OBSERVE: Occupancy-Based System for Efficient Reduction of HVAC Energy

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HVAC Energy Usage

HVAC: **H**eating, **V**entilation, and **A**ir-**C**onditioning

- HVAC accounts for 35% of the energy usage in the US
- Small efficiencies in HVAC systems will significantly impact total energy consumption

HVAC Inefficiencies

- HVAC systems often assume maximum occupancy for rooms
- Rooms are often unoccupied or partially occupied
- This assumption leads to inefficient environmental conditioning

Conditioning for Temperature and CO_2

Temperature:

- Typically a binary indication of occupancy is sufficient

Ventilation:

- Actual CO_2 levels and/or total occupancy of a space

Passive Infrared Sensors (PIR)

- Cheaply provide an occupancy indication
- Cannot count the total number of people

CO_2 sensors

- Require significant time before detection of CO_2 buildup
- Prone to calibration errors

Real Time Occupancy Monitoring

If we have real time knowledge of occupancy, the climate control system can be adjusted optimally

Temperature:

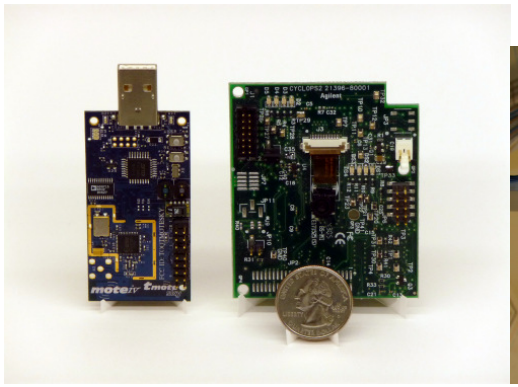
- Adjust based on **if** a room is occupied

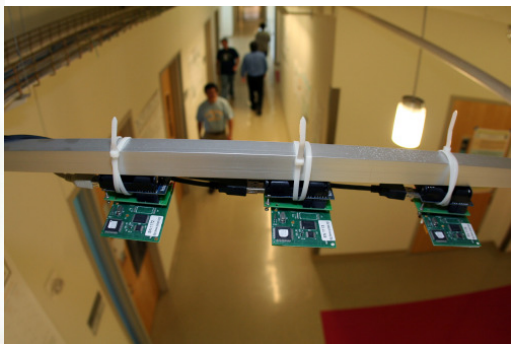
Ventilation:

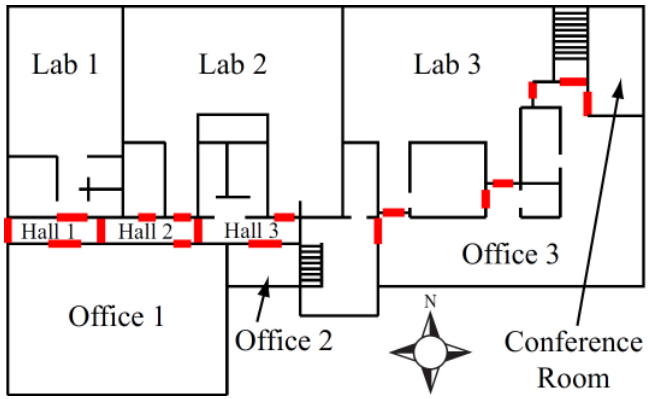
- Adjust based on **how many people** occupy a room

SCOPES: Smart Camera Object Position Estimation System

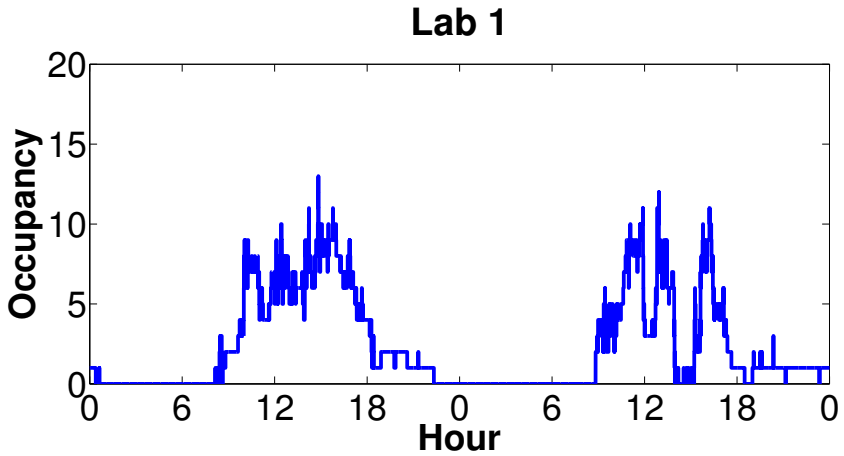
- **S**mart **C**amera **O**bject **P**osition **E**stimation **S**ystem[1]
- Detects transitions between areas (camera turnstile)
- 85% of true transitions captured
- 16 TMote+Cyclops nodes deployed at UC Merced
- 30 iMote2+IMB400 nodes in future deployment







[1] A. Kamthe, EWSN 2008


Lab 1
Occupancy
Hour
0
5
10
15
20
0
6
12
18
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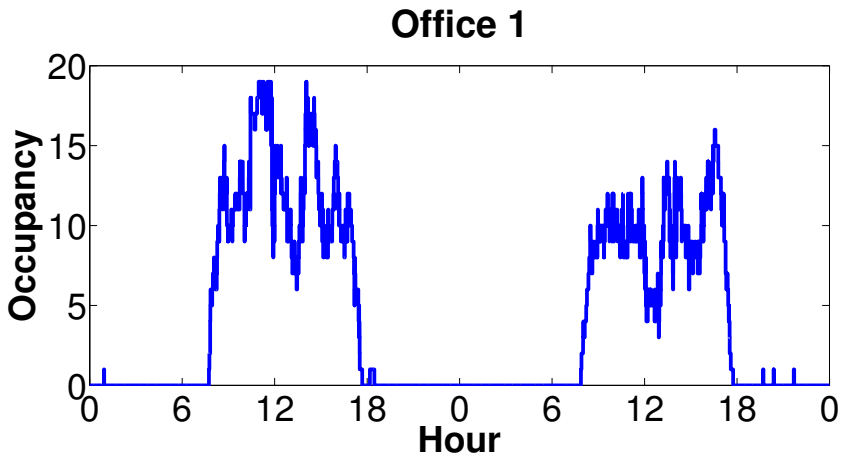
6
12
18
0


Office 1
Occupancy
Hour
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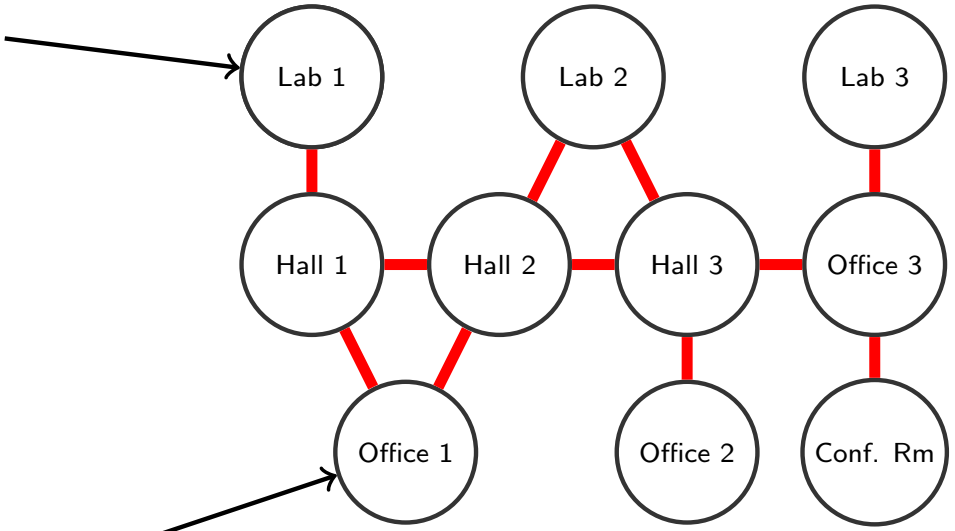
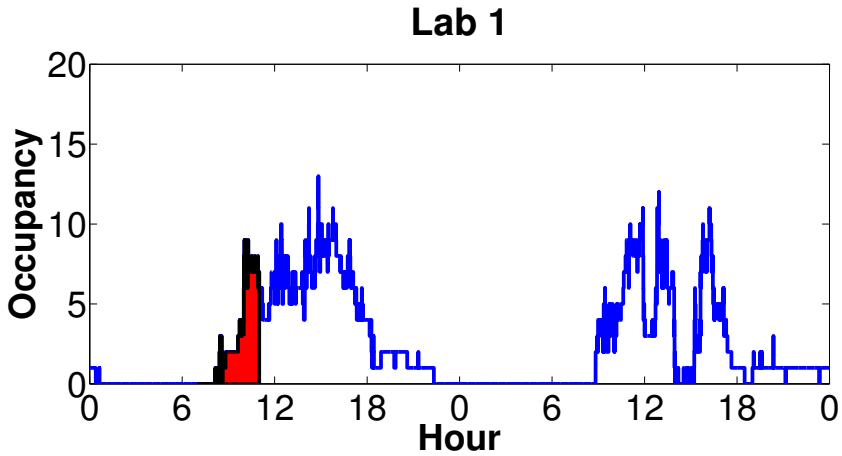
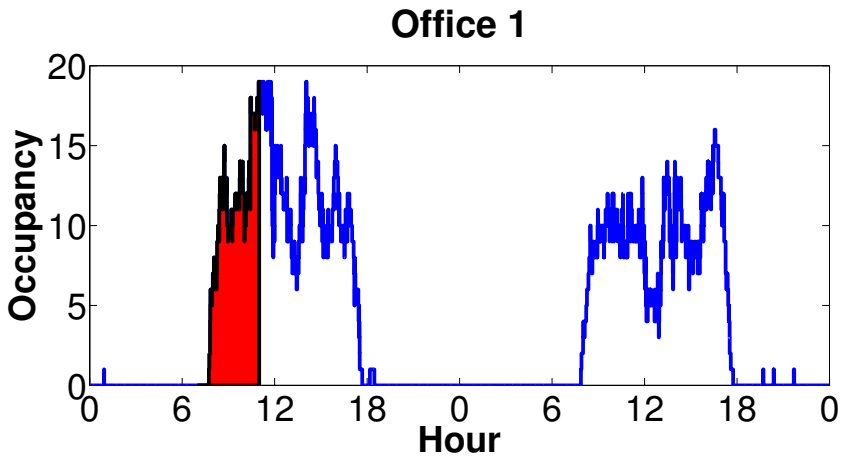
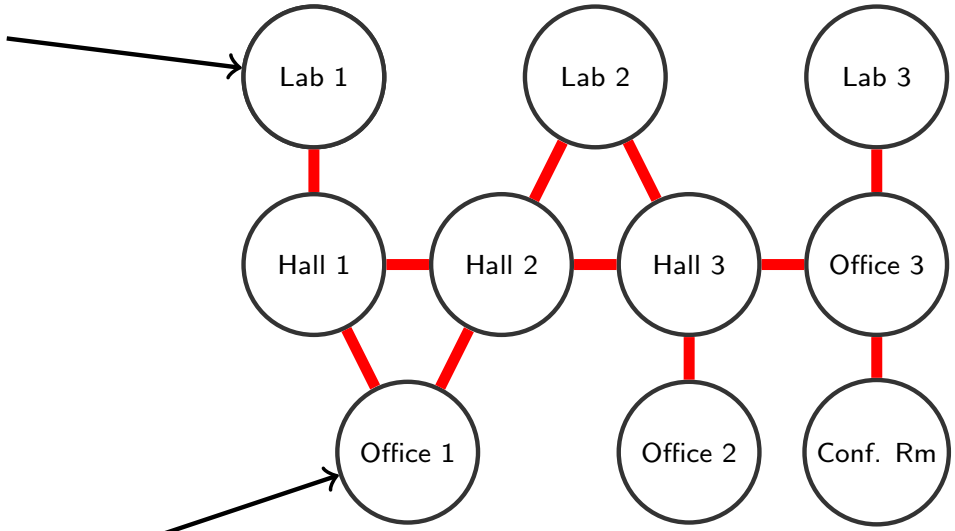
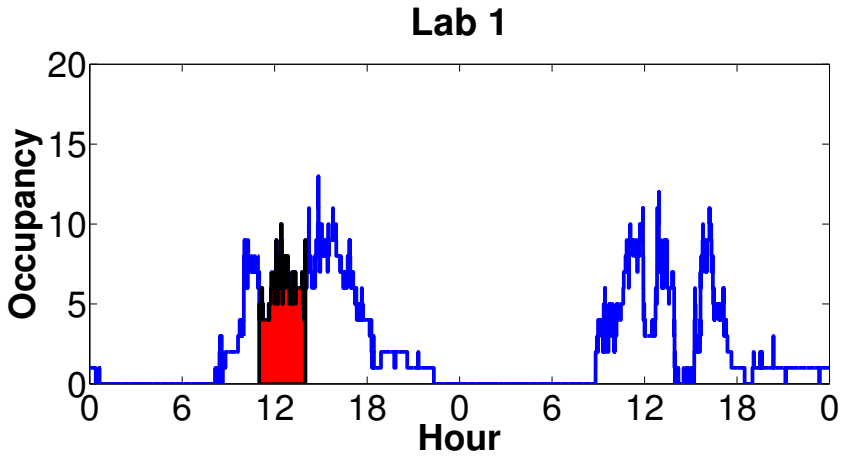

