Smart Thermostats: How much Can One Really Save?

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Ubiquitous Computing Seminar 2015

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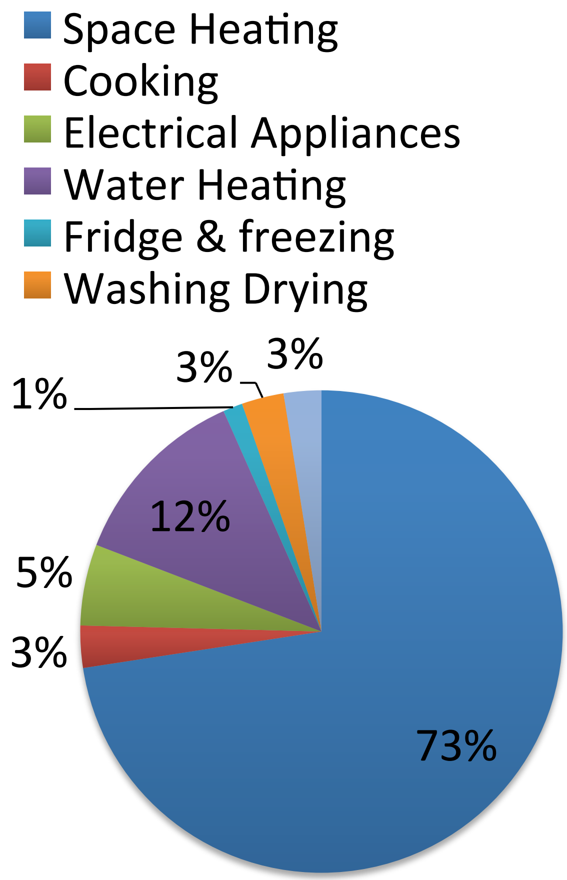
Thermostats-Motivation

- Space Heating consists of 73% of energy use in residential sector

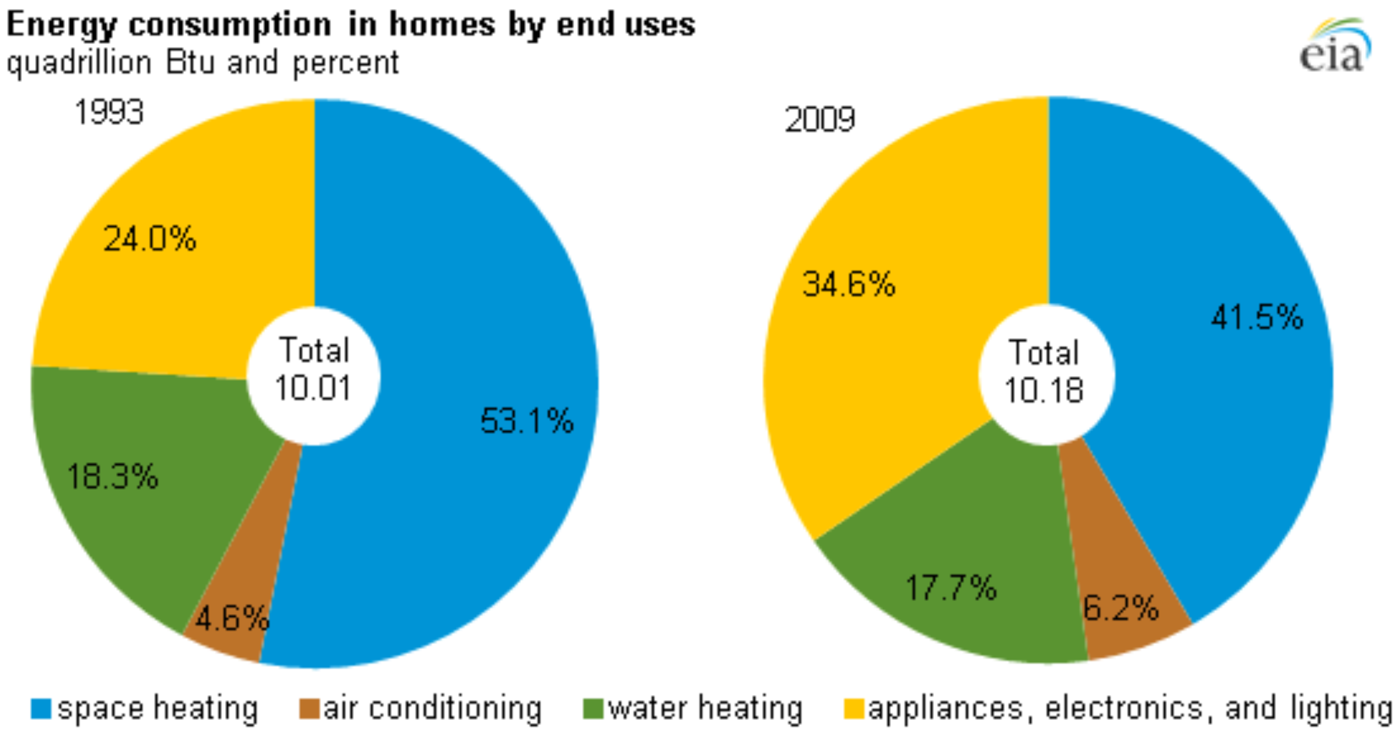
Switzerland Residential Energy use



Switzerland:[7]

Thermostats-Motivation

In United States



United States:[11]

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Thermostats-Manual

- Need to manually set the setpoint temperature
- Need to set setback temperature while leaving
- Not convenient

Manual Thermostat :[9]

