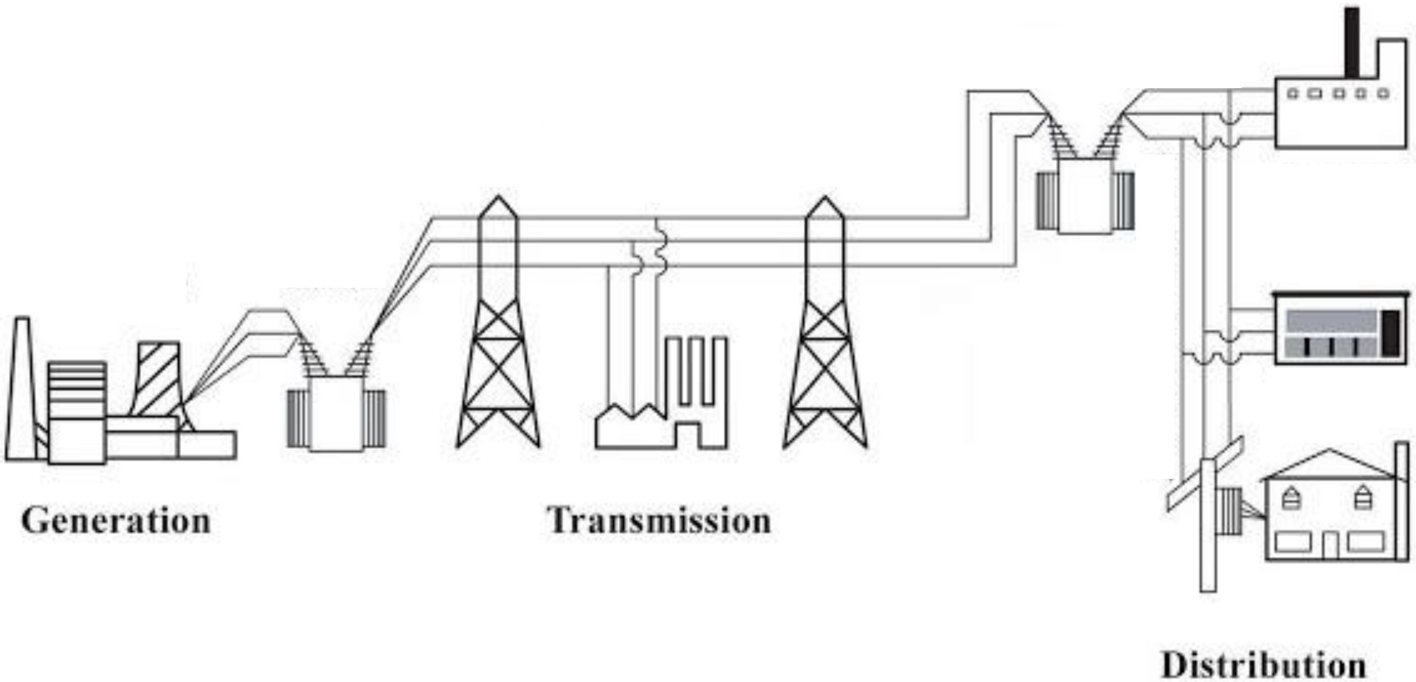
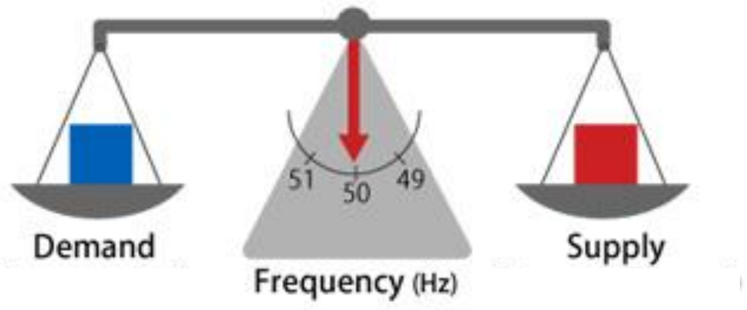
An electric power network is the equipment to transport electrical energy from producers (generators) to consumers (loads).



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

Electricity supply and demand must be balanced, and a system operator uses frequency regulation to achieve this balance.



[TEPCO "Where does excess electricity go?"]

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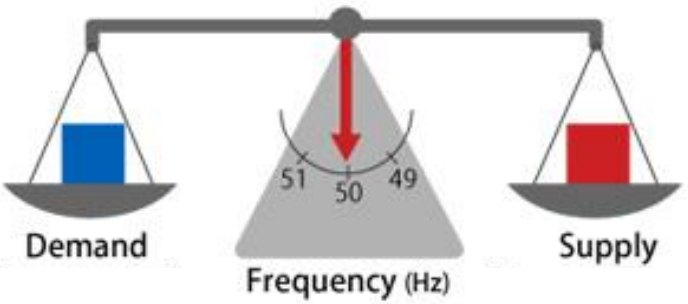

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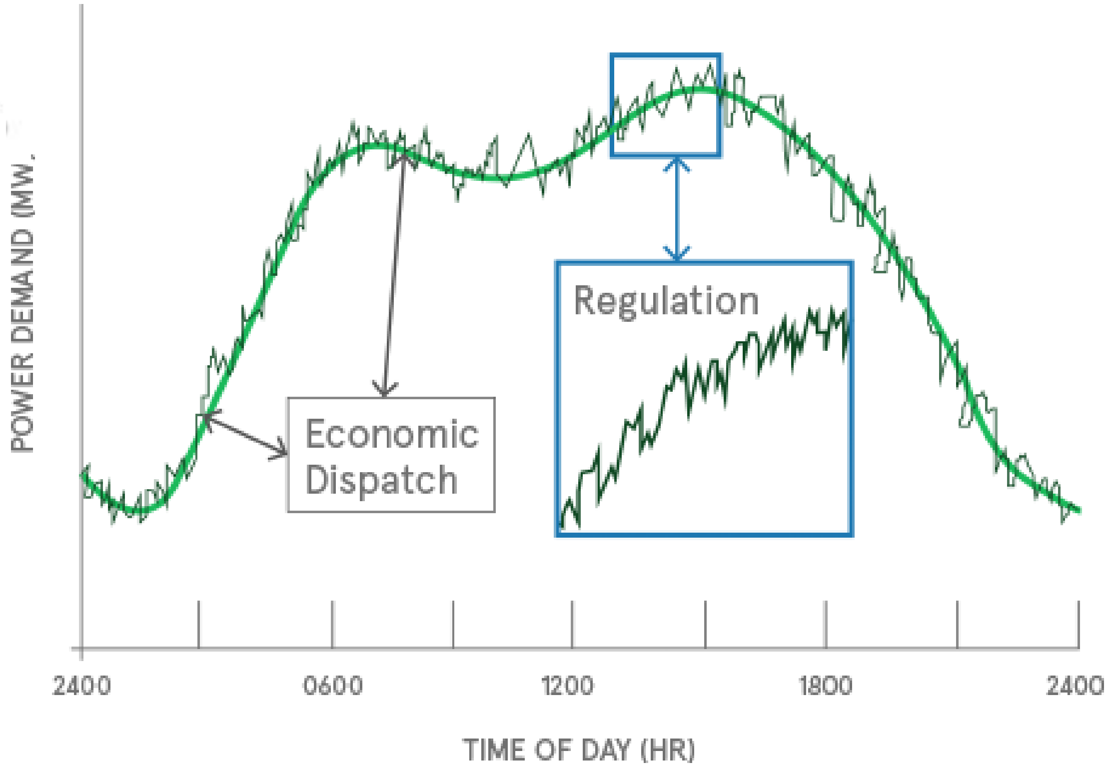

[Distributed energy solutions for the 21st century grid. Solar City.]

A current demand response research trend investigates using 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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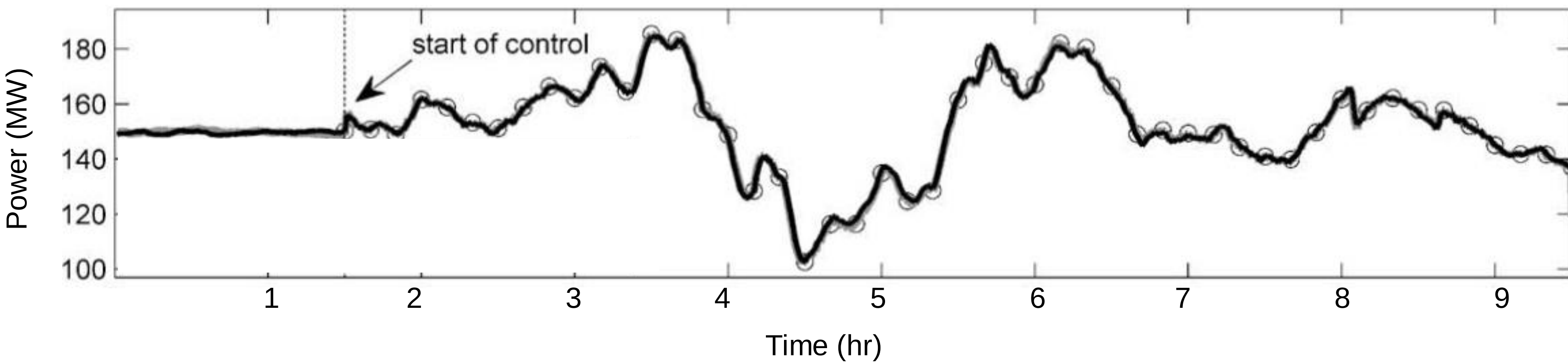

[Callaway 2009]

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

[Ryan Kh 2015]

[Solar Panel Permits]

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[Smart meter, Wikipedia]

[Atkinson 2017]

[Solar Panel Permits]

[Lacoma 2016]

Research objective:

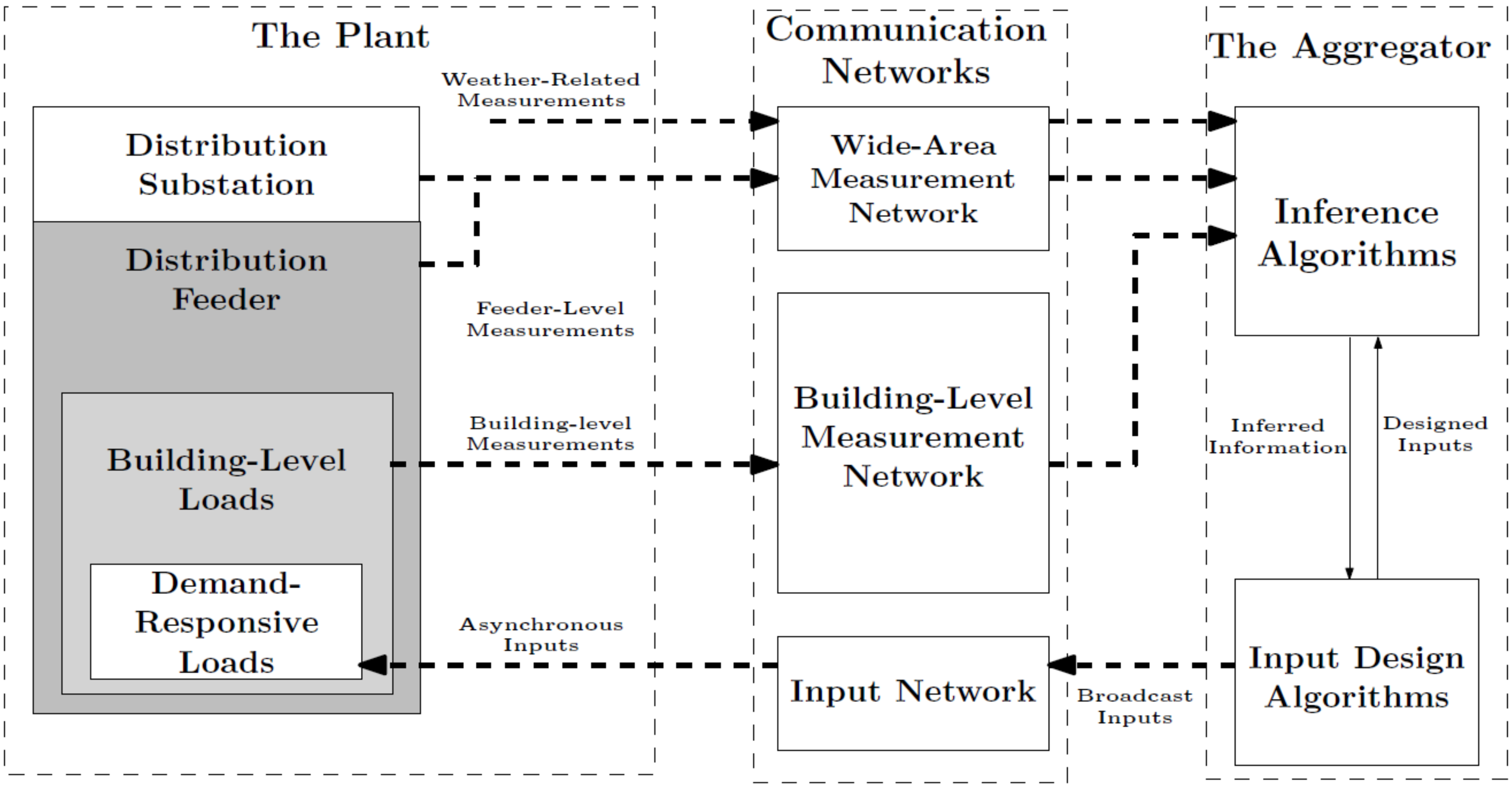
Develop algorithms for automated, residential demand response that provide frequency regulation and that take into account practical limitations of the communication and sensing infrastructure

Contents

1. General Problem Framework
2. Modeling Preliminaries
3. Managing Communication Delays
4. Real-Time Feeder-Level Energy Disaggregation
5. Future Work

Contents

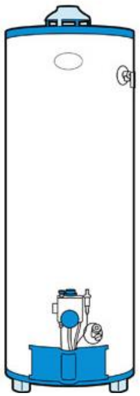
This work focuses on aggregator that is providing frequency regulation using an aggregation of residential, demand-responsive loads.



