

A optimal load-shifting via internet-based thermostat control and sensors for improved residential load management

STEVEN A. GABRIEL, UNIVERSITY OF MARYLAND

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Co-presenters:

Michael Siemann, Whisker Labs
Jaden Crawford, Whisker Labs
Rachel Moglen, University of Maryland
Pattanun Chanpiwat, University of Maryland

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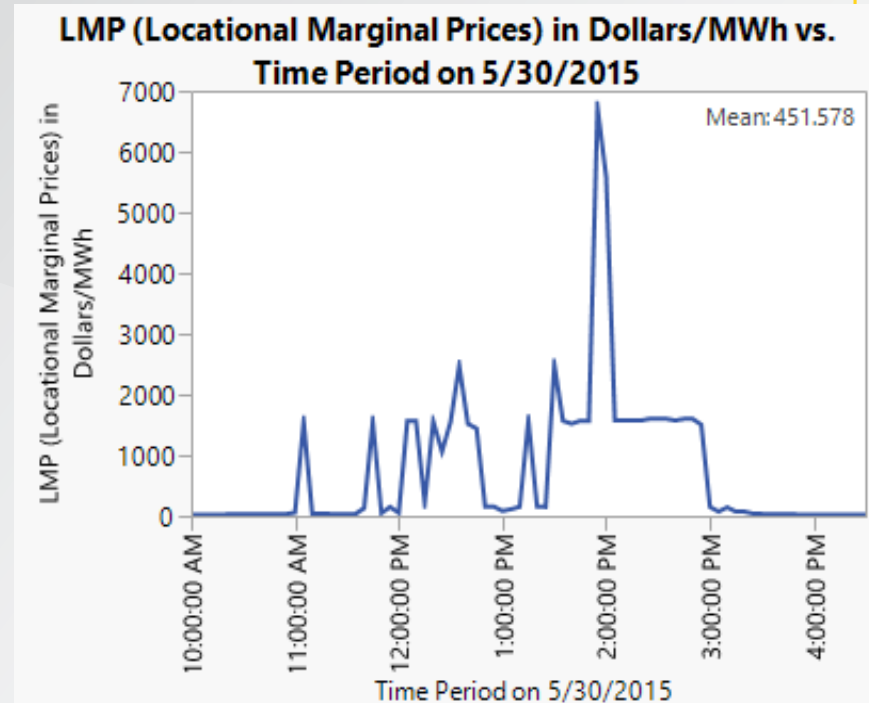
Outline

1. Motivation
2. Industrial Partner Background (Whisker Labs)
3. Some Initial Results



Motivation

- Volatile market: prices can increase by two orders of magnitude in 30 minutes
- Customers pay a constant rate, so the electric providers are fully exposed to these spikes
- Price spikes in 2011 put several retail electric power providers (REPs) out of business



