9^{th} Seminar for the Next Generation of Researchers in Power Systems

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Lab: The Michigan Power and Energy Lab (MPEL)

University: The University of Michigan (UofM)

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Part I: General Background

UofM is located roughly 30 minutes from Detroit, MI; 16K graduate and 30K undergraduate students enrolled.

- ECE in 2016:
  - **759** graduate students (283 PhD)
  - **69** faculty
  - **$36.5M** in research
    - 70 Invention Disclosures
    - 41 US Patents
    - 6 Licenses

Profs Mathieu and Hiskens are interested in uncertainty, distributed energy resources, and stability in power systems.

- **Johanna Mathieu**

  - » Demand response
    - respecting distribution network constraints, improving power system stability margins, investigating environmental impacts, investigating energy efficiency impact on buildings
    - Taking into account communication and sensing limitations
  - » Energy storage
    - environmental impacts, multitasking and aggregation
  - » Stochastic optimal power flow

- **Ian Hiskens**

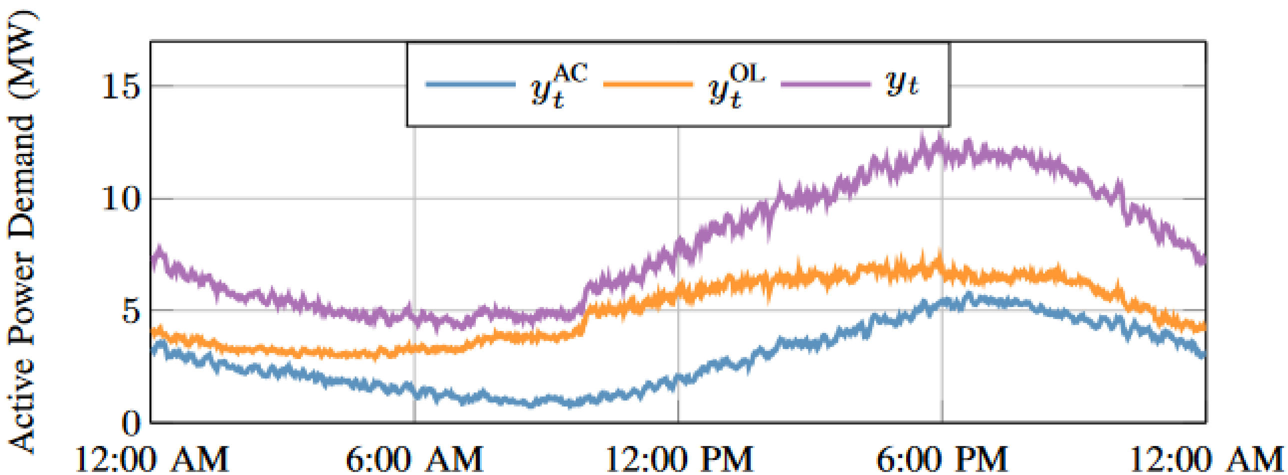
  - » Stochastic optimal power flow
  - » Grid integration of renewable generation
  - » Stability boundaries for nonlinear systems.
  - » Fast-acting, non-disruptive demand response
  - » Dynamical systems with uncertainties

Part II: Research Presentation

"Real-Time Energy Disaggregation of a Distribution Feeder's Demand Using Online Learning" [1]

[1] Ledva et al. 2017. (Under Review). Available on Arxiv

The goal is to separate demand measurements for a distribution feeder into components as they arrive