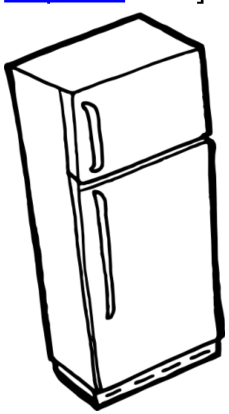
Contents

Modeling (1/3)

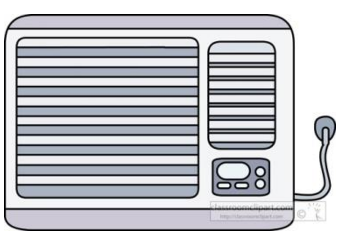
Residential demand response commonly control a class of appliances called thermostatically controlled loads (TCLs).



[Consumer Reports 2016]



[clker 2006]



[okclipart]

Two-state TCL model [Chong 1979]

$$\theta_t^j = \left[\theta_t^{a,j}\right]$$

$$\theta_{t+1}^j = A^j \theta_t^j + B^j m_t^j + E^j d_t^j$$

$$m_{t+1}^j = \begin{cases} 0 & \text{if } \theta_{t+1}^{a,j} < \theta^{\mathrm{set},j} - \theta^{\mathrm{db},j}/2 \\ 1 & \text{if } \theta_{t+1}^{a,j} > \theta^{\mathrm{set},j} + \theta^{\mathrm{db},j}/2 \\ m_t^j & \text{otherwise,} \end{cases}$$

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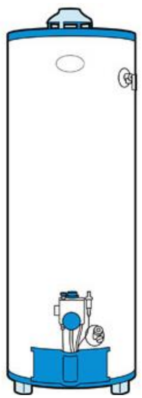

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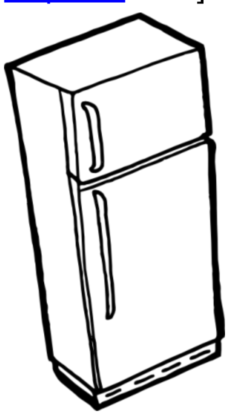

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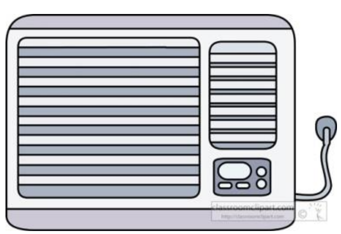

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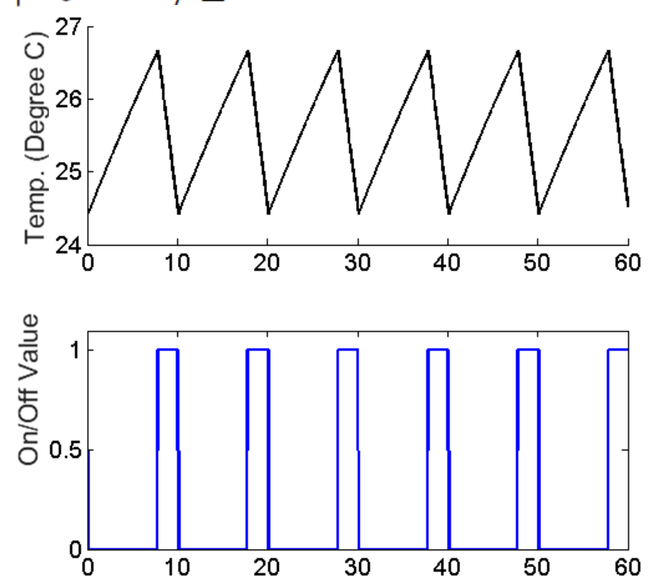

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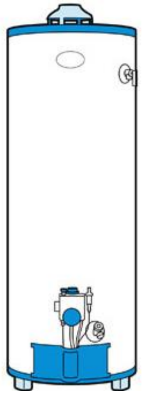

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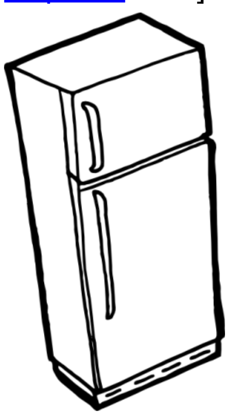

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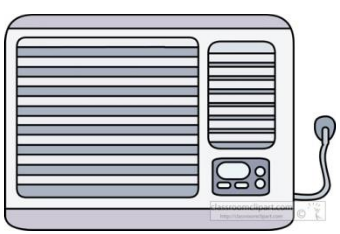

[okclipart]

Three-state TCL model [Sonderegger 1978]

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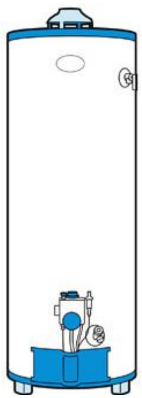

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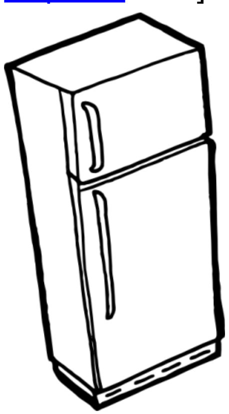

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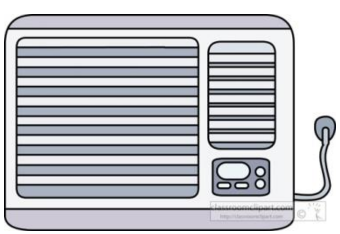

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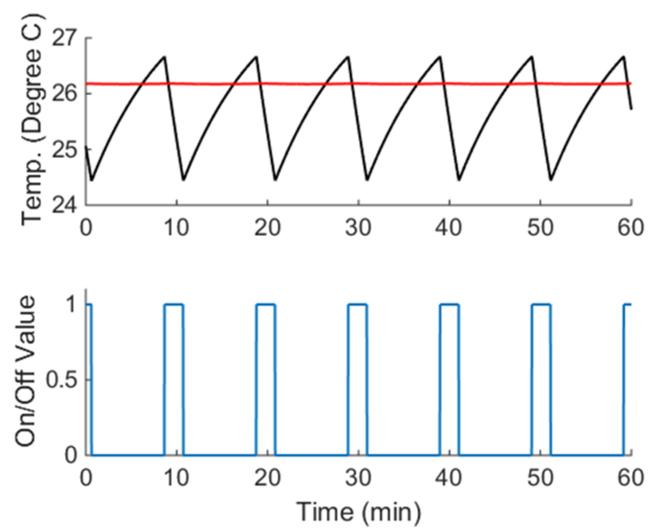
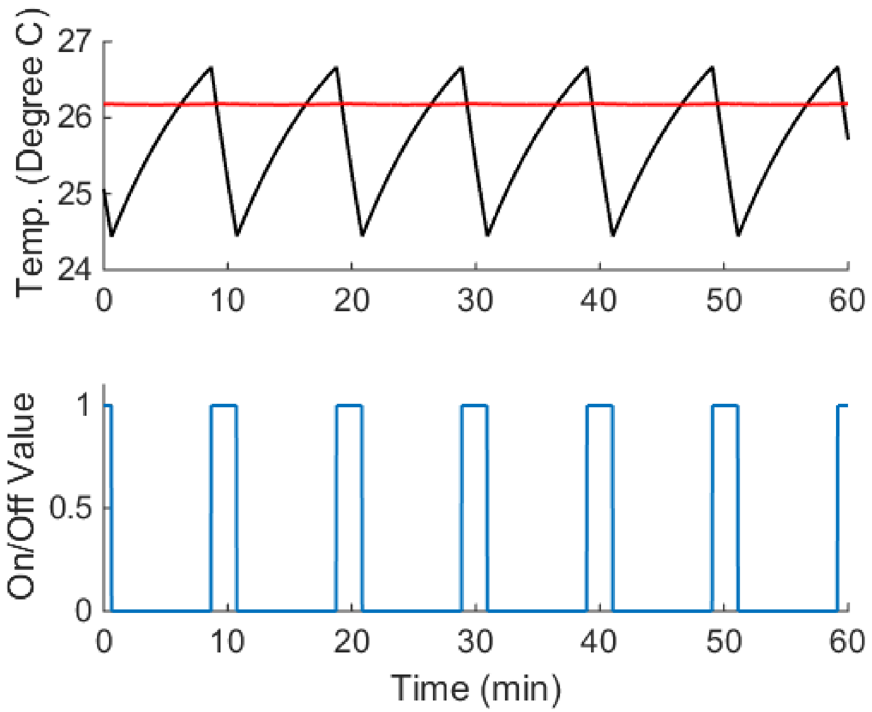
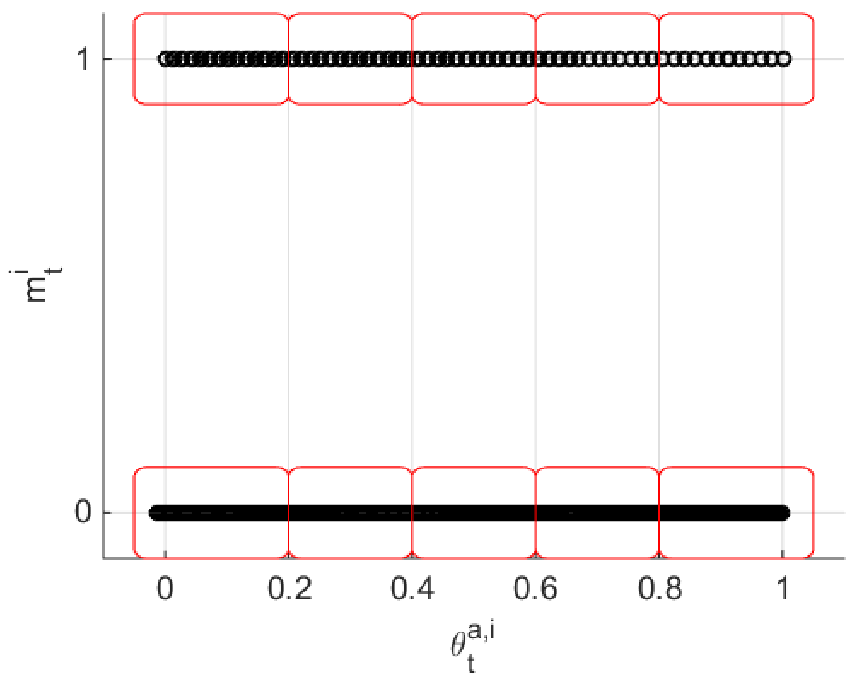
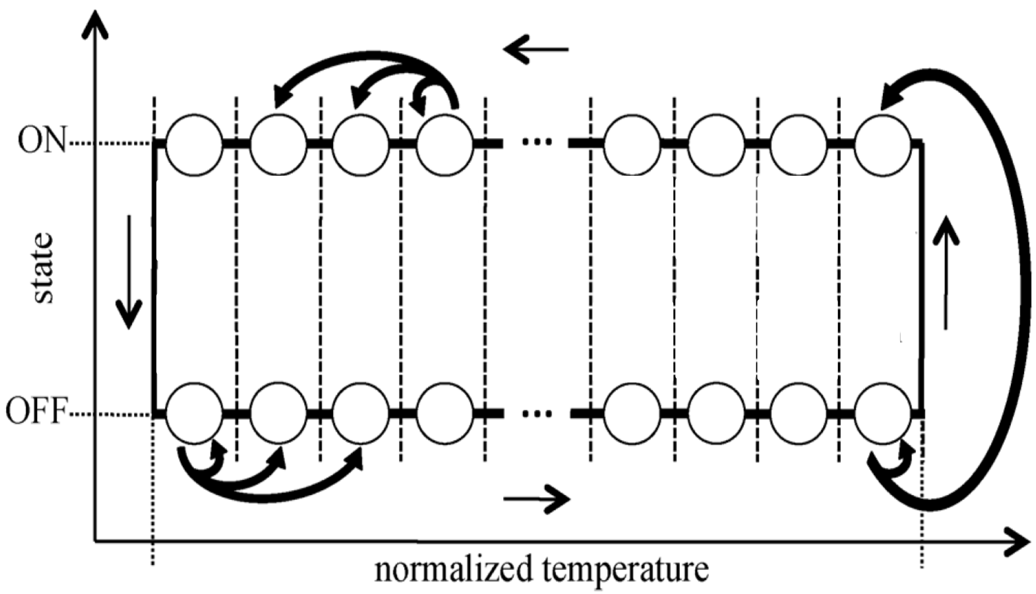


The internal air temperature and on/off mode of these models can be represented using a set of discrete states.





An aggregate model describes the probability of portions of the TCL population transitioning from one discrete state to another.



[Mathieu 2013]

Aggregate Model

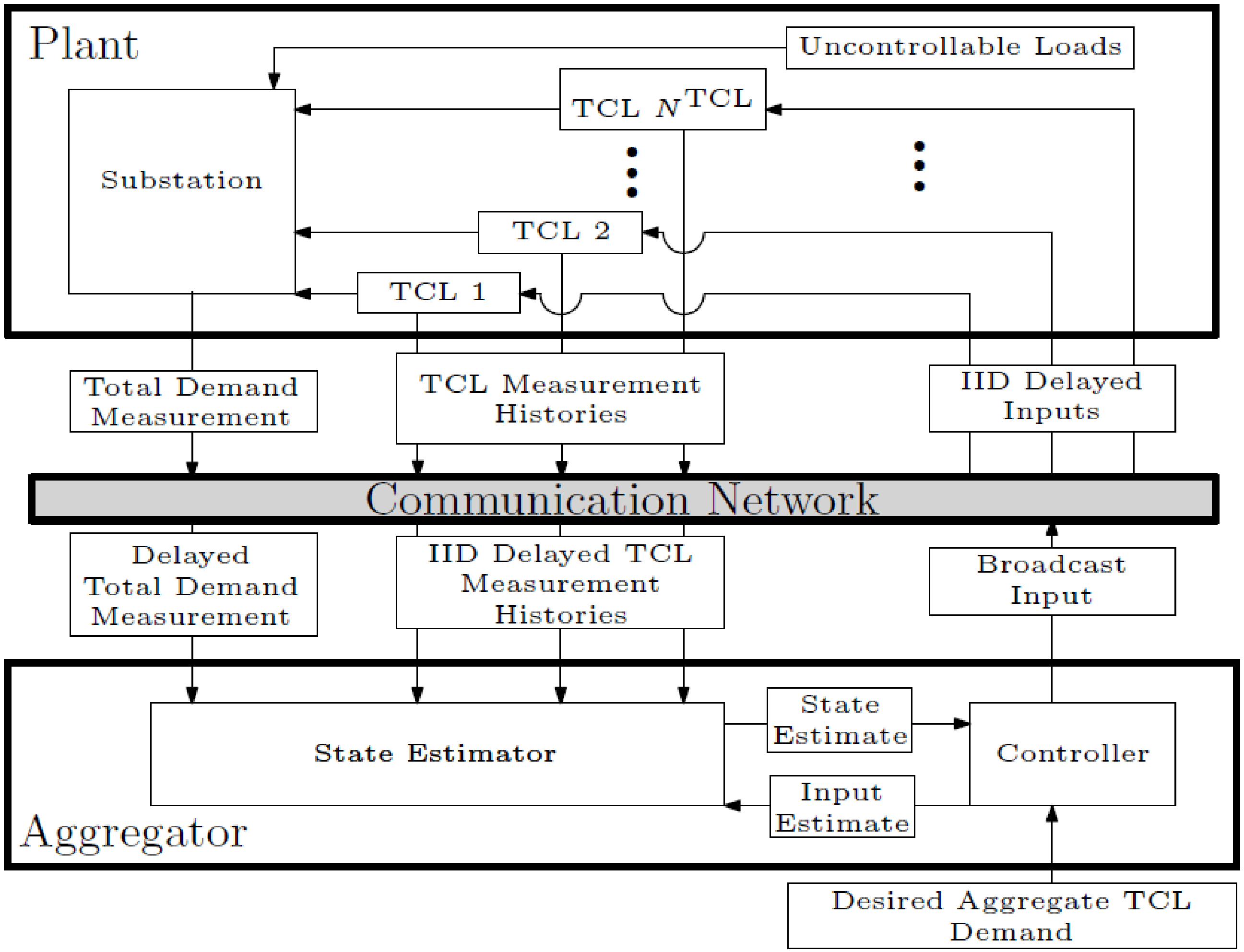
$$x_{k+1} = A\,x_k + B\,u_k$$
$$y_k = C\,x_k$$

