Michigan Power & Energy Laboratory

Inferring the Behavior of Distributed Energy Resources with Online Learning

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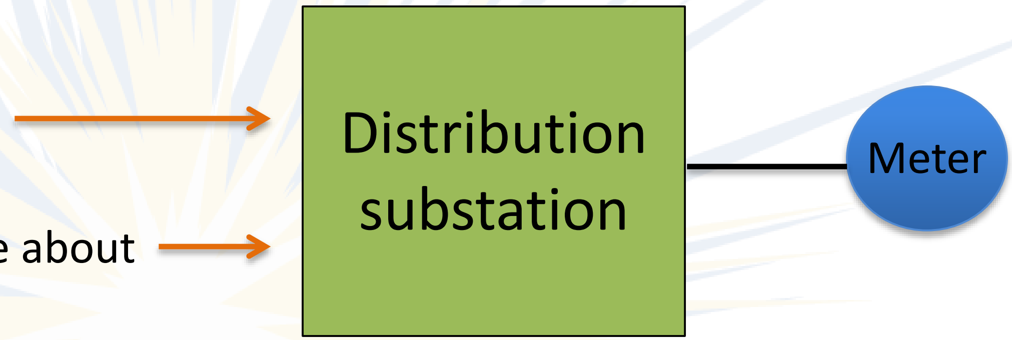
Disaggregating substation load data

Power consumption of all the loads/generators we care about

Power consumption of all the loads/generators we DON'T care about



Why do we want to disaggregate resources at the feeder?

- Energy efficiency via conservation voltage reduction
- Contingency planning
- Optimal reserve contracting
- Demand response event signaling
- Demand response bidding
- Load coordination feedback

Disaggregation methods

e.g., [Berges et al. 2009; Kolter et al. 2010; Dong et al. 2013]

- State estimation
  - Linear techniques require LTI system models
  - Nonlinear techniques can be computationally demanding
- Online learning
  - Optimization formulations
  - Model-free
- Hybrid approach: 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

- Dynamic Mirror Descent
- Problem setting: Plant data/models
- Algorithm Models
- Results
- Next steps

Dynamic Mirror Descent

- Mirror Descent: online algorithm to estimate a fixed state
- Dynamic Mirror Descent: online algorithm to estimate a dynamic state using a *collection of models* [Hall & Willet 2015]
  1. Compute the error between the model predictions and the measured data (i.e., loss function)
  2. Update the state in the direction of the negative gradient of the loss function

