Smart Heating

Energy Savings Through Occupancy Sensing and Prediction

Ubiquitous Computing Seminar 2014

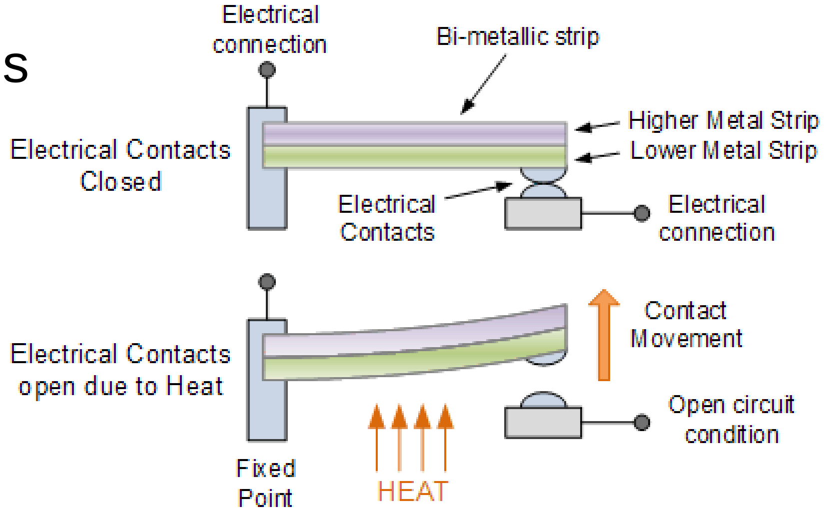
Motivation

- Heating, Ventilation and Air Conditioning (HVAC) systems consume lots of energy
- Residential HVAC systems account for 9% of total energy consumption in U.S. *
- Cost can be reduced by optimization
- Minimal cost for maximum comfort

** Gupta et al, Adding GPS-Control to Traditional Thermostats…*

Thermostat - History

- 1620
  - Cornelis Drebbel
  - Mercury thermostat for egg incubator
- 1830
  - Andrew Ure
  - Bimetallic thermostat for textile mills
- 1885
  - Warren S. Johnson
  - First electric room thermostat



www.wikipedia.org

Thermostats Today

- Manual Thermostat
  - Manually adjust setpoint to desired temperature
  - Adjust everytime when leaving/coming home
  - Sacrifice comfort
- Programmable Thermostat
  - Define a schedule for heating/cooling
  - Often complicated interfaces
  - Schedule changes

Thermostat Numbers

Table 1. Thermostat usage statistics in the U.S (summarized from [4]).

(In millions)	**Estimated no. of homes not using setback when away**
Manual Thermostat	40.46
Programmable Thermostat	14.60
Total	**55.06**

55.06

U.S. DOE Residential Energy Consumption Survey [cited 08/15/2008]

Smart Heating

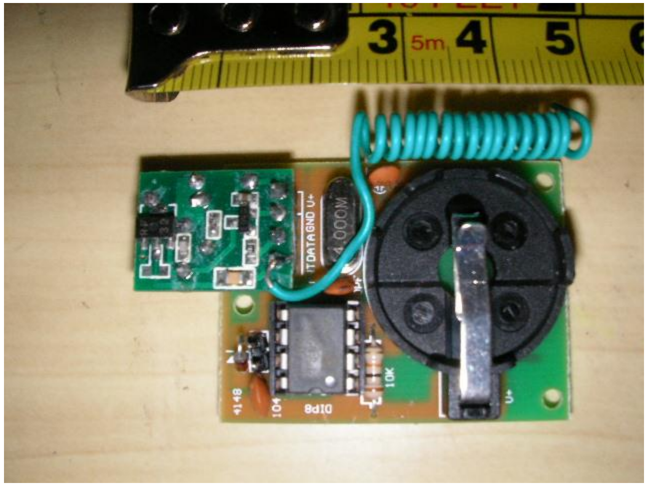
- Sense occupancy
- Predict occupancy
- Adjust heating and cooling devices accordingly
- Users don't have to manually adjust thermostat or define schedules

Occupancy Sensing – Devices

- PIR (Passive infrared occupancy sensors)
- Ultrasonic occupancy sensors
- Microwave sensors
- Audible sound/passive acoustic sensors
- Light barriers
- Video cameras
- Dual technology