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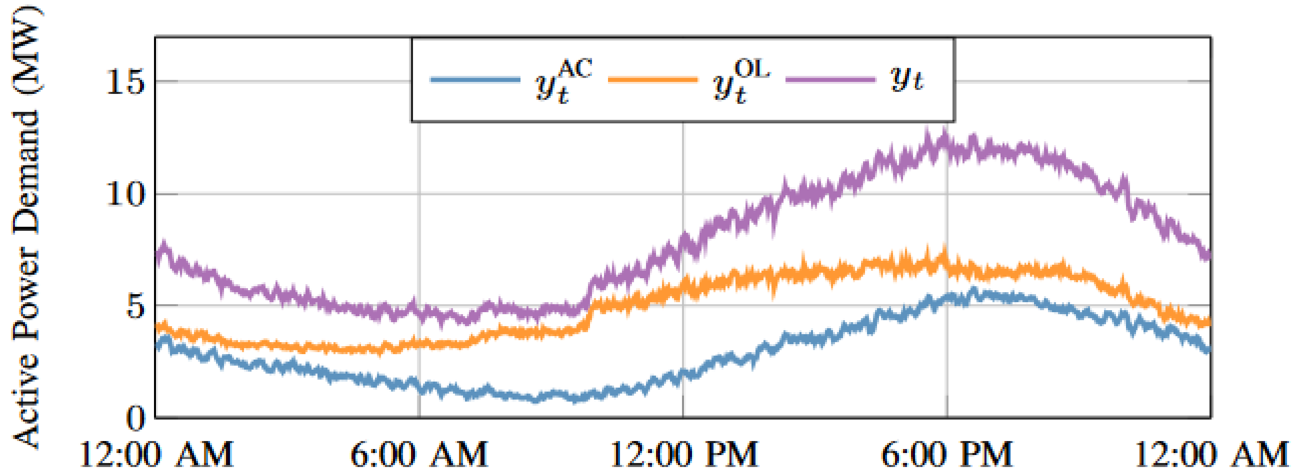

Why is this useful?

- Inform balancing reserve requirements
- Plan demand response actions
- Inform real-time demand response capacity
- Feedback signal for demand response

“Real-Time Energy Disaggregation of a Distribution Feeder’s Demand Using Online Learning” [1]