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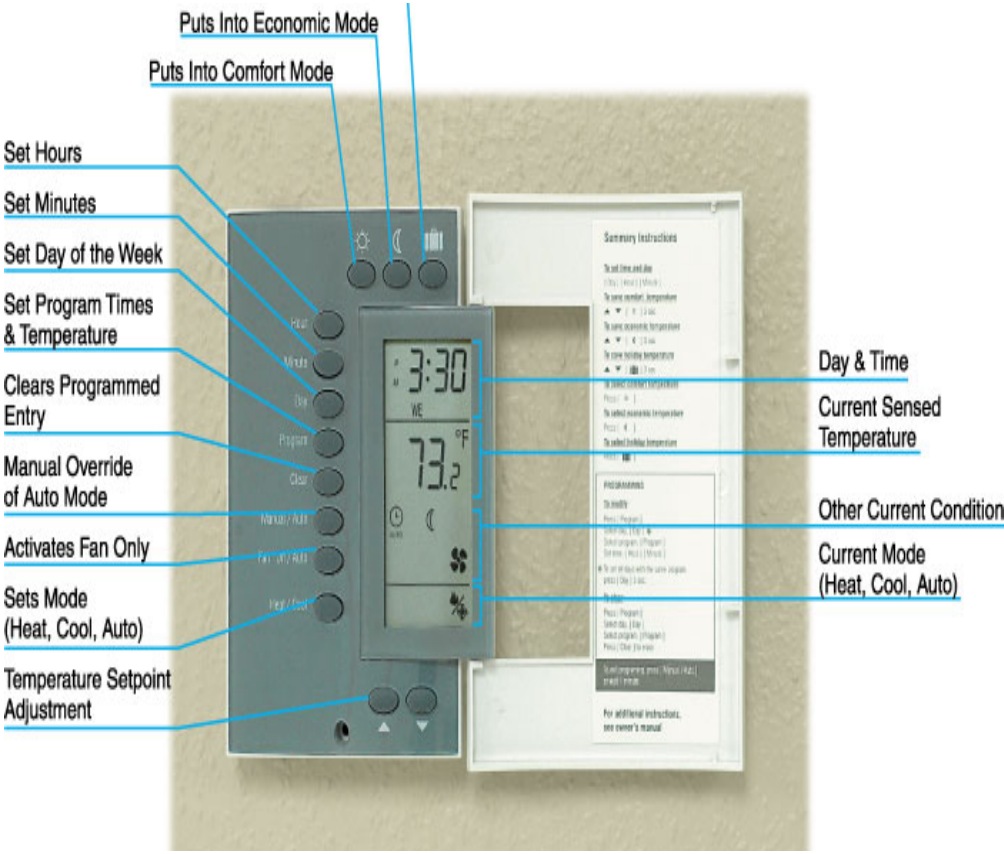
Thermostats-Programmable Thermostats

- Pre-defined, deterministic working schedule.
- Complex to program.
- User-interface unintuitive.
- 40-70% people use improperly.
- Price range : 30-40 $
- Ideal energy savings : 10-30%



Programmable :[8]

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Thermostats-Smart thermostats

- Program themselves- adapts control to user context.
- Promise better & less complex interface.
- Remote Access.
- Aim : Reduce energy spent & increase comfort.
- Price range : 200-500 $.
- Energy savings ranges from :10 - 25 %.

Smart Thermostat :[9]

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Thermostats-Smart Thermostats Examples

Ecobee :[8]

Tado :[6]

Honeywell wifi :[9]

Honeywell wifi with voice:[9]

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Nest-Introduction

- First mass market thermostat to feature machine learning
- **Costs :** 249 $

- **Promises to generate a heating/cooling schedule that :**

1. **Provides comfort**
2. **Energy savings**
3. **Enjoyable interaction**
4. **Convenience**

- **Energy savings :** 10-12% for heating & 15% for cooling

Nest:[2]

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Nest-Study

- Study by University of Michigan
- Group had 19 participants
- In general highly skilled
- Interested in technology

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Yang et al :[10]

Nest-Does it get the programming right?

Nest-Does it get the programming right?

Not Always…..but why?

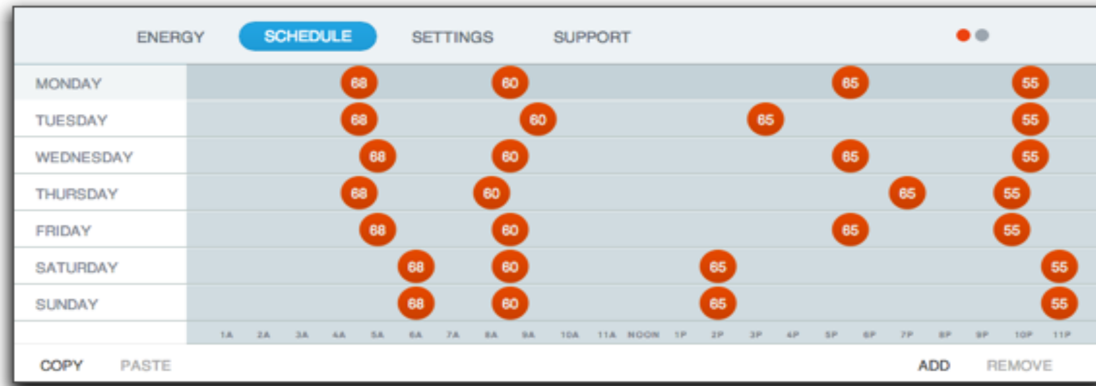
Nest-Obstacles

- Nest did not understand what the input meant
- Occupants did not understand what nest was doing
- Hence occupants didn't know how to optimally interact with Nest to create an optimal schedule
- Houses with multiple occupants suffered the most :
  1. Multiple changes in temperature by multiple people caused erroneous schedule
- Auto away sometimes malfunctioned

Yang et al :[10]

Nest-How Occupants made it work ?