Contents

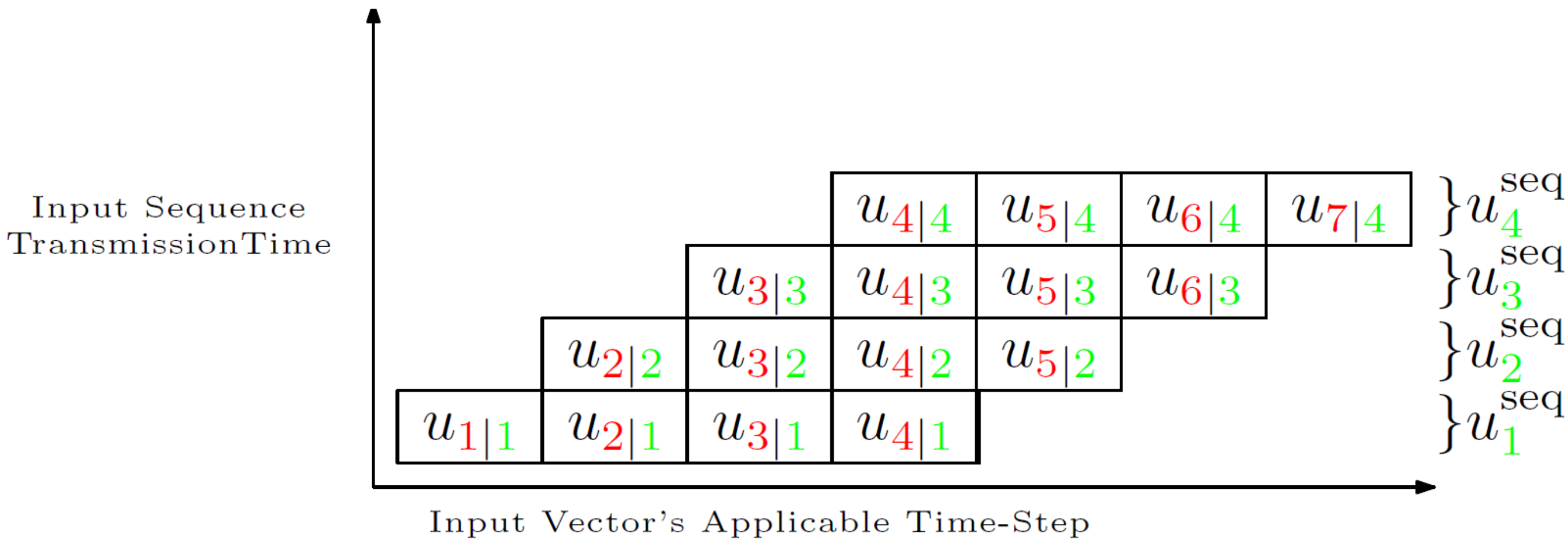
Enabling communication infrastructure may be present and working within its limitations can reduce the need for upgrades.

- Existing comm. infrastructure may exist [Eto 2012]
  - May have significant delays (e.g., 70 seconds)
- Smart meters have significant communication limitations [Armel 2013]
- Existing work investigates unavailable TCL measurements:
  - E.g., [Mathieu 2013, Borsche 2013, Vrettos 2014, Ghaffari 2015]
- [Hao 2014] investigates delays but does not compensate for them
- **Research goal:** design estimation and control algorithms that incorporate realistic delay information to mitigate the effects of delays

This work develops algorithms that mitigate the effects of communication delays by incorporating delay information.



At each time-step, we transmit an input sequence and allow TCLs to select an input based on the realized delays.



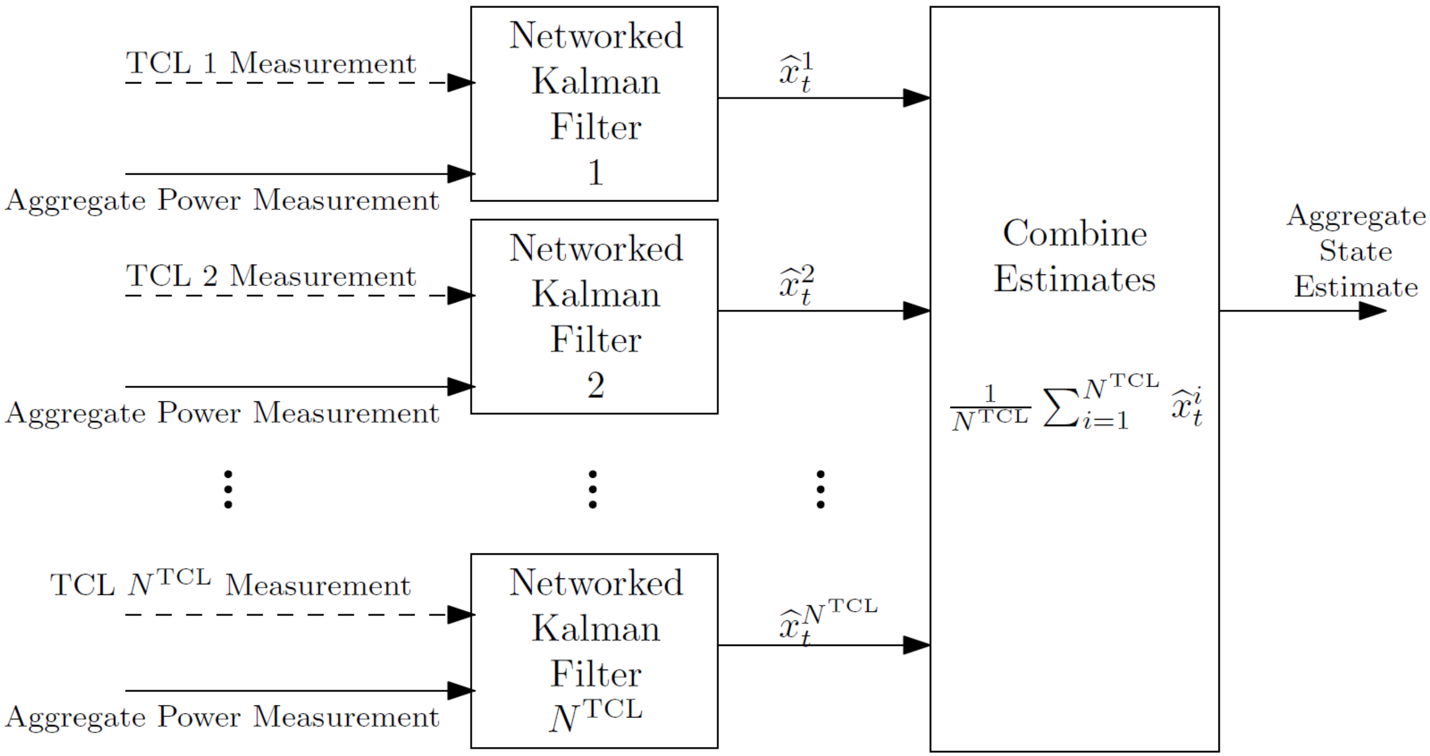
The controller is formulated as a quadratic program similar to a finite-horizon, tracking LQR with state and input constraints.

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

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

This work creates two state estimators that adapt a networked Kalman filter to the demand response scenario.

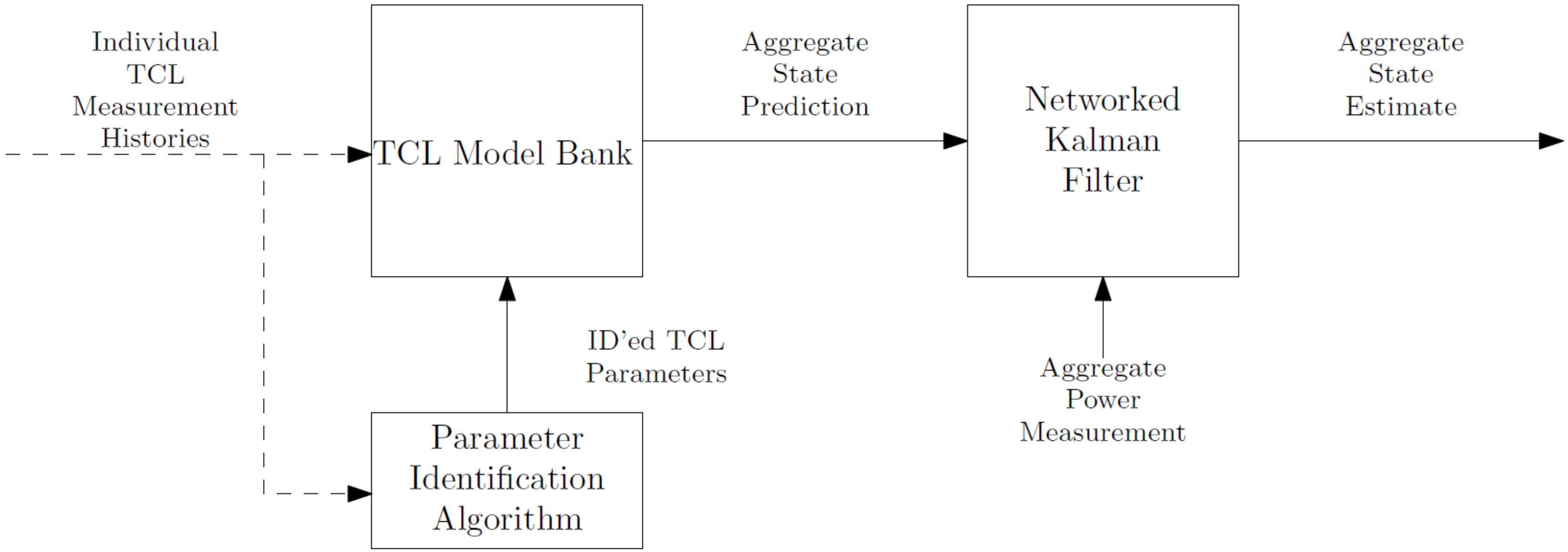
Estimator 1



The networked Kalman filter was developed in cite [Schenato 2007]

This work creates two state estimators that adapt a networked Kalman filter to the demand response scenario.

Estimator 2

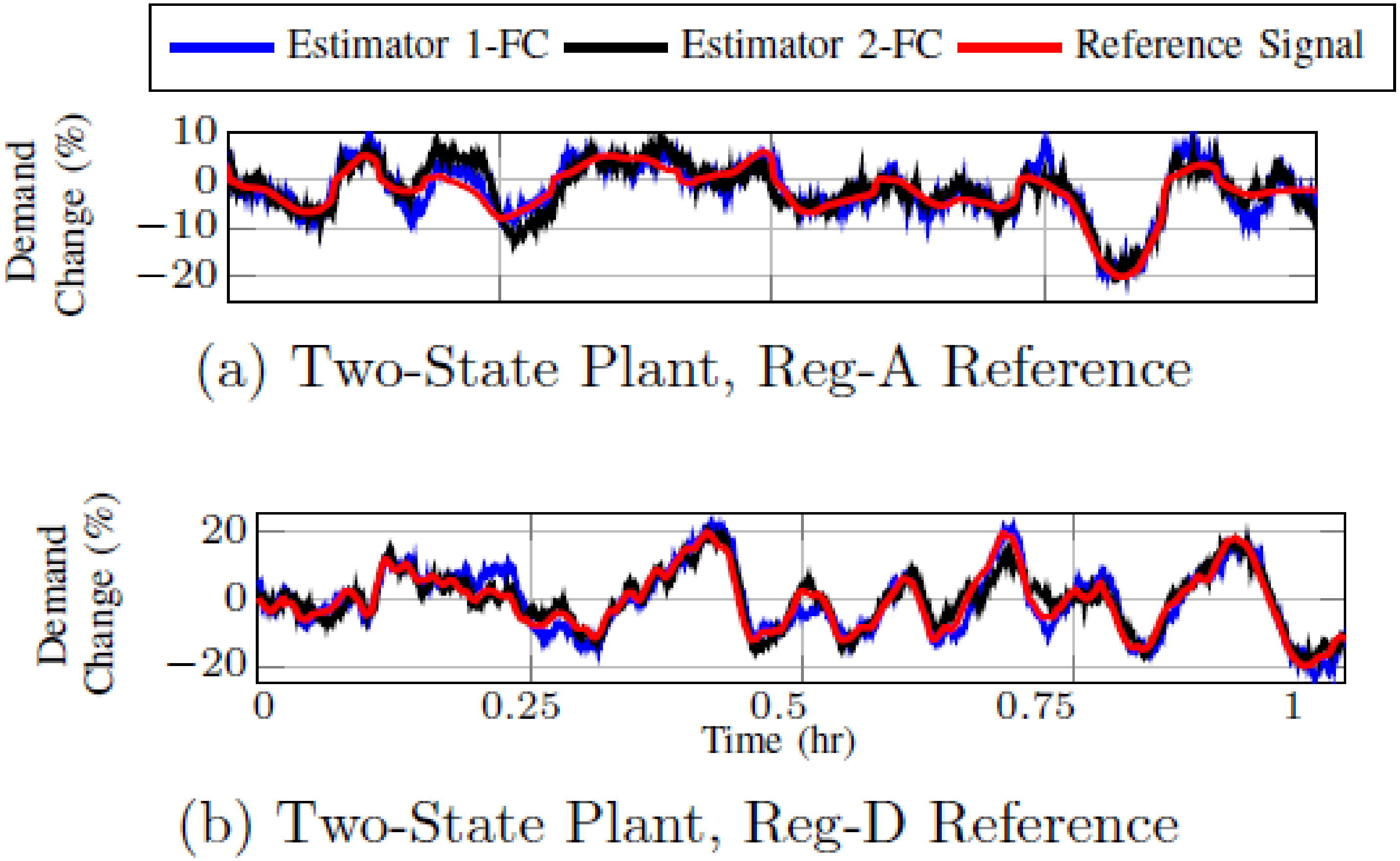


The networked Kalman filter was developed in cite [Schenato 2007]