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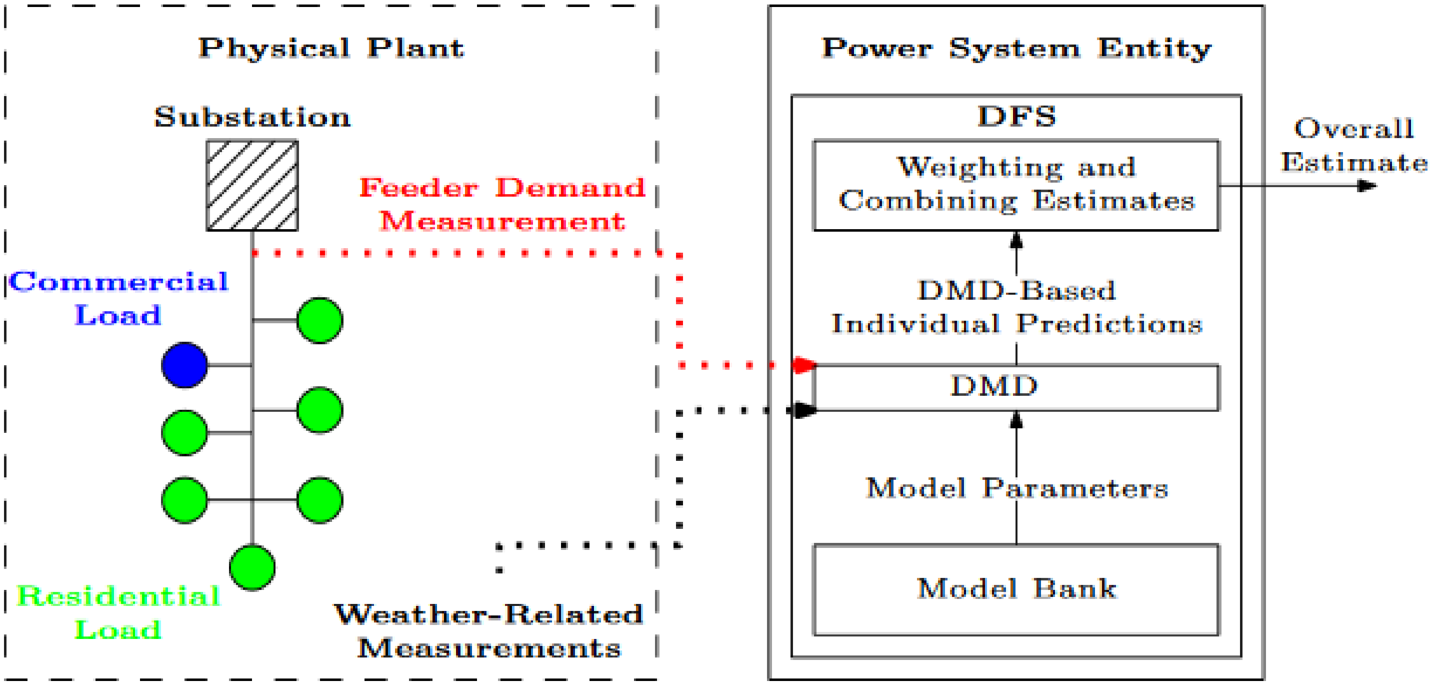
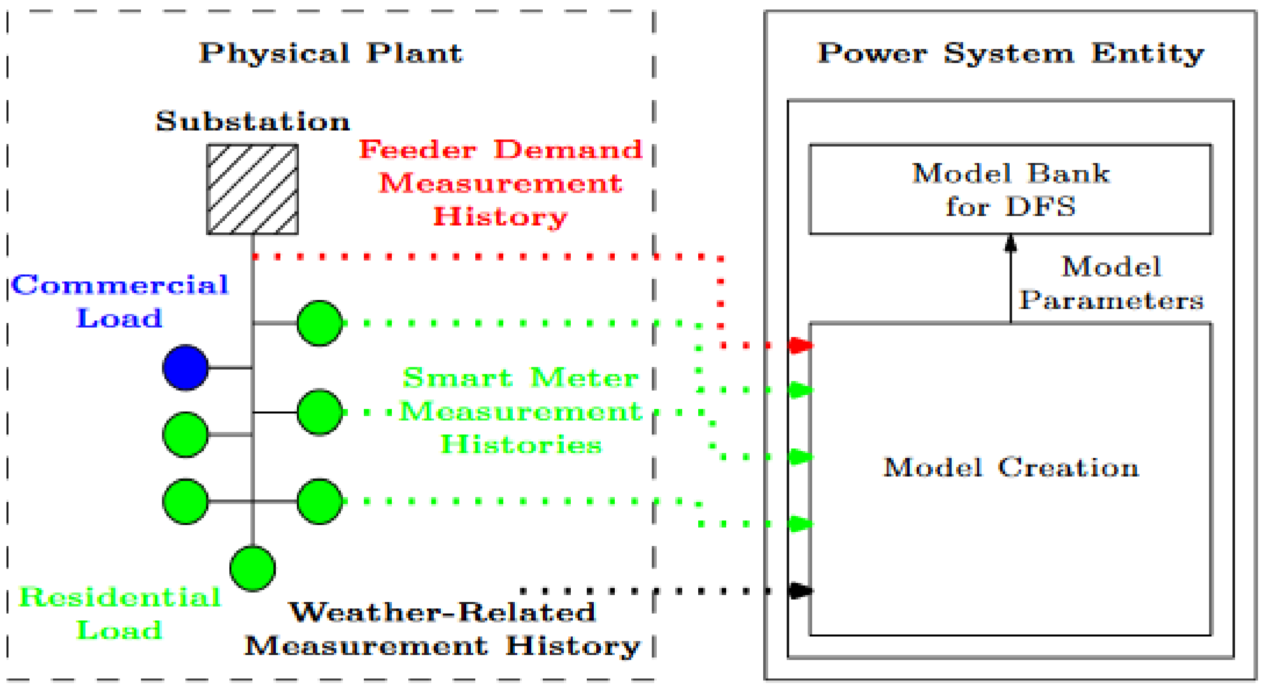
Energy disaggregation is performed on real-time demand measurements using DFS, an online learning algorithm.



(a) Real-time estimation mode

DFS incorporates predictions from models that are generated from historical building- and device-level data.