- Correcting the schedule



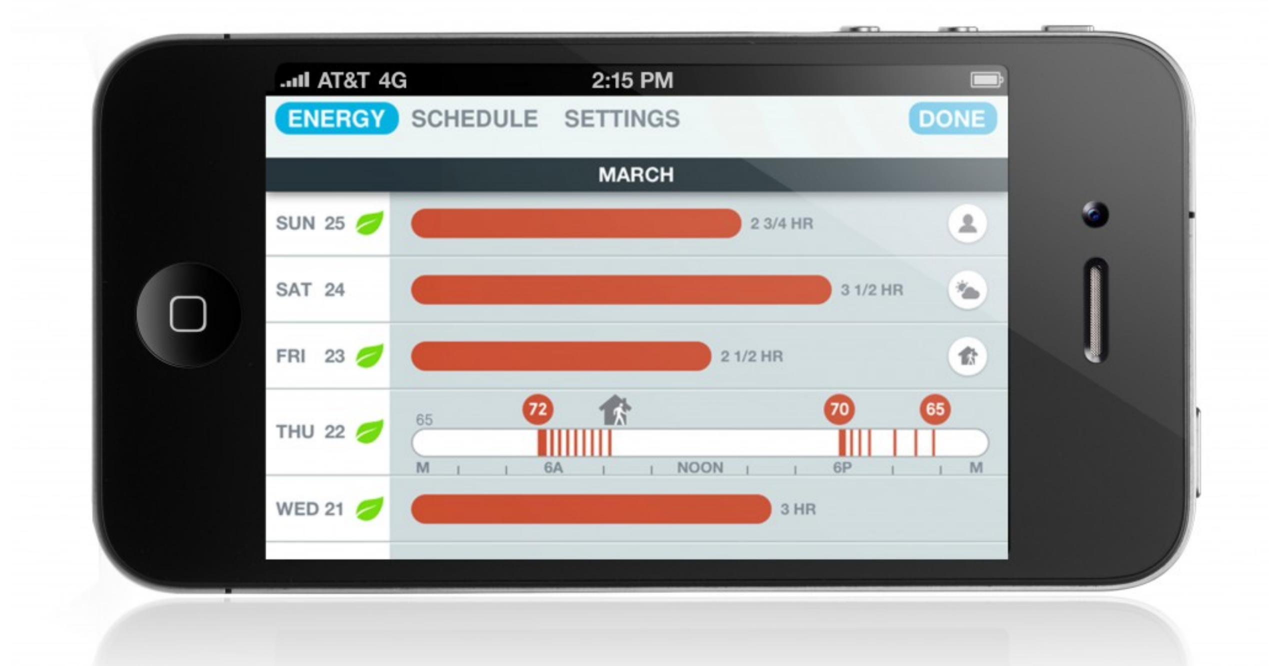
Schedule :[2]

- Teaching & guiding the learning :
  1. Learning to interact with Nest
  2. Occupants understood Nest better with time

Yang et al :[10]

Nest-How Occupants made it work ?

- Monitoring :
  1. The Schedule
  2. Energy history



Energy Hist :[2]

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Nest-How Occupants made it work ?

- In multiple occupant homes, it helped that :
  1. Only 1 person operated the thermostat
  2. The temperature range was locked by the main occupant

Nest-Energy Savings

		Pre-Nest Usage		Energy Savings	
Fuel	N	Total	HVAC	Total	% of HVAC
Natural Gas (therms/yr)	735	774	584	56 ±12	**9.6% ±2.1%**
Electricity (kWh/yr)	624	12,355	3,351	585 ±97	**17.5% ±2.9%**

Source Nest Labs savings analysis: [12]

- Natural gas savings averaged 56 therms per year equal to 9.6% of pre-Nest heating use
- Electricity savings averaged 585 kWh per year equal to 17.5% of pre-Nest HVAC usage

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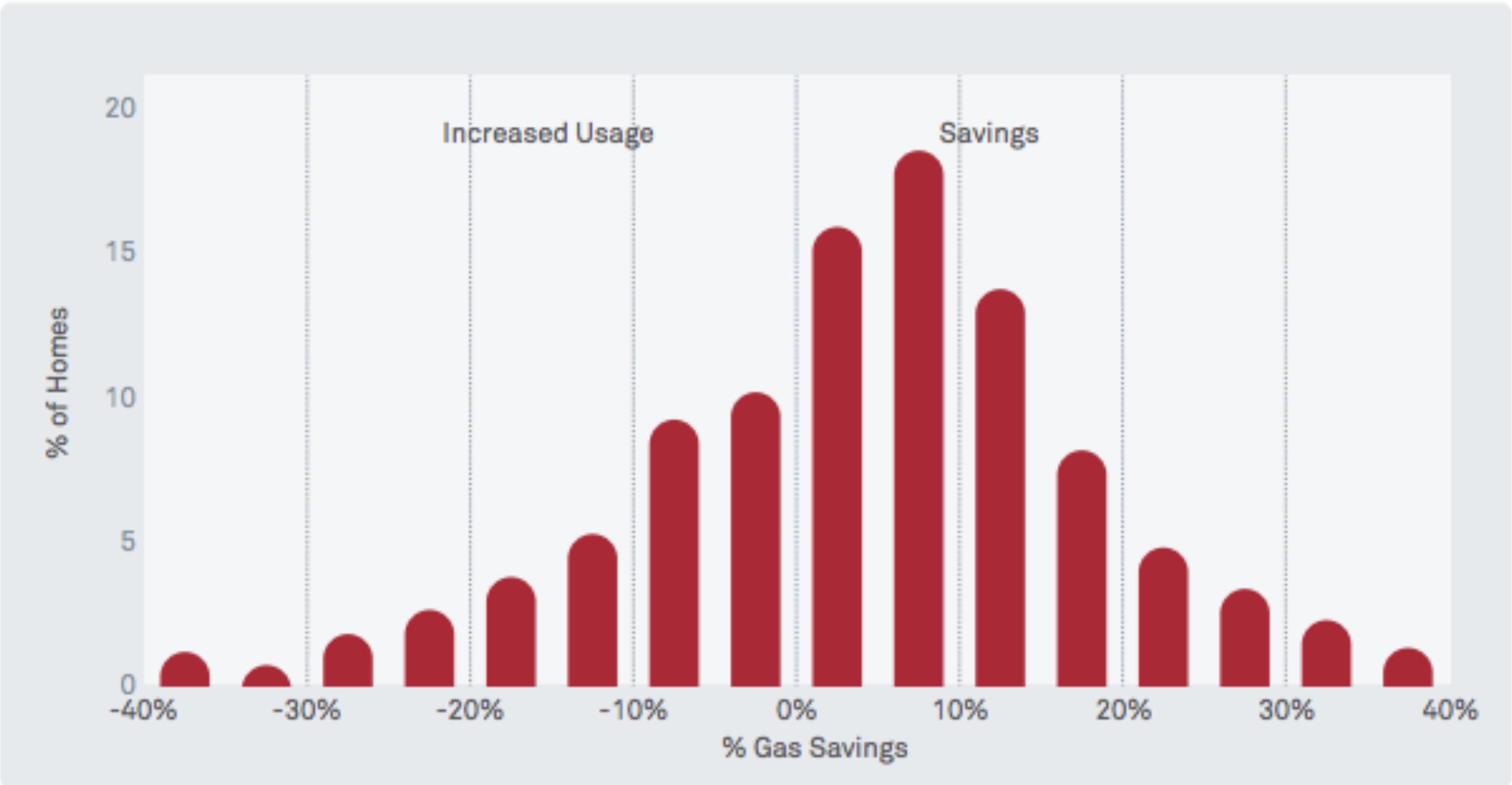
Nest- % Energy Savings compared to previous usage