Occupancy Sensing - Examples

- Active RFID tags
  - Send signal when in range
  - One per resident
  - $22 per tag and $30 for receiver*
  - Per house
- GPS Location
  - Phones
  - GPS loggers
  - Per house



*prices and picture from www.ananiahelectronics.com

Occupancy Sensing – Smart Thermostat

- Combining PIR and a magnetic reed switch on entrance door
- $5 per sensor (select set 3-5 sensors <$25, full set 12-20 <$100)
- Currently house level

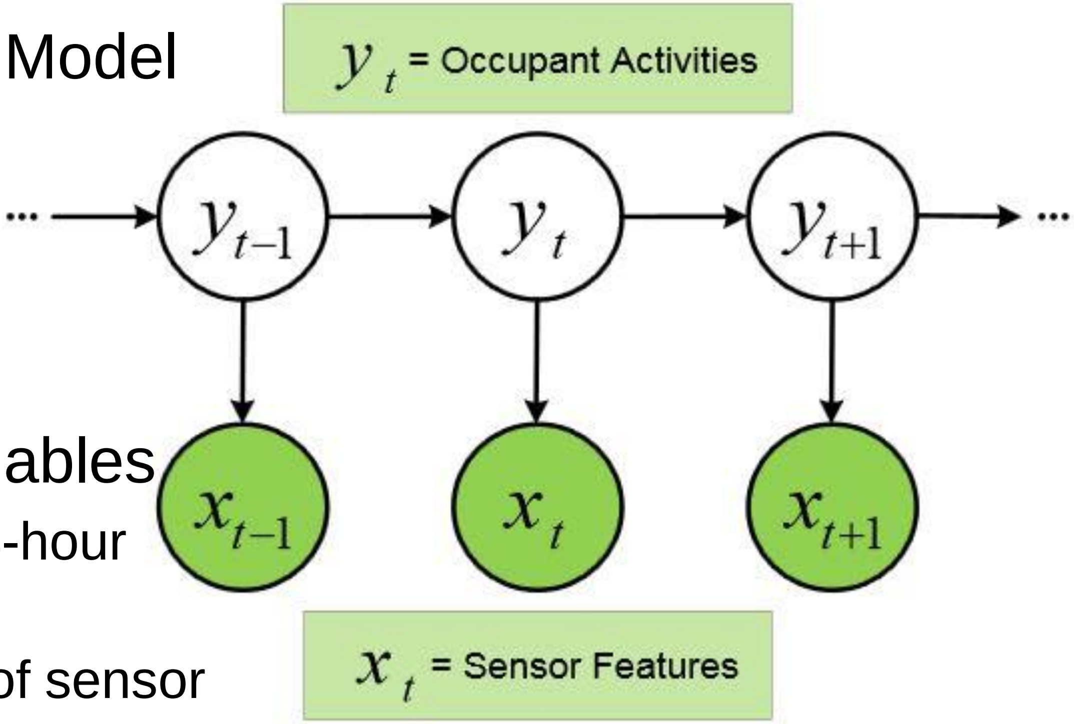
(a) Motion Sensor (b) Door Sensor

Figure 3. The smart thermostat uses motion sensors (left) and contact switches on doors (right).

Lu et al, Smart Thermostat

Occupancy Sensing – Smart Thermostat

- Hidden Markov Model
- States (y_t):
  - Active
  - Away
  - Sleep
- Observable variables
  i. Time of day (4-hour granularity)
  ii. Total number of sensor firings in dT
  iii. Binary features indicating presence of specific sensor firings