(b) Offline model generation mode

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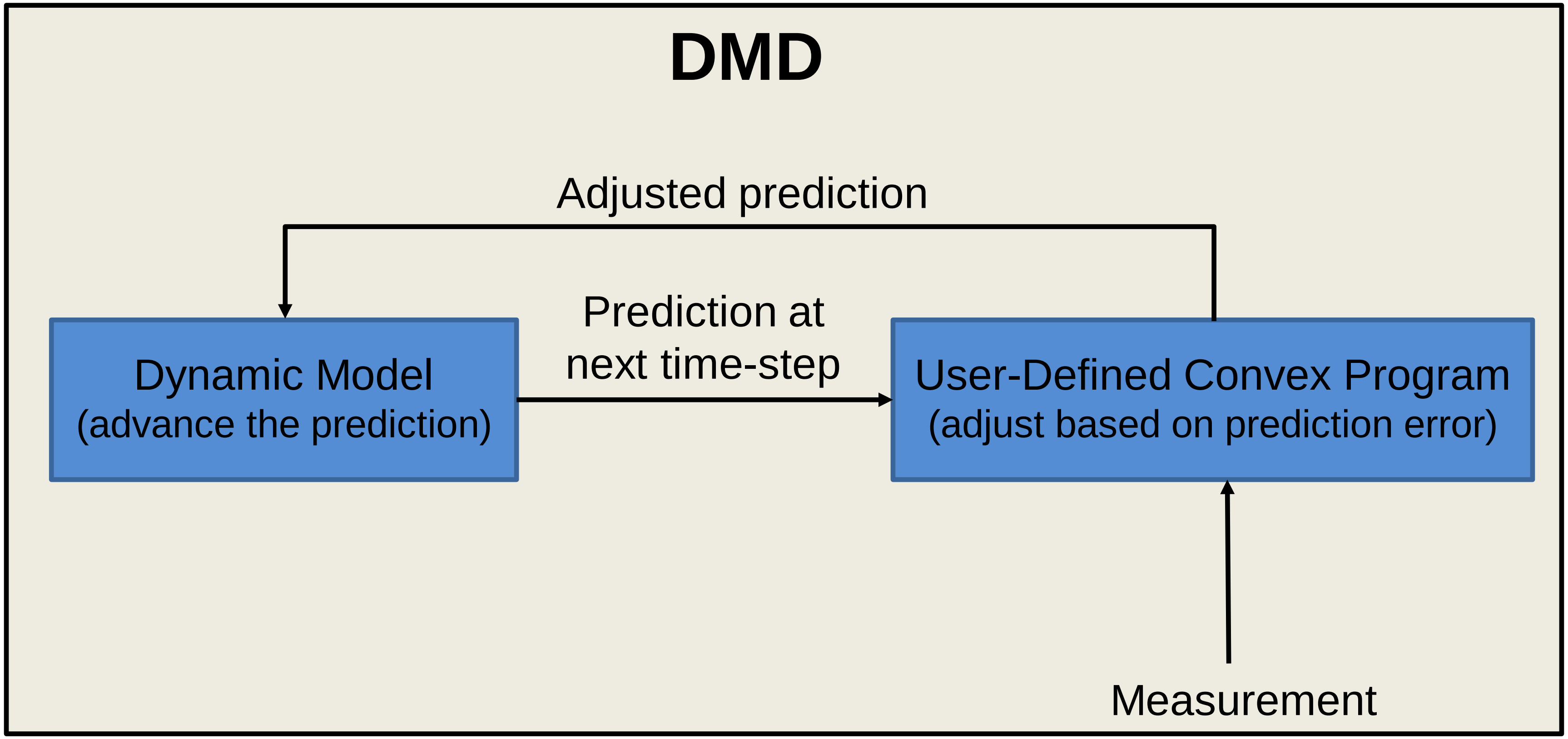
