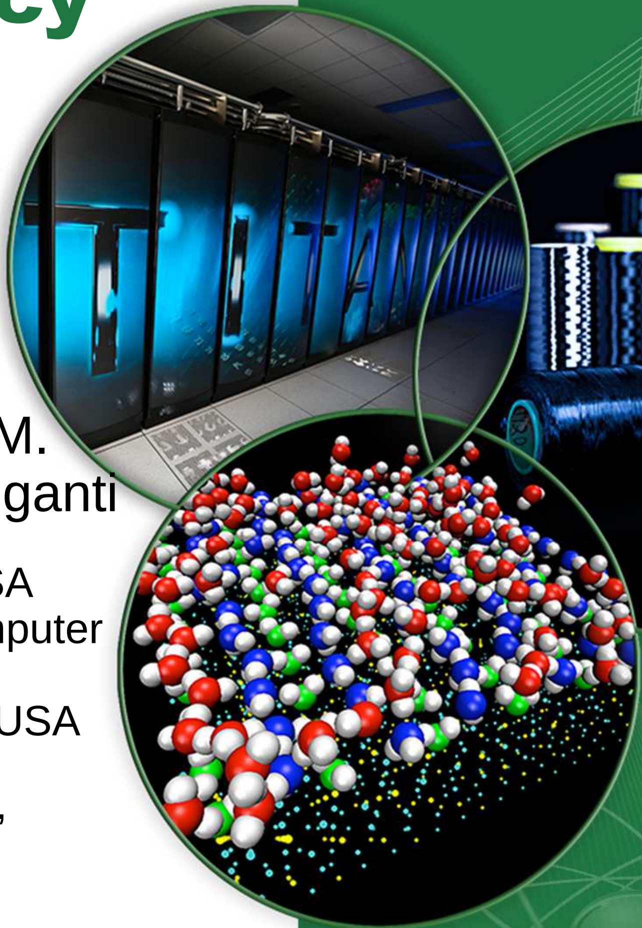
Stochastic Modeling of Short-term Occupancy for Energy Efficient Buildings



Jin Dong, Chris Winstead, Seddik M. Djouadi, **James J. Nutaro**, Teja Kuruganti

University of Tennessee, Knoxville, TN, USA
Department of Electrical Engineering and Computer Science
Oak Ridge National Lab oratory, Oak Ridge, USA

Email: {jdong,cwinste2,djouadi}@utk.edu, {nutarojj,kurugantipv}@ornl.gov

July 13, 2016

4th International High Performance Buildings Conference at Purdue

ORNL is managed by UT-Battelle
for the US Department of Energy

OAK RIDGE National Laboratory

Table of content

Introduction and Motivation

Heating, Ventilating and Air Conditioning units (HVAC) are a major electrical energy consumer in the buildings.

- Most modern buildings still condition rooms with a set-point assuming maximum occupancy rather than actual usage.
- Rooms are often over-conditioned needlessly.
- Reduce energy consumption by 10% ~ 42% using a proper HVAC control strategy that accounts for actual occupancy levels [Erickson et al. (2011)].
- Any off-line strategy for pre-defined control parameters is unable to achieve high accuracy occupancy estimation.

HVAC, Occupancy and Set-point

Hierarchy of Occupancy based Control:

- The first step is estimation of the occupancy.
- The second step is determination of temperature set-point.

Key Information:

