Engaging Distributed Flexible Electric Loads in Power System Operation

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Benefits and Challenges of the Modern Electric Grid

• Grid sensing and communication systems are becoming more prevalent
  – Cost & privacy concerns
  – Need methods to infer grid/load information from existing measurements

• Renewable energy resources are also becoming more prevalent
  – Most (e.g., wind and solar) are intermittent and uncertain
  – Need new sources of power system reserves
• **Control:** Controlling distributed electric loads to provide power system services with sparse measurements and input/measurement delays

[Ledva, Vrettos, Mastellone, Andersson & Mathieu, HICSS 2015 & IEEE TPWRS (in review)]

[Ledva & Mathieu, ACC 2017 (in review)]

• **Inference:** Energy disaggregation at the feeder to infer the aggregate power of flexible loads

[Ledva, Balzano, & Mathieu, Allerton 2015]
How can loads provide reserves?
→ your refrigerator is already flexible

normal operation

non-disruptive load control
Thousands of thermostatically controlled loads (TCLs) can track signals and provide reserves.

TCLs: air conditioners, heat pumps, space heaters, electric water heaters, refrigerators.

[Mathieu, Koch, and Callaway *IEEE Transactions on Power Systems* 2013]
Simulation results:
1000 ACs tracking 5-minute market signal

Controller gets temperature/state of each load every 2 seconds

Controller infers TCL behavior from power measurements at the substation

The more the controller knows about the loads, the better it can track a signal

[Mathieu, Koch, and Callaway IEEE Transactions on Power Systems 2013]

11/5/16
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Data from loads

• Parameters
  – the make/model of the load?
  – its temperature setpoint/dead-band width?
  – some information about the household?

• Real-time data
  – Measurements of the on/off state and/or internal temperature?
  – Household smart meter data?
  – Power measurements from the distribution network?

• Recorded data
  – high resolution power measurements of each load?

→ Modeling

→ Feedback control

High quality, infrequent
Low quality, frequent

→ Auditing
Communication and control scenario

Load aggregator

Infrequent state measurements

Delay

Substation

Frequent aggregate power (output) measurements

Delay

Broadcast ((()()((()())))
The Challenge

• Design an estimator and controller to enable loads to track a signal *despite delays*

• Assuming...
  – Control inputs & measurements are time-stamped
  – Delay statistics are known
  – State measurements are taken frequently; measurement *histories* are transmitted infrequently
  – Aggregate power measurements are *very* noisy (though the noise is normally distributed, zero-mean, and the standard deviation is known)
Two-state TCL model

Each TCL $i$ is modeled with a stochastic hybrid difference equation:

Temperature of the space

$$\theta_i(k + 1) = a_i \theta_i(k) + (1 - a_i)(\theta_{a,i} - m_i(k)\theta_{g,i}) + \epsilon_i(k)$$

On/off state

$$m_i(k + 1) = \begin{cases} 0, & \theta_i(k + 1) < \theta_{set,i} - \delta_i/2 \\ 1, & \theta_i(k + 1) > \theta_{set,i} + \delta_i/2 \\ m_i(k), & \text{otherwise} \end{cases}$$

$A$, thermal parameter

$\theta_g$, temperature gain

$\theta_a$, ambient temperature

$\epsilon$, noise

$\theta_{set}$, set point

$\delta$, dead-band width

\[
    x(k + 1) = Ax(k) + Bu(k) + B_\omega \omega(k) \\
    y(k) = Cx(k) + \nu(k)
\]

Aggregate System Model

Similar models in the literature:
- Lu & Chassin 2004/2005
- Bashash & Fathy 2011/2013
- Kundu & Hiskens 2011
- Zhang et al. 2013

[Mathieu, Koch, and Callaway *IEEE Transactions on Power Systems* 2013]
Estimator Designs

• Based on Kalman Filtering
  – Estimator 1: Parallel filter estimator
    • One Kalman Filter per load
    • Each time a measurement arrives, filter it
    • Synthesize aggregate estimate from individual estimates
  – Estimator 2: Single Kalman Filter Using Aggregate State Predictions
    • Use state measurement histories to estimate *individual* load parameters (two-state model)
    • Use individual load models to predict current state
    • Use predictions as “measurements” in Kalman Filter
Controller Design