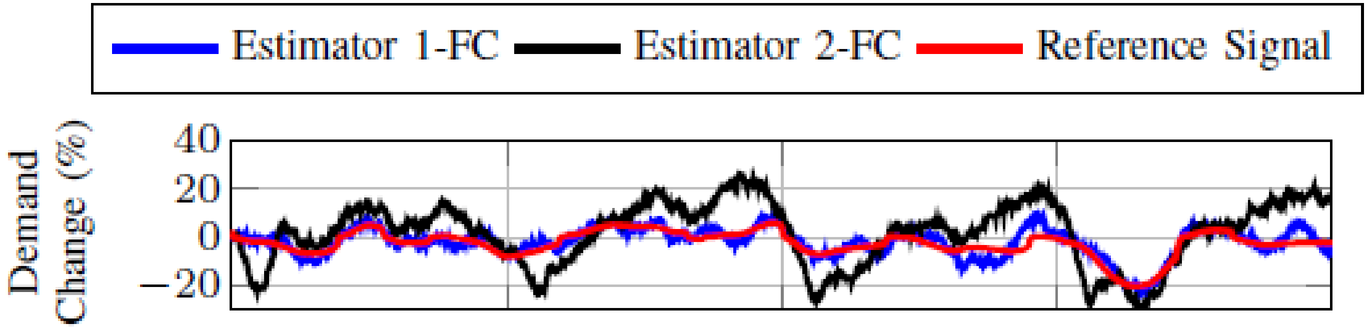
Case studies simulated 10,000 residential air conditioners with two second time-steps over an hour with a constant outdoor temperature.

- Simulate two variations of the plant
  - Two-state TCL model
  - Three-state TCL model
- Use three delay distributions
  - No delays
  - Average delays of 10 seconds with log-normal distribution
  - Average delays of 20 seconds with log-normal distribution
- Use three levels of delay compensation
  - No compensation (NC)
  - Time-stamping only (TS)
  - Full compensation (FC)
- Ten instances per case study

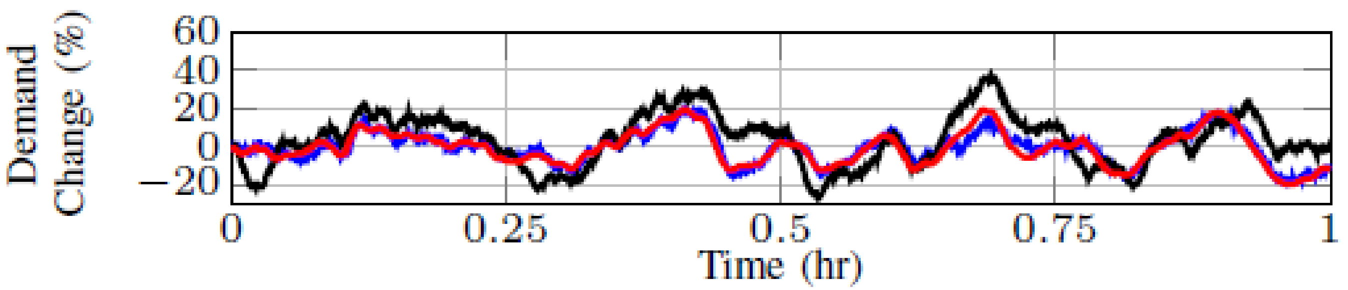
With average delays of 20 sec. and the two-state TCL model, both controller-estimator pairs track the references effectively.



With the three-state TCL model, only Estimator 1 achieves reasonable tracking, and Estimator 2 is less effective due to model mismatch.

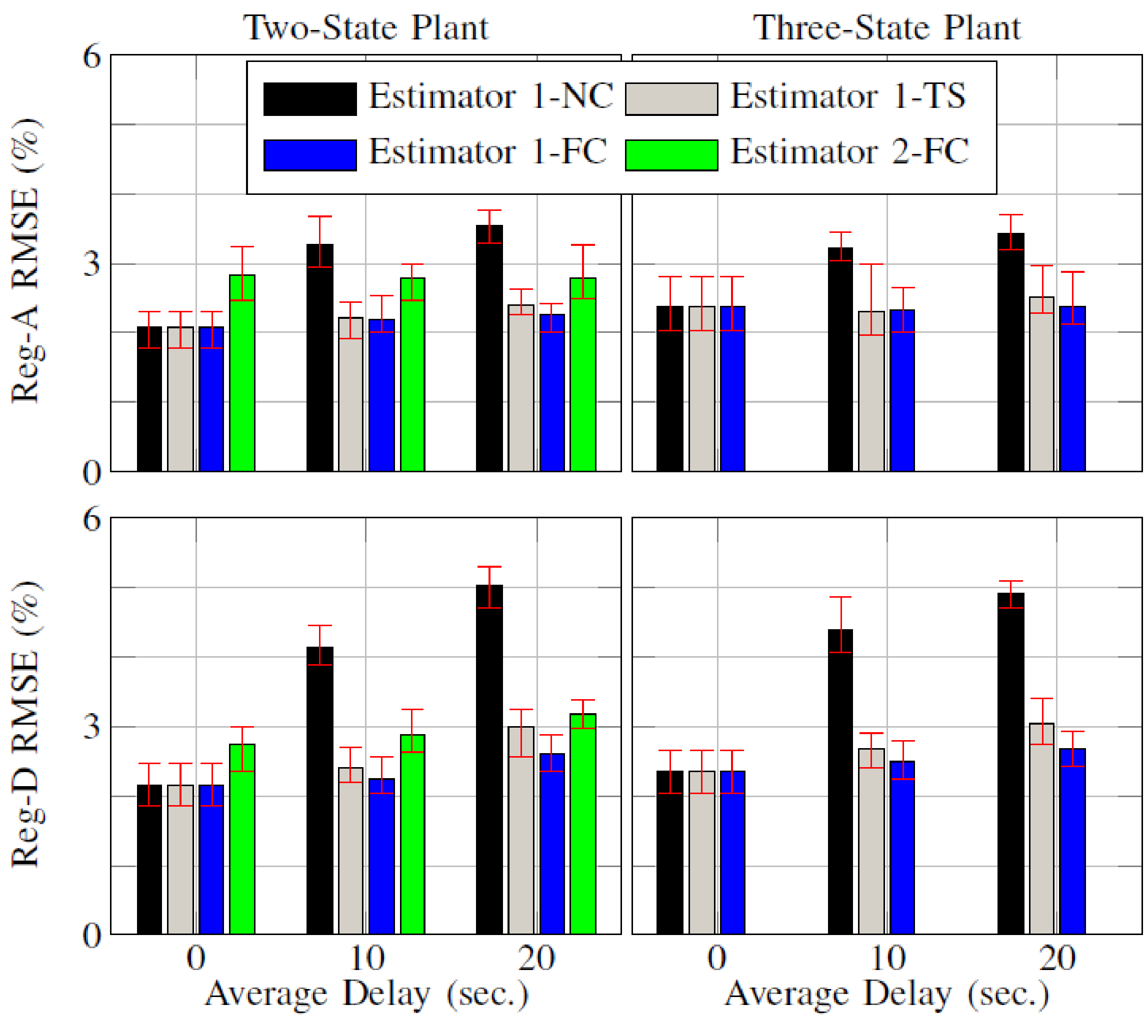


(c) Three-State Plant, Reg-A Reference



(d) Three-State Plant, Reg-D Reference

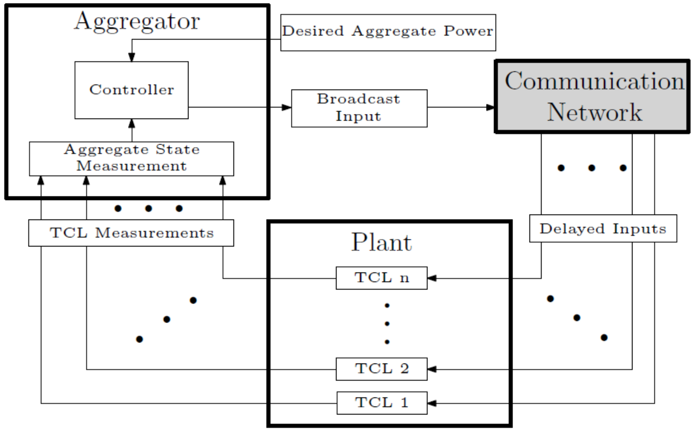
Accounting for the delays within the algorithms reduces the effects of the delays, and time-stamping alone is also effective.



In summary, this work developed a controller and two estimators to mitigate the effects of communication delays while investigating model mismatch.

- The controller-estimator pairs can effectively provide frequency regulation with average delays up to 20 seconds
- Results for Estimator 2 are heavily dependent on model accuracy

- Chapter 4 develops a simplified controller
  - Linear control law
  - Reduced computation
  - Minor reduction in tracking
    versus the MPC controller
    due to the exclusion of constraints



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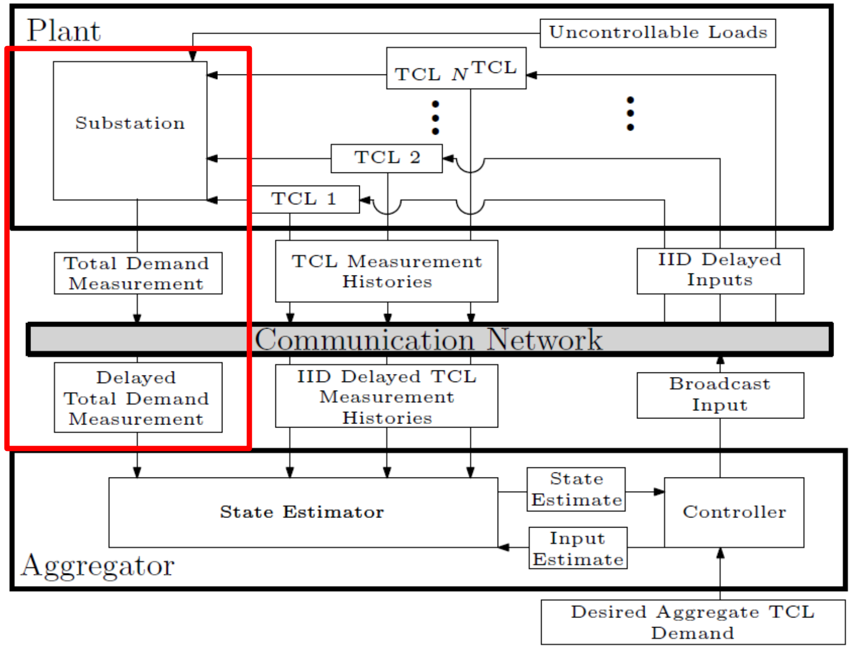
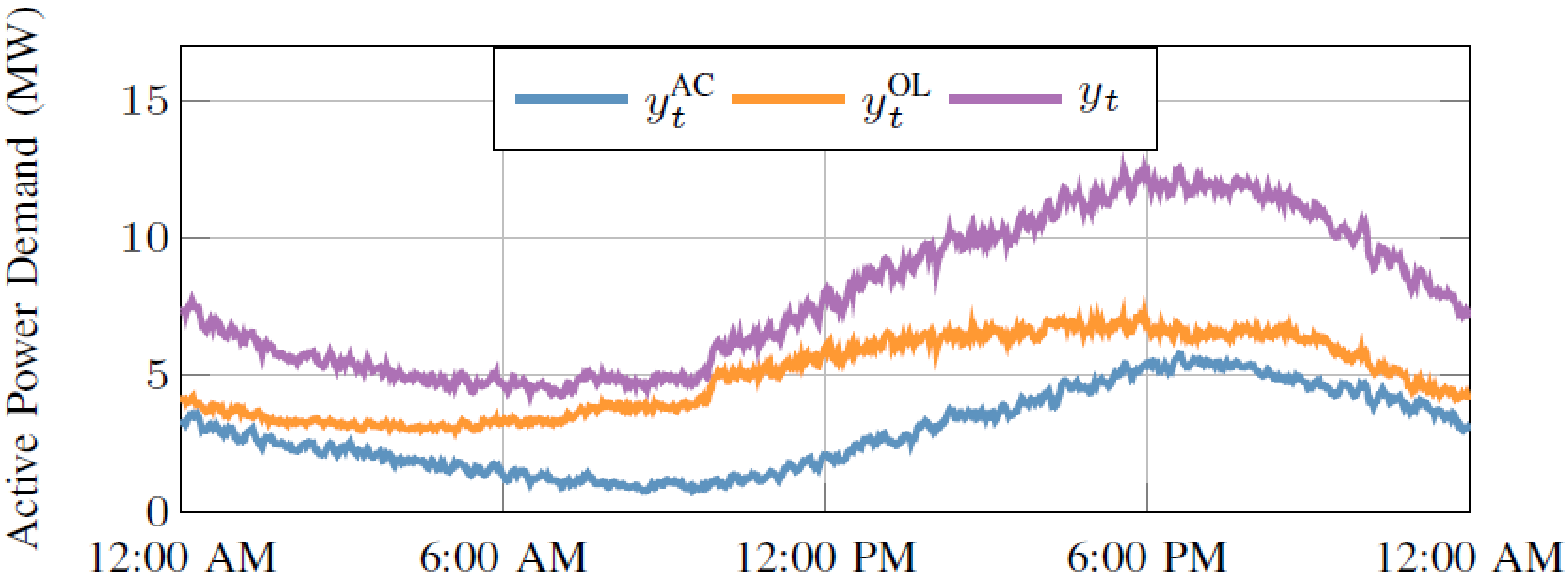
The previous work assumed that aggregate measurements of the demand-responsive load were available, but obtaining these in real-time is an open question.