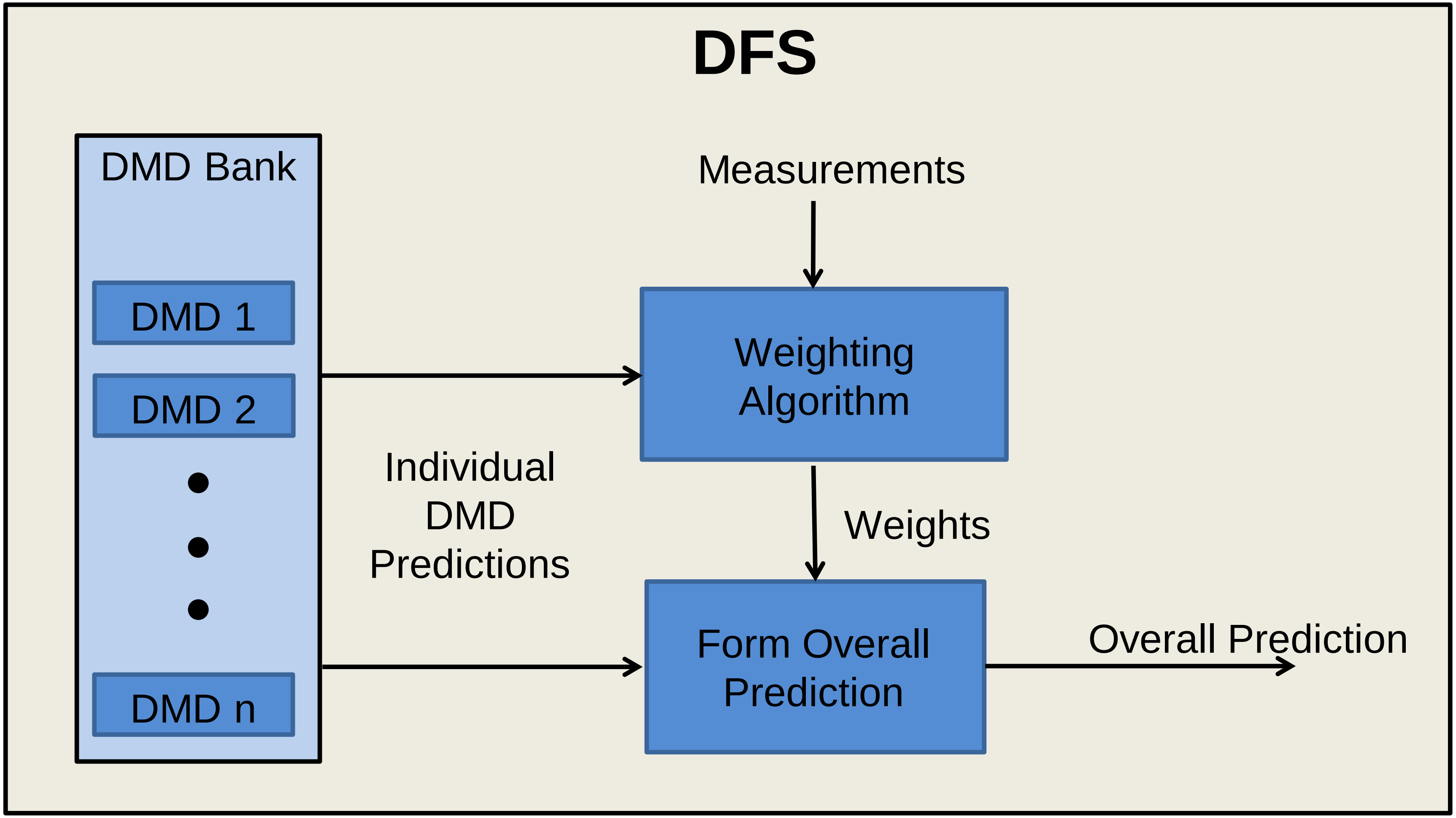
Dynamic mirror descent (DMD) is an algorithm that uses a model, measurements, and a user-defined convex program.