Lu et al, Smart Thermostat

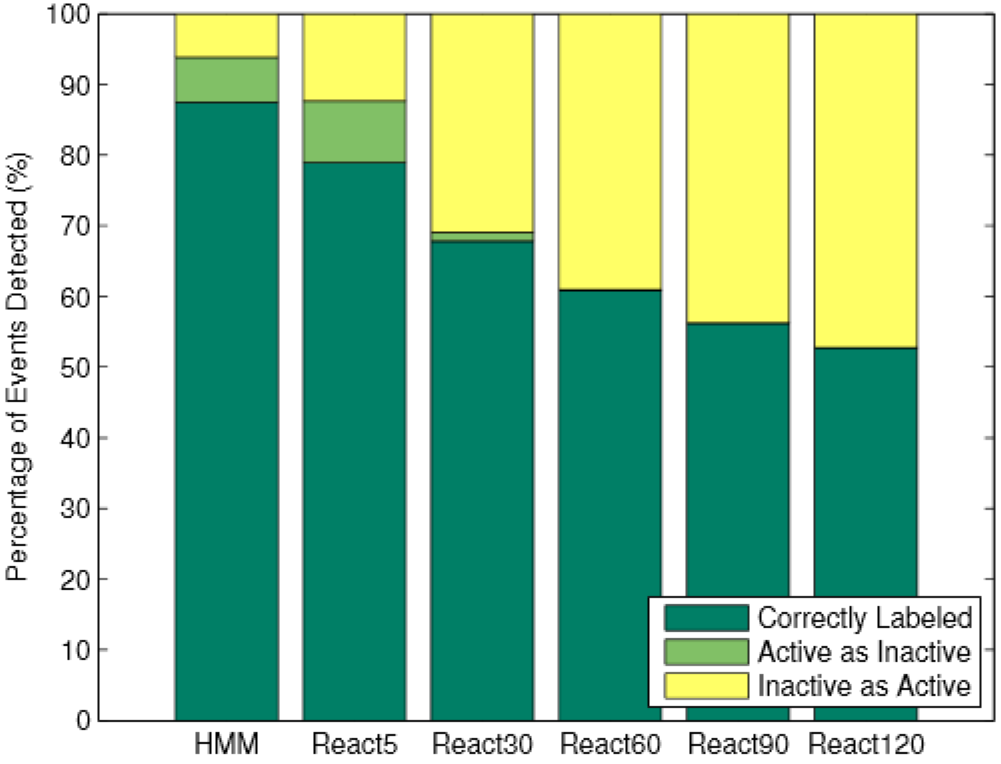
Occupancy Sensing – Smart Thermostat

- Trained using data trace from home with known occupancy states
- $P(y_t|y_{t-1})$ and $P(x_t|y_t)$ represented in discrete conditional probability table
- Calculated using frequency counting
- To accommodate for the bigger domain in ii (number of sensor firings) use generative Gaussian model

Lu et al, Smart Thermostat

Occupancy Sensing - Results

- 15-minute intervals
- Percentage of the whole day
- 12% wrong
  → 2 hours



Lu et al, Smart Thermostat

Occupancy Prediction

- Analyze recorded occupancy data
- Derive probabilities for occupancy in future time slots or make guesses for return time
- Lots of different models for calculations

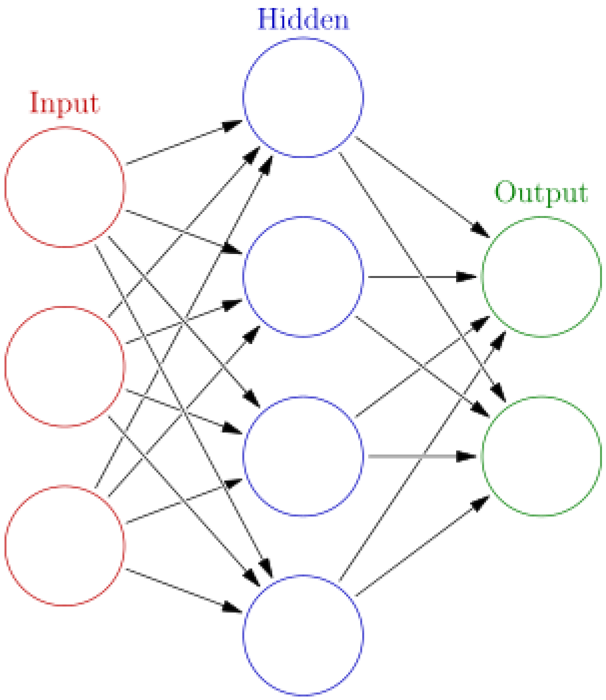
Occupancy Prediction – Neurothermostat

- Using neural network
- Inputs
  - Time of the day
  - Day of the week
  - Occupancy in next 10,20,30 minutes from past 3 days and 4 past same day of the week
  - Occupancy in past 60,180,360 minutes