- Building-level energy disaggregation is long-studied [Hart 1992]
- Could use many device-level sensors and fast communication ($$$)
- Could work within capabilities of distribution network sensors and smart meters ($$$)

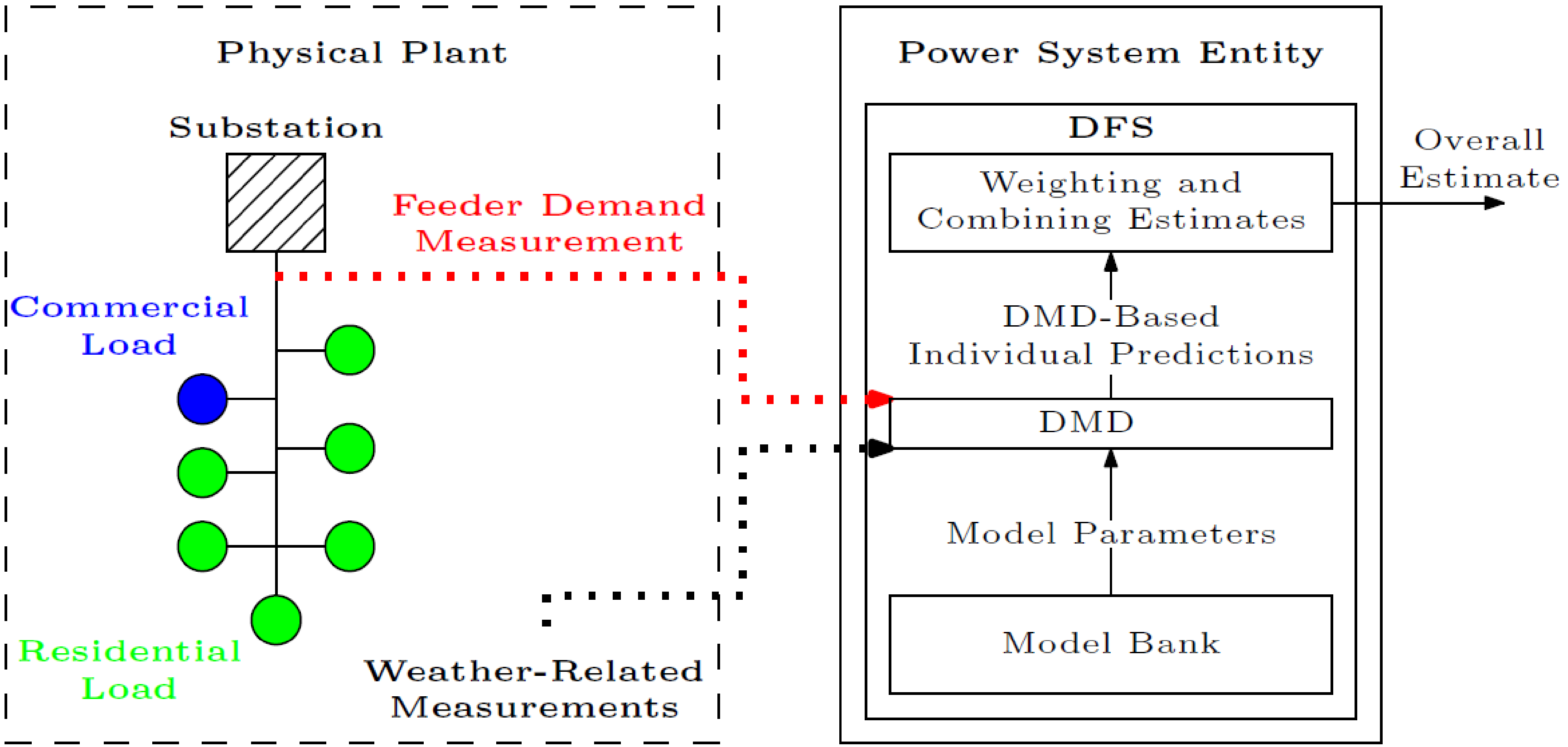


- Knowing real-time demand-responsive load provides
  - Feedback signal for controller
  - Information on capacity for bids into ancillary service markets

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

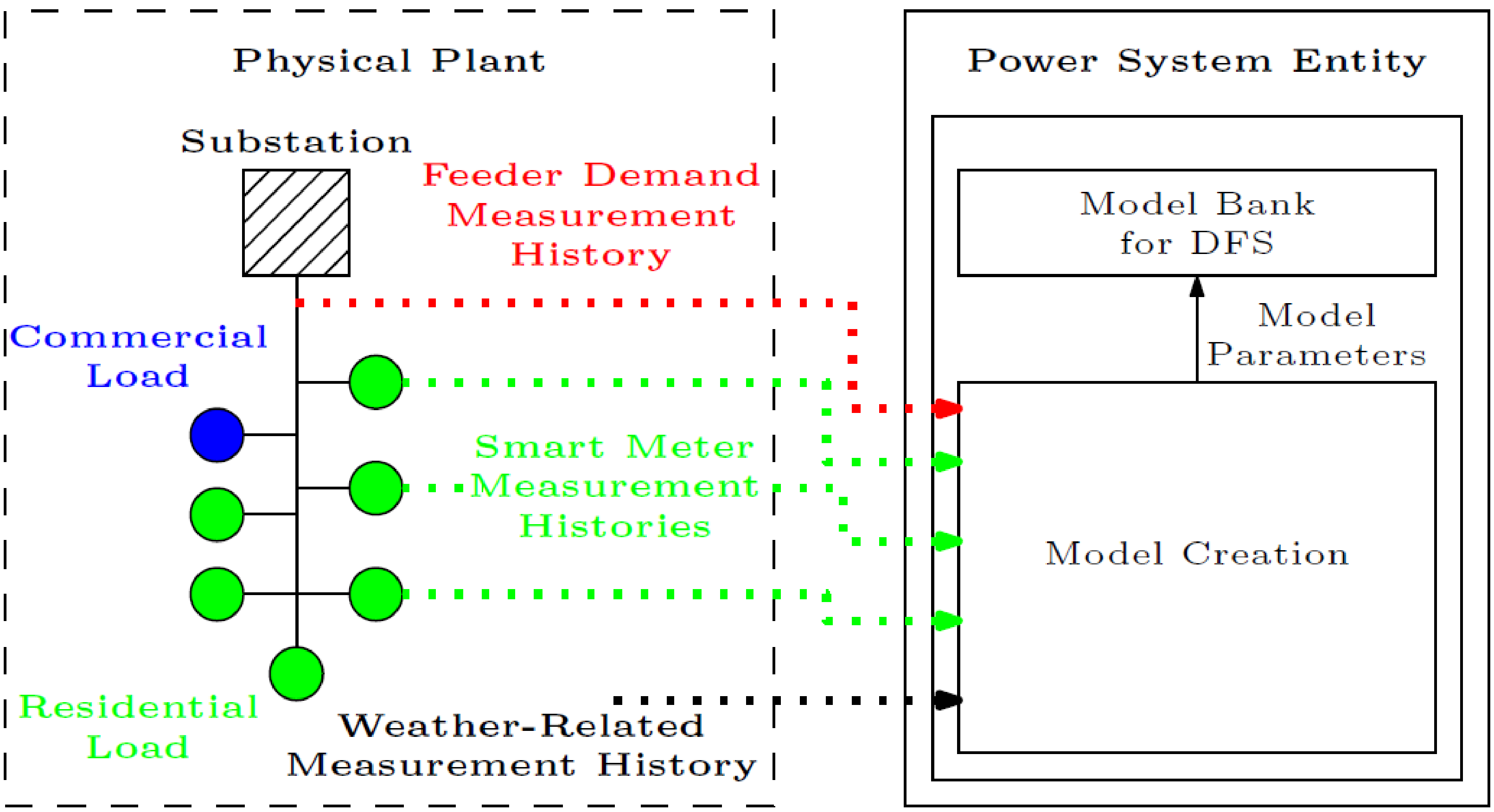


Energy disaggregation is performed on real-time demand measurements using Dynamic Fixed Share (DFS), an online learning algorithm.



(a) Real-time estimation mode

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

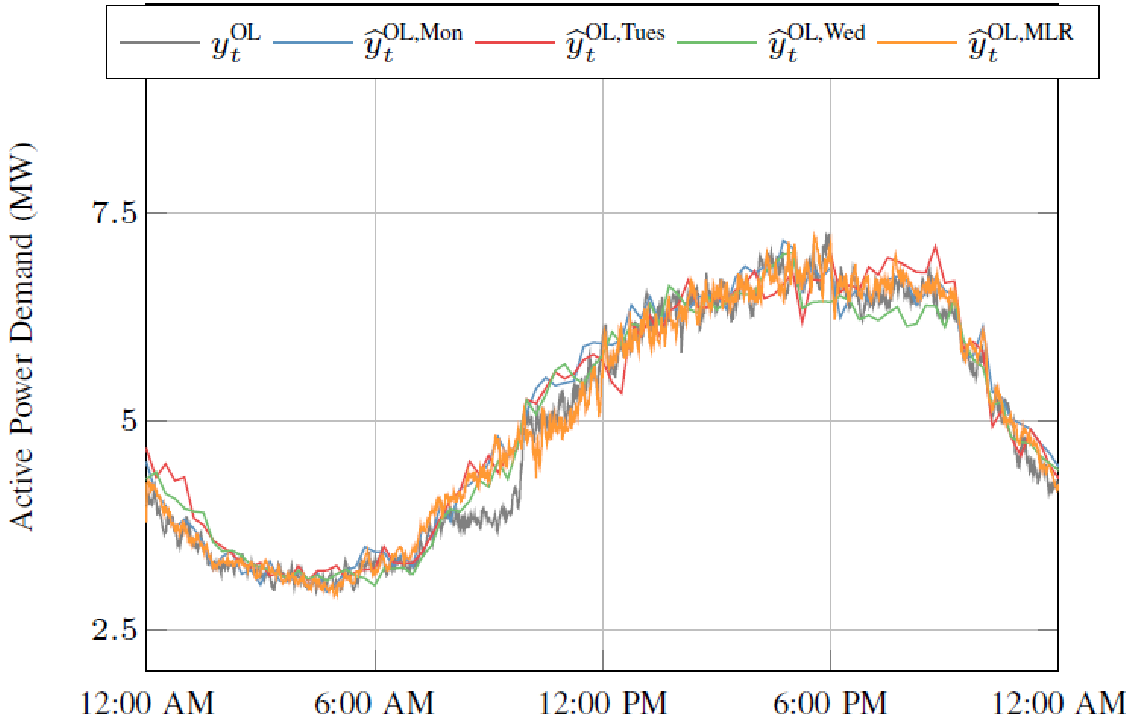


(b) Offline model generation mode

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

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

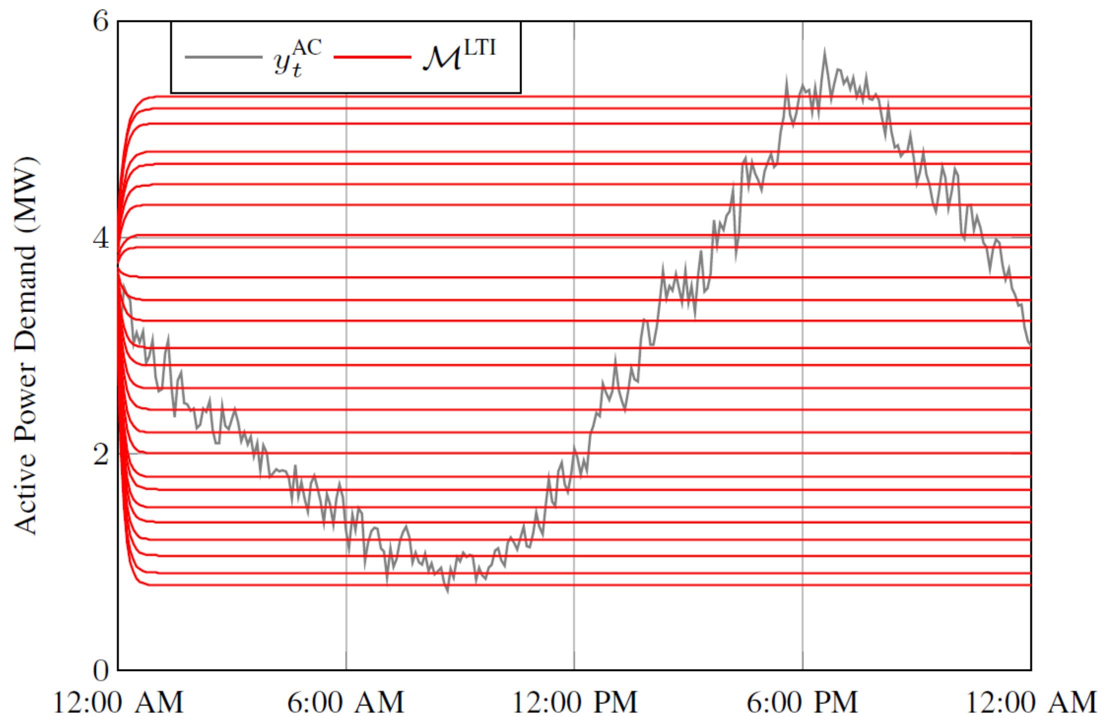
$$\begin{aligned}\widehat{y}_t^{\mathrm{OL,MLR}} &= \widehat{y}_t^{\mathrm{OL,res}} + \widehat{y}_t^{\mathrm{OL,com}} \\ &= \beta^{\mathrm{OL,res}} x_t^{\mathrm{OL,res}} + \gamma^{\mathrm{OL,com}} x_t^{\mathrm{OL,com}}\end{aligned}$$