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

Dynamic Mirror Descent

3. Use the estimated states to evaluate the models for the next time step

$$\widehat{\theta}^i_{t+1} = \Phi^i_t(\widetilde{\theta}^i_t)$$

4. Compute a weighted version of the estimates

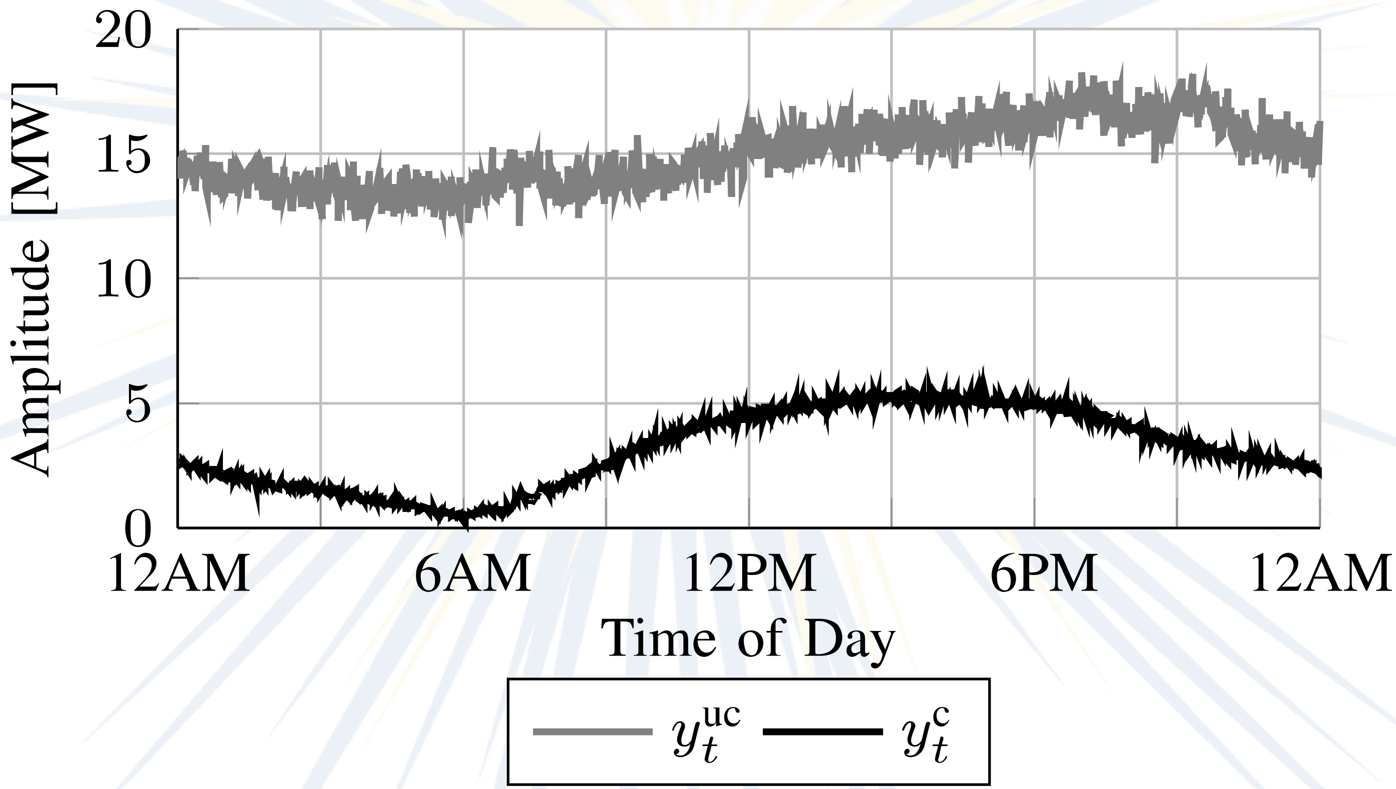
$$\widehat{\theta}_{t+1} = \sum_{i=1}^{N^{\text{mdl}}} w^i_{t+1} \widehat{\theta}^i_{t+1}.$$