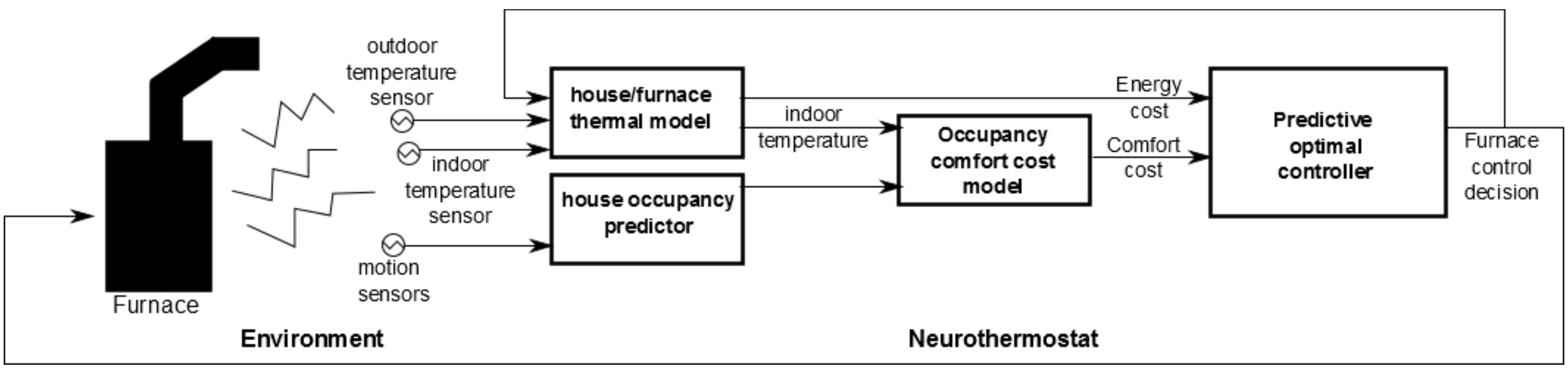
Source Nest Labs savings analysis: [12]

Nest-How can it save us energy?

- Help users understand how the system interprets and acts upon data.
- Help Nest understand the intent of the occupant
- Explicitly mention what ought to be forgotten
- Occupant should be motivated to save energy

Neurothermostat(NT)-Introduction

- Uses Neural networks (NN) (used for learning and pattern recognition)
- Takes 150 days to train
- It acts as an optimal controller :
  - Tries to minimize energy use
  - Maximize comfort of occupant



University of Colorado, Boulder: [4]

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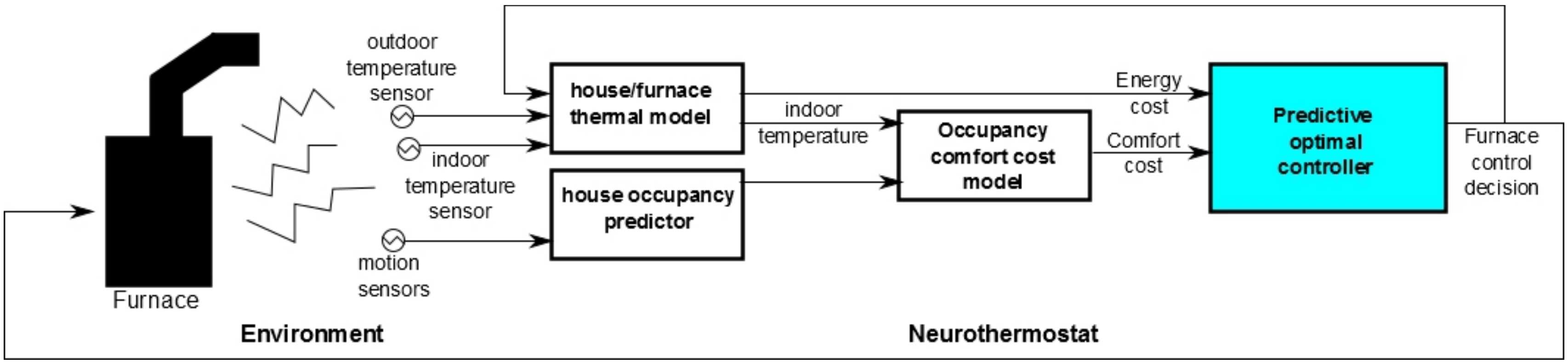
Neurothermostat-Predictive Optimal Controller

- Considers all possible decision steps over the horizon (K steps, δ minutes each) called ‘u’

  Min Cost (u) = Heating Cost + Misery Cost

- Only takes the sequence of decision steps that minimize the total cost
- It executes the first decision of this sequence
- Repeats procedure again after δ minutes