Lab 1
Lab 2
Lab 3
Hall 1
Hall 2
Hall 3
Office 3
Office 1
Office 2
Conf. Rm



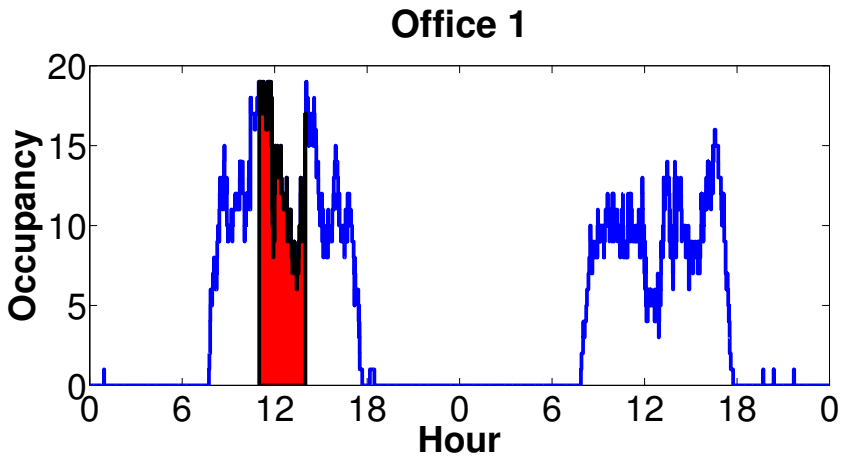
Arriving in the morning

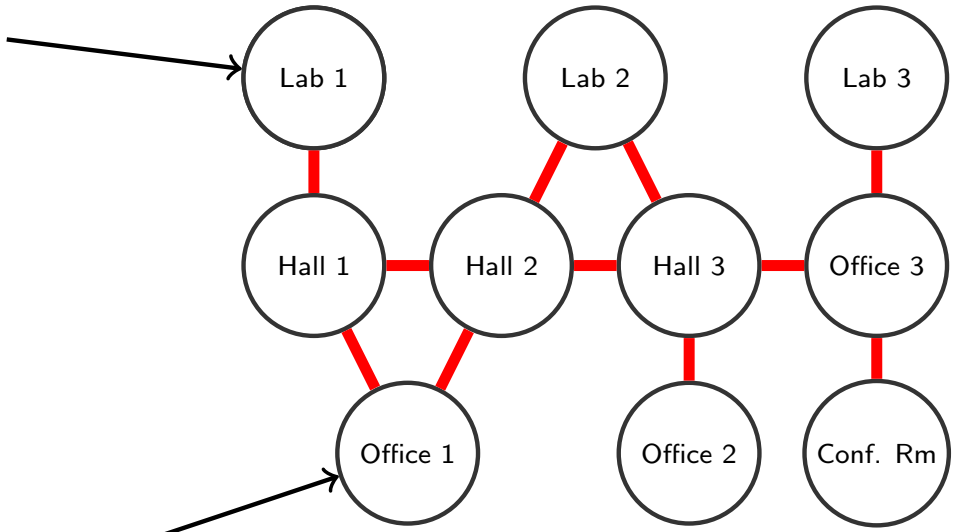


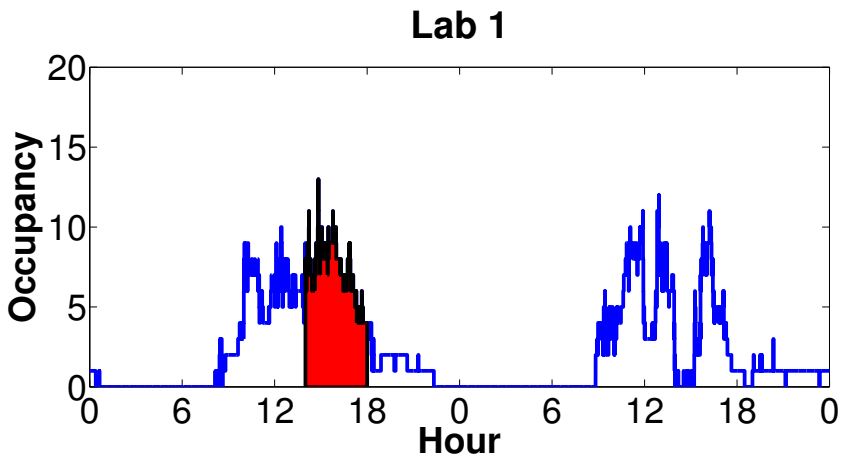


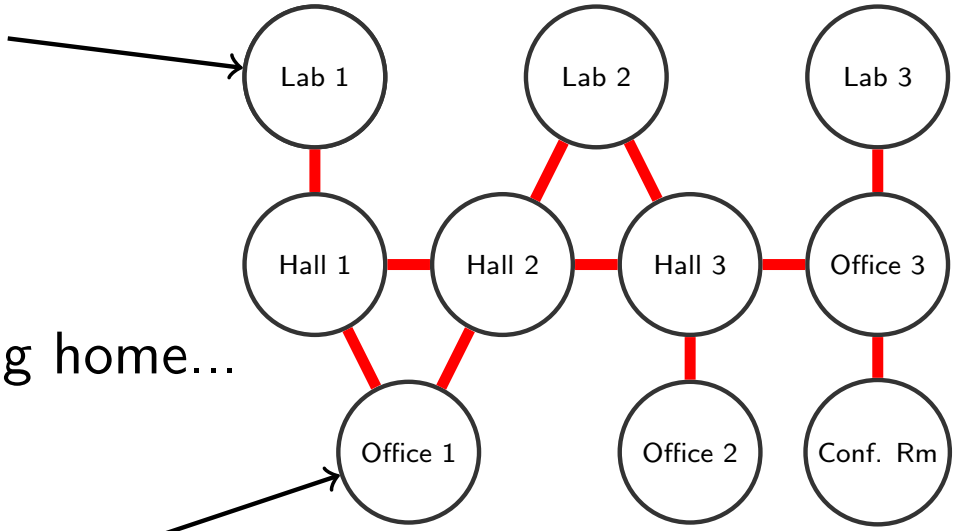


Leaving for lunch

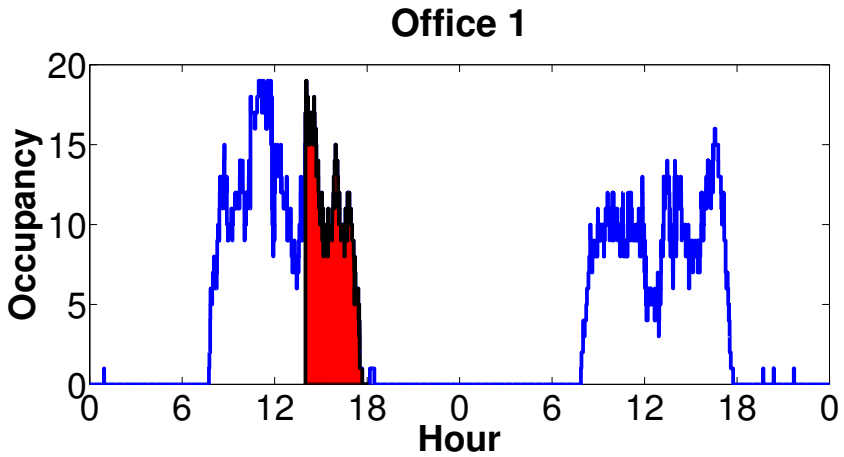


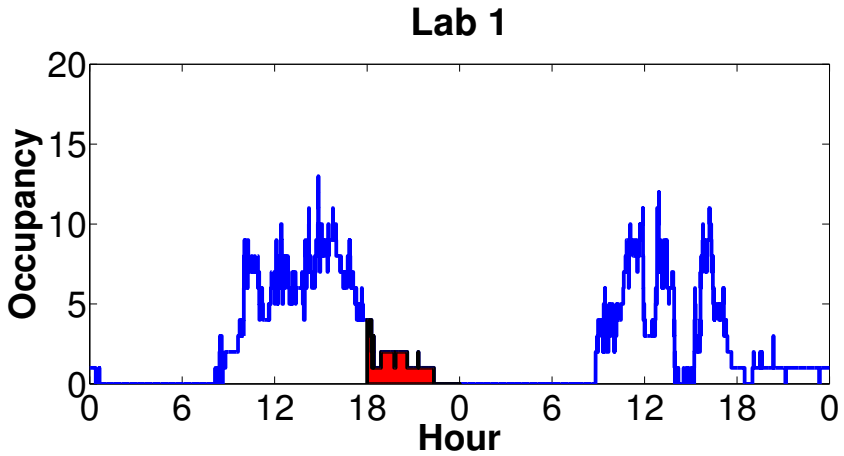


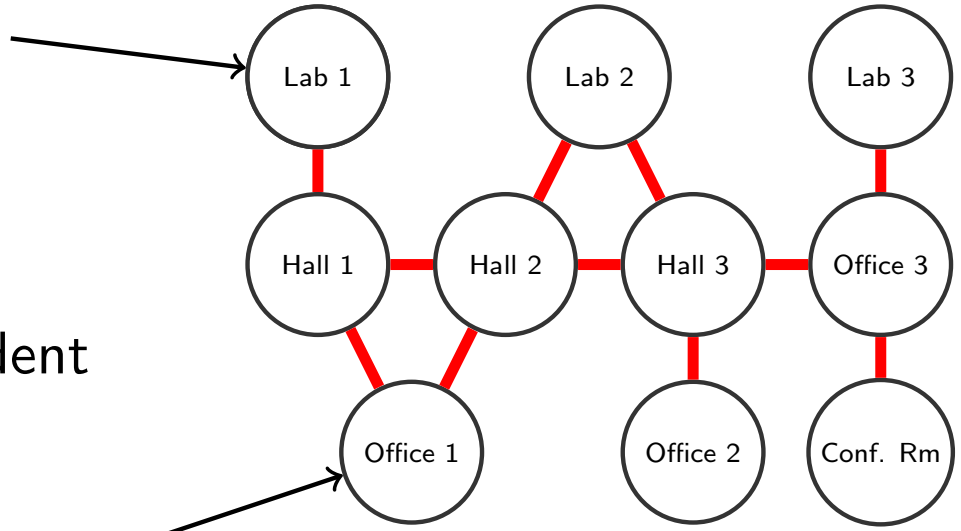




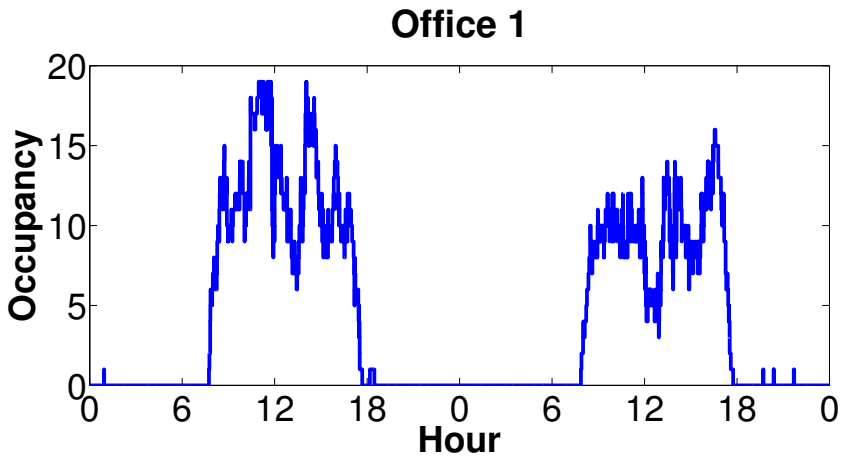
Back from lunch and eventually going home...







Unless you are a graduate student



Occupancy Prediction

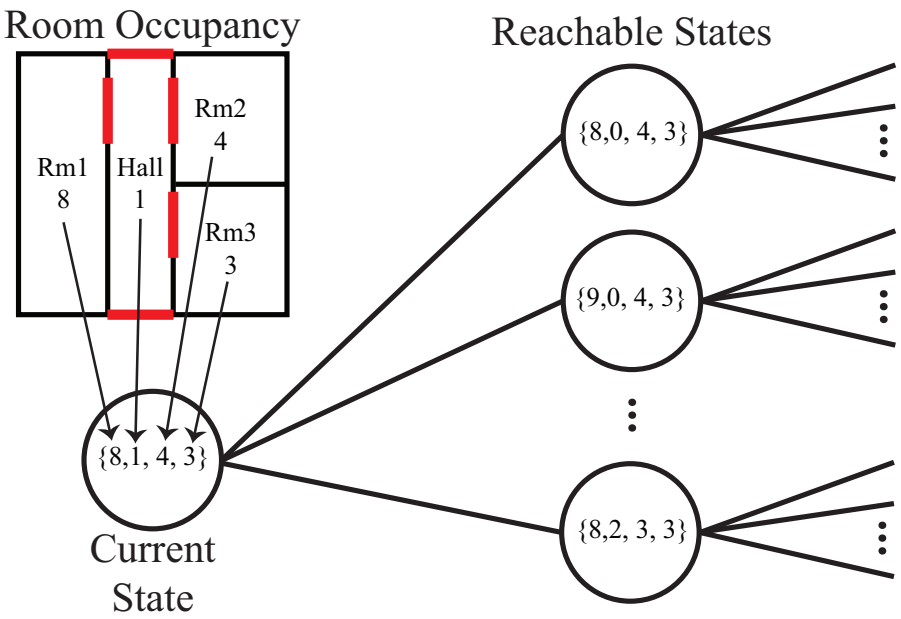
- Instantaneous temperature change not possible. A prediction model is required to adjust room temperatures beforehand.
- Data from SCOPES deployment can be used for an offline/online occupancy model
- Several models considered in paper
- We found a Markov Chain approach worked best

Markov Chain

- A building can be thought of a system where the state of the room occupancies change over time
- Model room occupancies as a discrete Markov Chain

State Representation s

- $s = \{r_0, r_1, \ldots, r_n\}$
  n rooms
  r_i occupancy of room i
- Assuming maximum room occupancies, we can determine the set of observable occupancy states S



Transition Matrices

- Transition matrix gives probabilities of moving among states

	$\cdots$	$\{8, 0, 4, 3\}$	$\{9, 0, 4, 3\}$	$\cdots$	$\{8, 2, 3, 3\}$	$\cdots$
$\vdots$						
$\{8, 1, 4, 3\}$	$\cdots$	0.08	0.05	$\cdots$	0.01	$\cdots$
$\vdots$						