Note: DMD is similar to a Kalman filter but the user has more flexibility

Dynamic fixed share (DFS) combines predictions from different models into an overall prediction.



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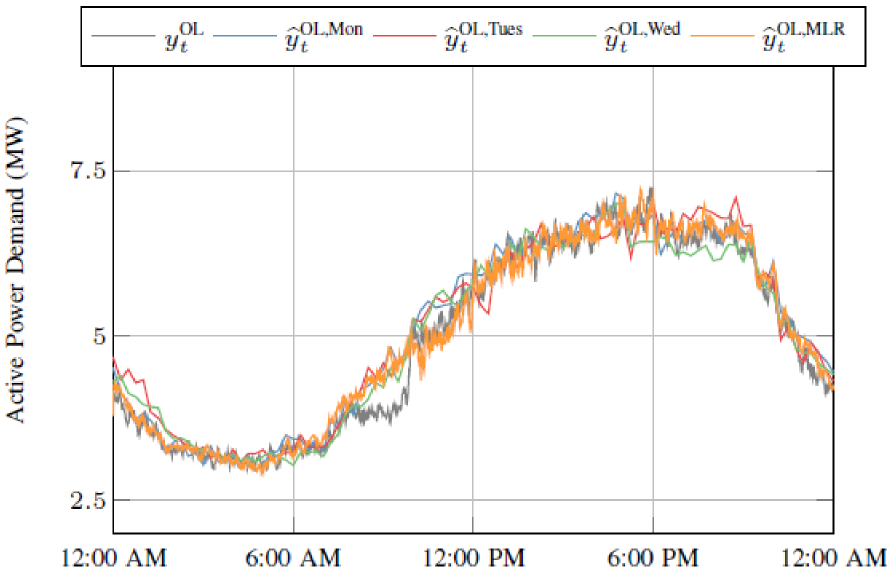
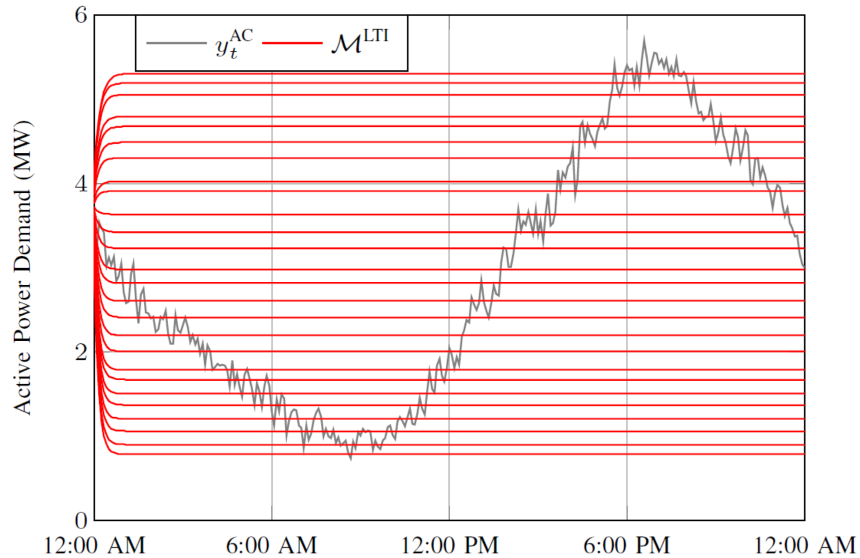
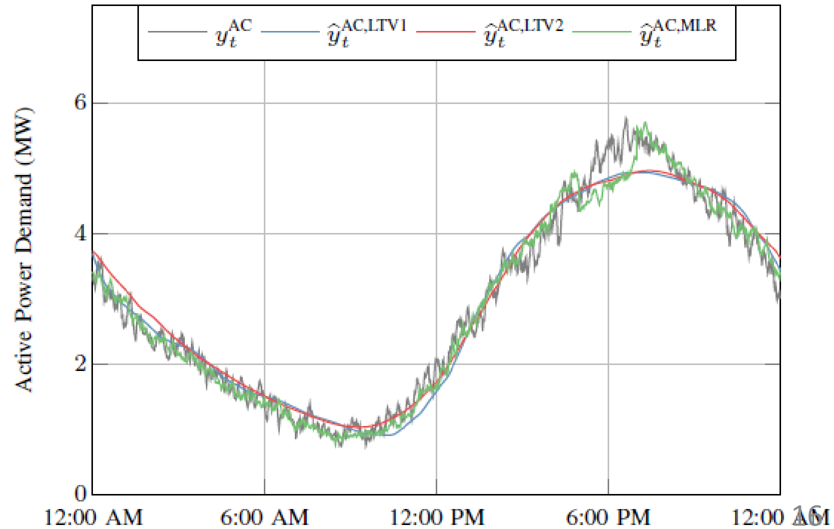
The models used are based on linear regression, linear time-invariant systems, and linear time-varying systems.







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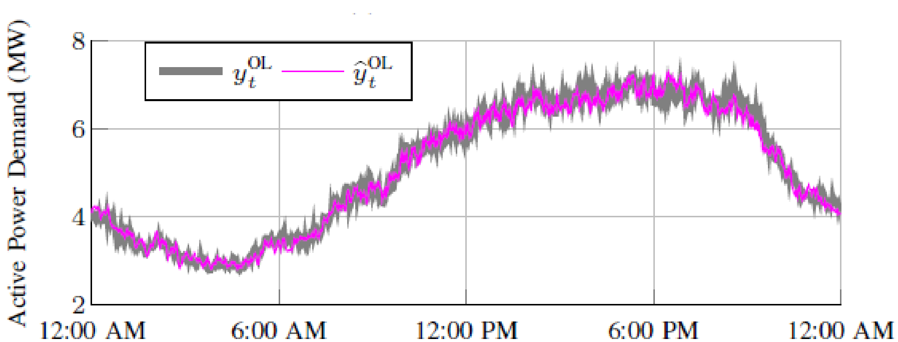
The simulation setup uses real-world data at the device level, allowing the true AC demand to be known.

