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

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University: The University of Michigan (UofM)

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Part I: General Background
Background: The University of Michigan, the ECE department, and MPEL

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]
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]

Contents

• Problem Framework
• Online Learning Algorithms
• Models
• Results
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Energy disaggregation is performed on real-time demand measurements using DFS, an online learning algorithm.
DFS incorporates predictions from models that are generated from historical building- and device-level data.
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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
Results

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

<table>
<thead>
<tr>
<th>Model Set Algorithm</th>
<th>$\mathcal{M}^{\text{Full}}$ DFS</th>
<th>$\mathcal{M}^{\text{Red}}$ DFS</th>
<th>$\mathcal{M}^{\text{KF}}$ DFS</th>
<th>$\mathcal{M}^{\text{KF}}$ BKF</th>
<th>$\mathcal{M}^{\text{KF}}$ AKF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Demand</td>
<td>196.8</td>
<td>100.0</td>
<td>99.7</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>AC Demand</td>
<td>308.0</td>
<td>220.6</td>
<td>226.5</td>
<td>195.3</td>
<td>259.4</td>
</tr>
<tr>
<td>OL Demand</td>
<td>291.4</td>
<td>222.3</td>
<td>228.2</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

(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


Questions?
Recent Works by Prof. Hiskens and Mathieu