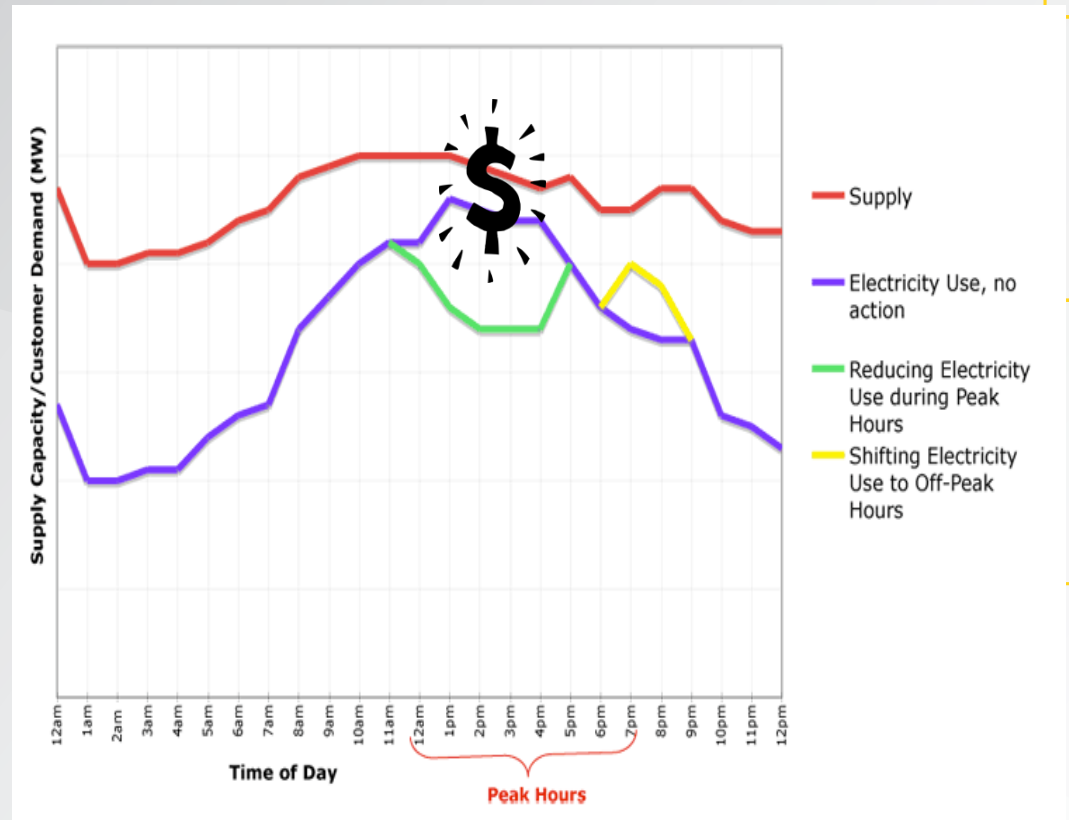
Houston, TX



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Current State of the System

- Use demand response (DR) to curtail load during periods of grid stress and high prices
- No DR:
 - Risks: Full exposure to price spikes
- Manual DR guided by human intuition:
 - Risks: Missed events, suboptimal scheduling