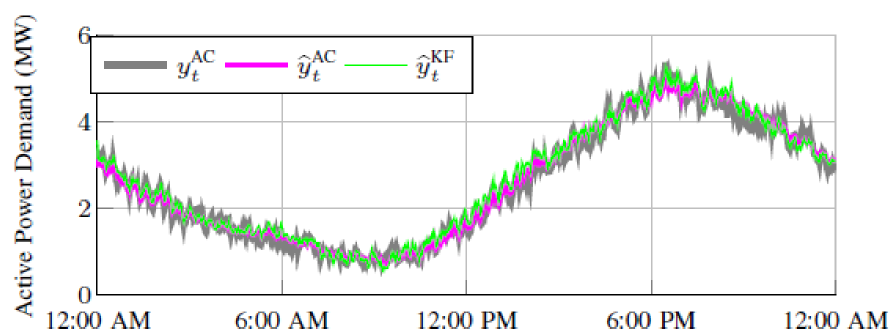
- Demand data sources
  - Feeder model from Gridlab-D feeder taxonomy [2]
  - Commercial building data from PG&E
  - Residential building and device data from Pecan Street [3]
- One minute time-steps
- Three model sets
  - All models
  - Reduced set of models
  - LTV AC models only
- Benchmark Algorithm
  - Kalman filters

RMS prediction errors (kW) for the DFS scenarios averaged over 10 simulated days and example time series.

Model Set	$\mathcal{M}^{\text{Full}}$	$\mathcal{M}^{\text{Red}}$	$\mathcal{M}^{\text{KF}}$	$\mathcal{M}^{\text{KF}}$	$\mathcal{M}^{\text{KF}}$
Algorithm	DFS	DFS	DFS	BKF	AKF
Total Demand	196.8	100.0	99.7	-	-
AC Demand	308.0	220.6	226.5	195.3	259.4
OL Demand	291.4	222.3	228.2	-	-