• Based on Model Predictive Control
  – Use knowledge of delay distributions and past control inputs

First control sequence: \[ u_1, u_2, u_3, \ldots, u_n \]

Second control sequence: \[ u_2, u_3, \ldots, u_{n+1} \]

Third control sequence: \[ u_3, u_4, \ldots, u_{n+1} \]

Input estimate: \[ \hat{u}_k = U_k \mathcal{P} \]
Control Formulation

\[
\begin{align*}
\text{minimize} \quad & \sum_{k=t}^{t+N^{mpc}-1} \left[ c^y (y_k^{err})^2 + c^\delta (\delta_k^- + \delta_k^+) \right] + \\
\text{s.t.} \quad & x_{k+1} = A x_k + B \hat{u}_k \\
& \hat{u}_k = U_k P \\
& y_k^{err} = y_k^{P, \text{ref}} - C^P x_k \\
& u_i^k | m \leq x_i^k \\
& -u_i^k | m \leq x_i^{N^x+1-i} \\
& \delta_k^- \leq x_k \leq 1 + \delta_k^+ \\
& 0 \leq \delta_k^-, \delta_k^+.
\end{align*}
\]
Case Studies

- PJM Regulation Signals, Reg-A & Reg-D
- Average input delay of 20 seconds
- (Delayed) state histories arrive every 15 minutes
Results: Tracking

- Estimator 1
- Estimator 2
- Reference Signal

Demand Change (%)

Reg-A

Reg-D

Time (hr)
Results: Model Mismatch

<table>
<thead>
<tr>
<th>Demand Change (%)</th>
<th>Demand Change (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>20</td>
<td>20</td>
</tr>
<tr>
<td>40</td>
<td>40</td>
</tr>
<tr>
<td>60</td>
<td>60</td>
</tr>
<tr>
<td>80</td>
<td>80</td>
</tr>
<tr>
<td>100</td>
<td>100</td>
</tr>
</tbody>
</table>

- **Estimator 1**
- **Estimator 2**
- **Reference Signal**

**Legend:**
- Reg-A
- Reg-D

Time (hr)
Control Results: Reg-A

![Diagram showing the comparison of discrete state bin distributions in steady-state for Two-State Plant and Three-State Plant. The bars represent the average RMSE for different delays and estimation methods.]

- **Estimator 1-NC**
- **Estimator 1-TS**
- **Estimator 1-FC**
- **Estimator 2-FC**

### Table III: PJM Scores

<table>
<thead>
<tr>
<th>Method</th>
<th>Reg-A RMSE (%)</th>
<th>Reg-D RMSE (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Estimator 1-NC</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Estimator 1-TS</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Estimator 1-FC</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Estimator 2-FC</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: Error bars indicate the range of values achieved across the ten instances of each scenario.
Control Results: Reg-D

Focusing on Estimator 1-FC, PJM scores for the Reg-D reference are slightly better than those for the Reg-A reference, while Estimator 2-FC's performance is dependent in all scenarios; however, it performs worse than Estimators 1-NC, 1-TS, and 1-FC.

Because the trends are different for each performance metric, it is unclear whether the Reg-A or Reg-D cases are superior. Three-State Plant and Two-State Plant performance is roughly comparable, as the baseline results are similar for all models. Performance can be improved by accounting for the delay, however this is not possible with current models. The delay compensation would be needed in order to account for the resulting RMSE, which is high for all scenarios.