- State transition probabilities change over time
  Consider someone in a hallway
  - 8am: More likely moving to a room
  - 8pm: More likely leaving the building
- Define one transition matrix per hour

State Space

- Observable State Space
  - eg. 4 rooms with max occupancy of 20 people
  - For each hour, $20^4 = 160$K states
  - Total model has 3.84M states
- Not practical to consider all possible states
  - Only consider states observed in training
  - Only produces transitions to states observed in training
  - Given enough training data, this produces a realistic model

Sink State

The Markov Chain so far:

- We have different transition matrices for each time slot
- Only states in the training set are represented

Sink State Problem:

- State X in hour h may not exist in h+1
- Adding a small ϵ to zero transition values results in a random walk until a transition to an observed state

Solution:

- "Blend" transition matrices to include all observed states

Blended Markov Chain

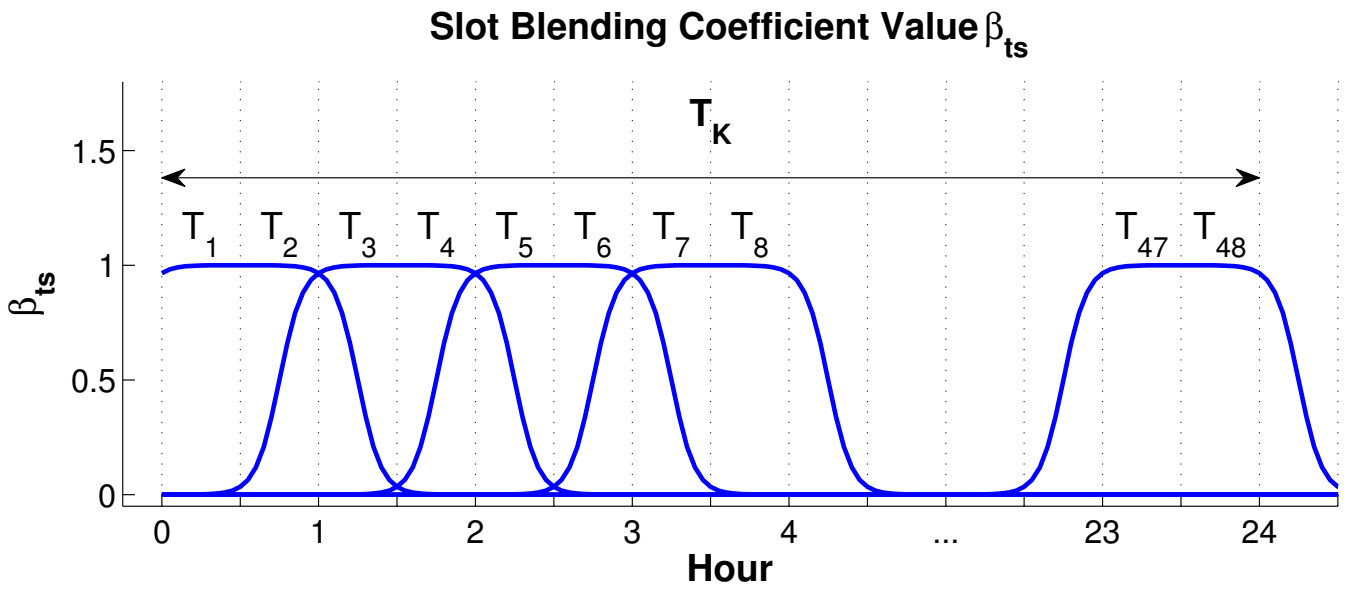
- Partition day into K transition matrices $T_1 \dots T_K$
- Linearly combine $T_1 \dots T_K$ to obtain K blended transition matrices $\overline{T}_1, \dots, \overline{T}_K$

$$\overline{T}_t = \sum_{s=1}^{K} \beta_{ts} T_s$$

where coefficients $\beta_{t1}, \dots, \beta_{tK}$ are positive and sum to one

Blending Coefficient β

$$\overline{T}_t = \sum_{s=1}^{K} \beta_{ts} T_s$$



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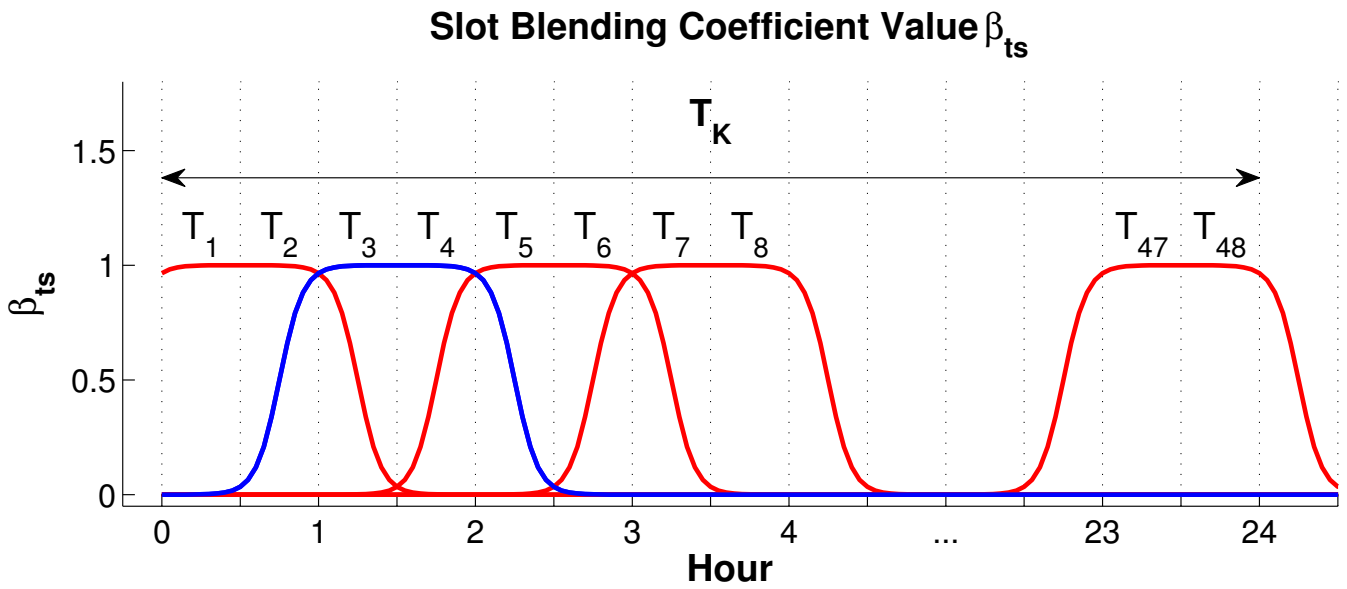