5. Update the model weights

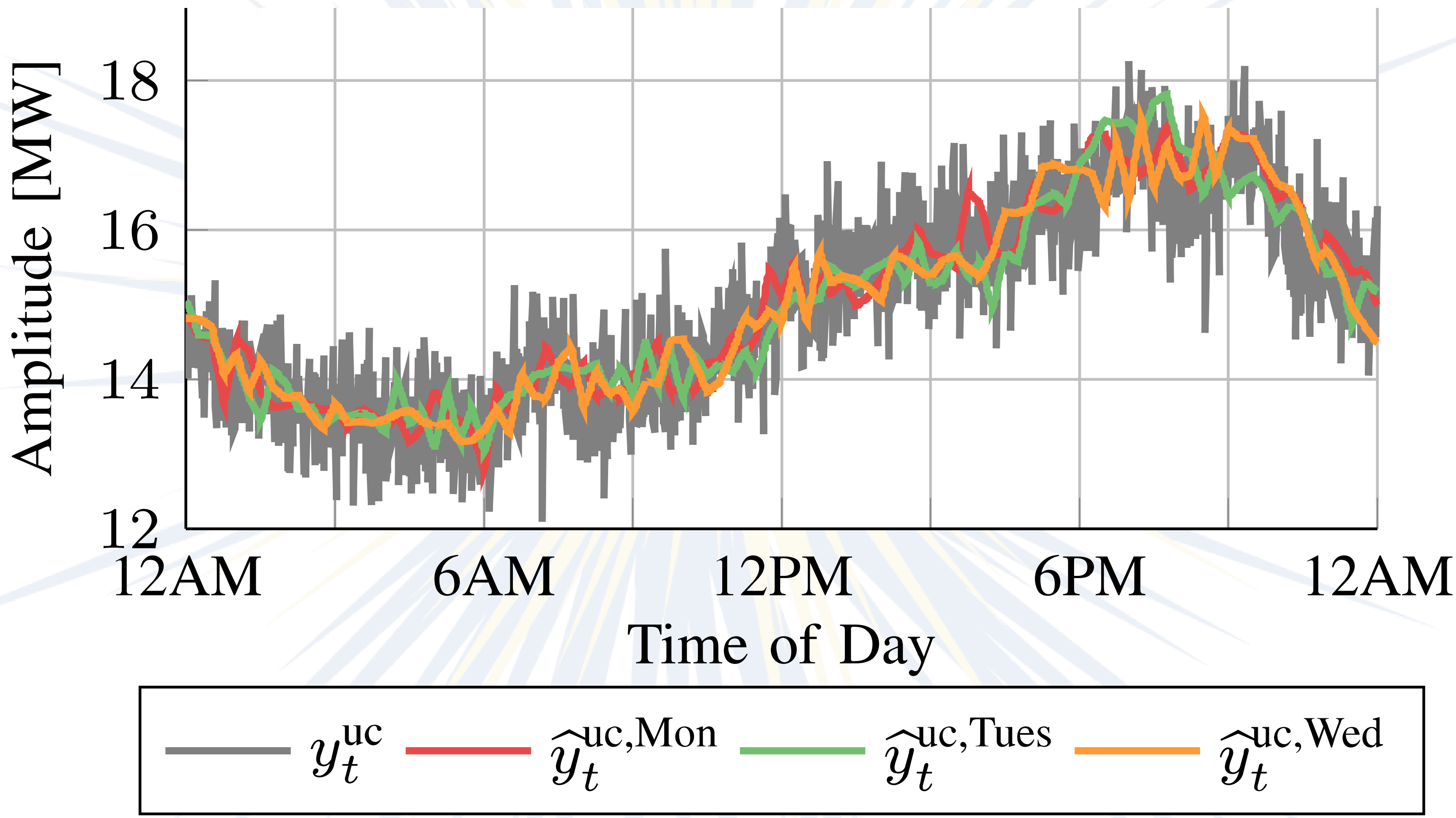
$$w^i_{t+1} = \frac{\lambda}{N^{\text{mdl}}} + (1-\lambda) \frac{w^i_t \exp\left(-\eta^r \ell_t \left(\widehat{\theta}^i_t, y_t\right)\right)}{\sum_{j=1}^{N^{\text{mdl}}} w^j_t \exp\left(-\eta^r \ell_t \left(\widehat{\theta}^j_t, y_t\right)\right)}$$