Occupant activity and control preferences

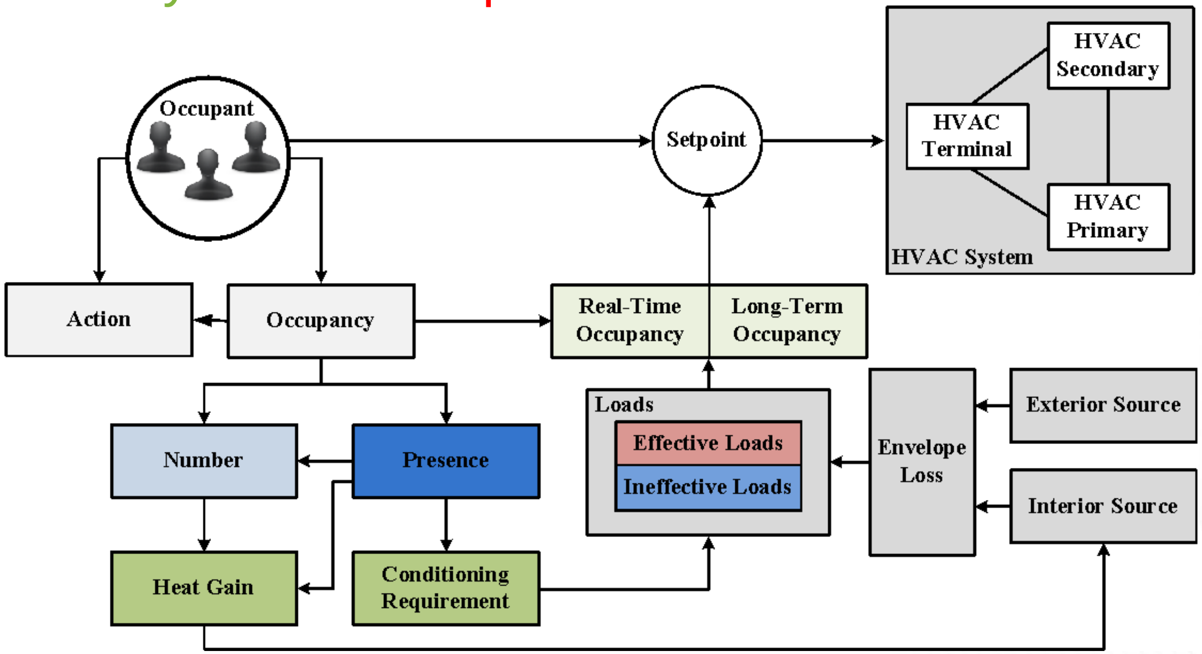
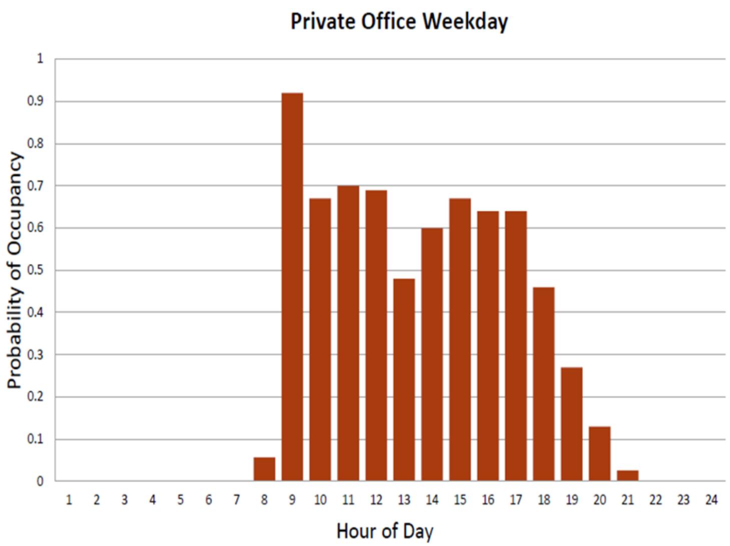
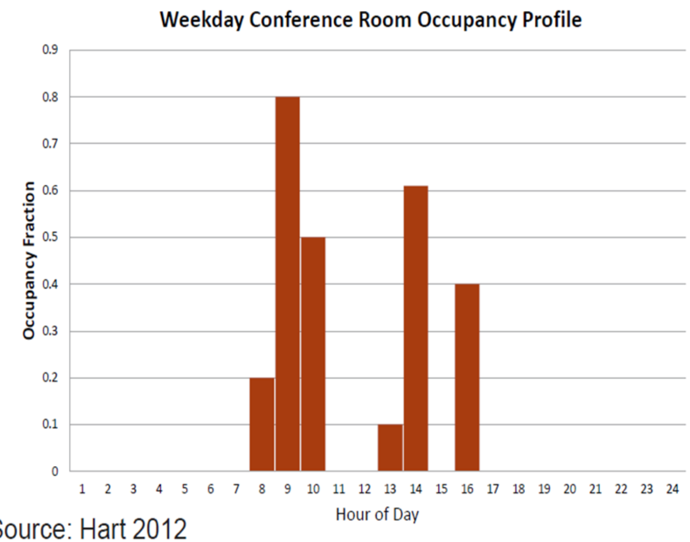


Figure 1 The importance of occupant in HVAC energy consumption

Occupancy Heterogeneity

A typical occupancy profile of a office/conference room in weekday.





Source: Hart 2012

Gap Analysis

1) What is the probability for this room to be occupied?
2) How many people are in the room?

Discrepancies from measurements

NO practical estimation algorithm for occupancy and HVAC control

- Effects of occupancy on HVAC energy consumption;
- HVAC response to occupancy based HVAC controls;

Binary occupancy state

- Use $\gamma(t)$ ($\eta(t)$) to denote the number for the room to be occupied (unoccupied).
- For next time step $(t+1)$
- If the room is occupied, we do $\gamma(t+1) = \gamma(t) + 1$
- If the room is unoccupied, we do $\eta(t+1) = \eta(t) + 1$

Table 1: Binary count for $\gamma(j)$ and $\eta(j)$

Actual Time	Time Sequence	Count
12:00 AM	1	$\gamma(1)$ and $\eta(1)$
12:30 AM	2	$\gamma(2)$ and $\eta(2)$
⋮	⋮	⋮
11:00 PM	47	$\gamma(47)$ and $\eta(47)$
11:30 PM	48	$\gamma(48)$ and $\eta(48)$

- So the probability to be occupied is denoted as: $P(j) = \frac{\gamma(j)}{\gamma(j)+\eta(j)}$ for $j = 1 \cdots 48$.
- So the probability NOT to be occupied is denoted as: $P(j) = \frac{\eta(j)}{\gamma(j)+\eta(j)}$ for $j = 1 \cdots 48$.