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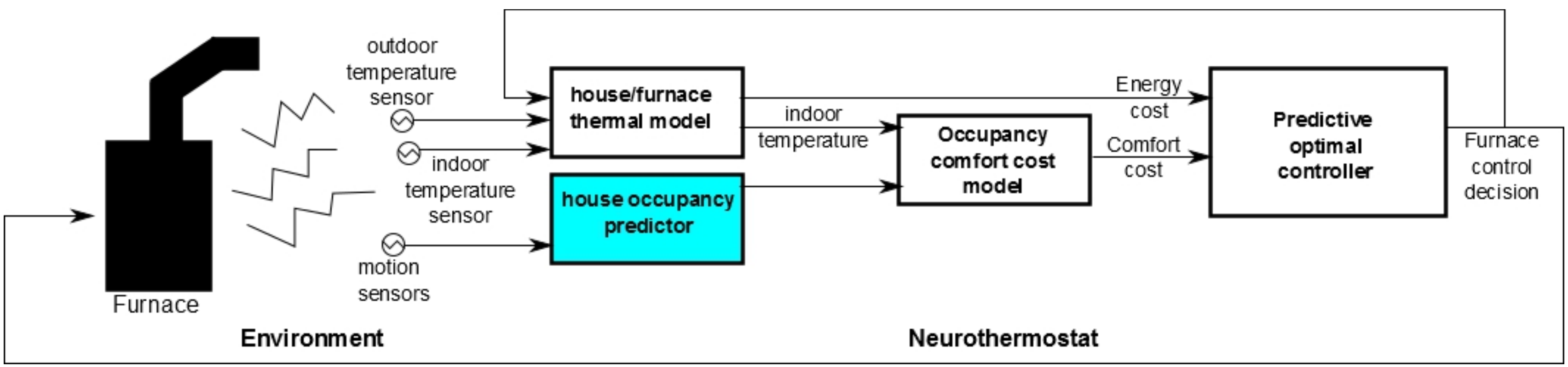
Neurothermostat-House occupancy predictor

Inputs to NN :

1. Time
2. Day
3. Current occupancy
4. Occupancy in previous 10, 20, 30 minutes from present time on previous 3 days & same day for the past 4 weeks
5. Proportion of time occupied in the past 60, 180, 360 minutes



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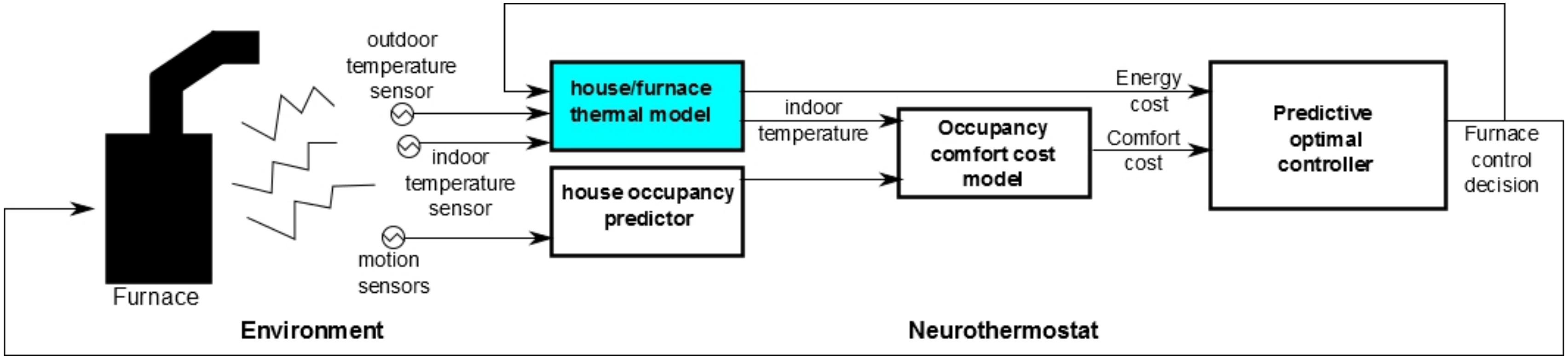
Neurothermostat-House thermal model

- Finds the future indoor temperature & energy cost
- Uses RC(resistance-capacitance) model
- Current indoor temperature
- Current outdoor temperature
- Furnace operation(on/off)



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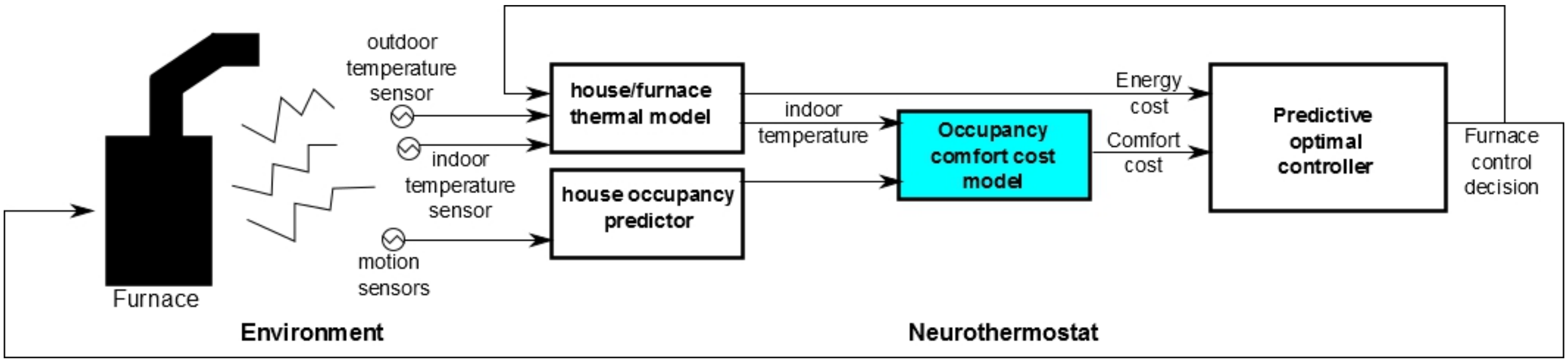
Neurothermostat-Occupant comfort cost model