Problem Setting: Plant Data/Models

- Uncontrollable loads: data from Pecan Street Inc. Dataport
- Controllable loads: equivalent thermal parameter (ETP) models of air conditioners [Sonderegger 1978]



Algorithm Models: Uncontrollable loads



Algorithm Models: Controllable loads

- Two-state hybrid models of air conditioners [Mortensen & Haggerty 1988]
  - Temperature and ON/OFF mode
- Sets of Linear Time Invariant (LTI) aggregate system models [Mathieu et al. 2013]

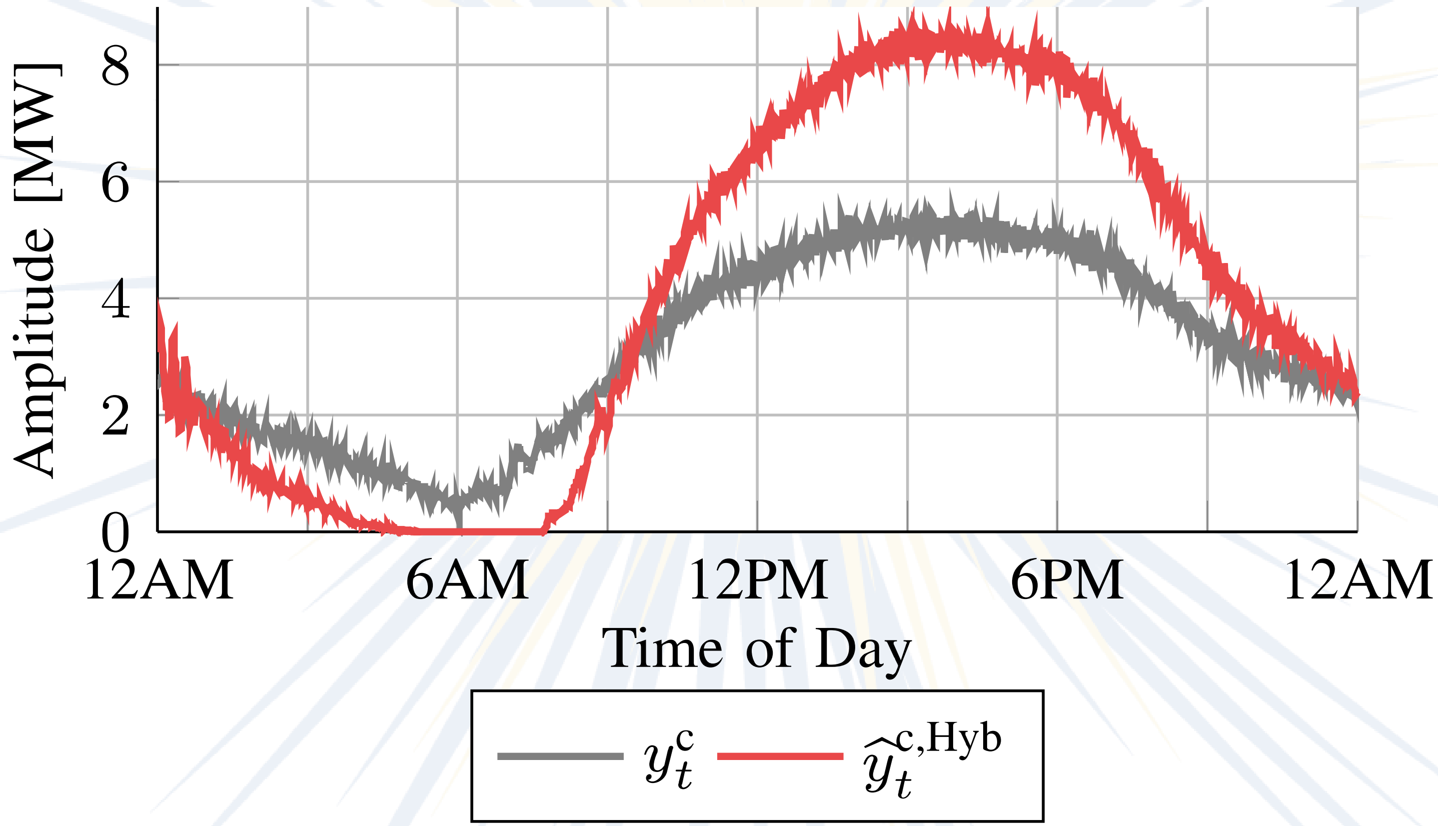
$$x^i_{t+1} = A^i \, x^i_t \qquad i \in \mathbb{N}^{\text{temps}}$$
$$\widehat{y}_t^{\text{c,LTI},i} = C^i \, x^i_t \qquad i \in \mathbb{N}^{\text{temps}}.$$