Mozer et al, The Neurothermostat

Occupancy Prediction - Neurothermostat

- Trained by backpropagation
- Number of hidden weights determined by cross validation over several models
- Needs a long time to train
  - 150 days



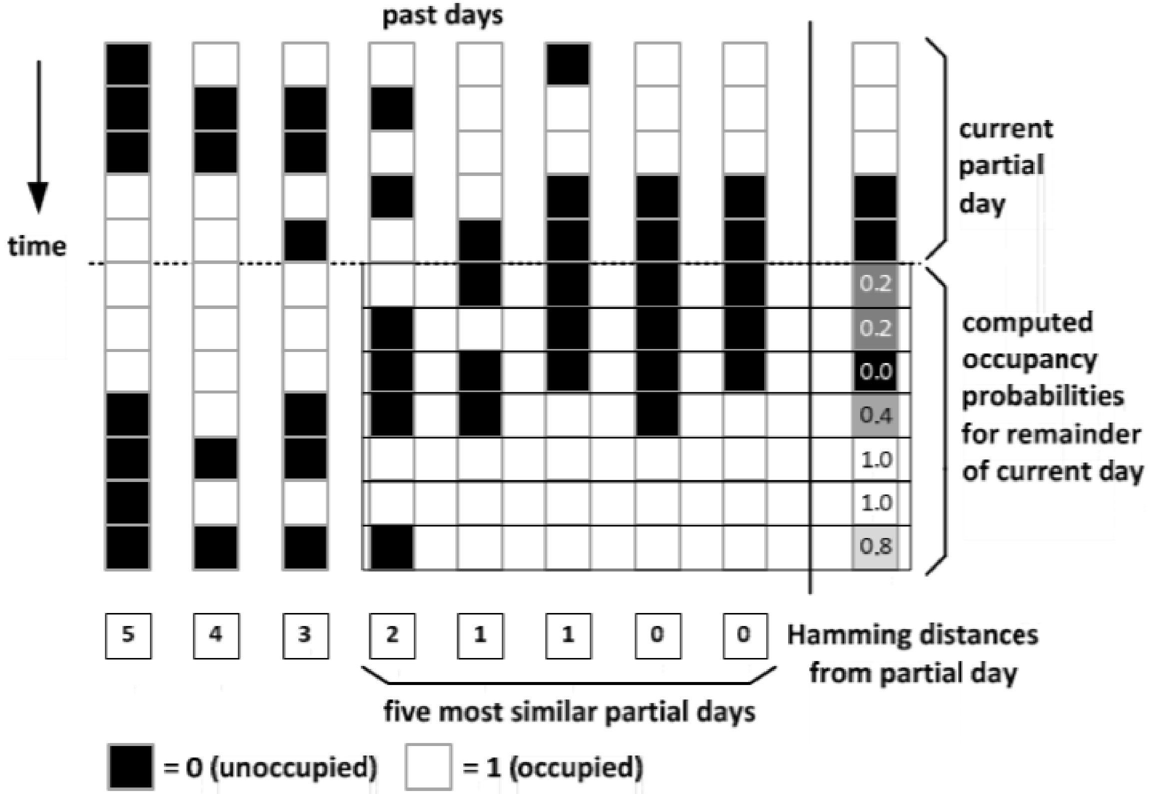
Mozer et al, The Neurothermostat

Occupancy Prediction - PreHeat

- Occupancy represented as a binary vector
- Current day (up to current time) is compared to previous days
- Use K most similiar days to derive occupancy for future timeslots