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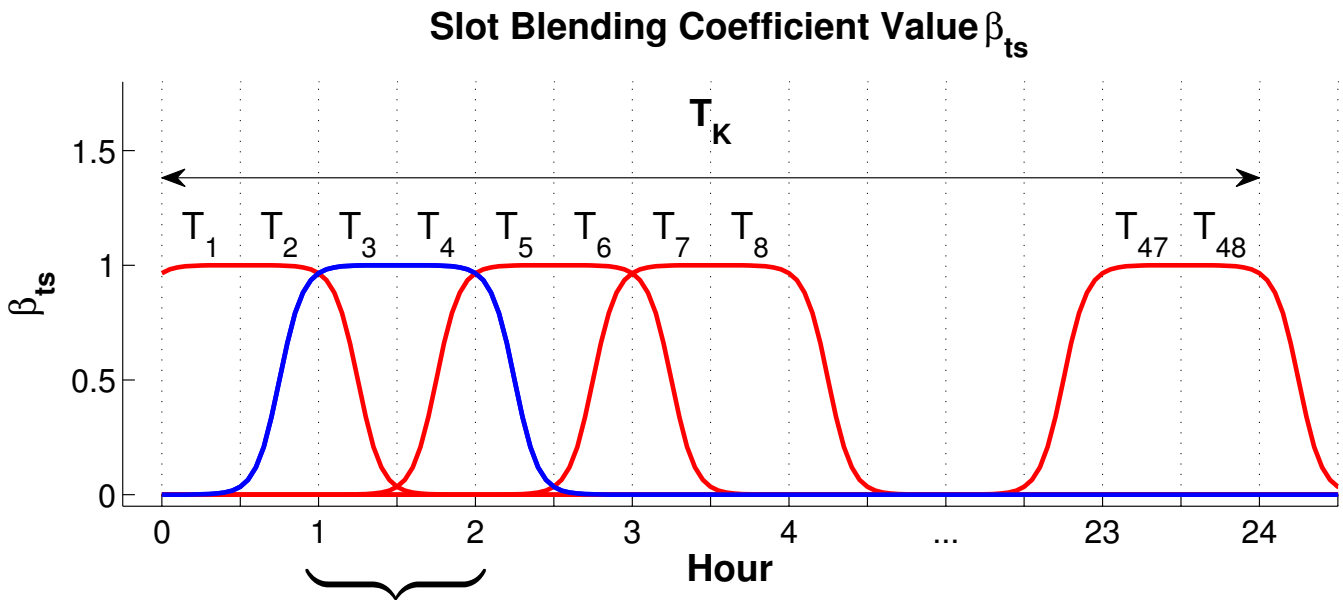

States of T_3 and T_4 given most weight

Blending Coefficient β

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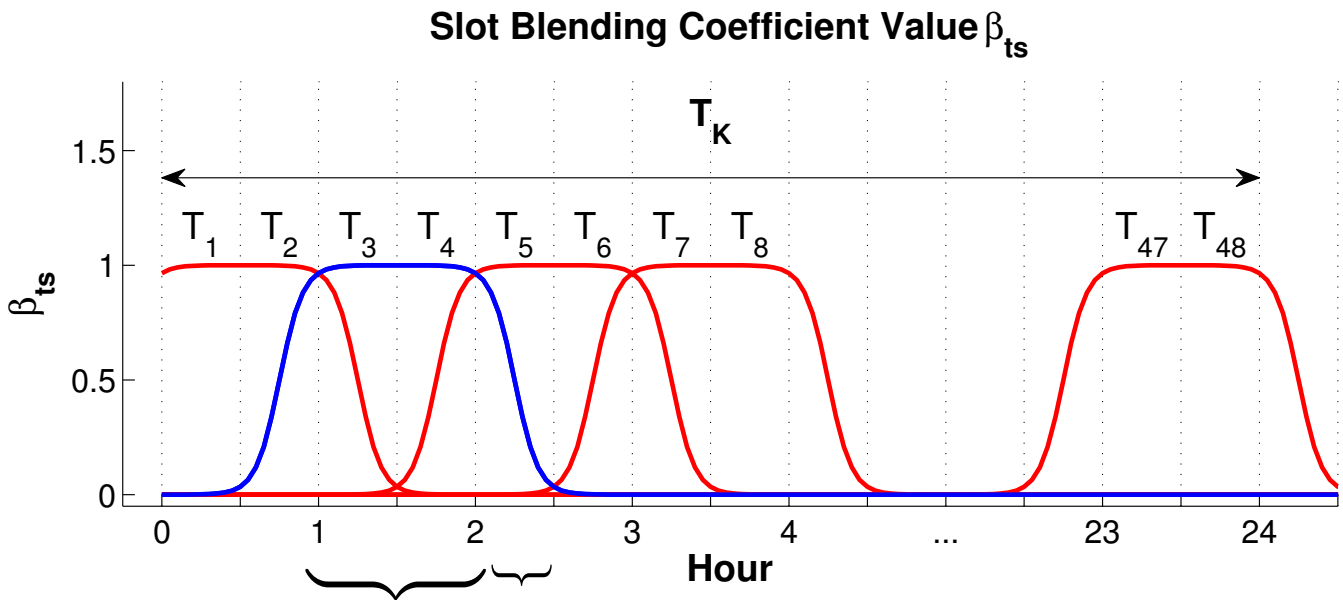
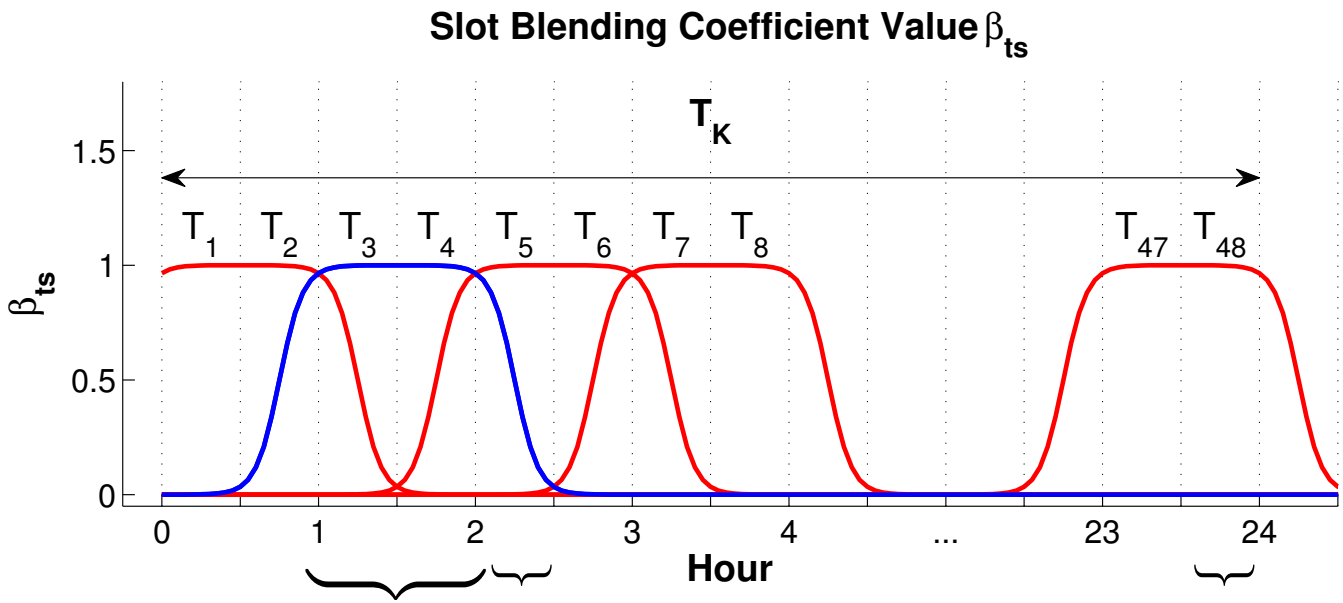