- Sets of Linear Time Varying (LTV) aggregate system models

$$x_{t+1} = A_t \, x_t$$
$$\widehat{y}_t^{\text{c,LTV}} = C_t \, x_t.$$

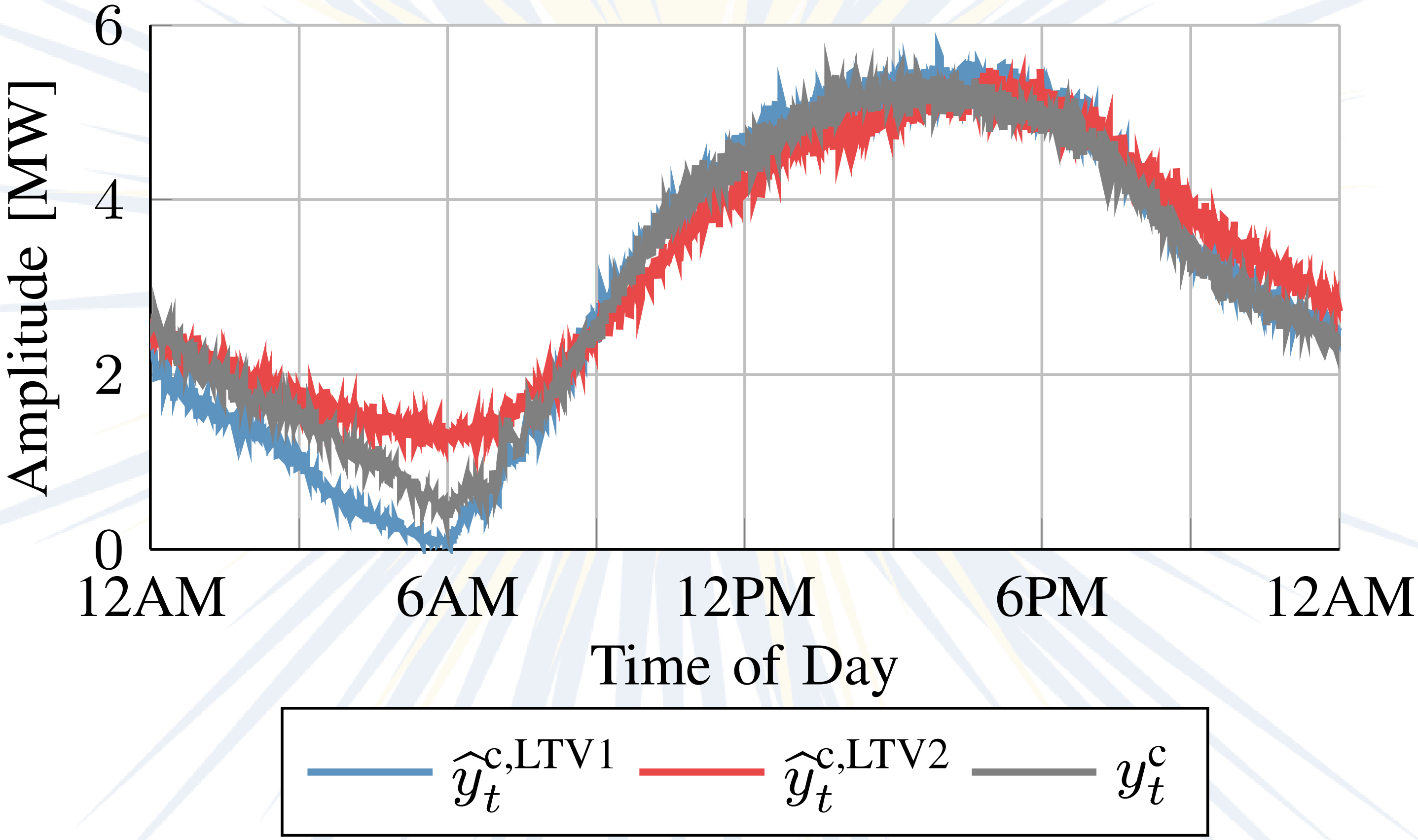
Algorithm Models: Controllable loads

- Two-state hybrid AC models do not work well.



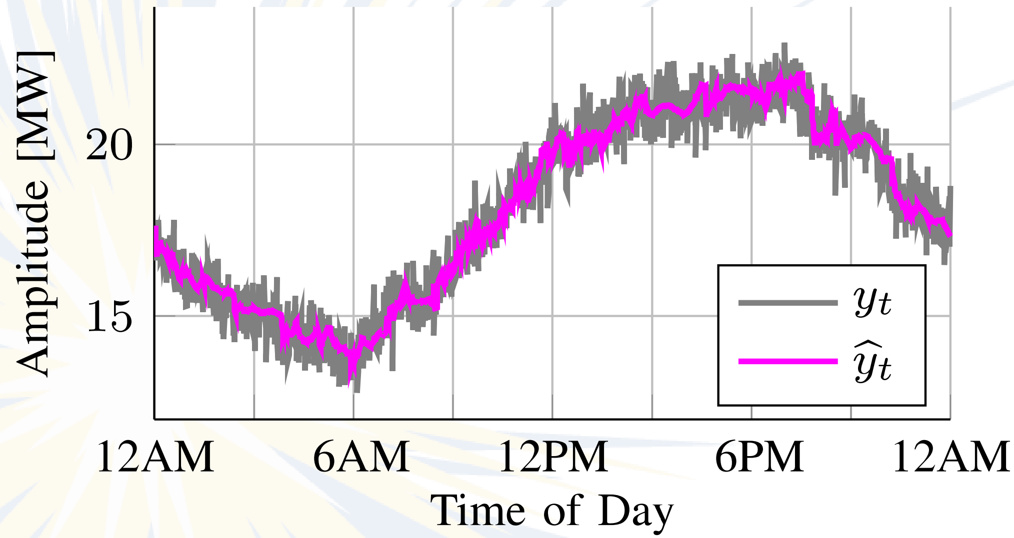
Algorithm Models: Controllable loads

- LTV models work better.