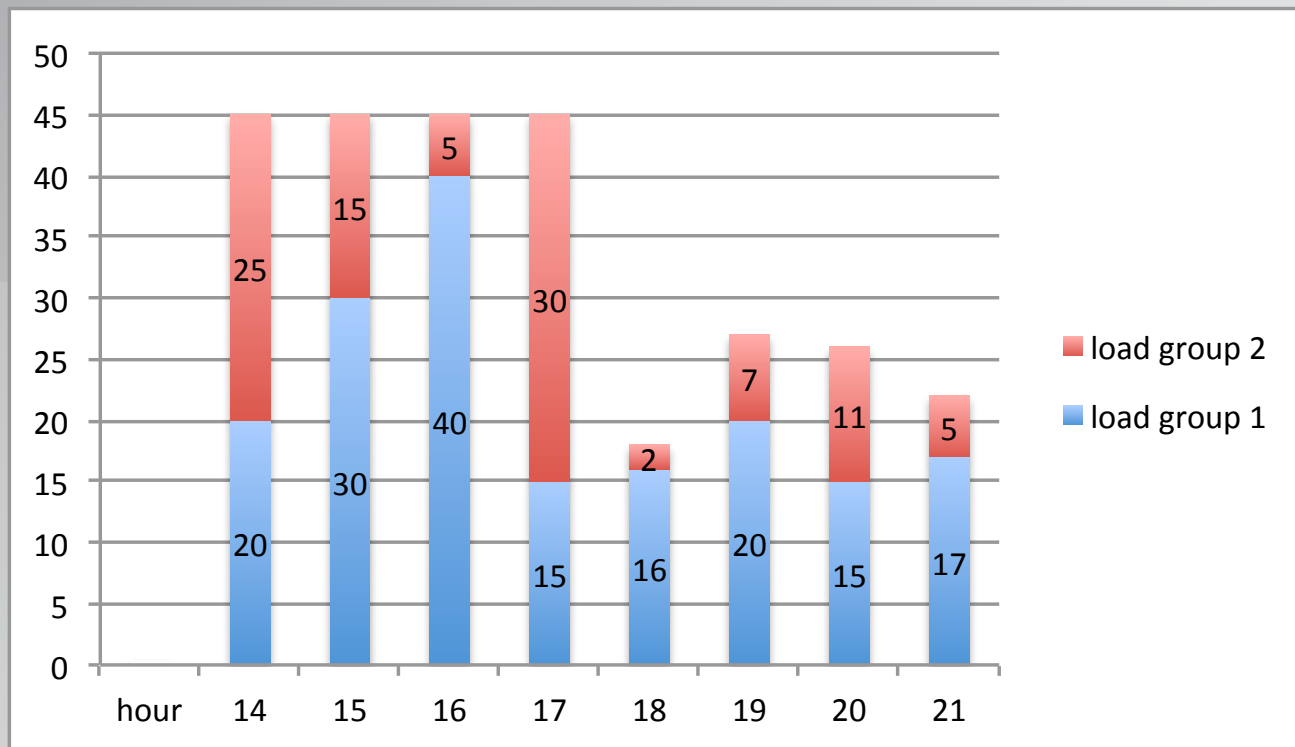


http://sites.suffolk.edu/didyboo/files/2011/09/now_shifting_graph1.gif



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Overview of Modeling



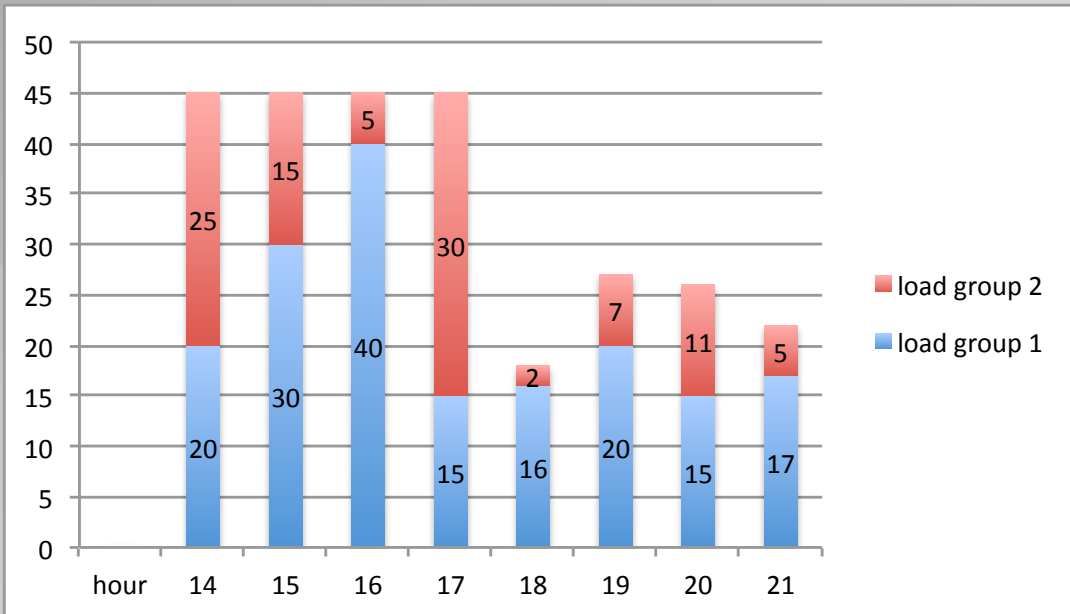
Typical day considered:

- Hours ending 14-21

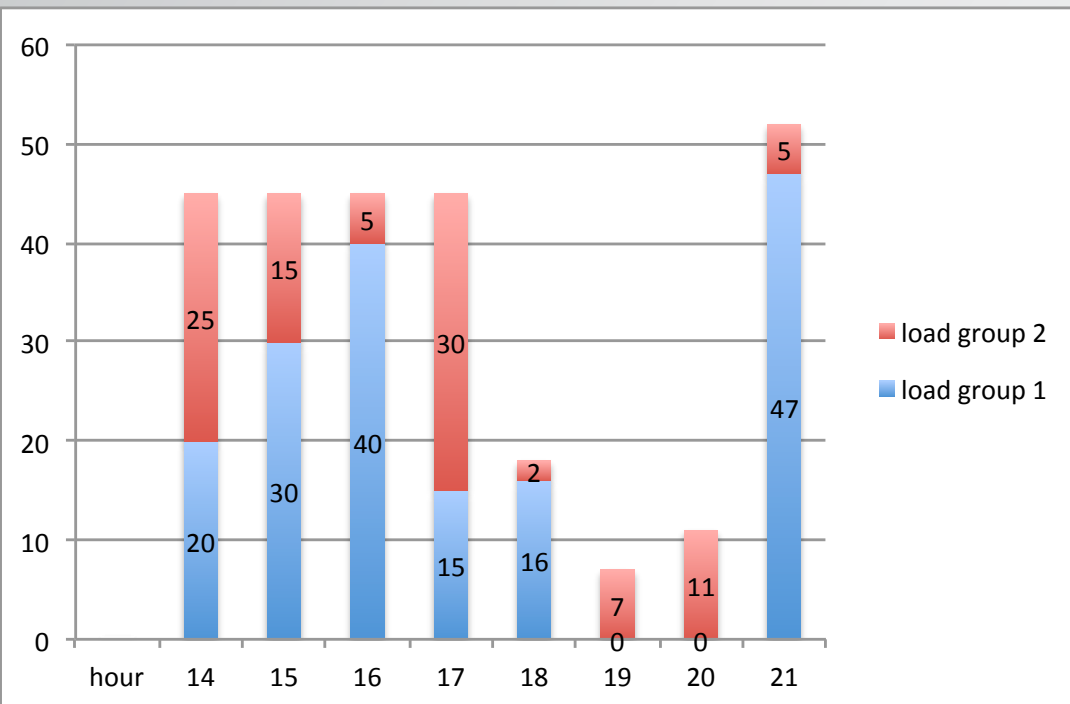
- **Central Question:** How much of each customer group's load (2 shown here) should be shifted from a current hour(s) to a contiguous hour? The shifted load will be reduced by a certain factor (set points, etc.)
- **Benefits:** If the load is shifted to a less expensive hour, then retail electric providers (REPs) will be able to procure the needed power for less money. Even though less load, the overall effect may be beneficial in terms of expected profit and financial risk, less need for peaking machines for the energy producer, less negative environmental impacts.