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

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

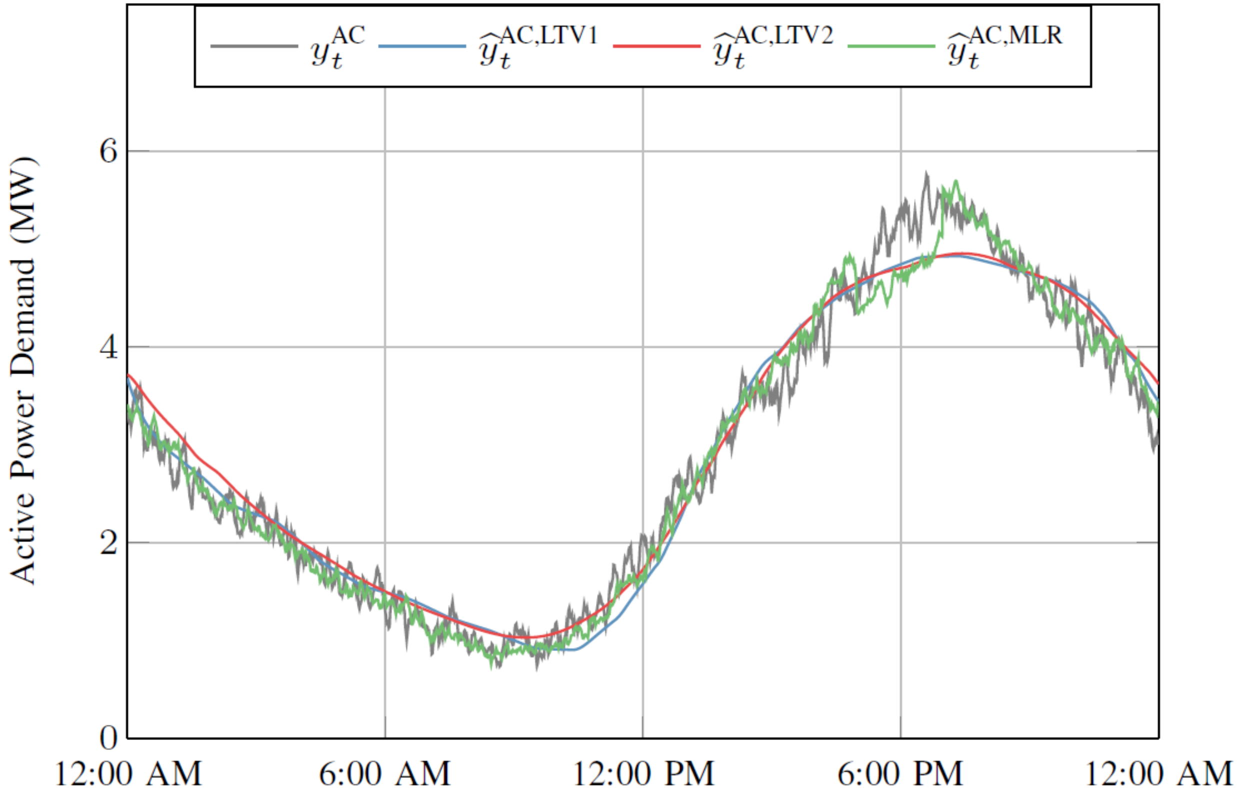
$$m \in \mathcal{M}^{\mathrm{LTI}} = \{1,\ldots,N^{\mathrm{LTI}}\}$$



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 (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]

Chapter 5 developed Dynamic Mirror Descent updates that were identical to those of a Kalman filter by appropriately choosing the loss and divergence functions.

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

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

$$\Downarrow$$

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

(See Chapter 5 for more details)

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]

Due to the different models used within this work, a modified version of DMD was developed that runs models in open-loop.

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

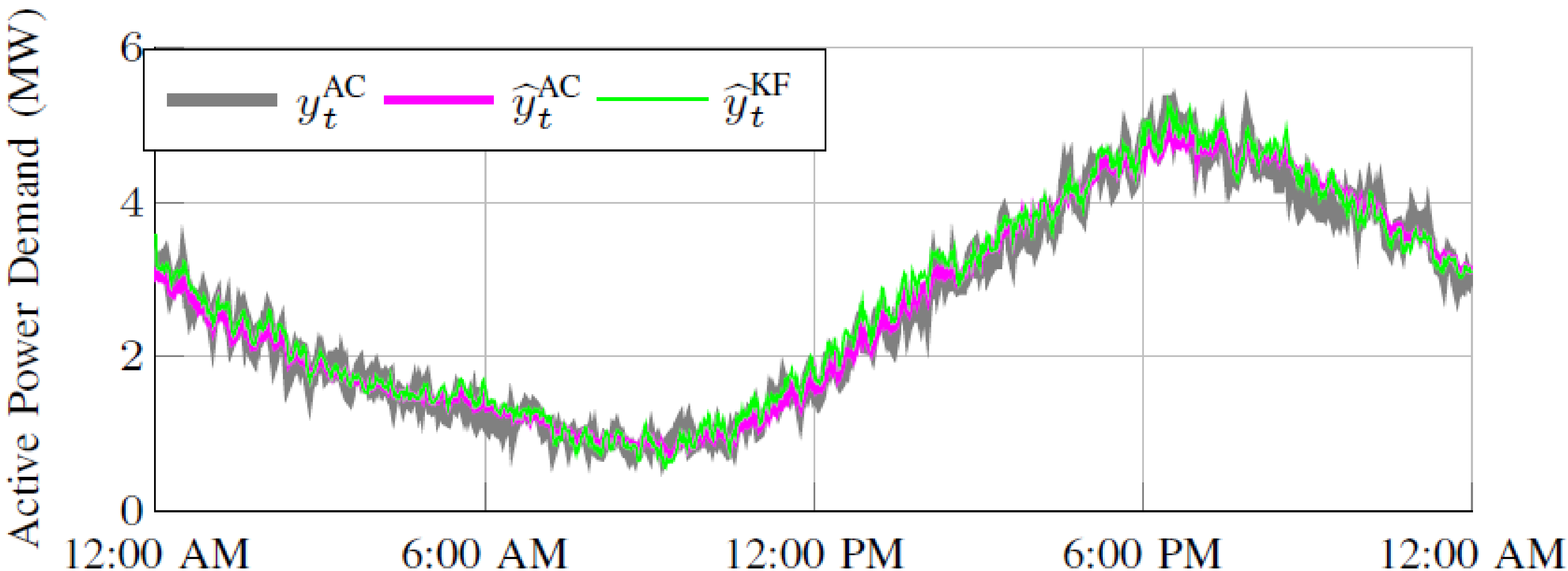
$$\check{\theta}_{t+1} = \Phi(\check{\theta}_t)$$

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

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
  - Commercial building data from PG&E
  - Residential building and device data from Pecan Street
- 10 separate “testing” days
- One minute time-steps
- Three model sets
  - $\mathcal{M}^{\text{Full}}$: all model combinations
  - $\mathcal{M}^{\text{Red}}$: model combinations excluding the LTI AC models
  - $\mathcal{M}^{\text{KF}}$: 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 $\mathcal{M}^{\text{KF}}$
  - Average Kalman filter: average of all filters from the set of models $\mathcal{M}^{\text{KF}}$

Running Dynamic Fixed Share with Update Method 1 and $\mathfrak{M}^{Red}$ effectively estimates the AC demand in real-time.



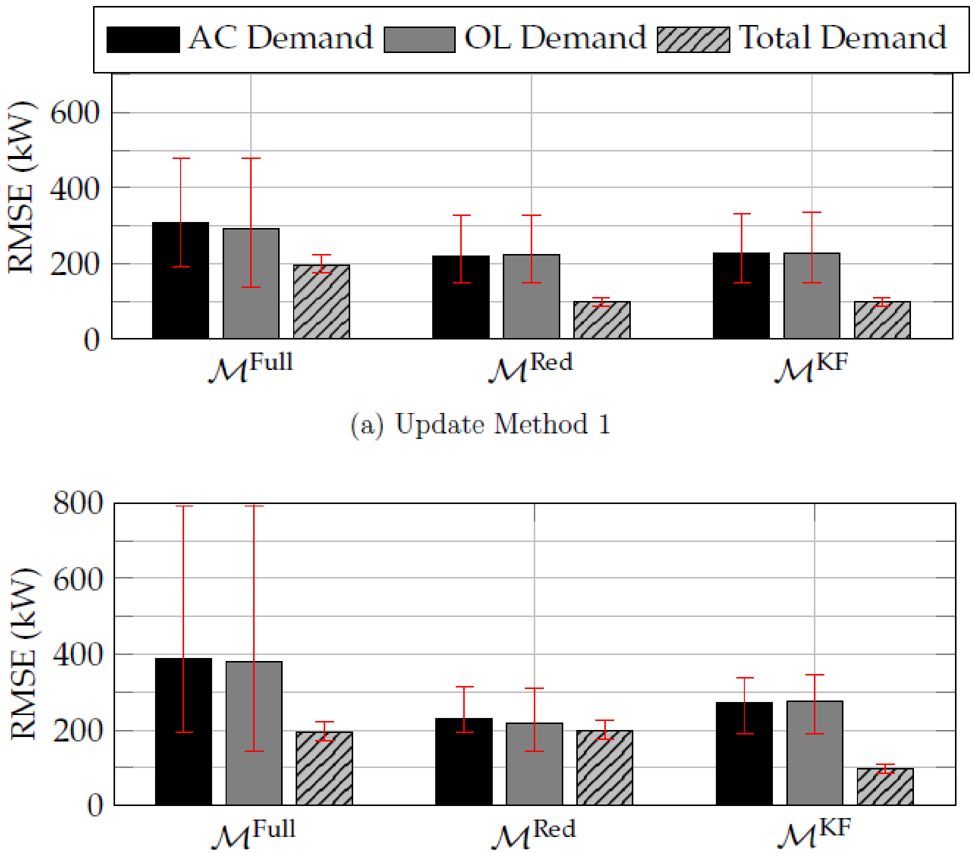
(c) AC Demand

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

<u>RMSE of the AC demand</u>

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

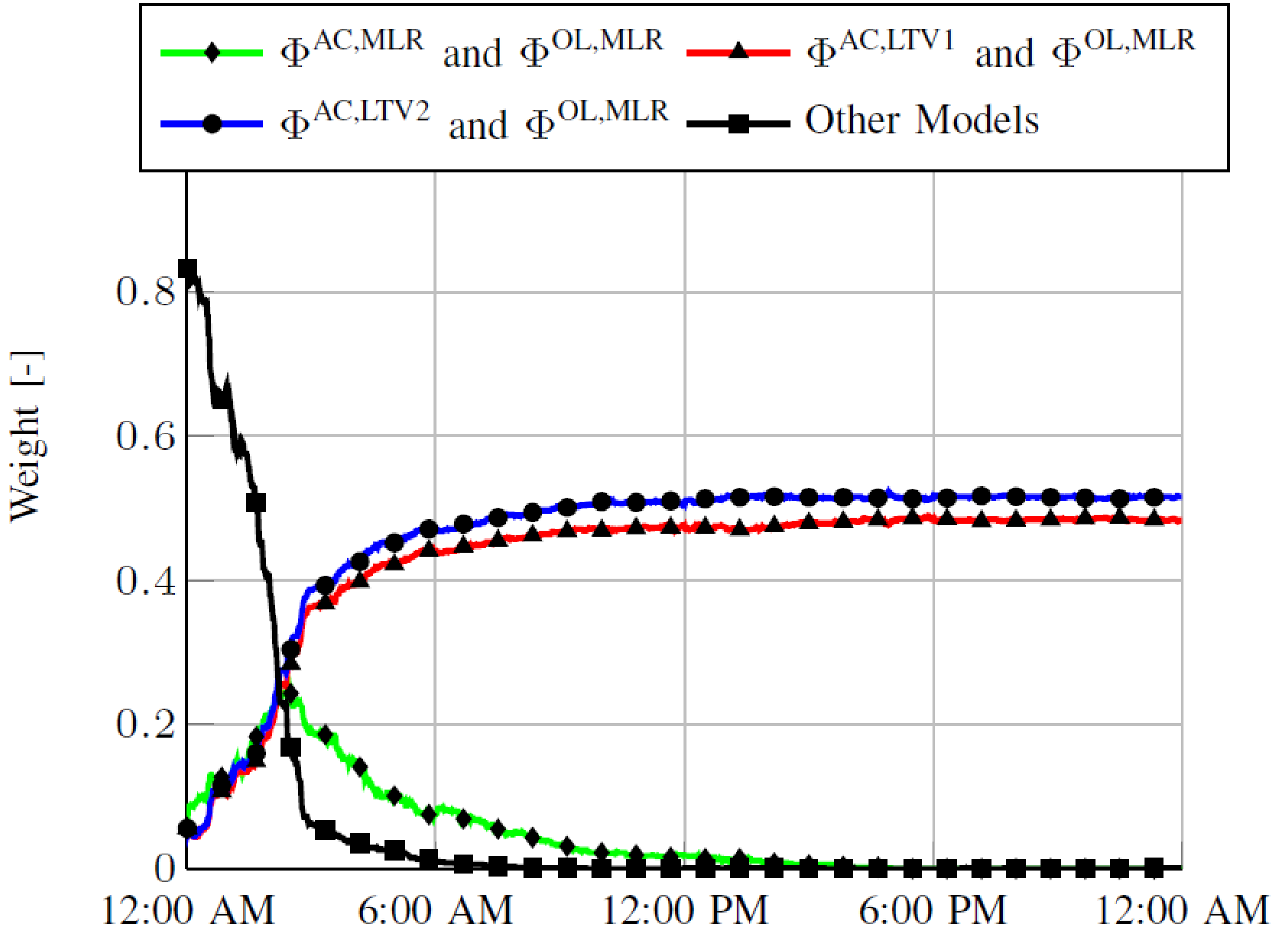
Average Kalman Filter:
- min = 173.1 kW
- mean = 259.4 kW
- max = 357.5 kW