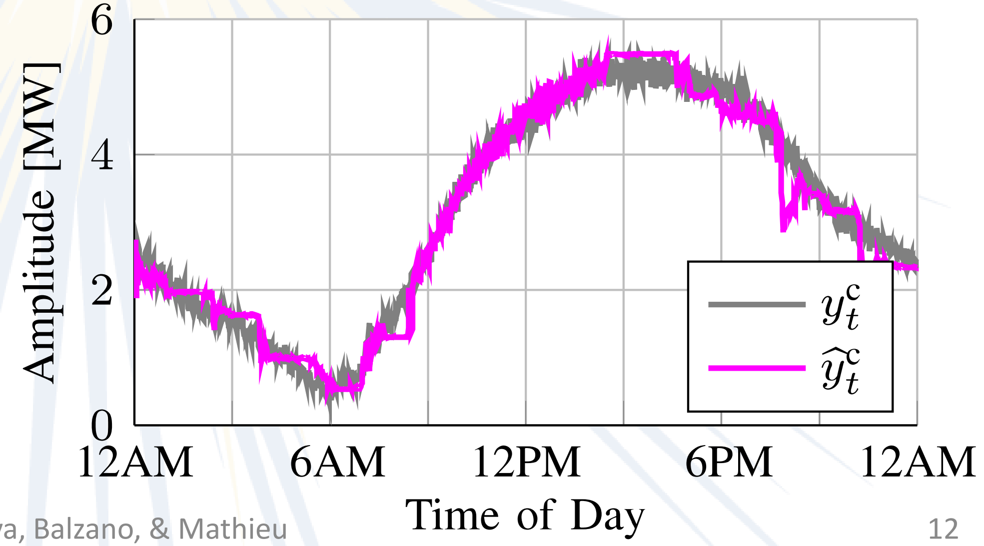


Results: All combinations of models

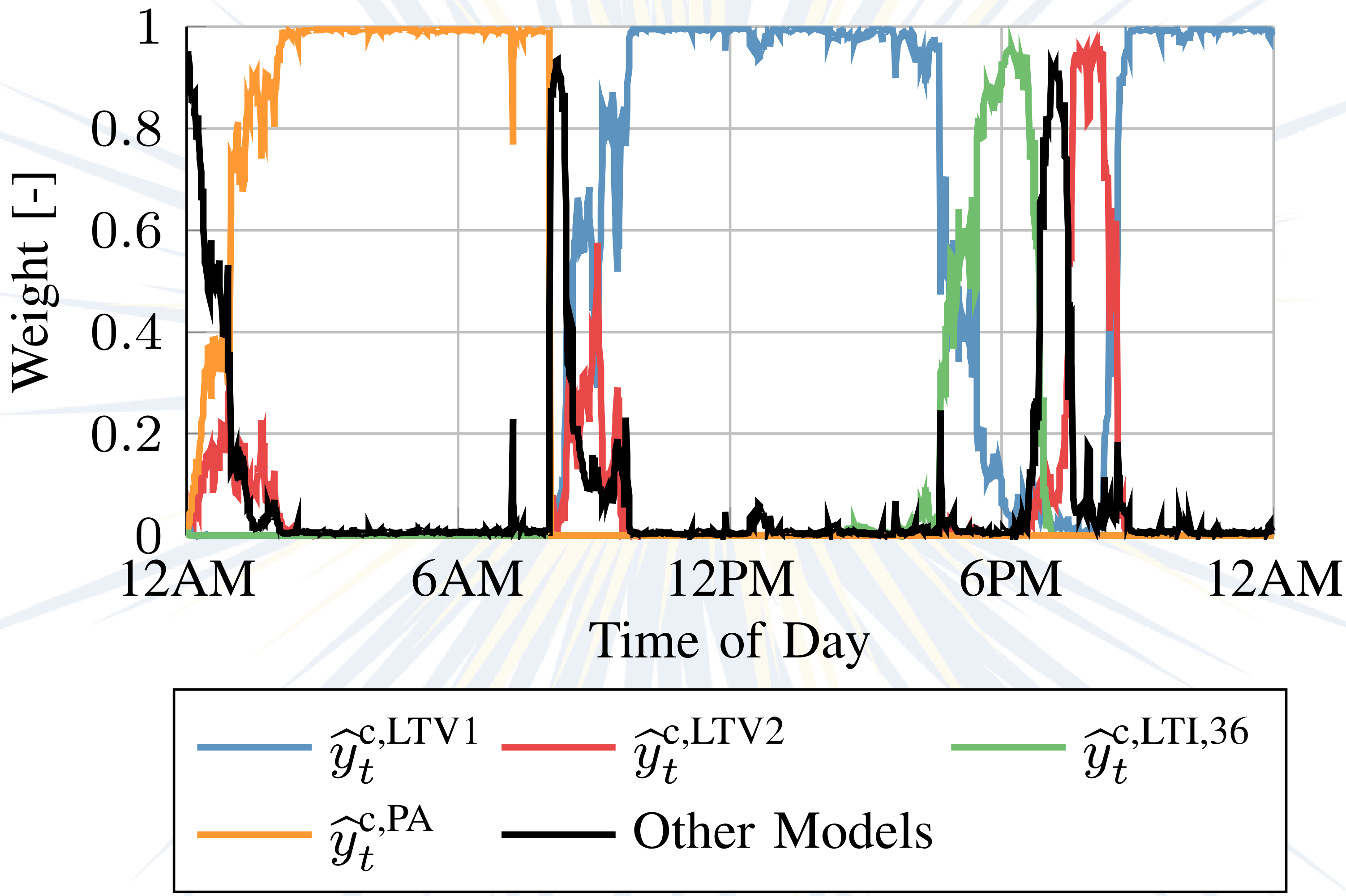
Total Load