Example of 2-Hour Load Shift



- Original load by group
- Group 1's load in hours ending 19 and 20 is 35 MW

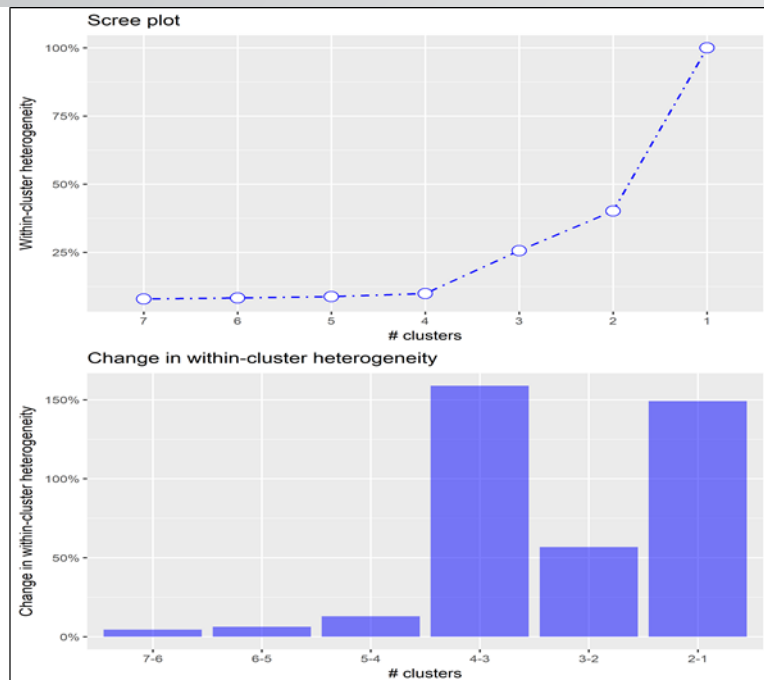
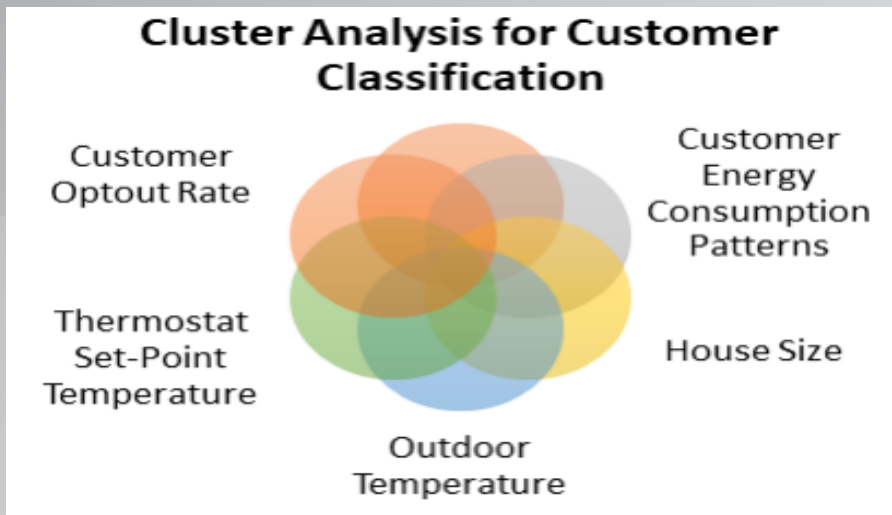


- Group 1's load for hours 19 & 20 shifted to hour 21
- 35 MW reduced to 30 MW



Household Clustering

- A cluster analysis is used to group consumers into smaller subgroups based on their household energy consumption.
- Such a set of distinct customer groups will better pinpoint load profiles for use in the DR models.
- An initial study grouped consumers that are statically similar into segment(s).
- A “hierarchical cluster analysis” performed to determine the number of segments.
- Then, a “K-Means cluster analysis” used to generate the details for the final segments.



The graphs of hierarchical average hourly energy use of 122 households on 2017_06_01



Industrial Partner Whisker Labs

Company Overview

- Sensor & software services platform company delivering total home intelligence
- Expertise in big data processing, thermodynamic modeling & consumer engagement
- HQ in Oakland, CA w/ lab in Germantown, MD - privately held, backed by top VCs