Scott et al, PreHeat: Controlling Home Heating…

Occupancy Prediction - PreHeat



Scott et al, PreHeat: Controlling Home Heating…

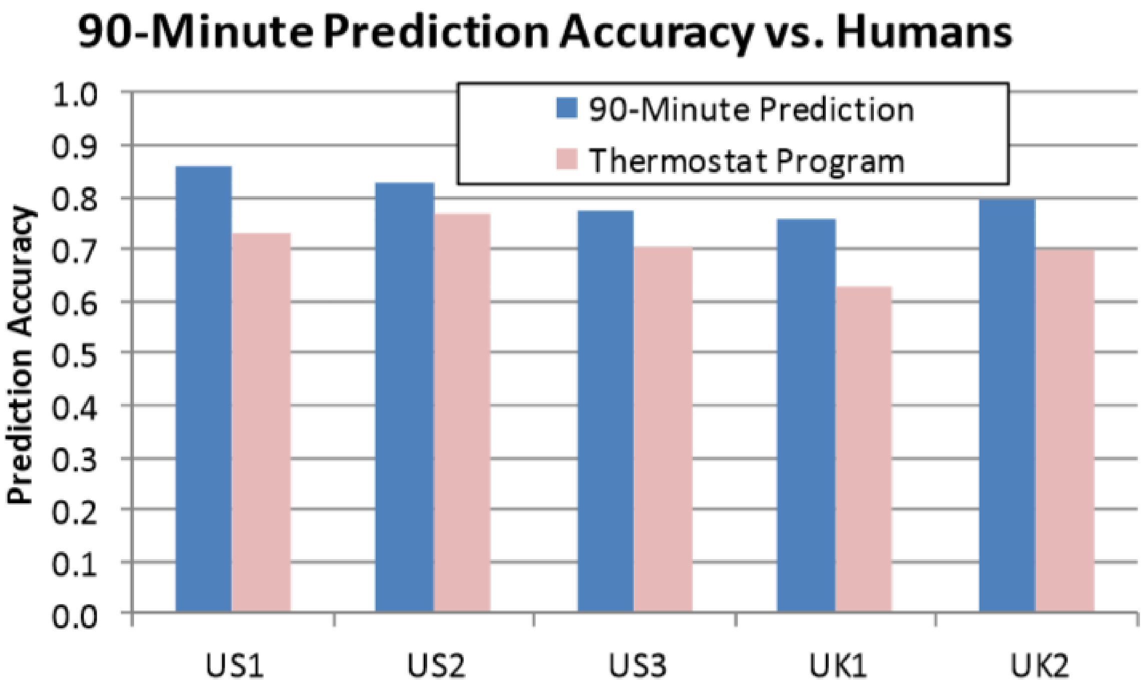
Occupancy Prediction - PreHeat

- Minor adjustments to algorithm
  - Padding at beginning and end of the day
  - Differ between weekdays and weekends

- Set threshold to individual preference
  - Lower threshold → more comfort
  - Higher threshold → more savings
- Limitations
  - Only daily patterns are compared
  - Could we change the weights?

Scott et al, PreHeat: Controlling Home Heating…

Occupancy Prediction Results



Scott et al, PreHeat: Controlling Home Heating…

Occupancy Prediction - GPS – Travel-to-home-time

- Use GPS sensors to keep track of current location of residents
- Evaluate minimal time to get home using MapQuest
- House is guaranteed to be at desired temperature upon return

- Benefit increases for residents having longer commute times

Gupta et al, Adding GPS-Control to Traditional Thermostats..

Occupancy Prediction - Krumm and Brush

- GPS data from logger carried by residents for occupancy sensing
- Linear matrix problem

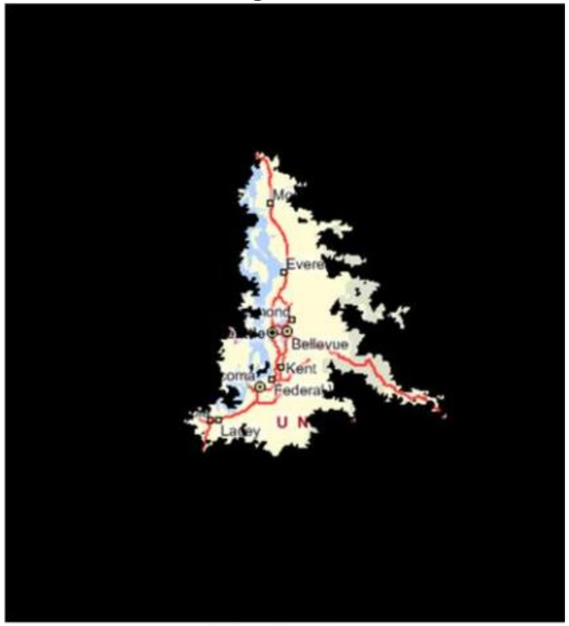
$$A\begin{pmatrix}\boldsymbol{p}_{week}\\ \boldsymbol{p}_{generic\ weekday}\end{pmatrix} = \boldsymbol{b}$$

$$(0\ 0\ \ldots\ 1\ \ldots\ 0\ 0\ |\ 0\ 0\ \ldots\ 1\ \ldots\ 0\ 0)\cdot \boldsymbol{p} = \frac{n_{away}}{n_{away} + n_{home}}$$