TABLE III

<table>
<thead>
<tr>
<th>Control Setup</th>
<th>Avg. Delay (sec.)</th>
<th>Reg-A</th>
<th>Reg-D</th>
<th>Reg-A</th>
<th>Reg-D</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>0</td>
<td>0.785</td>
<td>0.882</td>
<td>——</td>
<td>——</td>
</tr>
<tr>
<td>Estimator 1-NC</td>
<td>50</td>
<td>0.852</td>
<td>0.899</td>
<td>0.810</td>
<td>0.894</td>
</tr>
<tr>
<td>Estimator 1-TS</td>
<td>100</td>
<td>0.846</td>
<td>0.908</td>
<td>0.821</td>
<td>0.901</td>
</tr>
<tr>
<td>Estimator 1-FC</td>
<td>0</td>
<td>0.849</td>
<td>0.903</td>
<td>0.824</td>
<td>0.903</td>
</tr>
<tr>
<td>Estimator 1-TS</td>
<td>0</td>
<td>0.727</td>
<td>0.821</td>
<td>0.735</td>
<td>0.835</td>
</tr>
<tr>
<td>Estimator 1-FC</td>
<td>10</td>
<td>0.849</td>
<td>0.908</td>
<td>0.814</td>
<td>0.901</td>
</tr>
<tr>
<td>Estimator 1-N</td>
<td>20</td>
<td>0.849</td>
<td>0.908</td>
<td>0.814</td>
<td>0.901</td>
</tr>
<tr>
<td>Estimator 1-T</td>
<td>20</td>
<td>0.849</td>
<td>0.908</td>
<td>0.814</td>
<td>0.901</td>
</tr>
<tr>
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<tr>
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<td>40</td>
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<tr>
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<td>60</td>
<td>0.849</td>
<td>0.908</td>
<td>0.814</td>
<td>0.901</td>
</tr>
</tbody>
</table>

Note that with no delay, the RMSE and PJM scores of Estimator 1-NC are lower than Estimator 1-TS, which could certify a change in the plant, Estimator 2-FC's PJM scores are acceptable over the 0.75 threshold, except Estimator 1-NC when used to maintain certification for an arbitrary reference signal.
Controller Reformulation

Original Model

\[ x_{k+1} = A x_k + B u_k \]
\[ y_k = C x_k. \]

Modal Model

\[
\begin{bmatrix}
1 \\
\tilde{x}_{k+1}
\end{bmatrix}
= \begin{bmatrix}
1 & 0 \\ 0 & \tilde{A}
\end{bmatrix}
\begin{bmatrix}
1 \\
\tilde{x}_k
\end{bmatrix}
+ \begin{bmatrix}
0 \\ \tilde{B}
\end{bmatrix} u_k
\]
\[ y_k = \begin{bmatrix}
y_{ss} & \tilde{C}
\end{bmatrix}
\begin{bmatrix}
1 \\
\tilde{x}_k
\end{bmatrix}
\]

Reduced-Order Model

\[ \tilde{x}_{k+1} = \tilde{A} \tilde{x}_k + \tilde{B} u_k \]
\[ \tilde{y}_k = \tilde{C} \tilde{x}_k. \]
Controller Reformulation

The linear controller uses constant gains generated from an output-regulating Linear Quadratic Regulator (LQR) with reference feedforward.

Linear Controller

$$u_t^{\text{seq}} = -K_x^{\infty} \: \bar{x}_t - K_w^{\infty} \: w_t + K_y^{\infty} \: y_t^{\text{des}}$$

LQR Formulation

$$\min_u \: \sum_{k=t}^{\infty} \begin{bmatrix} \bar{x}_k \\ w_k \end{bmatrix}^T \begin{bmatrix} \bar{C}^T & q^{y} \bar{C} \\ 0 & q^{w} \end{bmatrix} \begin{bmatrix} \bar{x}_k \\ w_k \end{bmatrix} + \left( u_k^{\text{seq}} \right)^T \: R \: u_k^{\text{seq}}$$

subject to

$$\begin{bmatrix} \bar{x}_{k+1} \\ w_{k+1} \end{bmatrix} = \begin{bmatrix} \bar{A} & 0 \\ \bar{C} & 0 \end{bmatrix} \begin{bmatrix} \bar{x}_k \\ w_k \end{bmatrix} + \begin{bmatrix} \bar{B} \\ 0 \end{bmatrix} \: u_k^{\text{seq}}$$

Feedforward Gain

$$K_y^{\infty} = \left( \bar{C} \{ zI - \bar{A} + \bar{B} \bar{K}_x^{\infty} \}^{-1} \bar{B} \right)^{-\dagger}$$
Case Studies

- PJM Regulation Signals, Reg-A & Reg-D
- Average input delay of 20 seconds
- Full state feedback, no measurement delay
- Three-state models used for the plant
Results Summary

Reg-A Reference

Reg-D Reference

<table>
<thead>
<tr>
<th>Delay Scenario</th>
<th>Average Delay (sec.)</th>
<th>Reg-A Reference</th>
<th>Reg-D Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0</td>
<td>1.14%</td>
<td>0.83%</td>
</tr>
<tr>
<td>10</td>
<td>0.2168</td>
<td>0.83%</td>
<td></td>
</tr>
<tr>
<td>20</td>
<td>1.14%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

LIN is 100 times faster than MPC
Key takeaways

• Communication network limitations necessitate controller/estimator designs that cope with delays, bandwidth limitations, etc.