States of T_3 and T_4 given most weight

States of T_5 given less weight

Blending Coefficient β

$$\overline{T}_t = \sum_{s=1}^{K} \beta_{ts} T_s$$



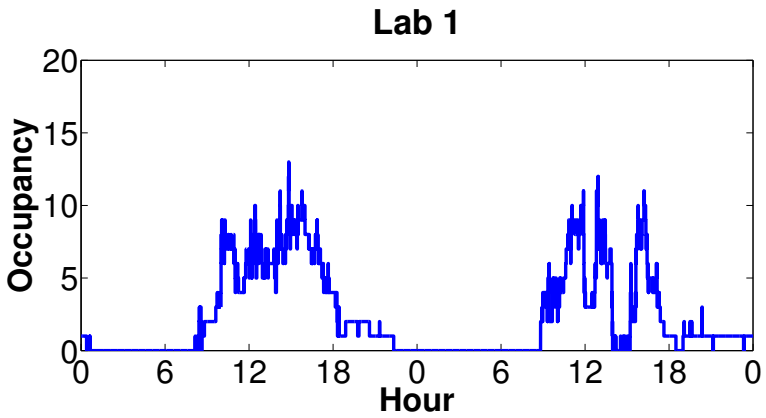
States of T_3 and T_4 given most weight

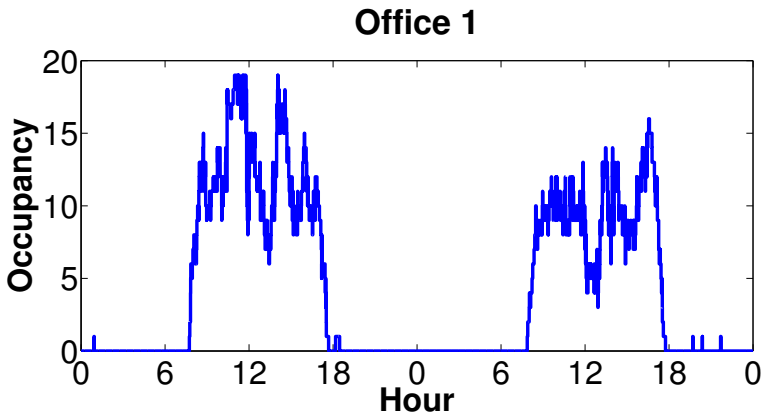
States of T_5 given less weight

States of T_{48} given almost no weight

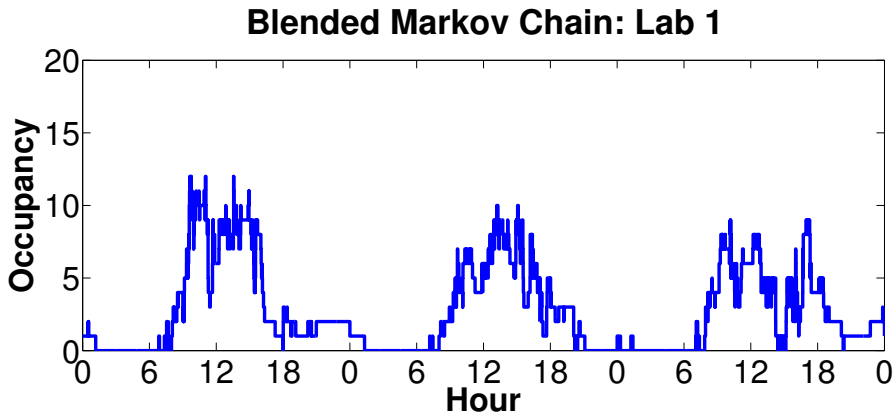
Qualitative Evaluation

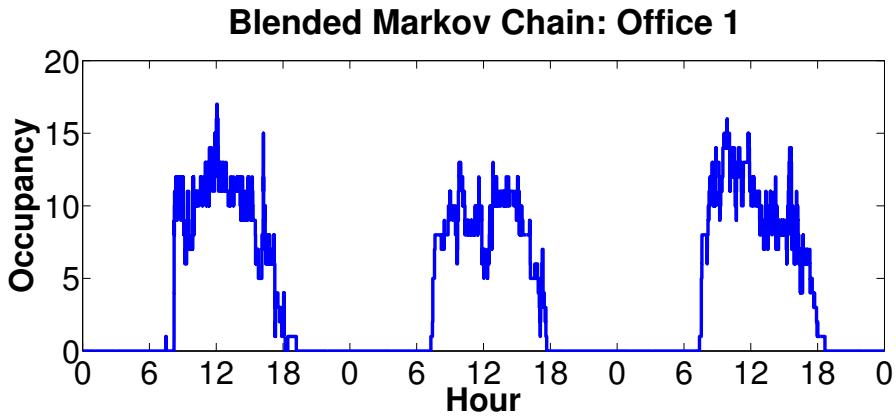
Partial Test Set





Blended Markov Chain





Quantitative Evaluation

Comparison Metrics

- Average duration of static occupancy (refer to paper)
  - Rooms stay at occupancy levels for specific lengths of time
- Jensen-Shannon Divergence (JSD)
  - Compares the similarity of two distributions

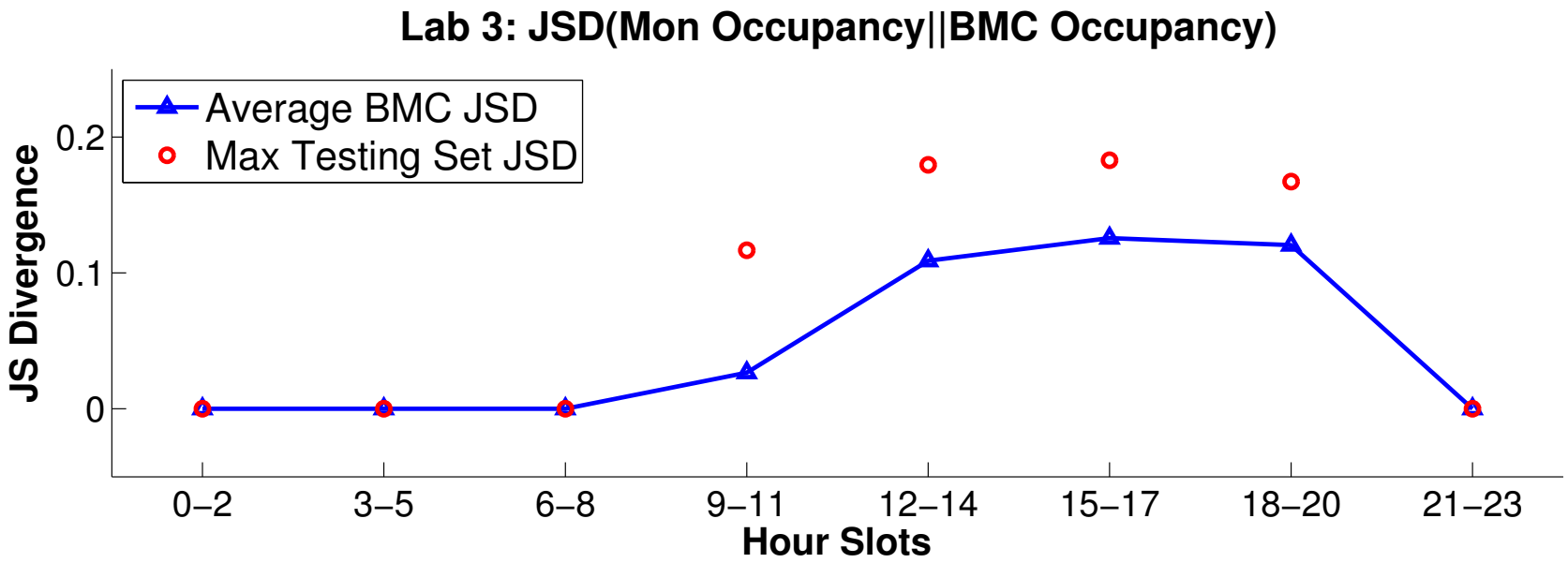
$$JSD(P\|Q) = \frac{1}{2}D(P\|M) + \frac{1}{2}D(Q\|M), \text{ where}$$

$$D(P\|Q) = \sum_i P(i)\frac{P(i)}{Q(i)}, \quad M = \frac{1}{2}(P+Q)$$

- Flow in/out of rooms
  - Examine the rate of flow in/out of rooms

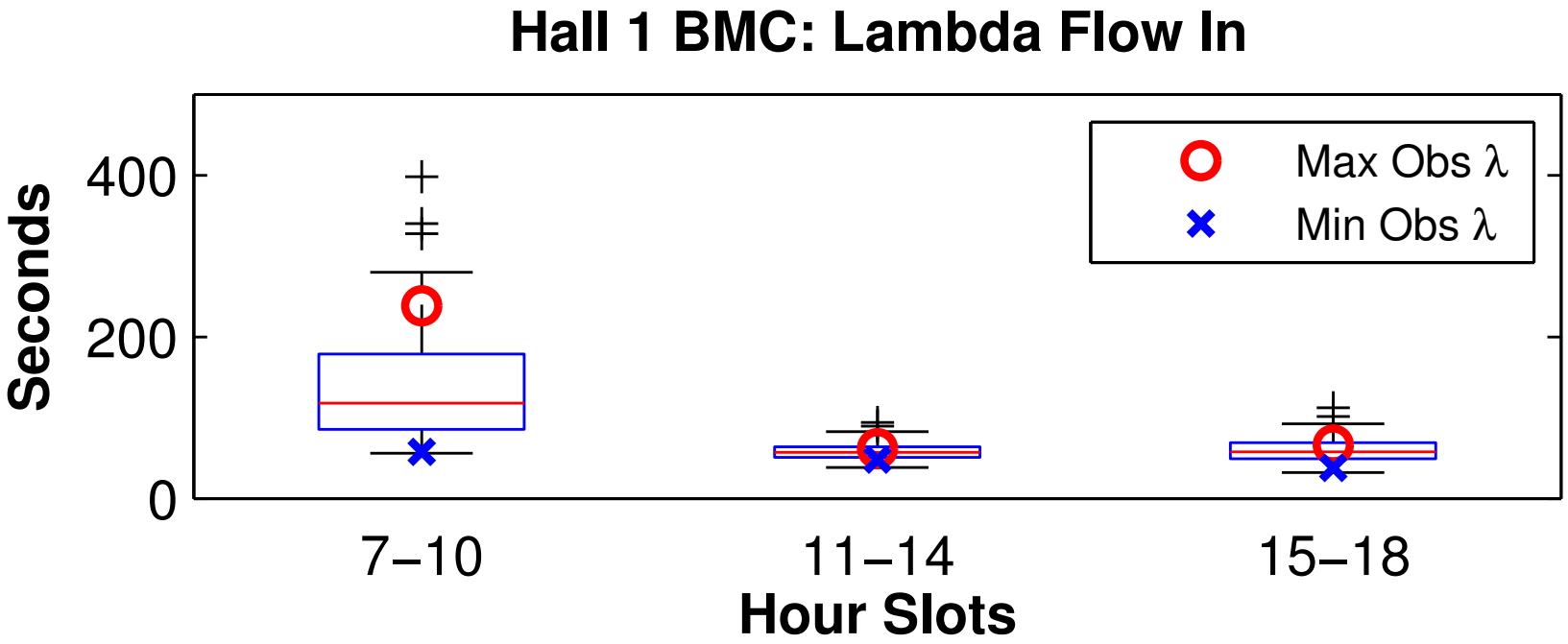
Jenson-Shannon Divergence (JSD)

- Examine room occupancy distributions for blocks of time
- Compare (Max testing set JSD) vs (Average BMC JSD) for each block of times
- BMC JSD remains below maximum testing set JSD



Occupant Flow

- Examine the flow in/out of rooms for blocks of time
- Min/Max flows found from testing set
- BMC flows between the min/max flows of the testing set



Evaluation Summary

- Paper examines two different Markov Chain models (Closest Distance Markov Chain) vs (Blended Markov Chain)
- BMC was found to have the best performance

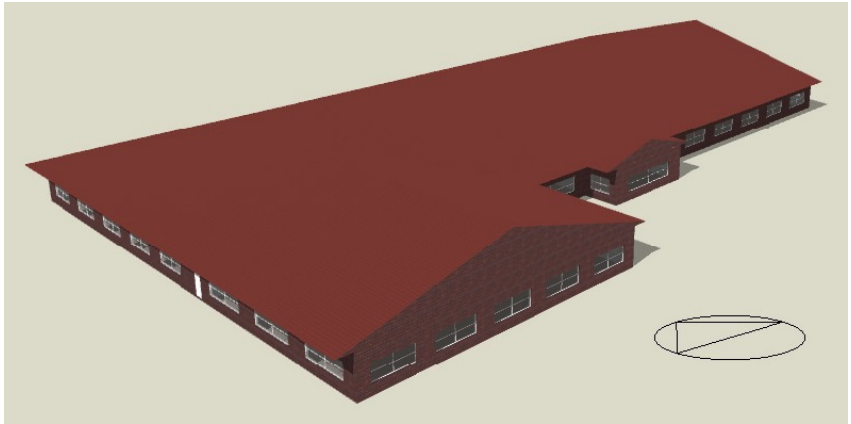
With a predictive occupancy model, we can develop a predictive HVAC control strategy:

- How much energy can be saved?
- How well are the spaces conditioned?