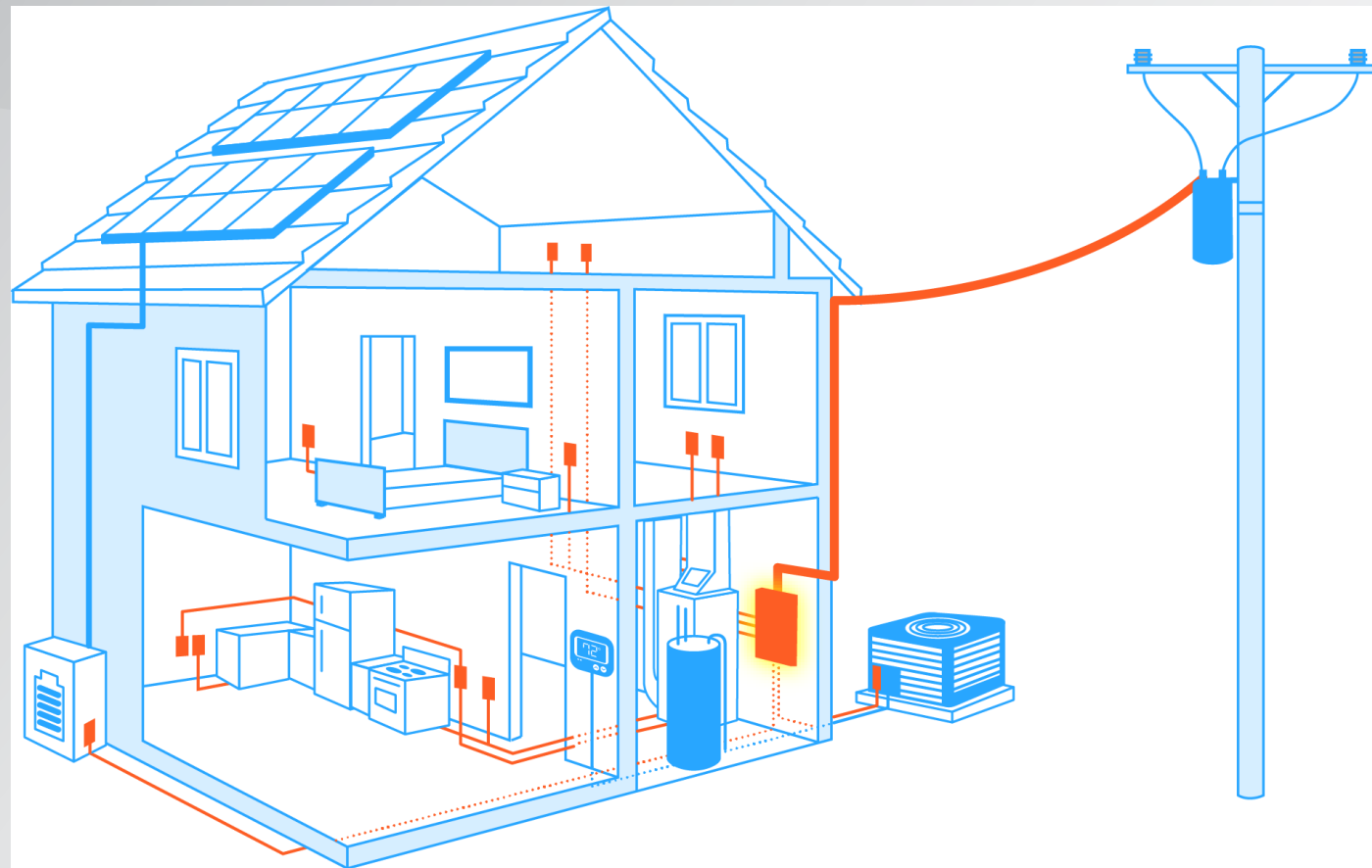


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Total Home Intelligence

- 1. Internet-based thermostat control (for DR events)
- 2. Energy sensor (attached to breaker box) for HH energy consumption profile