Krumm & Brush, Learning Time-Based…

Occupancy Prediction - Krumm and Brush Improvement

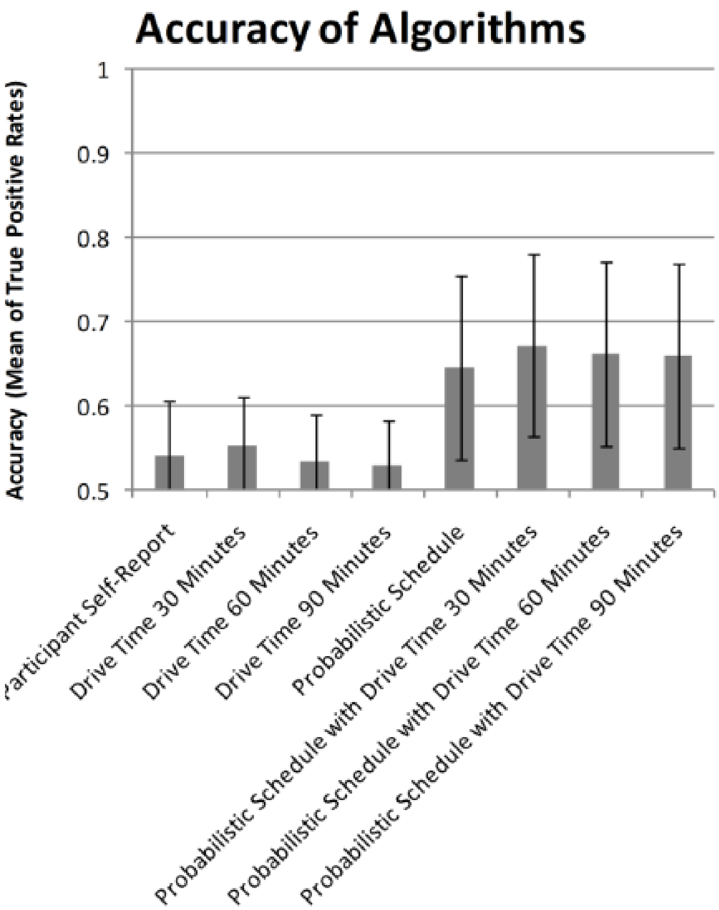
- Adding travel-to-home-time information
- Rule out return times deemed impossible by travel-to-home-time
- Effiency gain by creating drive time zones



90 minutes

Krumm & Brush, Learning Time-Based…

Occupancy Prediction – Krumm and Brush Results



- True positive rate over confusion matrix
- Better than self-reported schedules by participants
- Takes weekly and daily patterns into account
- Compared to PreHeat…

Krumm & Brush, Learning Time-Based…

Occupancy Prediction – Future Work

- Training of the models
  - Warm up time?
  - Pre-trained systems?
  - Complete schedule changes (new jobs)?
- House based to room/zone based?
  - How much can we apply directly?
  - What needs adjustment/new approaches?
- Combination of systems
  - Where does which algorithm work best?

Apply gained information to Heating

- General Idea
  - Go to setback temperature when occupants leave
  - Have house at desired setpoint when occupancy expected

- Can we do more?
  - Deep setbacks
  - …

Results and Evaluation

- Measuring heating-cost depends on a lot of factors
  - Isolation
  - Heating method
  - Outside temperature
  - Price of oil, gas etc.

- What about comfort?