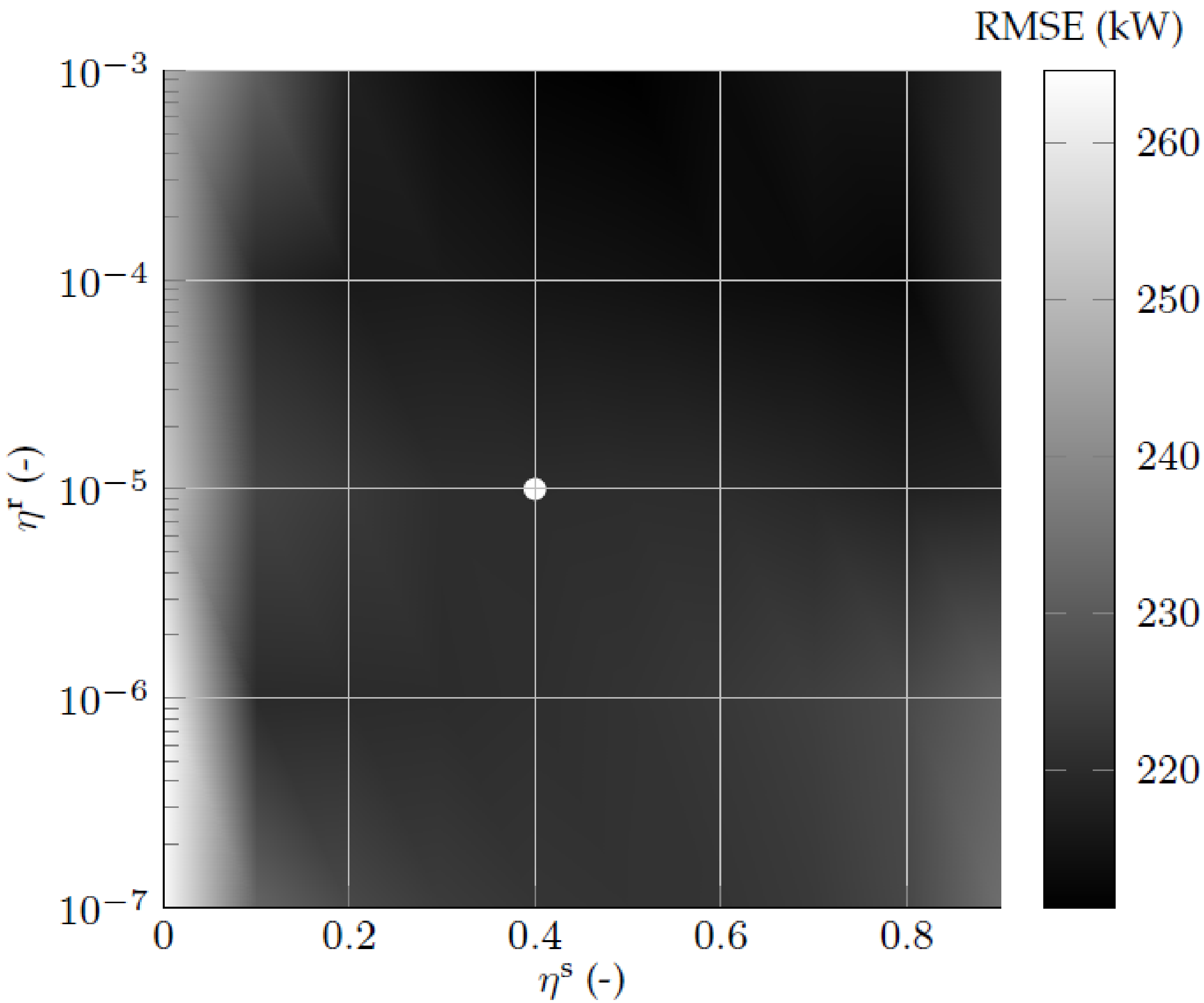
(a) Update Method 1

(b) Update Method 2

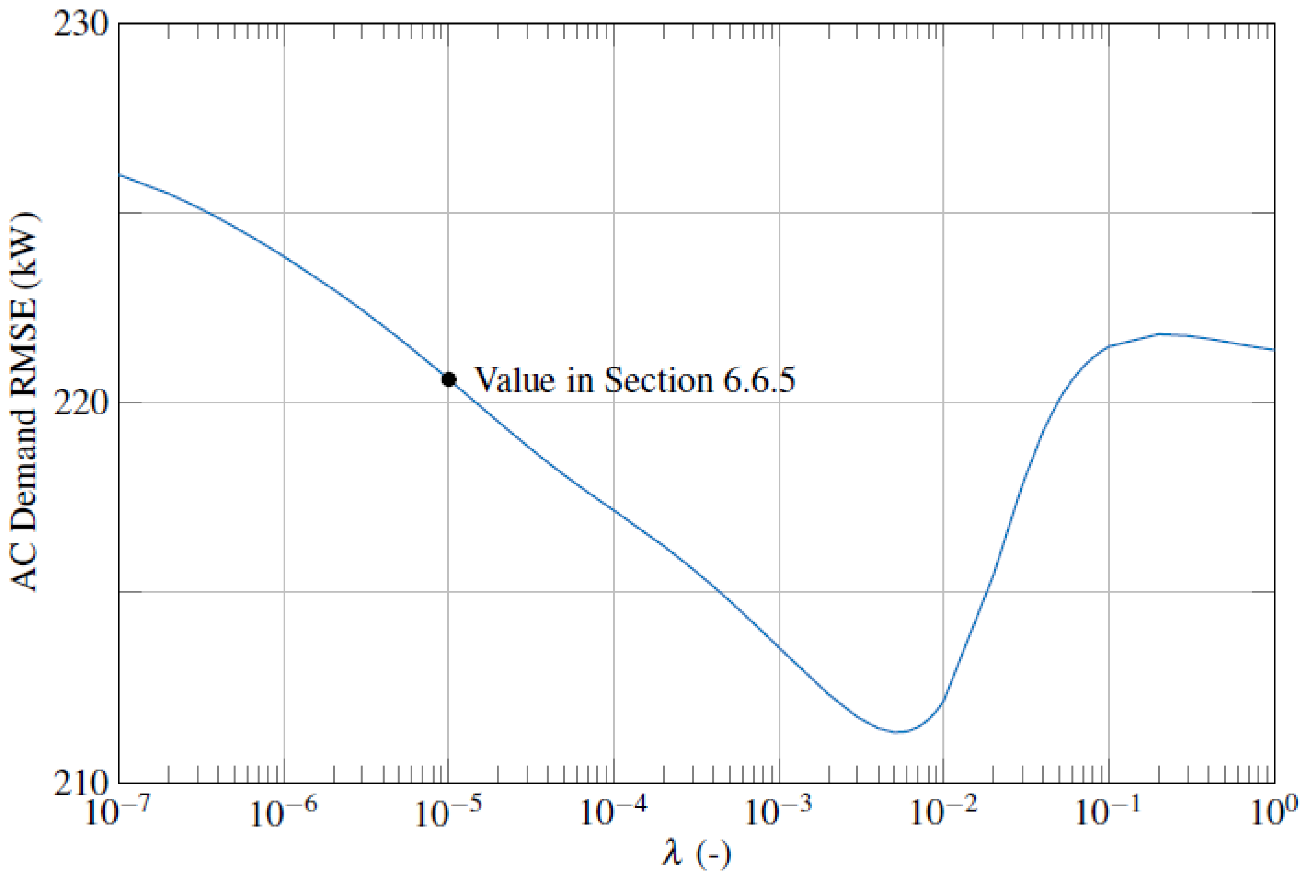
Time series of model weights indicating the most accurate (available) model is a combination of two candidate models.



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.



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



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

- DFS can effective perform the disaggregation problem
- Models within DFS strongly influence performance
- DFS achieved lower AC demand RMSE than AKF
- DFS achieves higher AC demand RMSE than BKF
- Further parameter tuning may improve results

- Additional results include different estimation error covariances within the DMD formulation, which is greatly influences the performance of DFS

Contents

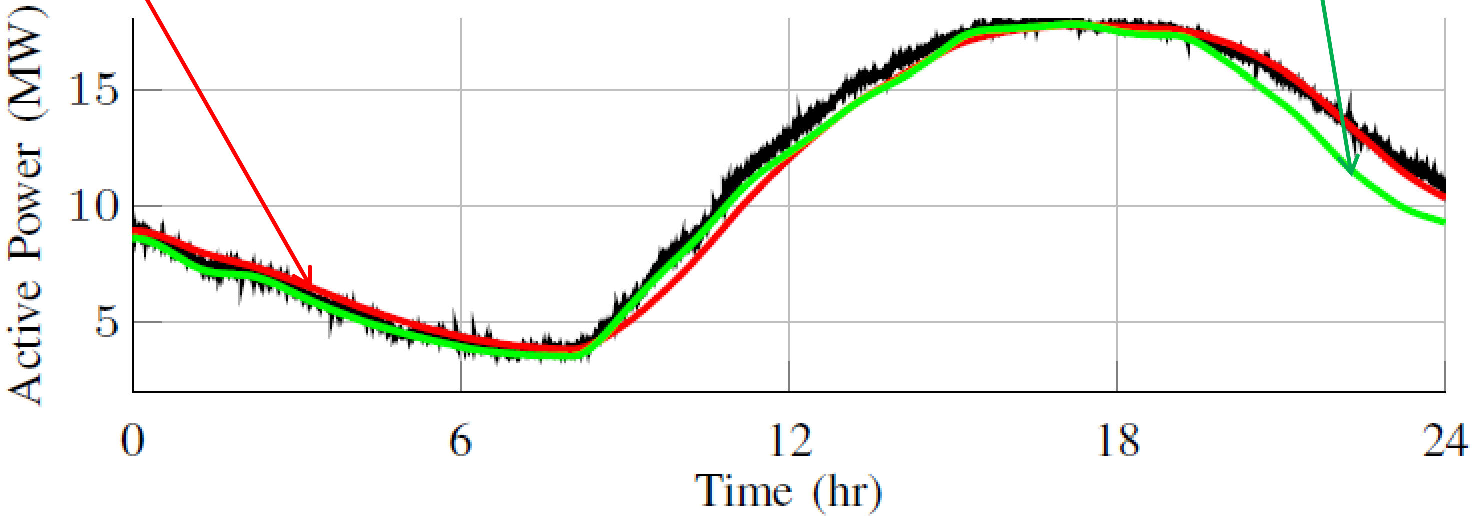
The first avenue of future work aims to benchmark existing aggregate models in a common simulation case study.

Temperature- Dependent Markov Model

$$x_{t+1} = A_t x_t$$
$$y_t = C_t x_t$$

Transfer Function Model [Mahdavi 2016]

$$x_{t+1} = A^{\mathrm{TF}}\, x_t + \left(T_t^{\mathrm{o}} - T_0^{\mathrm{o}}\right)$$
$$y_t = C^{\mathrm{TF}}\, x_t + y_0$$



The second avenue incorporates reactive power and voltage measurements into the energy disaggregation problem.

$$y_t = \begin{bmatrix} P_t^{\text{feeder}} \\ Q_t^{\text{feeder}} \end{bmatrix} = \begin{bmatrix} P_t^{\text{AC}} + P_t^{\text{OL}} \\ Q_t^{\text{AC}} + Q_t^{\text{OL}} \end{bmatrix}$$

$$\psi^i = \frac{P^i}{\sqrt{(P^i)^2 + (Q^i)^2}}$$

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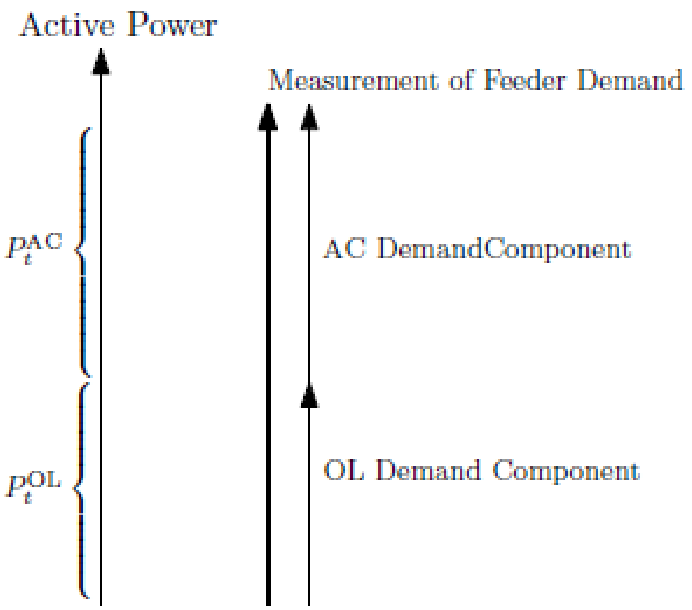

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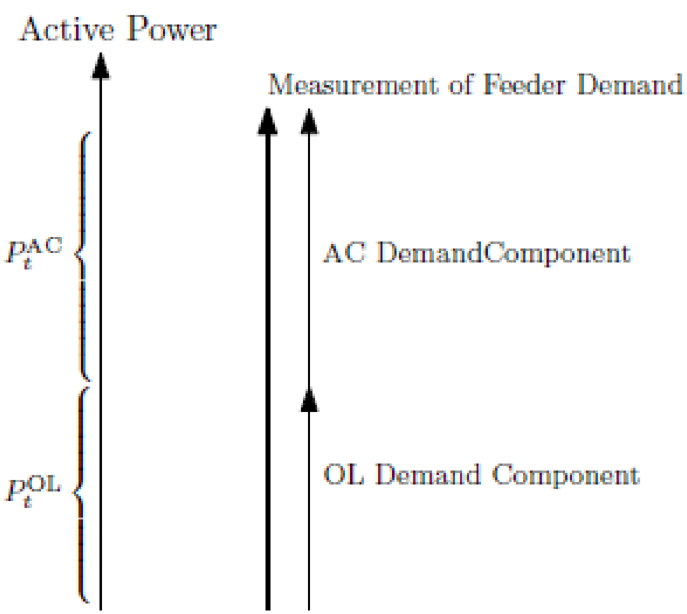