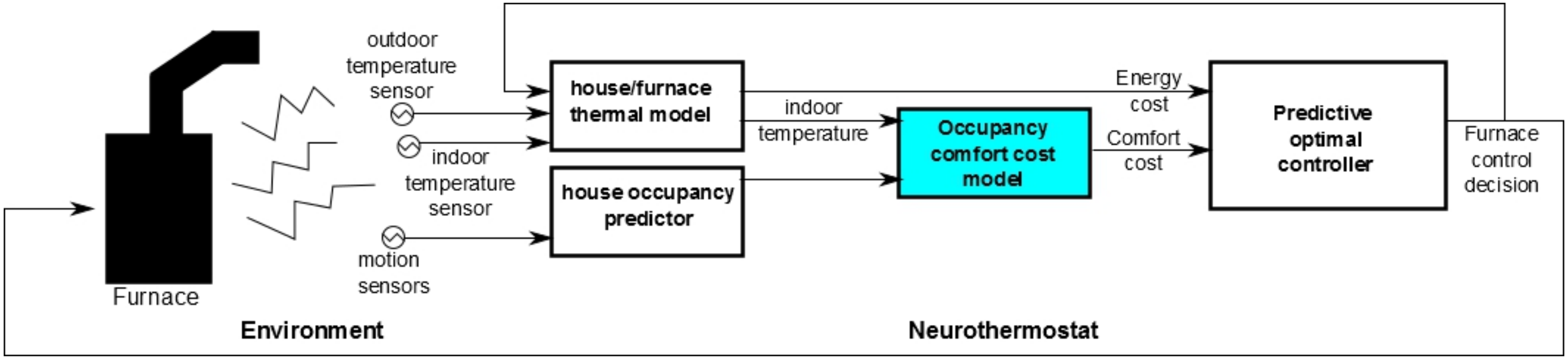
- Misery cost -

  1. 0 if house unoccupied
  2. Is a function of the deviation of the temperature from the setpoint temperature scaled in dollars



Neurothermostat-Occupant comfort cost model

- Inputs :
  - Current temperature
  - House occupancy
  - Hourly wage
  - Loss in productivity (ρ) (how much loss if 5 degrees lesser for 24 hour period)
  - Optimal setpoint
  - δ time interval



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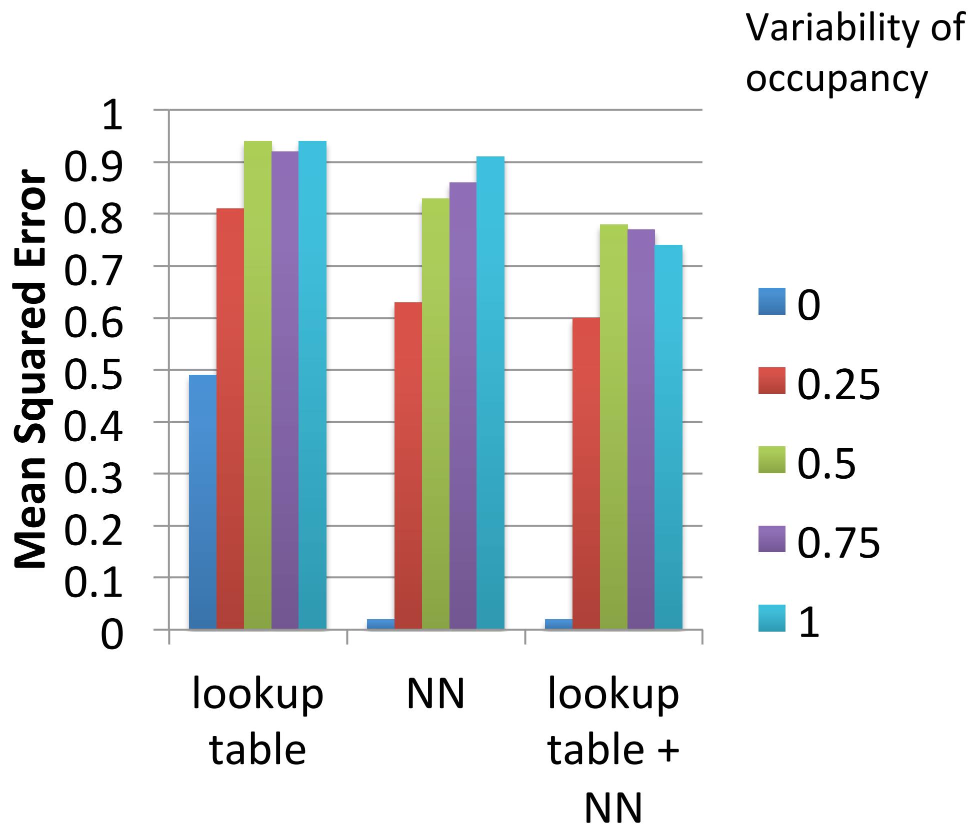
Neurothermostat-Result Details

- Study was done using generated 150 days of training and testing data, 8 times
- There are 75 sensors present in house, additional one at the main door
- The occupants schedule was going to work on weekdays, might come home for lunch, might go out on weekends and sometimes on trips.
- Real data also used (5 months training and 1 month testing)