Comfort Model – Ashrae 55

- Comfort factors
  - Air temperature
  - Mean radiant temperature
  - Air speed
  - Humidity
  - Metabolic rate
  - Clothing level
- CBE Thermal Comfort Tool

www.wikipedia.org

Comfort Model - MissTime

- Amount of minutes an occupied home is not at desired temperature
- Evaluated over a day
- Allow for values within a difference of 1°C to account for sensor discrepancies

- Does not take size of difference into account
- How about degree-hours? (How many degrees off for how long)

Lu et al, Smart Thermostat

Comfort Model - Neurothermostat

- Misery Cost
  - Express misery in dollars
  - Always 0 when not occupied
  - Enables direct comparison to energy/oil cost

- New optimization problem:
- Minimize Total Cost = Misery Cost + Heating Cost

Mozer et al, The Neurothermostat

Comfort Model - Neurothermostat

$$\widehat{m}(o,h) = o\alpha \frac{\delta}{24\times 60} \frac{\max(0, |\lambda - h| - \epsilon)^2}{25}$$

- Variables
  - o = occupancy (0/1)
  - h = temperature
  - α = conversion from misery units to dollars
  - δ = time interval
  - λ = setpoint

Mozer et al, The Neurothermostat

Comfort Model - Neurothermostat

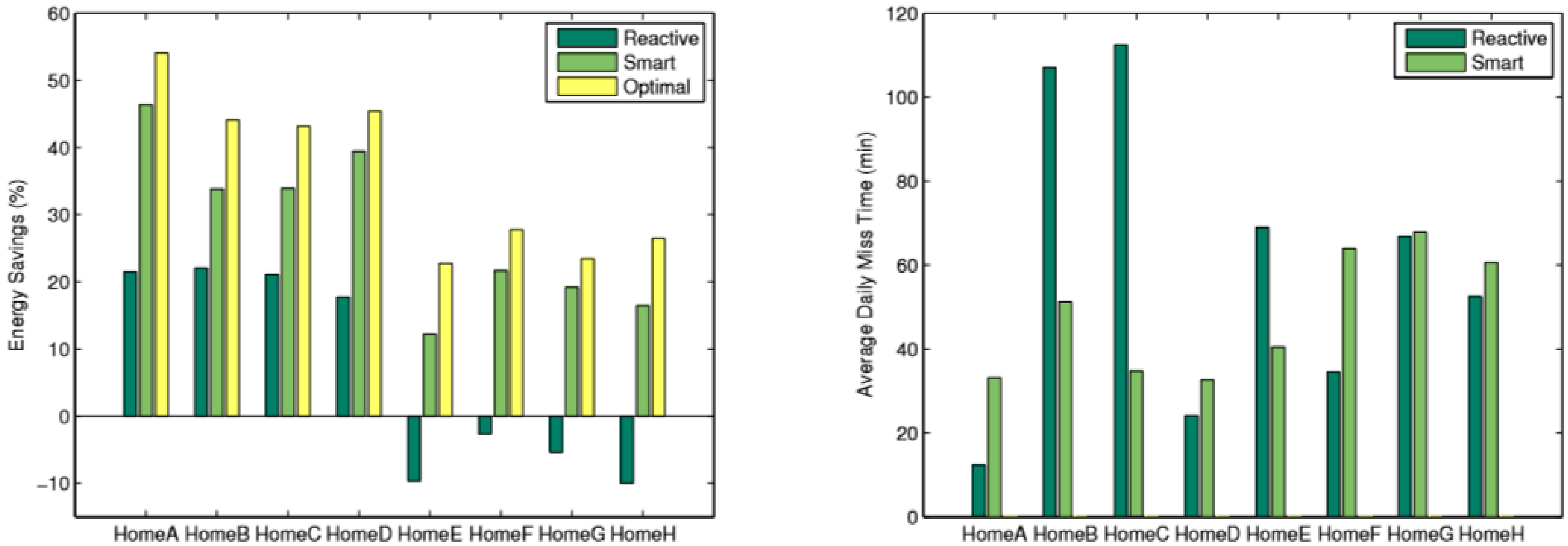
$$\widehat{m}(o,h) = o\alpha \frac{\delta}{24\times60} \frac{\max(0,|\lambda-h|-\epsilon)^2}{25}$$

- ρ = loss in productivity in 24 hours (in paper 1 or 3)
- γ = hourly salary
- α = γ ρ

- In CH: 1 hour home at 15°C (instead of 20°C)
- Hourly salary ~ 35CHF → Misery Cost of 1.50CHF