• Delays make loads less capable of providing fast services, but we can mitigate these impacts through delay-aware control and estimation.
• **Control:** Controlling distributed electric loads to provide power system services with sparse measurements and input/measurement delays

[Ledva, Vrettos, Mastellone, Andersson & Mathieu, HICSS 2015 & IEEE TPWRS (in review)]

[Ledva & Mathieu, ACC 2017 (in review)]

• **Inference:** Energy disaggregation at the feeder to infer the aggregate power of flexible loads

[Ledva, Balzano, & Mathieu, Allerton 2015]
Load Served by a Substation

Amplitude [MW]

Time of Day

12AM 3AM 6AM 9AM 12PM 3PM 6PM 9PM 12AM

11/5/16
Load Served by a Substation

![Graph showing load served by a substation over time, with separate lines for Total, Air Conditioning, and Other categories.](image)
Disaggregating substation load data

- Power consumption of all the loads/generators we care about (e.g., Air Conditioning)
- Power consumption of all the loads/generators we DON’T care about ("Other loads")

In this talk, we use measurements of real power only. We could consider additional measurements (reactive power, voltage, etc.) from multiple meters at different points in the distribution network.
Why disaggregate the substation load?

Uses in demand response...
- Load coordination feedback
- Load aggregator bidding
- Demand response event signaling (when/how much)

Beyond demand response...
- Energy efficiency via conservation voltage reduction
  - Disaggregate by load type
- Contingency planning
  - Disaggregate motor loads
- Reserve planning
  - Disaggregate PV production
Connections to other problems

• Non-intrusive load monitoring (NILM) [Hart 2010; Ziefman and Roth 2011; Berges et al. 2009; Zoha et al. 2012; Dong, Sastry, et al. 2014; ...]


Problem: Infer individual load behavior from a single power measurement (usually) sampled at high frequency (10kHz-1MHz) from the household main

Solution approaches: offline algorithms including change detection, supervised learning, unsupervised learning
Key differences

• We assume **measurements at the substation**, not the household

• We infer **aggregate load** (e.g., all air conditioning load), not individual load behavior

• We solve the problem **online**, not offline

• We use **lower frequency measurements** (e.g., taken every second to minute)

• In some cases, we may get to be “**intrusive,**” but not in this talk!
Possible Methods

• State estimation
  – Linear techniques require linear system models
  – Nonlinear techniques can be computationally demanding

• Online learning
  – Data-driven, 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


1. Compute the error between the model predictions and the measured data (i.e., loss function $\ell_t(\hat{\theta}_t^i, y_t)$)
2. Update the state in the direction of the negative gradient of the loss function

$$\tilde{\theta}_t^i = \arg \min_{\theta \in \Theta} \eta_t \left\langle \nabla \ell_t(\hat{\theta}_t^i, y_t), \theta \right\rangle + D \left( \theta \| \hat{\theta}_t^i \right)$$
Dynamic Mirror Descent

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

\[ \hat{\theta}_t^{i+1} = \Phi_t^i(\hat{\theta}_t^i) \]

4. Compute a weighted version of the estimates

\[ \hat{\theta}_t^{i+1} = \sum_{i=1}^{N_{mdl}} w_t^{i} \hat{\theta}_t^{i+1}. \]

5. Update the model weights

\[ w_{t+1}^{i} = \frac{\lambda}{N_{mdl}} + (1 - \lambda) \cdot \frac{w_t^{i} \exp \left(-\eta^r \ell_t \left(\hat{\theta}_t^{i}, y_t\right)\right)}{\sum_{j=1}^{N_{mdl}} w_t^{j} \exp \left(-\eta^r \ell_t \left(\hat{\theta}_t^{j}, y_t\right)\right)} \]
Algorithmic guarantees