Neurothermostat-Occupancy prediction Results



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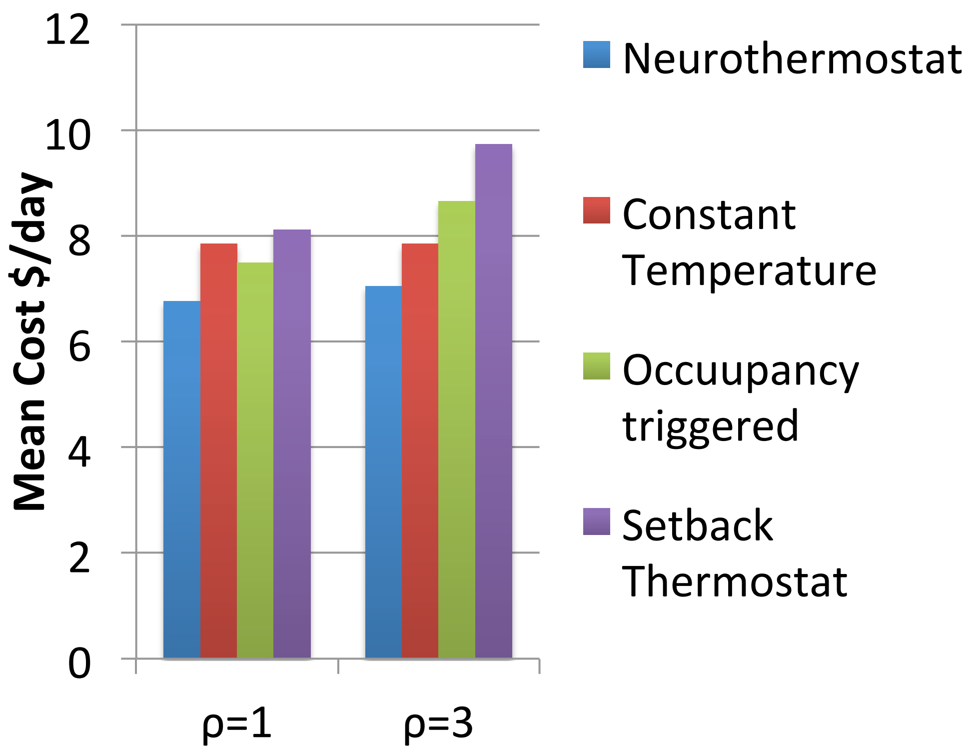
Neurothermostat-Cost savings results



Real data,5 months training, 1 month testing

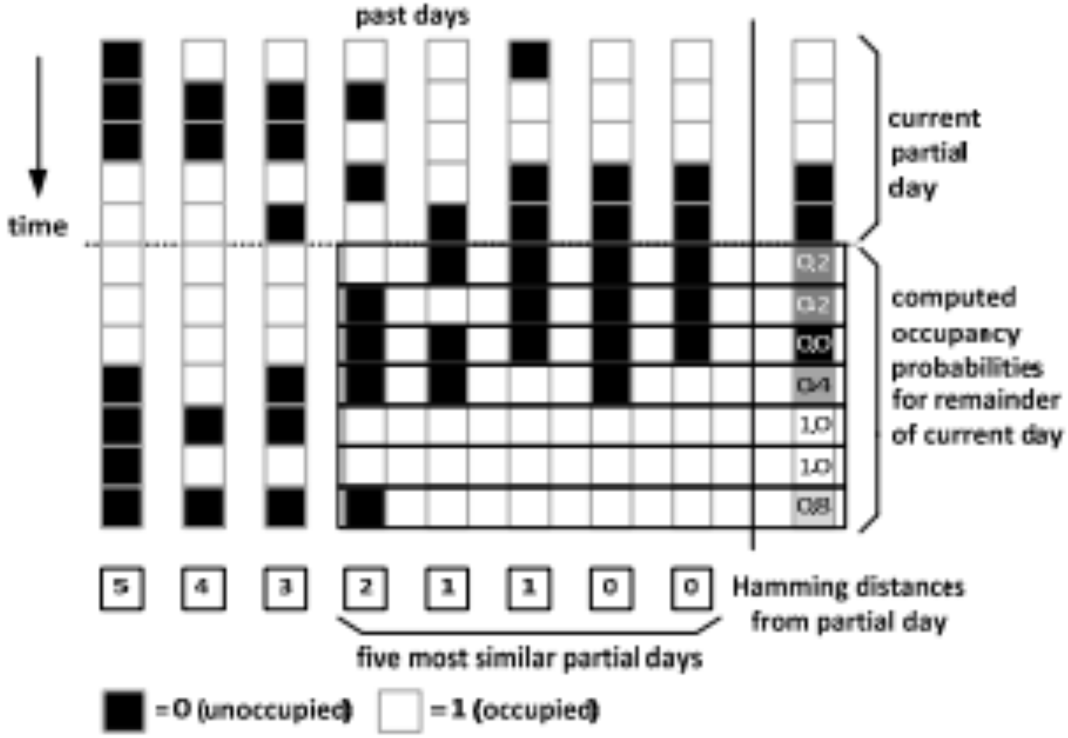
PreHeat(PH)-Introduction

- Occupancy sensing for learning : RFID tags to keys
- Set-points -> Wake-point & Sleep-point
- Set the Setback temperature
- Needs minimum 14 days data to work

Microsoft research & University of Lancaster :[5]

PreHeat-Occupancy Prediction

- 15 min window occupancy binary vector



[5]

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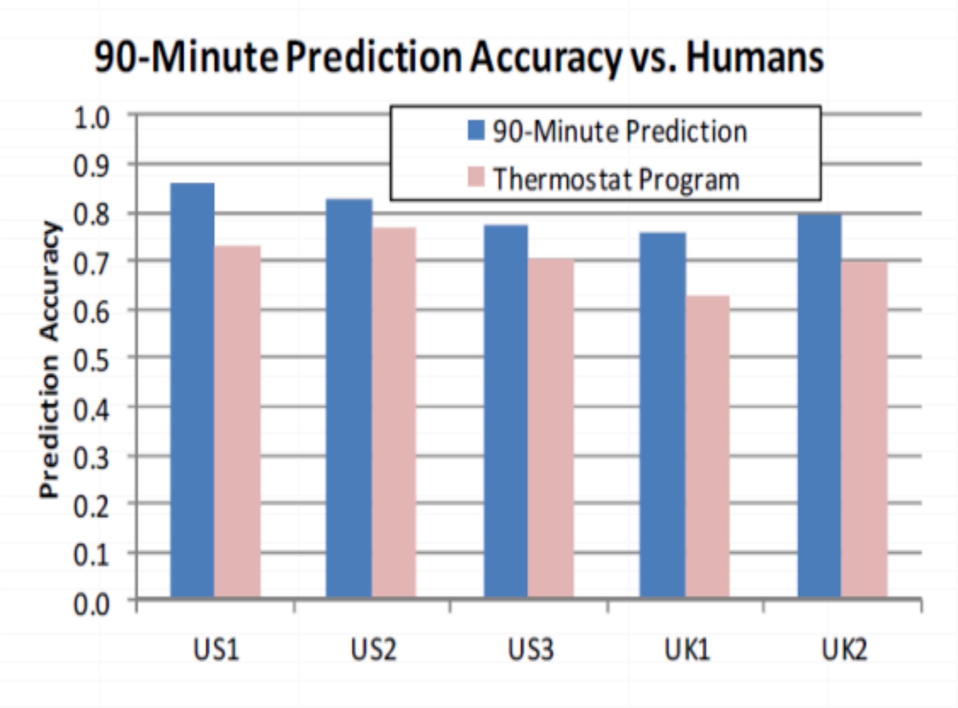
PreHeat-Occupancy Prediction