Controllable Load

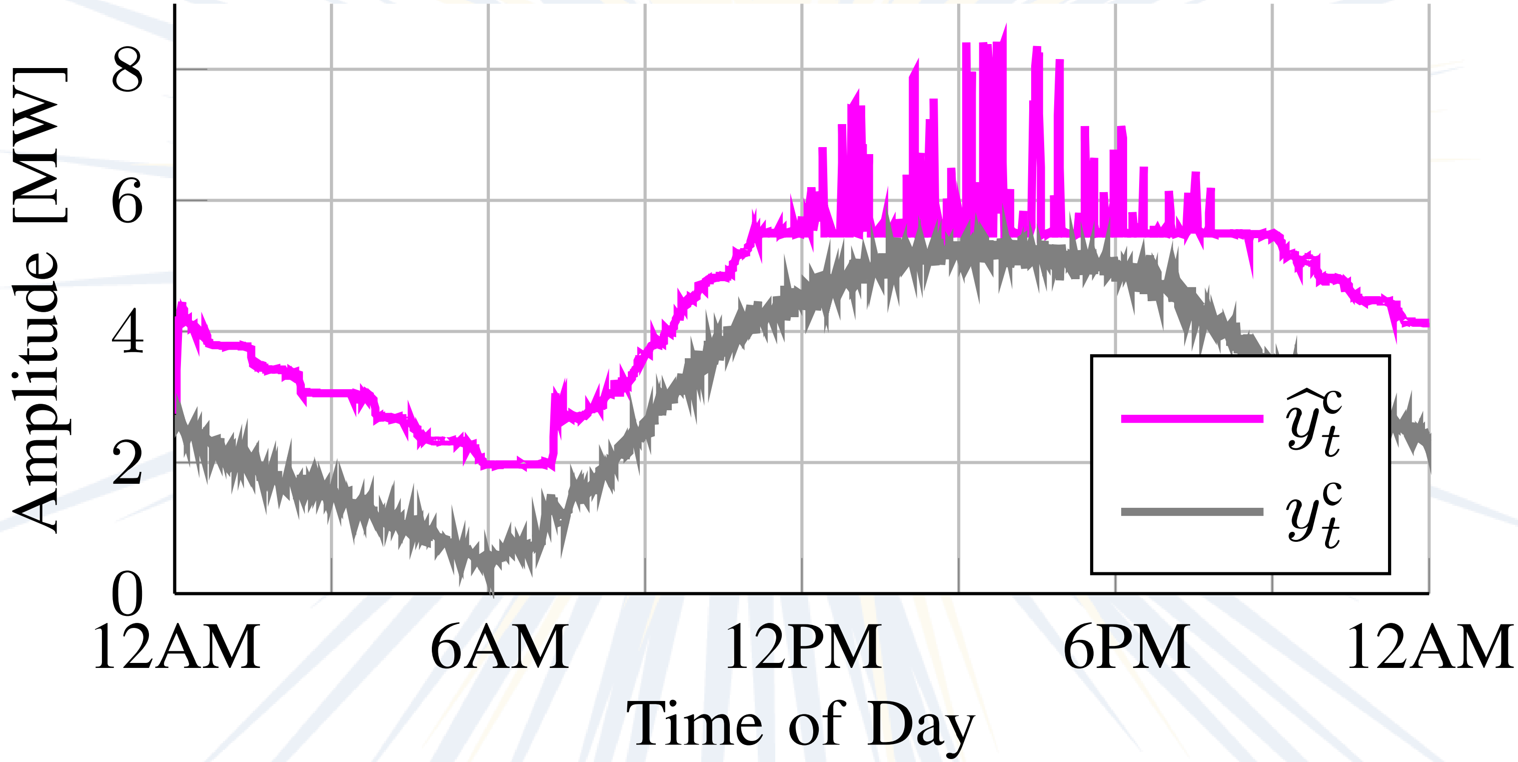


Results: Weightings



Results: Bad Models

- All uncontrollable load models are too low.