EnergyPlus Building Simulator

EnergyPlus: developed by US Department of Energy

- Considers many factors
- HVAC system
- Occupancy Schedules
- Weather
- etc



- ASHRAE: American Society of Heating, Refrigerating and Air-Conditioning Engineers
- Simulations were performed for an ASHRAE compliant building for three locations: Chicago, Fresno, and Miami

OBSERVE Temperature Control Strategy

Occupancy-**B**ased **S**ystem for **E**fficient **R**eduction of H**V**AC **E**nergy

$T_{TG} \leftarrow$ Target Temp. (most comfortable)
$T_{ASH} \leftarrow$ ASHRAE complaint Temp. (less comfort)
$pThresh \leftarrow$ Probability threshold of occupancy

$CurrOcc \leftarrow$ Current occupancy state
$occPred \leftarrow BMC(CurrOcc, predLen)$

$occupied \leftarrow$ All periods $occPred_{t \rightarrow t+60} > pThresh$

if $occupied >$ 5 mins of next 15 mins **then**
  $CondTemp_{t-60,t+15} = T_{TG}$
else if $occupied >$ 20 mins of next 60 mins **then**
  $CondTemp_{t-60,t+60} = T_{TG}$
else if $5 \leq CurrHour \leq 24$ **then**
  $CondTemp_{i,i} = T_{ASH}$
end if

- Temperatures set using ASHRAE 55
- $pThresh = 40\%$ for simulations
- Rooms conditioned 1 hour in advance

OBSERVE Temperature Control Strategy

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else if $5 \leq CurrHour \leq 24$ **then**
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end if

- Given the current occupancies, use the BMC to find the probabilities of spaces being occupied 1 hour from current time

OBSERVE Temperature Control Strategy

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end if

- Frequented often
- Short durations

OBSERVE Temperature Control Strategy

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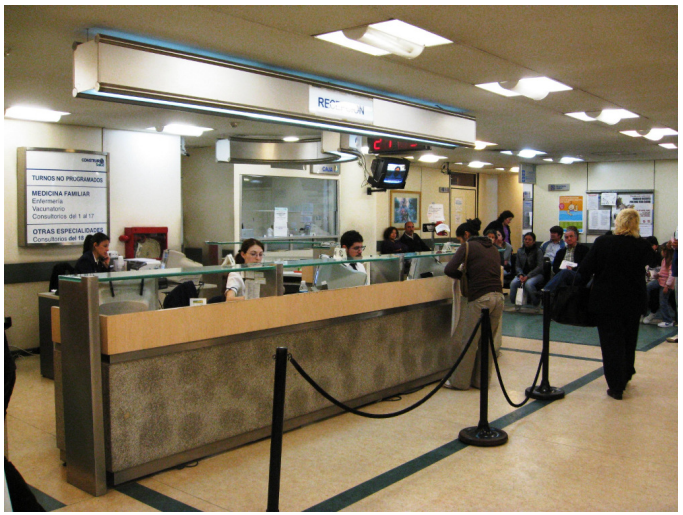

- Consistently occupied
- Long durations

OBSERVE Temperature Control Strategy

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else if $5 \leq CurrHour \leq 24$ **then**
  $CondTemp_{i,i} = T_{ASH}$
end if

- Condition space minimally even if empty

HVAC Strategies

Static Schedule (state-of-the-art baseline)

- Condition from 7:00 - 22:00
- Max ventilation during this period

Reactive

- Reactive temperature control
- Ventilation assuming max occupancy when occupied

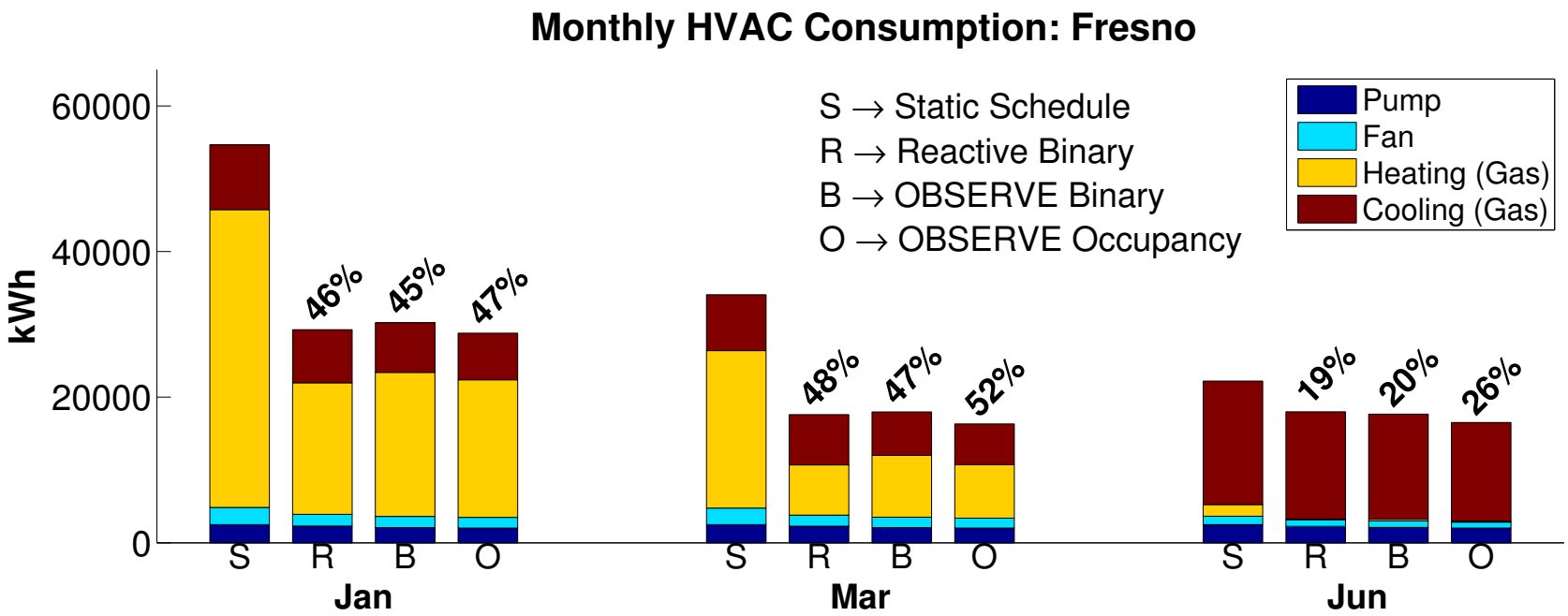
OBSERVE Binary

- Predictive conditioning using BMC trained with binary data
- Ventilation assuming max occupancy when occupied

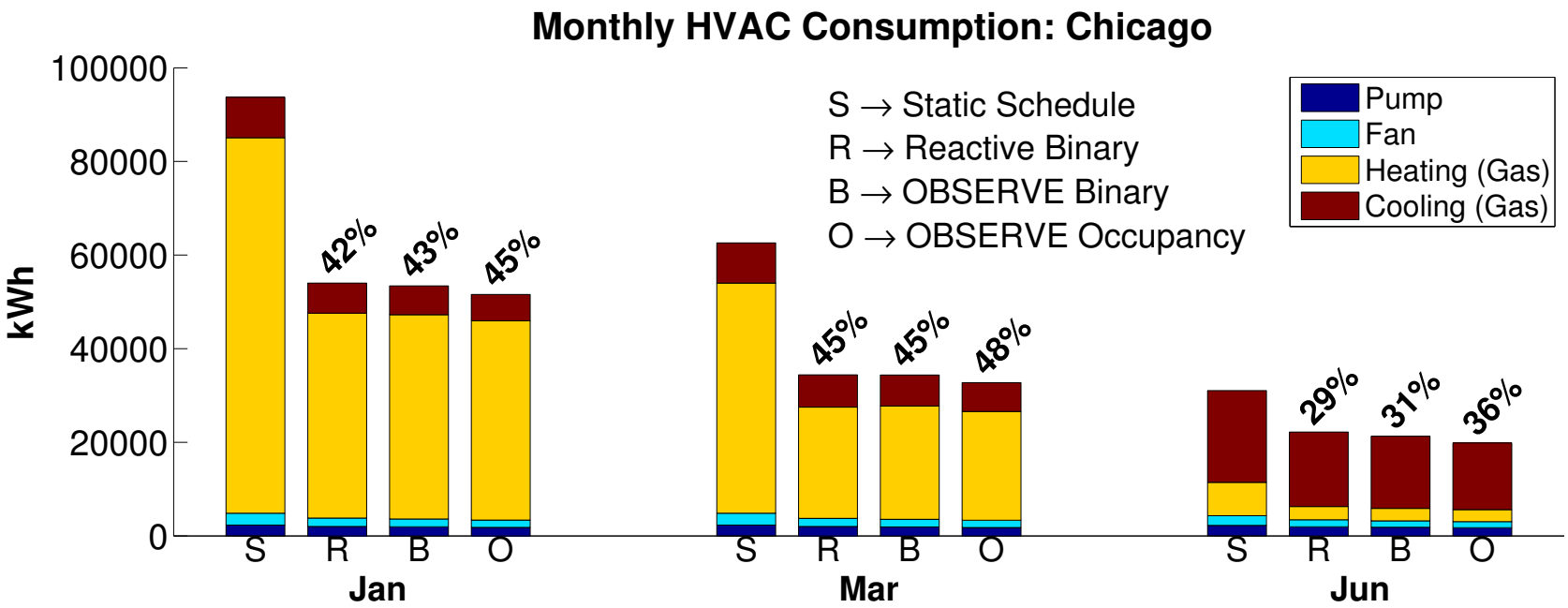
OBSERVE Occupancy

- Predictive conditioning using BMC trained with room occupancy
- Optimal ventilation based on current occupancy