- Consider k=5 recent days in most similar vectors (least hamming distance)
- Alg1 : Consider weekends and weekdays separately
- Alg2 : Pad day occupancy vector with 4 hours from previous day
- Can choose a probability threshold
    1. If high -> energy savings
    2. If low -> increase the comfort

PreHeat-Result Details

- Study done for 61 days in each home
- 3 Homes in the US and 2 homes in UK
- UK homes had per room heating, hence had per room sensors
- US homes had whole house heating
- Probability threshold = 0.5

PreHeat-Occupancy prediction Results



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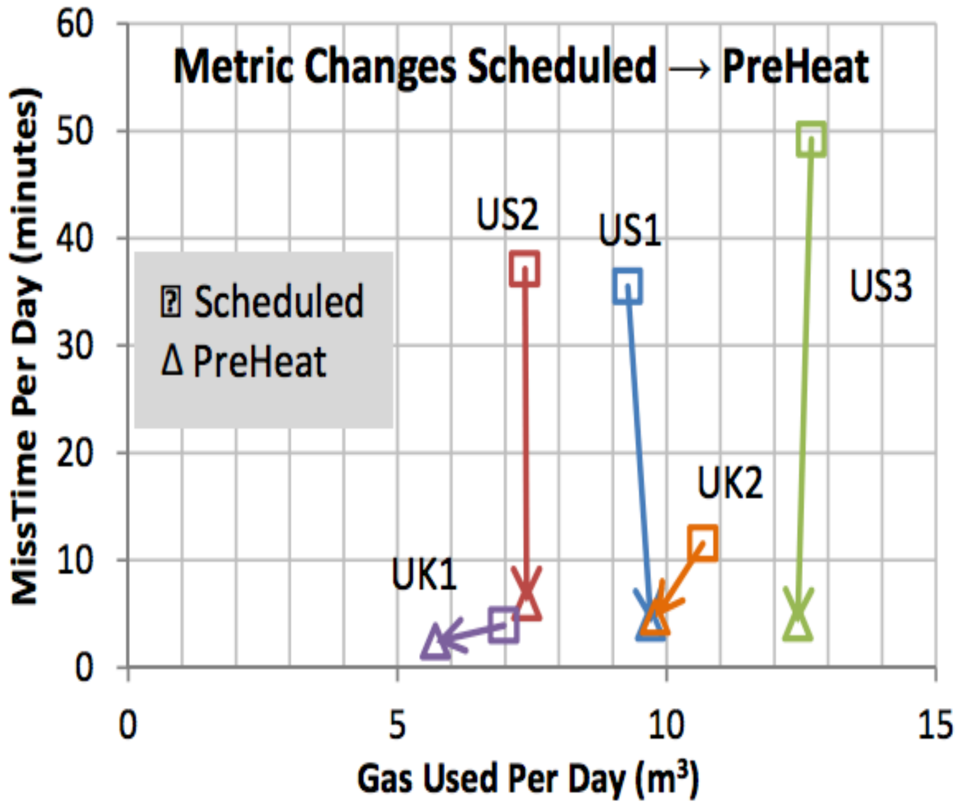
PreHeat-Energy savings results



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Comparison

Comparison	PH	NT	Nest
Motion sensors	RFID receiver near entrance, sometimes forget RFID keys	Has enough sensors to detect occupancy	Needs to be strategically placed, else cannot detect occupants
Interface	Does not motivate user to reduce consumption	Does not motivate user to reduce consumption	Motivates occupant to reduce consumption using small green leaf
Comfort Model	Reducing MissTime is the only comfort cost, could be changed to how deviant from setpoint the temperature is	Depends on comfort and energy equivalently	Learns temperature settings from occupants, their activities and tries to predict next occupancy

Comparison

Comparison	PH	NT	Nest
Training Period	14 days	150 days	After 1 week starts automatic scheduling
Multiple Occupants	Yes (each should have RFID keys)	Misery could be scaled to a multiple person model Eg: Root mean square of all misery costs	yes
Per Room Heating	Yes,but less occupied room never heated	It only does full house heating(what about per room?)	It only does full house heating (it be scaled if sensors in all rooms?)

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Comparison

Comparison	PH	NT	Nest
Wifi access	No, but can be used to get data from internet	No,can be used to get data from internet	Yes
Learning, weighted days	No, but can be implemented	NN is a weighted model	No info
GPS tracker	No, could improve comfort	No, could improve comfort	No, could improve comfort
Energy History	No, but can be incorporated	No, but can be incorporated	Can be improved by giving average consumption in area
Remote Control	Can be	Can be	Already is

Gupta et al :[13]

Conclusion

- Programmable thermostats promise 10-30% energy savings
- But they are not used the way they are intended to
- Smart thermostats can help this by observing your activities, without the need for programming
- They also promise comfort
- Occupants can save 10-25 % in theory
- Actual saving depend on how motivated occupants are
- If you are already energy conscious, smart thermostat might not help much

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