Mozer et al, The Neurothermostat, www.admin.ch

Results - SmartThermostat



(a) Home Energy Savings

(b) Home Miss Time Benchmark

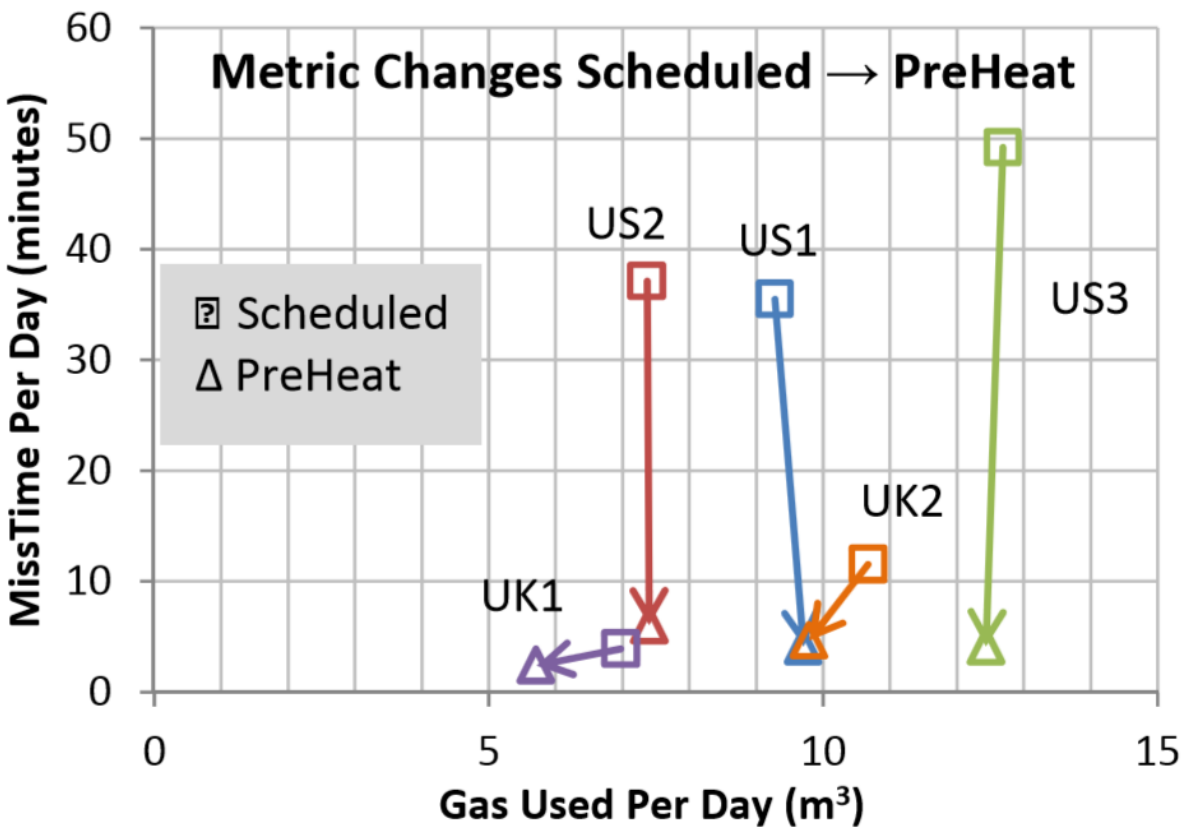
Lu et al, Smart Thermostat

Results - SmartThermostat

- More sophisicated occupancy prediction can improve miss time
- How does it work with other heating systems

Lu et al, Smart Thermostat

Results - PreHeat



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Potential Savings for the US

- Dividing the US in to 5 climate zones

Climate Zones	Locations
Zone 1	Minneapolis / St. Paul, MN
Zone 2	Pittsburgh, PA
Zone 3	Washington, D.C. / Stirling, VA
Zone 4	San Francisco, CA
Zone 5	Houston, TX

Table 3. Weather conditions used in our analysis

- Total Savings
  - 113,9 billion kWh (~22 billion CHF)
  - 38.22% of elelctricity used for heating and cooling

Lu et al, Smart Thermostat

Summary

- Great potential in energy saving
- Eliminates problem of people not using setbacks
- Algorithms better in prediction than humans
- Low cost high reward

Future Work

- Which demographic is most suited for these approaches?
- Combination of different algorithms and implementations?
- What else can be done to make heating smarter and more efficient?
  - Comfort Models (Ashrae 55)
  - Weather Data

Thank you for your attention

Bibliography

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