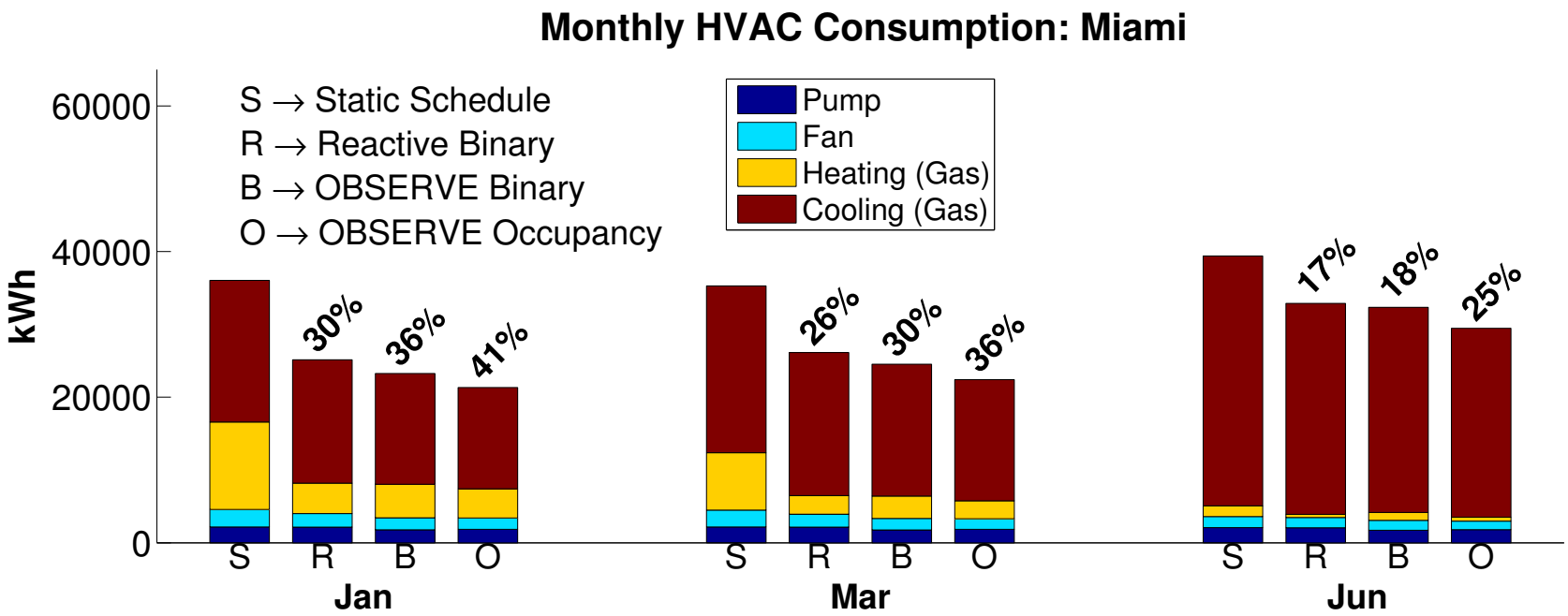
Energy Savings



Energy Savings



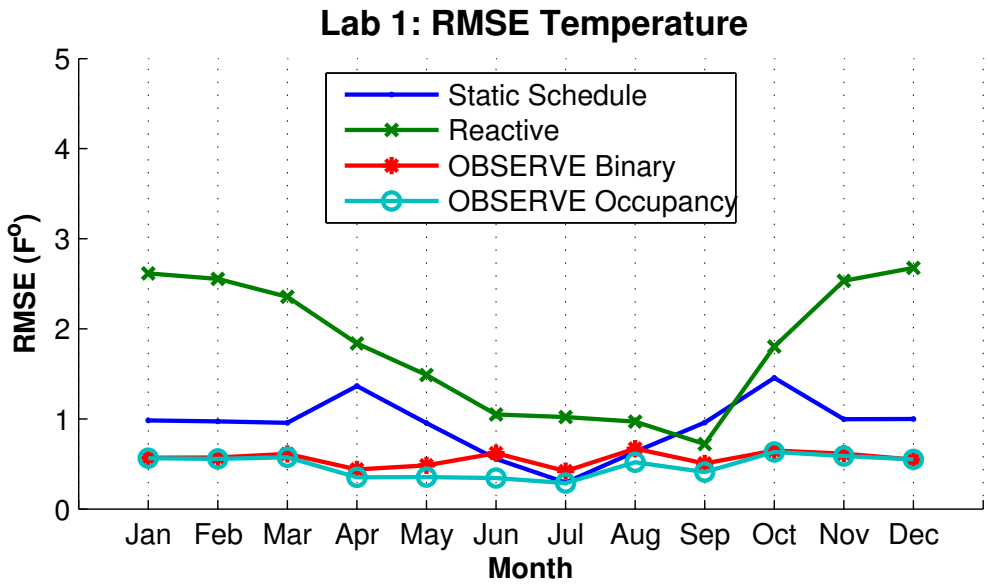
Energy Savings



Energy Usage Summary

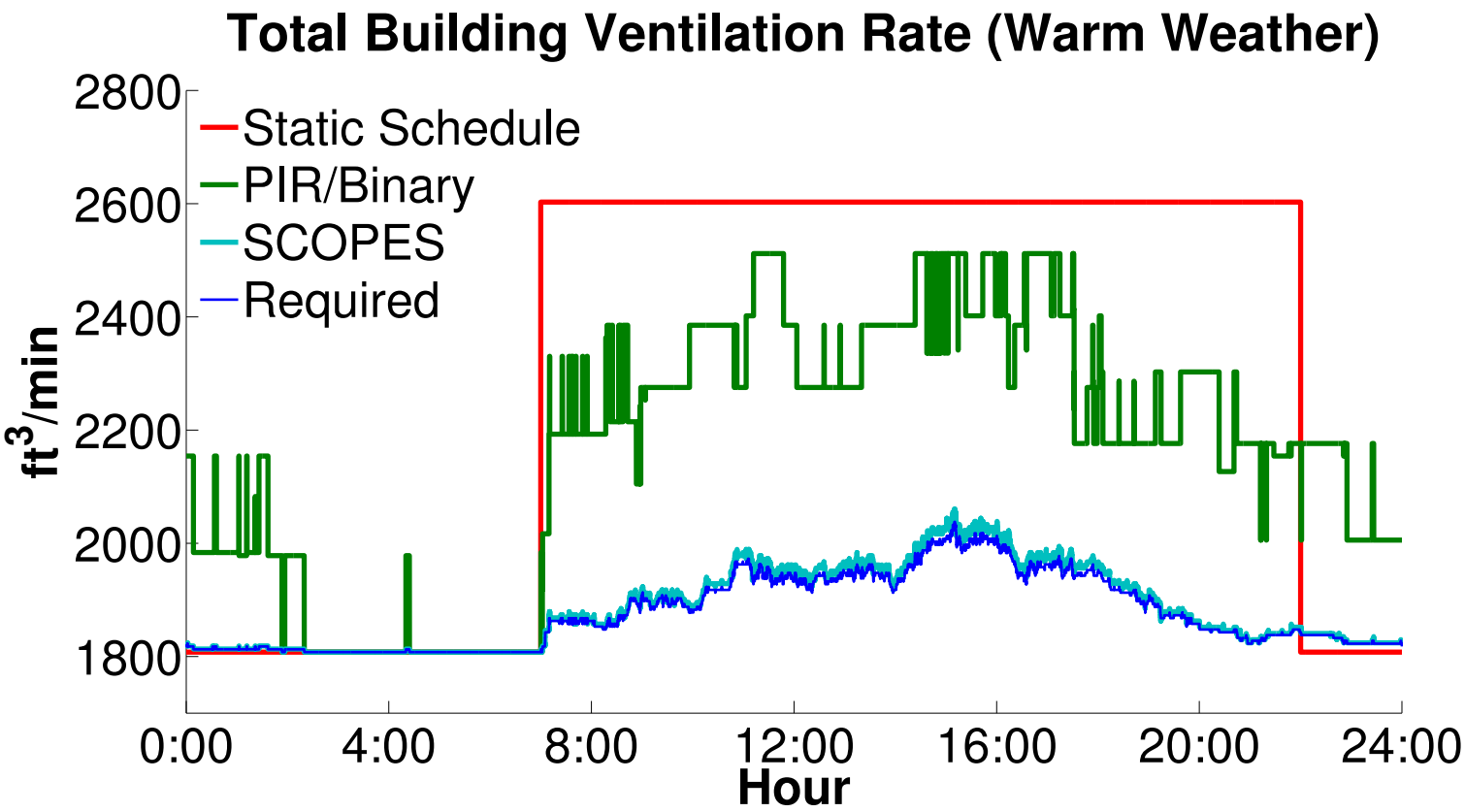
- Static conditioning is grossly inefficient:
  42% annual savings with predictive conditioning
- Ventilation matters
  - The main difference between OBSERVE Binary and OBSERVE Occupancy strategies is ventilation
  - Optimal ventilation is important for cooling (related to terminal re-heating HVAC system)
  - Existing terminal re-heat HVAC systems can be modified to be take advantage of optimal ventilation
- Significant energy savings are possible, but how well are rooms conditioned?

Temperature Effectiveness



- Root mean squared error of target temperature and actual temperature during times of occupancy
- Predictive strategies comparable to static scheduling
- In some cases, predictive strategies perform better
- Reactive strategies are *not able* to effectively condition

Ventilation Effectiveness



Lessons Learned

- 42% annual savings over standard (state-of-the-art) static strategies
- Predictive strategies show better energy savings
- OBSERVE Occupancy shows up to 12% improvement over reactive strategies
- Reactive strategies cannot provide adequate quality of service
- Actual level of occupancy is required to optimize ventilation

Conditioning Criteria

Ventilation: ASHRAE Standard 62.1

$$V = R_p P + R_a A$$

V: ventilation rate (CFM $= \text{ft}^3/\text{min}$)

R_p: min CFM/person

P: number of people

R_a: min CFM/ft^2

A: floor area

Temperature: ASHRAE Standard 55

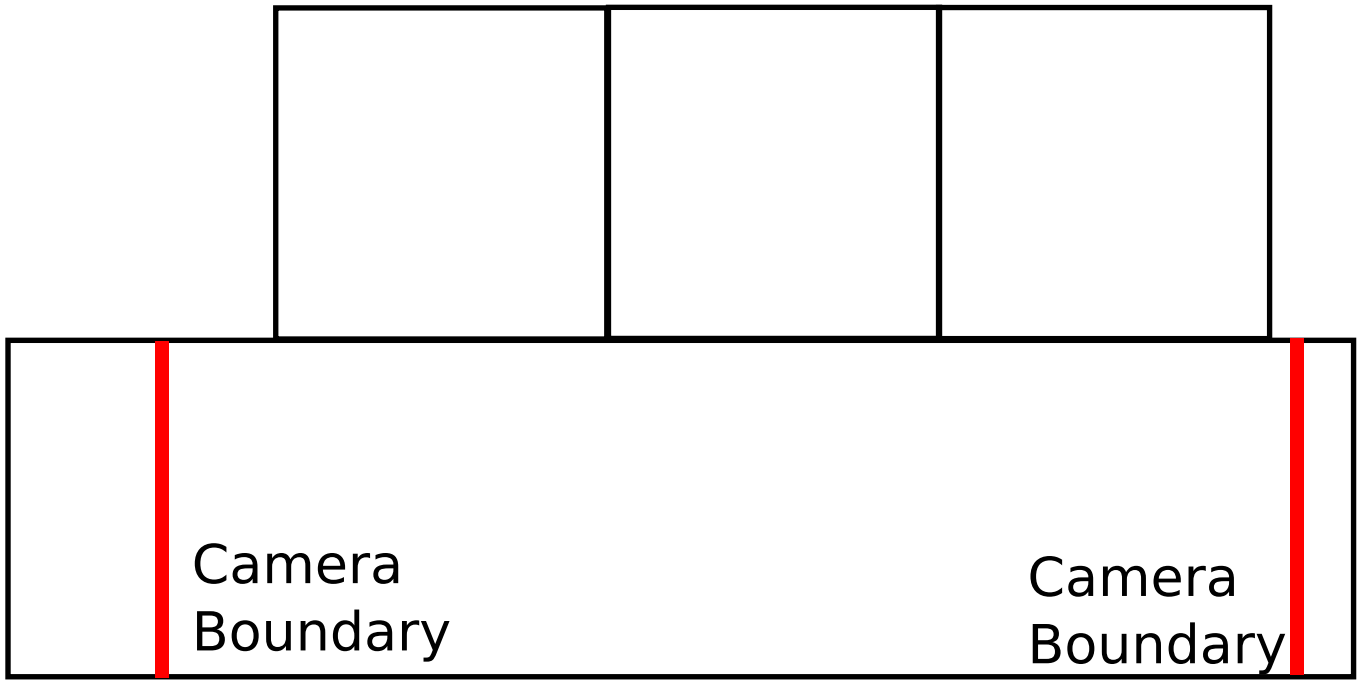
- Predicted Mean Vote (PMV) estimates thermal comfort
- Accounts for humidity, activity, clothing, airflow
- $PMV > 3$ (hot), $PMV = 0$ (neutral), $PMV < -3$ (cold)
- Temperatures set such that $-0.5 < PMV < 0.5$

