Using Machine Learning to Predict Occupant Hot Water Use and Improve HPWH COP

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ACEEE Hot Water Forum
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Acknowledgements

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- Funded through California Energy Commission GFO-17-304
- Applied research and technology deployment
- Creating an “Energy Marketplace” to deploy technologies
Introduction - Fundamentals

- Heat pump (HP) Coefficient of Performance (COP) > Electric Resistance (ER) COP
- HP COP = f(Water Temperature, Air Temperature)
- Time of Use (TOU) rates are coming

- Ergo, controls that...
  - Replace ER operation with HP operation,
  - Time HP use for favorable temperatures, or
  - Use electricity at low cost time of day
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Introduction - Hypothesis

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- Broad predictions of hot water draw profiles are impossible
  - Entirely too much variation between homes
- But...maybe individual occupants are fairly repeatable
  - Monitor how a specific household uses hot water
  - Develop understanding of common patterns
  - Reasonably predict future hot water use
Methods – Machine Learning Algorithms

• Use monitored data from 18 different sites

• Apply 3 machine learning techniques
  ○ Averaging bin
  ○ Averaging bin, last x days
  ○ Template matching

• Compare results:
  ○ Run time
  ○ Mean bias error (MBE)
  ○ Root mean square error (RMSE)
  ○ Visual comparison
Methods – Averaging Bin

![Graph showing volume per 1/2 hour (Gal) against time of day (Hr) for different dates in June.](image-url)
Methods – Averaging Bin

- Volume per 1/2 Hour (Gal)
- Time of Day (Hr)

Graph showing data points for different dates in June, with an arrow pointing to a smoothed average graph.
Methods – Averaging Bin, Last x Days
## Results – Calculation Time

<table>
<thead>
<tr>
<th>Method</th>
<th>Time (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Averaging Bin</td>
<td>320</td>
</tr>
<tr>
<td>Averaging Bin, Last 10 Days</td>
<td>299</td>
</tr>
<tr>
<td>Template Matching</td>
<td>18,780*</td>
</tr>
</tbody>
</table>

*And it overwhelms my computer*
## Results - Statistics

<table>
<thead>
<tr>
<th>Method</th>
<th>Bin Duration (Minutes)</th>
<th>Average Normalized Mean Bias Error (gal)</th>
<th>Average Root Mean Square Error (gal)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Averaging Bin</td>
<td>15</td>
<td>0.937</td>
<td>2.145</td>
</tr>
<tr>
<td>Averaging Bin</td>
<td>30</td>
<td>0.937</td>
<td>3.492</td>
</tr>
<tr>
<td>Averaging Bin</td>
<td>60</td>
<td>0.937</td>
<td>5.45</td>
</tr>
<tr>
<td>Averaging Bin, Last 10 Days</td>
<td>15</td>
<td>0.924</td>
<td>1.444</td>
</tr>
<tr>
<td>Averaging Bin, Last 10 Days</td>
<td>30</td>
<td>0.924</td>
<td>2.350</td>
</tr>
<tr>
<td>Averaging Bin, Last 10 Days</td>
<td>60</td>
<td>0.924</td>
<td>3.679</td>
</tr>
</tbody>
</table>
Results – Good Match
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Extremely accurate
Results – Good Match

Accurate enough?

Extremely accurate

- Water Consumption (gal)
- Average Water Consumption (gal)
Results – Good Match

Accurate enough?

Extremely accurate

Underpredicts

Hot Water Consumption (gal)

Time (hr)
Next Steps

• Best Performer: Averaging Bin, Last 10 days, 15 min bins
• Statistics and plots show potential
• But...is it good enough?
• Use it to drive simulation and testing study
  ○ Predicted profile  =>  Input to MPC
  ○ Actual profile    =>  Input to simulation/test
  ○ *Does it reduce occupant electricity cost?*