AMI DATA FOR ENERGY EFFICIENCY AND CONSERVATION

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Billing data is often used for efficiency and conservation studies

Empirical assessments of efficiency / conservation programs

- Must control for outdoor temperature effects which vary among groups
- There are standard models for accounting for temperature effects:
  - PRInceton Scorekeeping Method (PRISM)
  - Change point models (Fels 1988, Kissock 2002)

Baselines of current Infrastructure/behavior, enabled by AMI

Classification of cooling hours, and estimation of temperature response.

Estimated # of hours of AC use per house per year, (Dyson et al. 2014)
AMl data create potential for even more insights

<table>
<thead>
<tr>
<th>What do thermal models tell us about a residence?</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Thermal efficiency of infrastructure</strong></td>
</tr>
<tr>
<td>• Effective thermal resistance</td>
</tr>
<tr>
<td><strong>Efficiency / Behavior</strong></td>
</tr>
<tr>
<td>• Non-HVAC Energy Use</td>
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<tr>
<td>• HVAC Energy Use</td>
</tr>
<tr>
<td><strong>Behavior</strong></td>
</tr>
<tr>
<td>• HVAC Schedule</td>
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<table>
<thead>
<tr>
<th>What could we ask about energy efficiency or conservation?</th>
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<tbody>
<tr>
<td>• Baseline current infrastructure efficiency and behavioral practices.</td>
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<tr>
<td>• Test hypotheses of</td>
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<tr>
<td>▪ Landlord/tenant effects on efficiency versus behavior</td>
</tr>
<tr>
<td>▪ Geographic indicators of efficiency versus behavior</td>
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<tr>
<td>• Cluster consumers to target efficiency programs.</td>
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<tr>
<td>• Explain differing energy use within similar populations.</td>
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</table>
Bias in thermal models from smart meters

No measurement of indoor temperature or internal heat gains
  Implicitly assume that they are independent of outdoor temperature

No estimate of thermal mass of the home, which may dampen the effect of a periodic outdoor temperature signal.

Classification bias,
  Parameters are sensitive to classifications
  Classifications are sensitive to large deviations.
Models are more likely to misclassify ambiguous readings, which can lead to systemic bias.
This work

Evaluates a set of models (existing and novel) for their ability to identify thermal and behavioral properties from smart meter data, focus on bias in estimates
## Detailed data

<table>
<thead>
<tr>
<th>Thermostat Data</th>
<th>Thermostat: Room temp, Set point</th>
<th>Power Meter: AC electricity use</th>
</tr>
</thead>
<tbody>
<tr>
<td>~ 4000 Residences</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5-min resolution</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3 summer months</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Pecan St.</th>
<th>Power Meter: AC electricity use</th>
</tr>
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<tbody>
<tr>
<td>25 Residences</td>
<td>Power Meter: All other electricity use</td>
</tr>
<tr>
<td>5-min resolution</td>
<td></td>
</tr>
<tr>
<td>12 months</td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Forecast.io</th>
<th>Outdoor Temperature</th>
</tr>
</thead>
<tbody>
<tr>
<td>Zip-code</td>
<td>Clearness Index</td>
</tr>
<tr>
<td>1h resolution</td>
<td></td>
</tr>
</tbody>
</table>

#### Reduced to AMI data

60 min time resolution, aggregated total building use

![Graph showing power usage from Jan 2012 to Oct 2012](chart.png)

- **Non-AC (Pecan St.)**
- **AC (Landis Gyr)**
Comparison Method

Data
- Detailed Data (5-min)
  - AC Energy Use
  - Room Temperature
  - Outdoor Temperature
  - Solar Insolation
- AMI-like Data (60-min)
  - Total Energy Use
  - Outdoor Temperature

Models
- ARMA Model (Rabl, 1988)
- Set of AMI Data Models

Estimates
- Ground Truth
  - AC Energy Use
  - AC State (ON/OFF)
  - Eff. Thermal Resistance
  - Ave. change point
- AMI Estimates
  - AC Energy Use
  - AC State (ON/OFF)
  - Eff. Thermal Resistance
  - Ave. change point
AMI data Models

Change point only models
Similar to models used for energy efficiency evaluation (Fels, 1988, Kissock 2002)
Change point can be used as a breakpoint or a point to define HDH/CDH
Change point is estimated by maximum likelihood (or minimal RMSE)
AMI data Models

**Change point + classification models**

Similar to models used in (Dyson et al. 2014; Albert and Rajagopal, 2014)

Observations above the change point may or may not be in a cooling state.
AMI data Models

Intercept for cooling times
Allows the cooling energy to be non-zero at the change point.
Difficult to assign physical significance value when it is negative
AMI data Models

Daily data
Regress onto cooling degree hours instead temperature above change point
May average out specious correlations due to diurnal effects
AMI data Models

Kernel density errors
Assess probability of residuals using a kernel density estimator. Reduces the effect of outliers on the classification of ON/OFF.
Results

- Including classifications greatly reduces errors.
- Lowest RMSE from hourly data with Normal errors.
- Using Kernel errors raises RMSE slightly.

Changepoint Only Models

<table>
<thead>
<tr>
<th>Cooling Intercept</th>
<th>Hourly</th>
<th>Daily</th>
<th>Hourly</th>
<th>Daily</th>
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<tbody>
<tr>
<td>No</td>
<td>Normal</td>
<td>Kernel</td>
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Changepoint + Classification Models

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Prediction of Daily AC Energy Use

- The mean error displays whether models are biased in a specific direction
- Kernel error densities reduce bias, though they increase the average error
- Least biased model for predicting daily AC energy use
AC ON/OFF, Hourly

- Percent of “AC ON” classifications that are correct
- Percent of “AC ON” times that are classified as “ON”

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<th>Changepoint + Classification Models</th>
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<td></td>
<td>No Cooling Intercept</td>
<td>Cooling Intercept</td>
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<tr>
<td>Time</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hourly</td>
<td>Normal</td>
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Thermal Resistance and Change points

- Change point only models choose high change points and slopes

- Classification models choose low change points and slopes
Thermal Resistance and Change points

Models with kernel density errors perform with the least bias

Results

• Models with kernel density errors perform with the least bias
Concluding Remarks

Minimizing square or absolute errors may not give the best models

Additional detail is not always helpful.

Best arrangement we’ve found so far…
Endogenously classify readings by cooling mode, and to use a kernel density to estimate error distribution shapes.

Enabling new future research
Thank You

National Science Foundation Graduate Research Fellowship

Lawrence Berkeley National Laboratory
Sila Kiliccote
Emre Can Kara

Fellow Berkeley Students
• Mark Dyson
• Sam Borgeson
• Peter Alstone
• Imran Sheik