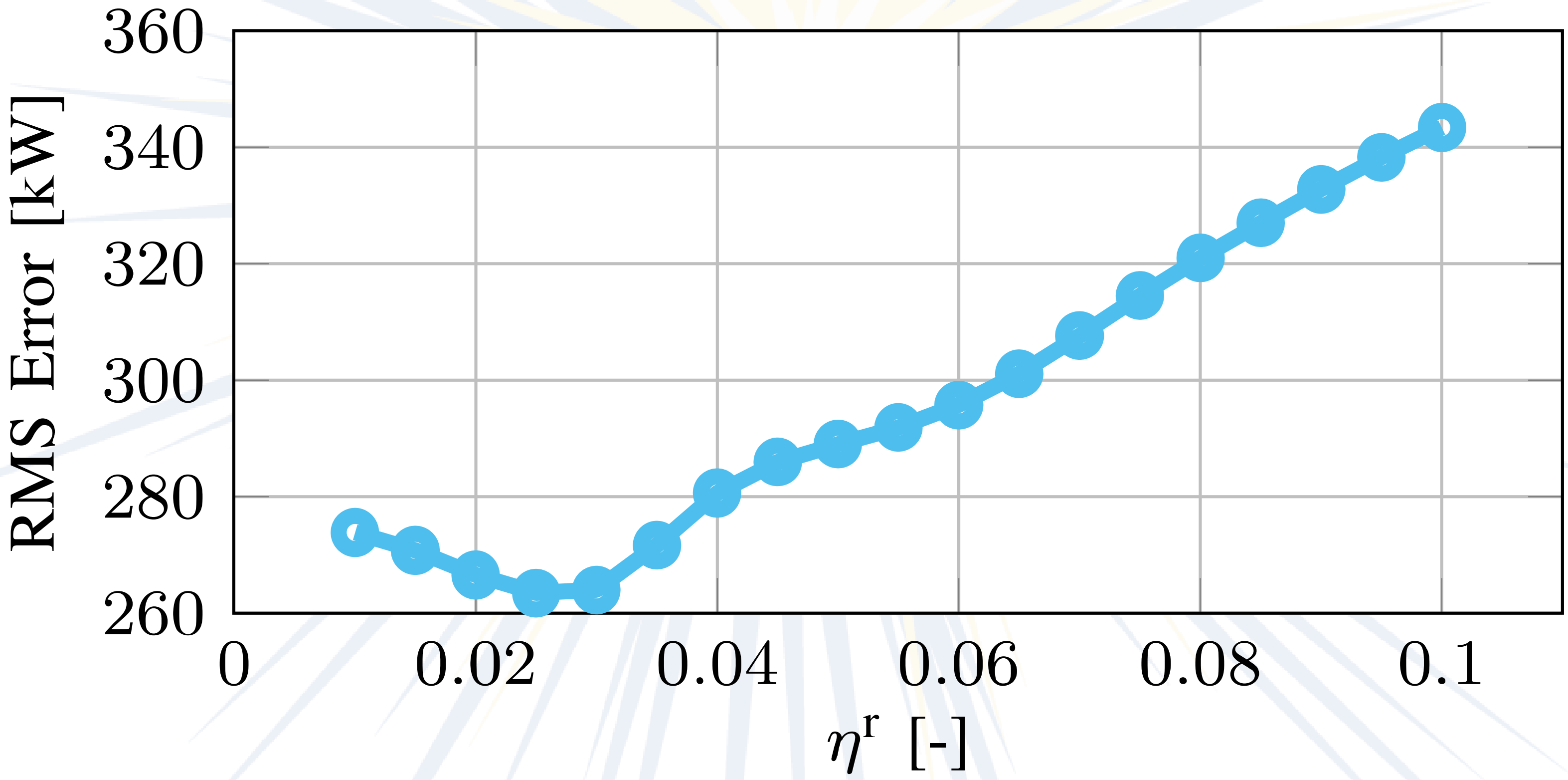


Results: Summary

Case	RMS Error (kW)
Benchmark: Use current outdoor temperature to evaluate simple controllable load model	738
DMD Case 1: Includes every combination of uncontrollable and controllable models	264
DMD Case 2: Case 1 models plus a smoothed version of the actual uncontrollable load	211
DMD Case 3: Case 2 models plus more accurate model of the controllable load over time periods where the other models are less accurate	175
DMD Case 4: Includes uncontrollable load models that underestimate the uncontrollable load	1392

Results: Varying Algorithm Parameters

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



Next steps

- Investigate more realistic settings (using more real data)
- Develop better load models
- Improve the algorithm, e.g., alternative weighting functions
- Investigate identifiability
- Incorporate additional measurements (reactive power, voltage) into the approach

Conclusions

- Dynamic Mirror Descent (DMD) enables us to solve the substation disaggregation problem leveraging dynamical models of arbitrary form
- DMD can work well (on simple examples); however, it is easy to find instances where it does not work well
- Many open questions!

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