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Whisker Labs Energy Sensor

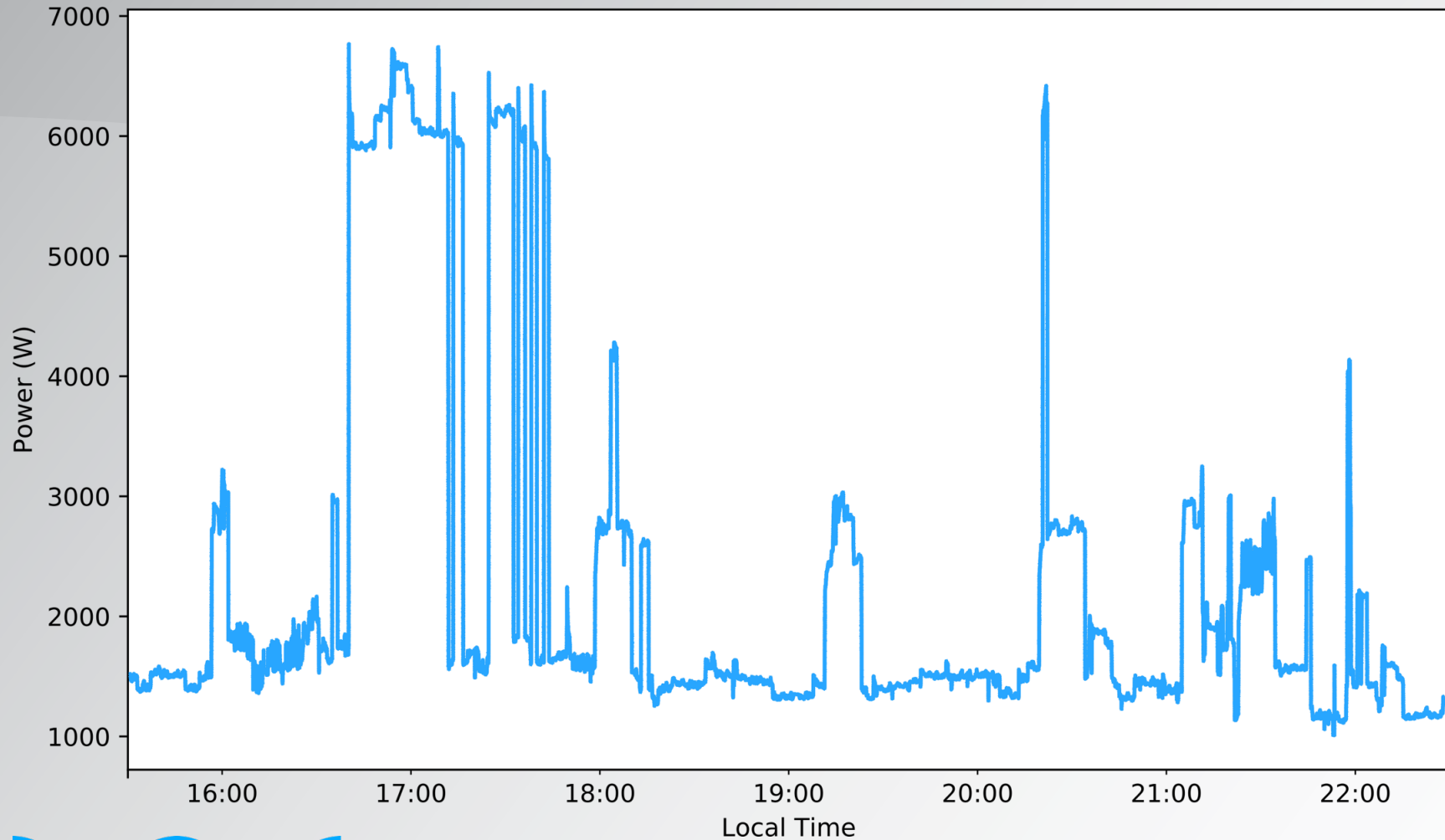


- Can be installed in <10 min
- No electrician
- No shutdown
- Compatible with 80% of breakers
- 2000 samples per second
- Wi-Fi Communication



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Whisker Labs Typical Energy Data



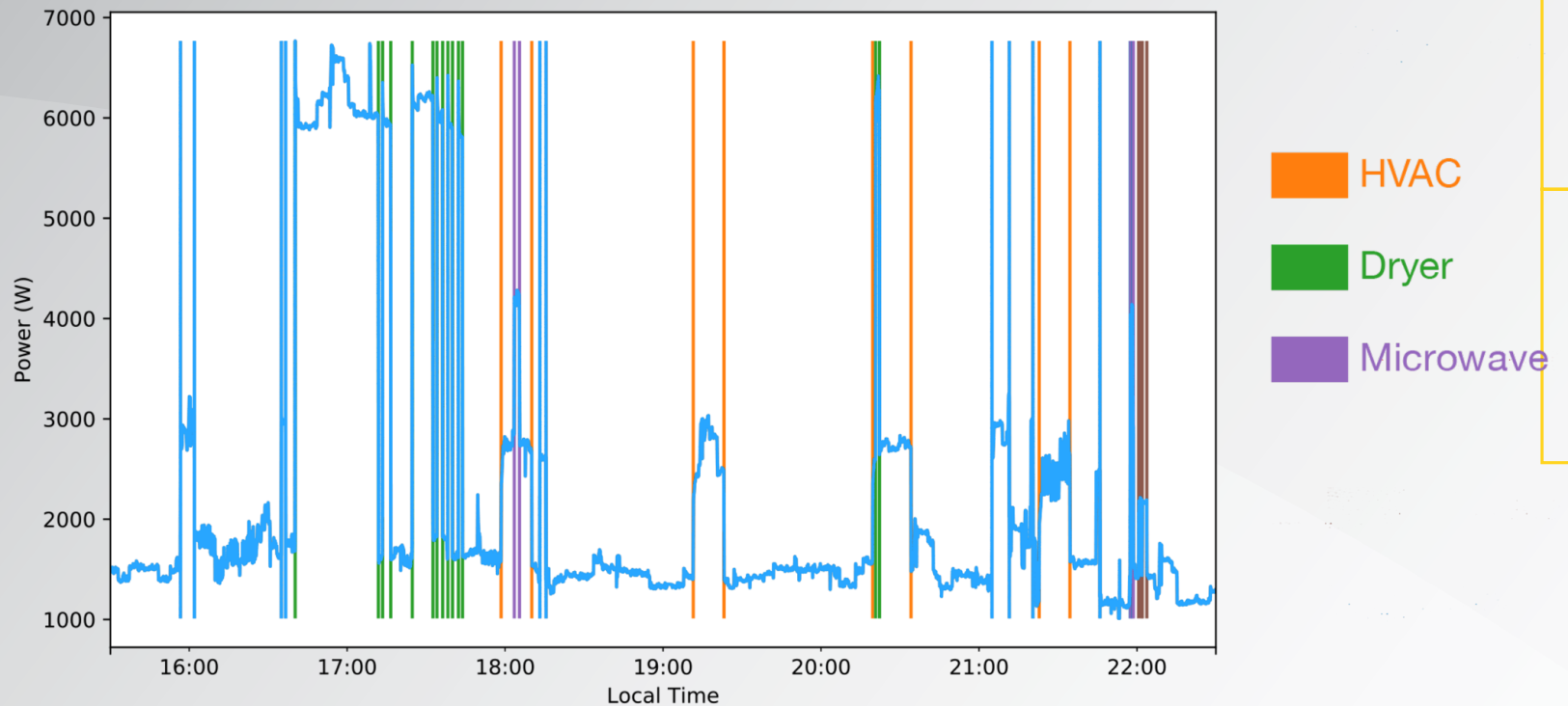
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Whisker Energy Data