• **Regret**: performance with respect to a comparator $\theta_T$

\[
R_T(\theta_T) \triangleq \sum_{t=1}^{T} \ell_t(\hat{\theta}_t) - \sum_{t=1}^{T} \ell_t(\theta_t).
\]

• Often the comparator is the performance of a batch algorithm

• Hall and Willet derive bounds on the regret and show that for many classes of comparators regret scales sublinearly in $T$
Plant Data/Models

• Air conditioners:
  – Three-state (hybrid) TCL models
• Other loads:
  – Data from Pecan Street Inc. Dataport
• **Air conditioners:**
  – Two-state (hybrid) TCL models
  – Linear time-invariant aggregate system model
  – Linear time-varying aggregate system model

• **Other loads:**
  – Smoothed data from previous days
Algorithm Models

Model Set Estimates

- 57 models
- \( \hat{y}_t \) = \( \hat{y}_t^c \) + \( \hat{y}_t^{uc} \)
  - ACs + Other
- AC models initialized at actual value, and run open-loop

Parameter Description Value

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Description</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>( Q_{db} )</td>
<td>Coefficient of Performance ([-] ]</td>
<td>[-3]</td>
</tr>
<tr>
<td>( C_{ach} )</td>
<td>Appliance Heat Transfer ([\text{kW}] )</td>
<td>[-17.7, -13.1]</td>
</tr>
<tr>
<td>( C_{iam} )</td>
<td>Internal Mass Heat Gain ([\text{kW}] )</td>
<td>0.5</td>
</tr>
<tr>
<td>( C_{ahc} )</td>
<td>Air Heat Capacitance ([\text{kW}] )</td>
<td>[0.16, 0.21]</td>
</tr>
<tr>
<td>( C_{env} )</td>
<td>Envelope Conductance ([\text{kW}] )</td>
<td>[0.84, 1.14]</td>
</tr>
<tr>
<td>( T_{set} )</td>
<td>Temperature Set-Point ([\text{°C}] )</td>
<td>[4.48, 6.07]</td>
</tr>
<tr>
<td>( t_{d} )</td>
<td>Time-Step Duration ([\text{s}] )</td>
<td>2</td>
</tr>
<tr>
<td>( t_{s} )</td>
<td>Parameter Description</td>
<td>Value</td>
</tr>
</tbody>
</table>
Prediction Results

Amplitude [MW]

Time of Day

12AM 6AM 12PM 6PM 12AM

0 2 4 6

11/5/16
Weightings:
each color is a different model
Prediction Results: Better Models

Time of Day

Amplitude [MW]

12AM 3AM 6AM 9AM 12PM 3PM 6PM 9PM 12AM

$y_t$ $\hat{y}_t$

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Weightings: Better Models

![Graph showing weightings by different models over time]

- **Weights**:
  - LTV1
  - LTV2
  - LTI,36
  - PA

- **Models**:
  - Other Models

- **Time of Day**:
  - 12AM
  - 6AM
  - 12PM
  - 6PM
  - 12AM

- **Weights vs. Time**
  - 0 to 1

Date: 11/5/16

J. Mathieu, University of Michigan
Prediction Results: Bad Models

- All “other load models” are too low.
## Results: Summary

<table>
<thead>
<tr>
<th>Case</th>
<th>RMS Error (kW)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Benchmark:</strong> Use current outdoor temperature, LTI models, and interpolation to predict</td>
<td>738</td>
</tr>
<tr>
<td>DMD Case 1: Includes every combination of aggregate air conditioner model and “other load model”</td>
<td>264</td>
</tr>
<tr>
<td>DMD Case 2: Case 1 models plus a smoothed version of the actual “other loads”</td>
<td>211</td>
</tr>
<tr>
<td>DMD Case 3: Case 2 models plus more accurate models of the aggregate air conditioning load over time periods where the other models are less accurate</td>
<td>175</td>
</tr>
<tr>
<td>DMD Case 4: Includes “other load models” that underestimate the “other load”</td>
<td>1392</td>
</tr>
</tbody>
</table>
Next steps

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

• 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.
Conclusions

• Need new sources of power system reserves
  – Coordination of distributed electric loads using delay-aware control/estimation

• Need methods to infer electric load behavior from existing measurements
  – Dynamic mirror descent applied to distribution substation measurements

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Funding: NSF Grant ECCS-1508943.