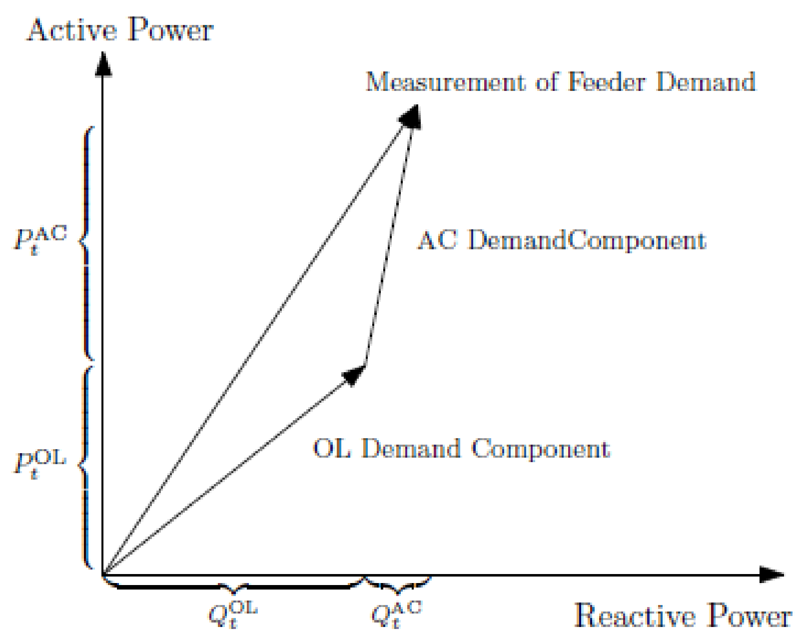

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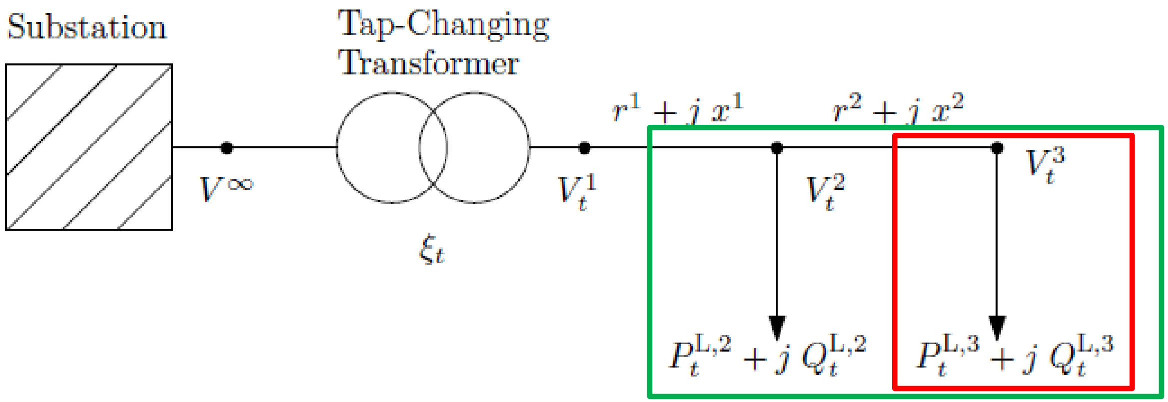
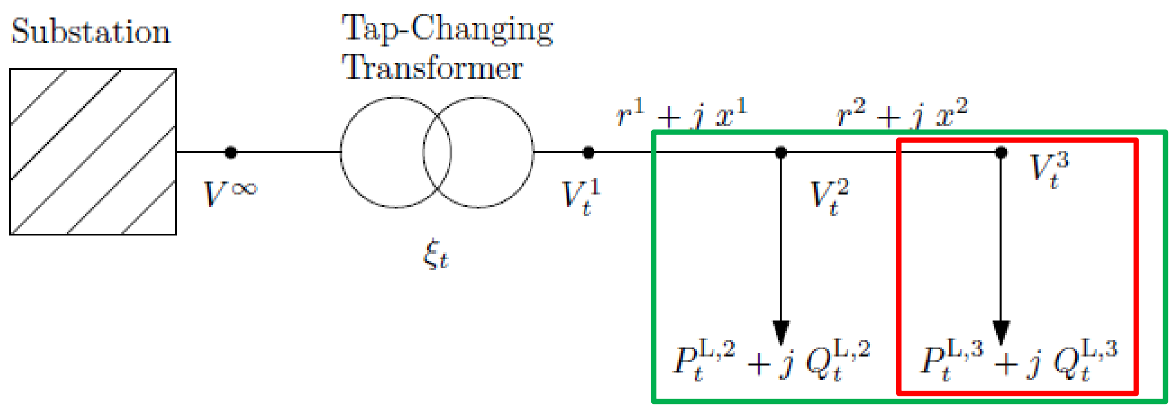
$$y_t = \begin{bmatrix} P_t^{\text{feeder}} \\ Q_t^{\text{feeder}} \\ V_t^{\text{feeder}} \\ V_t^{\text{nodes}} \end{bmatrix}$$



Future Work (3/4)

The second avenue incorporates reactive power and voltage measurements into the energy disaggregation problem.

$$y_t = \begin{bmatrix} P_t^{\text{feeder}} \\ Q_t^{\text{feeder}} \\ V_t^{\text{feeder}} \\ V_t^{\text{nodes}} \end{bmatrix}$$



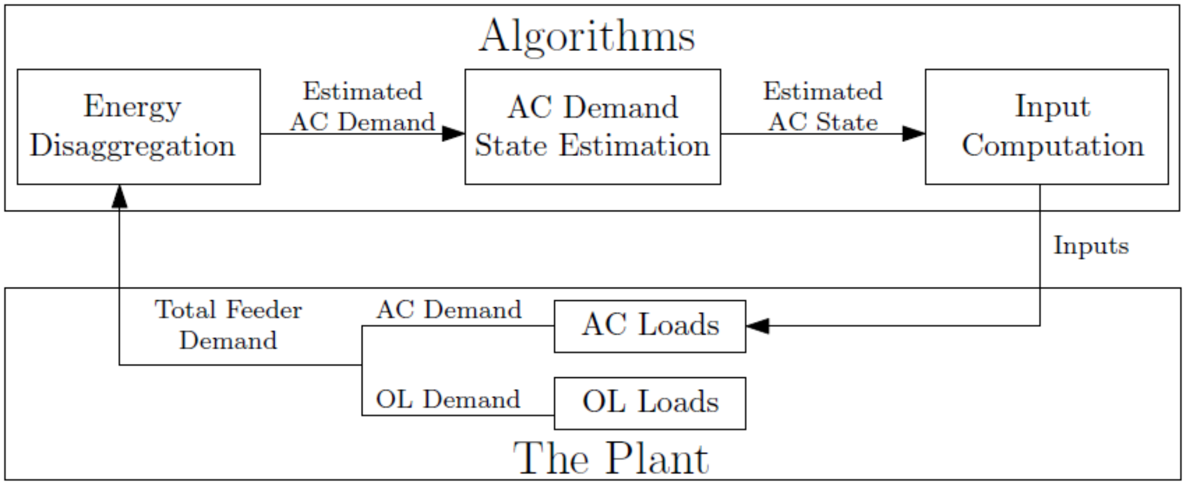
$$P_t^{k+1} = P_t^k - r^k \left(\frac{(P_t^k)^2 + (Q_t^k)^2}{(V_t^k)^2} \right) - P_t^{\text{L},k}$$

$$Q_t^{k+1} = Q_t^k - x^k \left(\frac{(P_t^k)^2 + (Q_t^k)^2}{(V_t^k)^2} \right) - Q_t^{\text{L},k}$$

$$V_t^{k+1} = V_t^k - 2(r^k\, P_t^k + x^k\, Q_t^k) + ((r^k)^2 + (x^k)^2)\, \frac{(P_t^k)^2 + (Q_t^k)^2}{(V_t^k)^2}$$

The DistFlow equations were developed in [Baran 1989]

The third avenue also incorporates active control of the AC load within the energy disaggregation problem.



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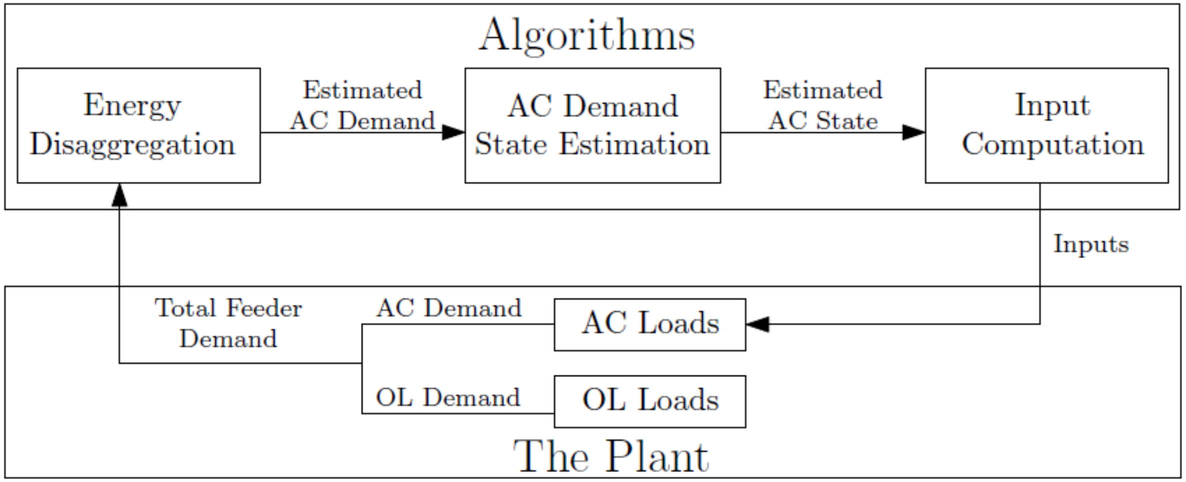
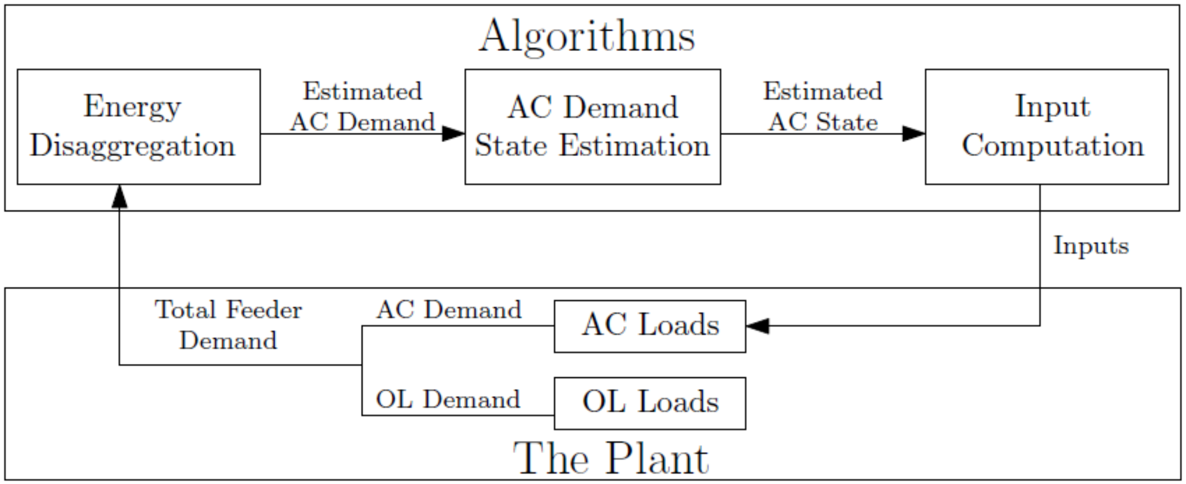


$$\begin{aligned} \underset{u_t}{\text{minimize}} \quad & (y_t - y_t^{\text{des}})^T \; Y \; (y_t - y_t^{\text{des}}) + u_t^T \; U \; u_t \\ \text{subject to} \quad & y_t = f(x_t, u_t) \\ & y_t^{\text{des}} = y_t^{\text{ref}} + \Delta y_t. \end{aligned}$$

The third avenue also incorporates active control of the AC load within the energy disaggregation problem.



$$
\begin{aligned}
\underset{u_t}{\text{minimize}} \quad & (y_t - y_t^{\text{des}})^T \, Y \, (y_t - y_t^{\text{des}}) + u_t^T \, U \, u_t \\
\text{subject to} \quad & y_t = f(x_t, u_t) \\
& y_t^{\text{des}} = y_t^{\text{ref}} + \Delta y_t .
\end{aligned}
$$

$$
\begin{aligned}
\underset{u_t}{\text{minimize}} \quad & (y_t - y_t^{\text{ref}})^T \, Y \, (y_t - y_t^{\text{red}}) + u_t^T \, U \, u_t + \alpha^T \, C_t \, \alpha \\
\text{subject to} \quad & y_t = f(x_t, u_t)
\end{aligned}
$$

References

1. U.S. Department of Energy, “Benefits of demand response in electricity markets and recommendations for achieving them," U.S. Department of Energy, Tech. Rep., February 2006.
2. Callaway, Duncan S. "Tapping the energy storage potential in electric loads to deliver load following and regulation, with application to wind energy." Energy Conversion and Management 50.5 (2009): 1389-1400.
3. Mathieu, Johanna L., Stephan Koch, and Duncan S. Callaway. "State estimation and control of electric loads to manage real-time energy imbalance." IEEE Transactions on Power Systems 28.1 (2013): 430-440.
4. C. Chong and A. Debs, “Statistical synthesis of power system functional load models," in Decision and Control including the Symposium on Adaptive Processes, 1979 18th IEEE Conference on, vol. 18. IEEE, 1979, pp. 264{269.
5. R. C. Sonderegger, “Dynamic models of house heating based on equivalent thermal parameters,” 1978.
6. Hall, Eric C., and Rebecca M. Willett. "Online convex optimization in dynamic environments." *IEEE Journal of Selected Topics in Signal Processing* 9.4 (2015): 647-662.
7. Herbster, Mark, and Manfred K. Warmuth. "Tracking the best expert." Machine Learning 32.2 (1998): 151-178.
8. Baran, Mesut E., and Felix F. Wu. "Network reconfiguration in distribution systems for loss reduction and load balancing." *IEEE Transactions on Power delivery* 4.2 (1989): 1401-1407.
9. Mahdavi, Nariman, Julio H. Braslavsky, and Cristian Perfumo. "Mapping the effect of ambient temperature on the power demand of populations of air conditioners." *IEEE Transactions on Smart Grid* (2016).
10. Schenato, Luca. "Optimal sensor fusion for distributed sensors subject to random delay and packet loss." *IEEE Conference on Decision and Control*. IEEE, 2007.
11. Hart, George William. "Nonintrusive appliance load monitoring." Proceedings of the IEEE 80.12 (1992): 1870-1891.
12. Eto, Joseph H., et al. "The Demand Response Spinning Reserve Demonstration--Measuring the Speed and Magnitude of Aggregated Demand Response." System Science (HICSS), 2012 45th Hawaii International Conference on. IEEE, 2012.
13. Armel, K. Carrie, et al. "Is disaggregation the holy grail of energy efficiency? The case of electricity." Energy Policy 52 (2013): 213-234.
14. Hao, He, et al. "Frequency regulation from flexible loads: Potential, economics, and implementation." American Control Conference (ACC), 2014. IEEE, 2014.
15. Borsche, Theodor, Frauke Oldewurtel, and Goran Andersson. "Minimizing communication cost for demand response using state estimation." PowerTech (POWERTECH), 2013 IEEE Grenoble. IEEE, 2013.
16. Vrettos, Evangelos, Johanna L. Mathieu, and Goran Andersson. "Control of thermostatic loads using moving horizon estimation of individual load states." Power Systems Computation Conference (PSCC), 2014. IEEE, 2014.
17. Ghaffari, Azad, Scott Moura, and Miroslav Krstic. "PDE-based modeling, control, and stability analysis of heterogeneous thermostatically controlled load populations." Journal of Dynamic Systems, Measurement, and Control (2015).