Large Device Runtime
by Circuit:

HVAC
Dryer
Microwave



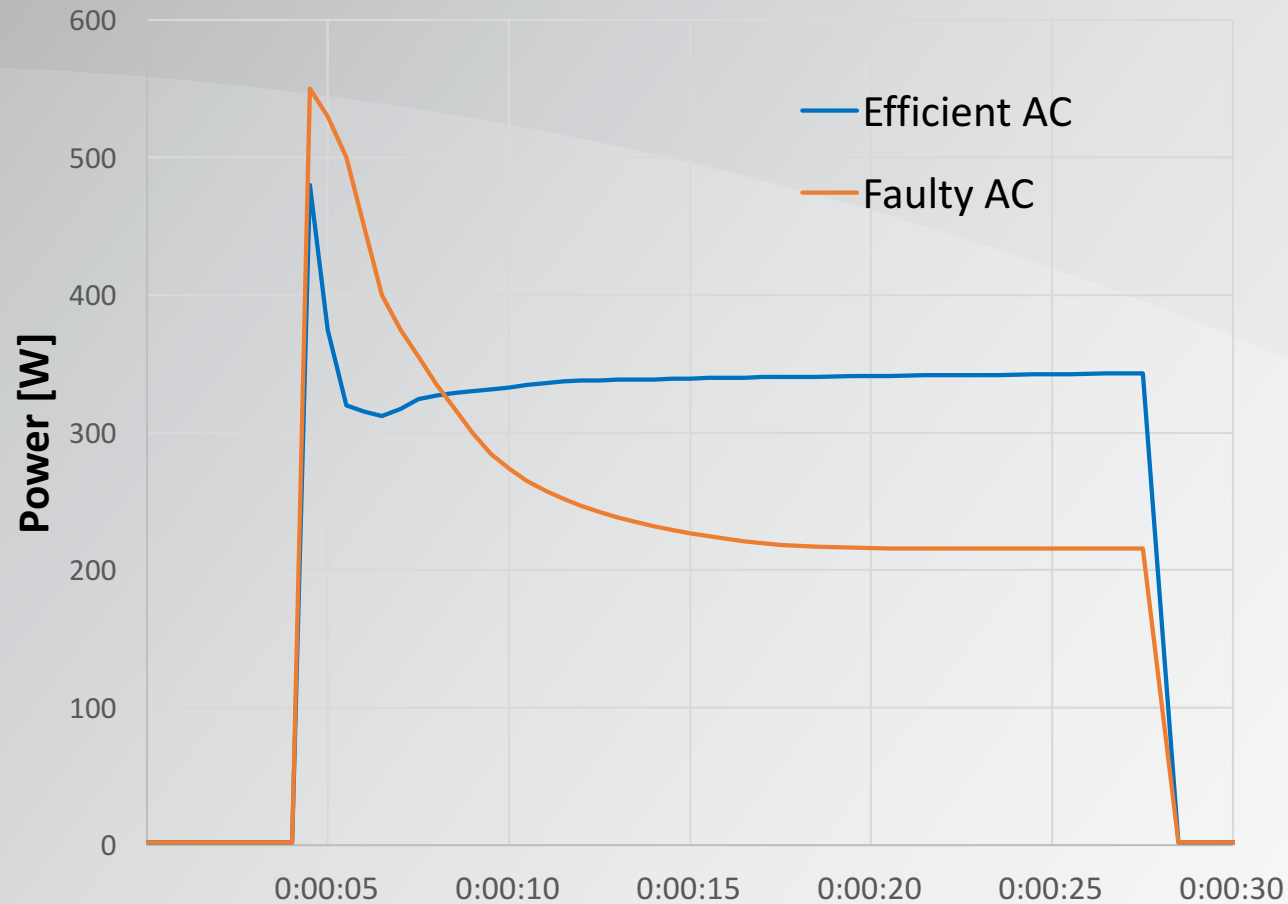
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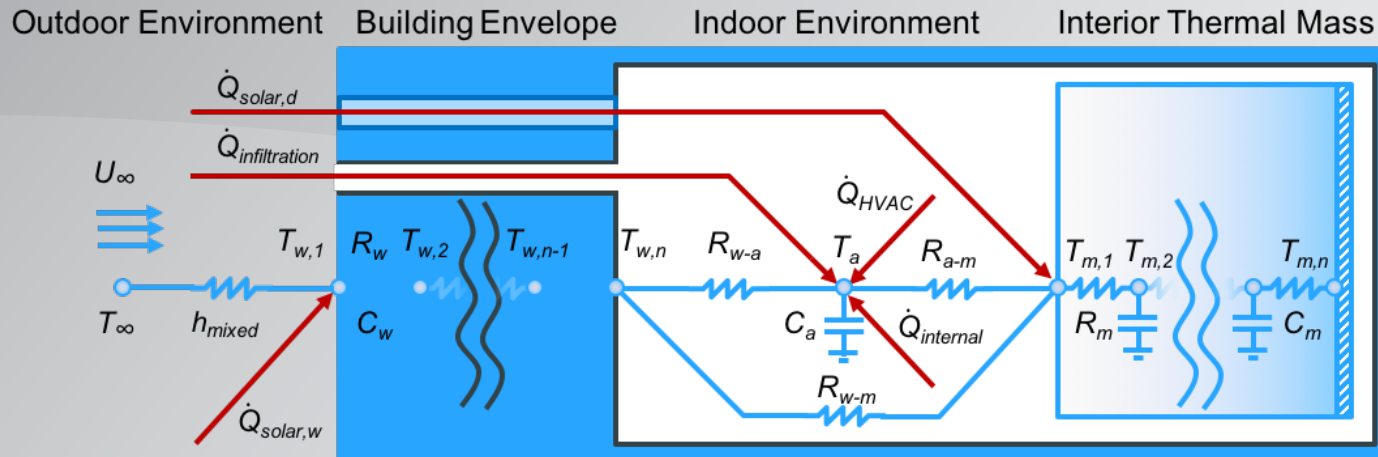
Detecting Efficient vs. Faulty Window AC