Savings Per Year

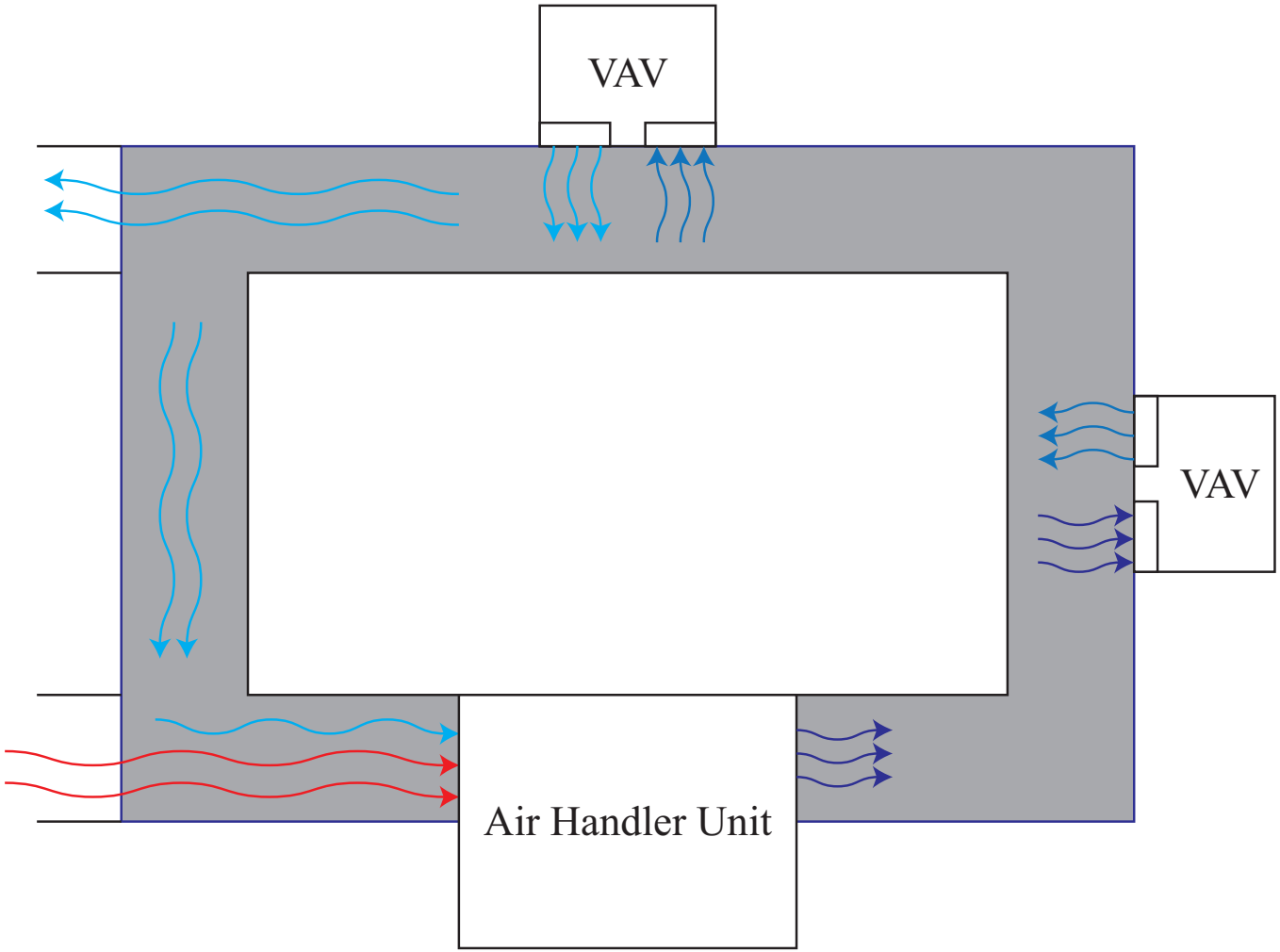
- $30,000-$55,000 per year (baseline vs OBSERVE Occupancy)
- Savings from a single year is enough to offset deployment cost for medium/large office buildings
- Node cost $400 (not optimized for mass manufacturing)

Privacy

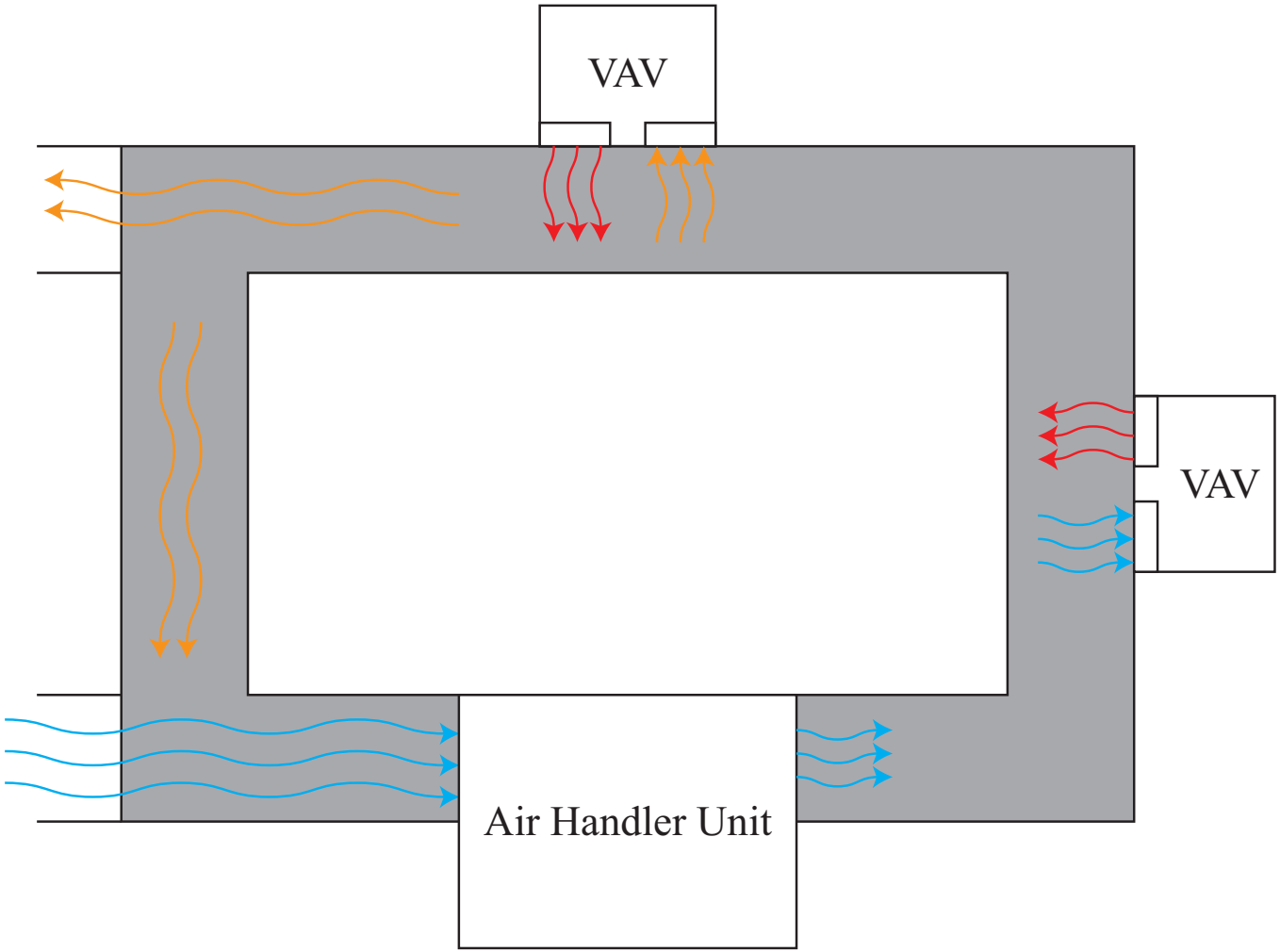
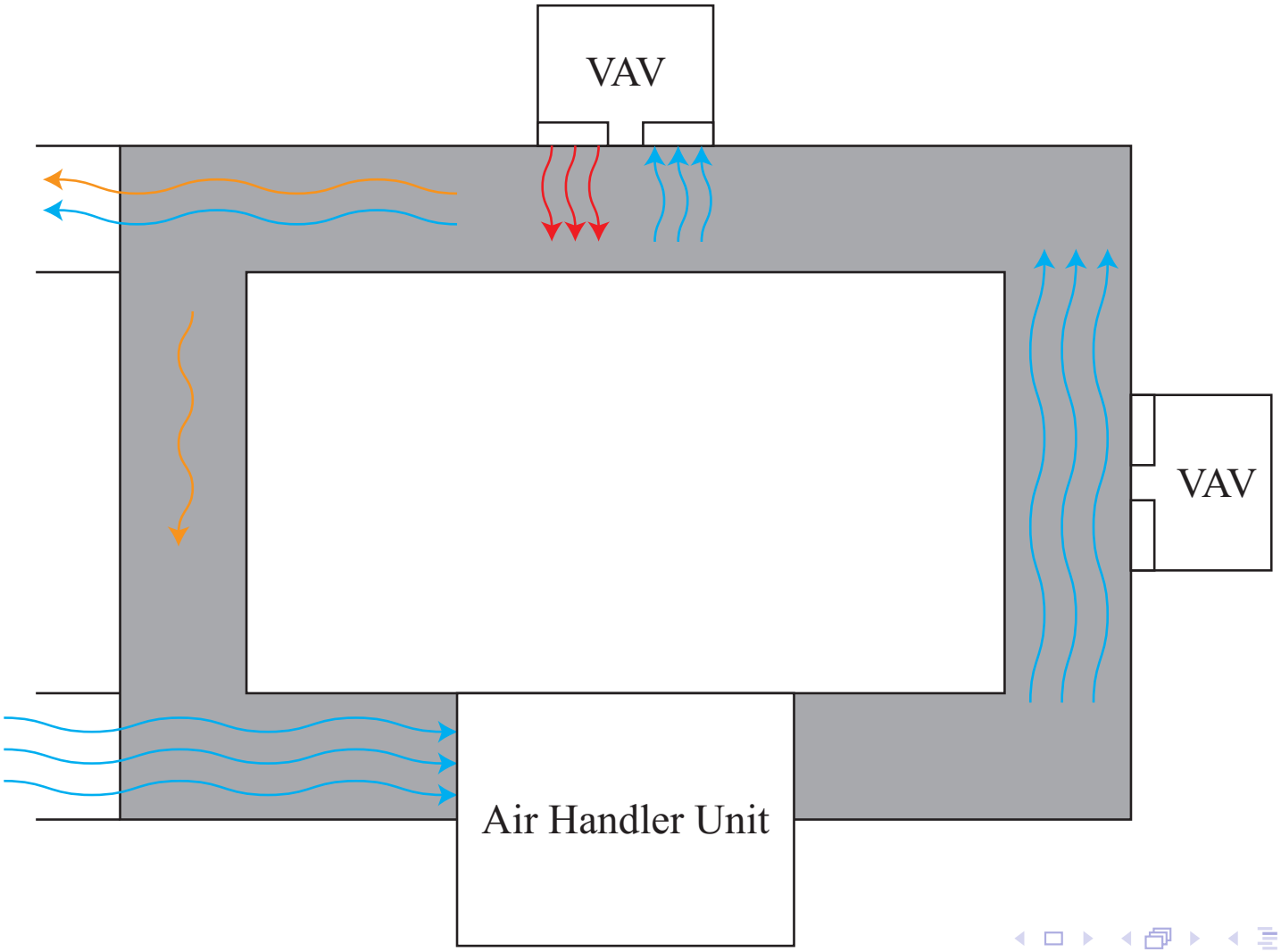
- Deployment ONLY in public halls (same as security cameras)
- Images not stored or even transfered from mote
- Does not require individual monitoring of individual doorways
- Can aggregate rooms for privacy/zone purposes



HVAC Cooling



HVAC Heating



HVAC Heating