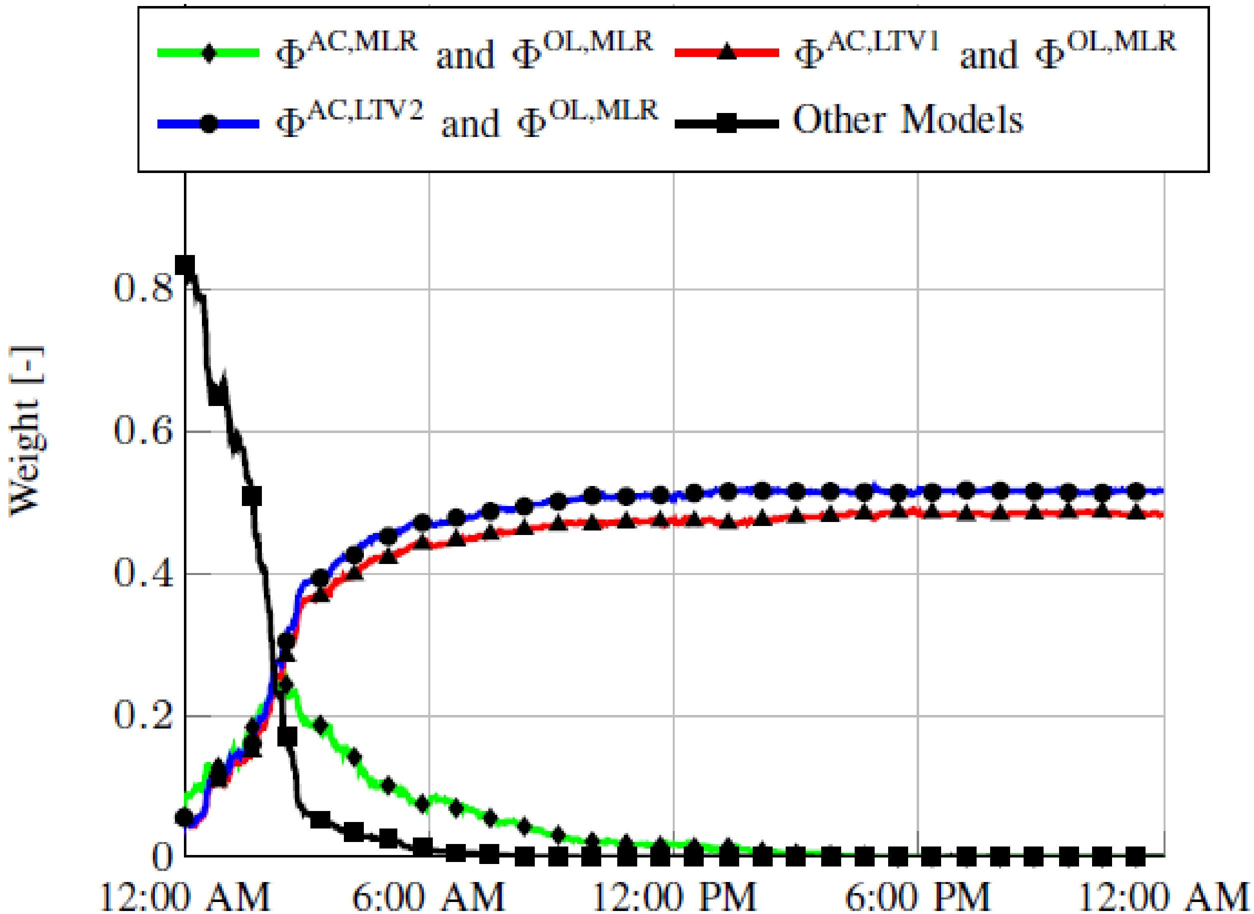


(b) OL Demand



(c) AC Demand

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



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The online learning algorithm is able to effectively separate the AC and OL demand in real-time

- Conclusions
  - Better models improve performance
  - Competitive with the “best” Kalman Filter
- Work under review
  - Comparison of DFS with Kalman filter methods
  - Incorporating statistical information into DFS
- Future work
  - Include active control
  - Use data sampled at faster rates (e.g., seconds)
  - Investigate transfer of theory between domains

Key References

[1] G.S. Ledva et al, "Real-Time Energy Disaggregation of a Distribution Feeder's Demand Using Online Learning," 2017, (Under Review), Available on Arxiv.

[2] K. P. Schneider et al., "Modern grid initiative distribution taxonomy final report," Pacific Northwest National Laboratory (PNNL), Richland, WA (US), Tech. Rep., 2008.

[3] Pecan Street Inc., "Dataport," 2016.

[4] E. C. Hall and R. M. Willett, "Online convex optimization in dynamic environments," IEEE Journal of Selected Topics in Signal Processing, vol. 9, no. 4, pp. 647–662, 2015.

Questions?

Recent Works by Prof. Hiskens and Mathieu

[1] J.F. Marley, D.K. Molzahn and I.A. Hiskens, "Solving multiperiod OPF problems using an AC-QP algorithm initialized with an SOCP relaxation", to appear IEEE Transactions on Power Systems.

[2] J.A. Martin and I.A. Hiskens, "Corrective model-predictive control in large electric power systems", IEEE Transactions on Power Systems, Vol. 32, No. 2, March 2017, pp. 1651-1662.

[3] Z. Ma, S. Zou, L. Ran, X. Shi and I.A. Hiskens, "Efficient decentralized coordination of large-scale plug-in electric vehicle charging", Automatica, Vol. 69, 2016, pp. 35-47.

[4] M.W. Fisher and I.A. Hiskens, "Parametric dependence of large disturbance response and relationship to stability boundary", submitted to IEEE Conference on Decision and Control, Melbourne, Australia, December 2017.

[5] M.S. Nazir and I.A. Hiskens, "Load synchronization and sustained oscillations induced by transactive control", to appear IEEE Power and Energy Society General Meeting, Chicago, IL, July 2017.

[6] J.A. Kersulis and I.A. Hiskens, "Renewable voltage regulation and the transformer tapping tradeoff", Proceedings of IEEE Innovative Smart Grid Technologies - Asia, Melbourne, Australia, November 2016, pp. 960-965.

[7] 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.