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Whisker Labs

WL Thermostat Greybox Model



- Correlate indoor to outdoor conditions
- Unique for every house
- Uses minimal customer data
- Developed in collaboration with University of Maryland



3x more energy efficiency
p/t-stat



15% more DR capacity
per home



Connected Savings Intelligence
DRMS



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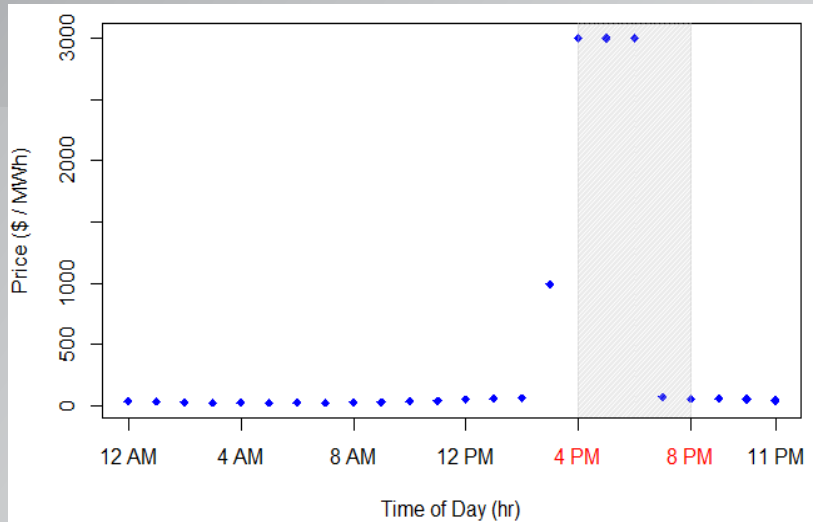
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Stochastic Optimization

- Use predicted prices and temperatures to optimally schedule households for DR events throughout the day
- “Optimally” defined as **maximizing** profit while **minimizing** risk:
 - Expected Profit
 - Customer Opt- out risk (on-going study)
 - CVaR of the profit distribution
 - Tailored to individual customer classes (clustering analysis)



Stochastic Optimization (SO)



Settlement-Point Prices in Houston, TX on 8/3/2011

- **\$10 / customer/ year:** with perfect information, how much DR scheduling using SO could have saved, on average
- **\$5.82 / customer:** How much the SO would have saved in the most extreme price event (08/03/ 2011)
- **5.9 million:** How many possible strategies there are for a 24-hour planning horizon
- **1.5 seconds:** How fast the SO can select the optimal strategy for the next 24 hours, allowing it to be used for real-time planning purposes



Challenges

The sensor and optimization technologies for real-time, household energy load-shifting/automated energy efficiency measures are present.

1. How best to convince energy policy decision-makers/energy market participants of the value added for adopting such systems as standard procedures? [Models, case studies, etc.]
2. How best to make residential load-shifting/energy efficiency “seamless” for customers and to motivate them to be part of such programs? [What incentives financial or otherwise, how to easily capture residential power load profiles by households, etc.]