Kalman Filter and Expectation Maximization (EM) algorithm

- EM is a filter-based iterative numerical scheme to compute maximum likelihood estimates of the parameters given the measurement data.
- State-space model used on-line and updated with new observations

State equation → $x_{k+1} = A_k x_k + B_k w_k$

Measurement equation → $y_k = C_k x_k + D_k v_k$

where $x_{k+1} \in \mathbb{R}^{n \times 1}$ ($\mathbb{R}^{n \times 1}$ denotes the space of real vectors of dimension $n \times 1$) is the state that characterizes the occupancy; it is a variable of the time series $\{x_k\}$ determined by the previous state x_k and the noise term $w_k \in \mathbb{R}^{m \times 1}$ introduced at each k. $A_k \in \mathbb{R}^{n \times n}$ and $B_k \in \mathbb{R}^{n \times m}$ are corresponding coefficients.

- Unknown system parameters $\beta_k = \{A_k, B_k, C_k, D_k\}$ and states $\{x_k\}$ can be estimated through a finite set of received signal measurement data.

Finite state automata (FSA)

Input/output behavior of FSA can be reconstructed by General Systems Problem Solver (GSPS) [George Klir, 1969].

round	time (v_1)	occupancy (v_2)
11	t_{11}	a
10	t_{10}	b
9	t_9	a
8	t_8	b
7	t_7	a
6	t_6	a
5	t_5	b
4	t_4	a
3	t_3	b
2	t_2	b
1	t_1	a

- a: Occupied
- b: Unoccupied

input	output	count	likelihood
aaa	a	47	0.959
	b	2	0.041
aab	a	0	0
	b	1	1
aba	a	1	1
	b	0	0
abb	a	0	0
	b	1	1
baa	a	1	0.5
	b	1	0.5
bab	a	1	0.33
	b	2	0.67
bba	a	0	0
	b	1	1
bbb	a	0	0
	b	4	1

Temperature setting algorithm

Discomfort tolerance index α is defined to model consumer choice on thermal comfort, which is used to capture the **trade-off** between thermal comfort and energy cost.

High discomfort tolerance (i.e., $\alpha > 0$); Low tolerance ($\alpha \leq 0$).

Algorithm 1 Temperature Setting Algorithm

Step 1:
  Initialize α
Step 2:
  $n \leftarrow \frac{T_{max} - T_{min}}{k} + 1$
for all hour $h = 1$ to 48 **do**
  $Range \leftarrow max(O_h) - min(O_h)$
  $r_0 \leftarrow min(O_h)$
end for
if $\alpha = 0$ **then**
  Go to step 3
else
  Go to step 4
end if
Step 3:
for all set-point j ($j = 1$ to n) **do**
  $r_j \leftarrow r_{j-1} + \frac{Range}{n}$
  Go to Step 5
end for
Step 4:
for all set-point j ($j = 1$ to n) **do**
  $r_j \leftarrow r_{j-1} + Range * \frac{2^{\alpha(j-1)}(1-2^{\alpha})}{(1-2^{\alpha n})}$
end for
Step 5:
for all hour $h = 1$ to 48 **do**
  $T_h^{set} \leftarrow k[argmin\{j : O_h \leq r_j\} - 1] + T_{min}$
end for

Experiment setup

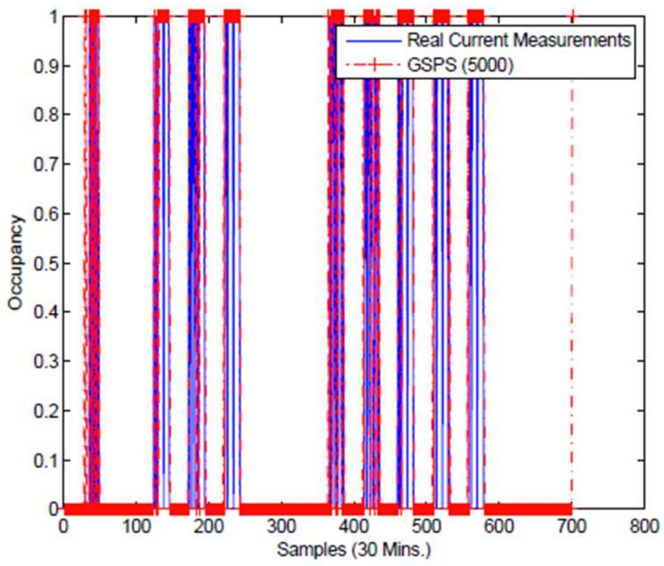
- We use a segment of real occupancy data, “10/13/2010 ~ 4/5/2011”.
- The sampling interval is 30 minutes, so any sensor collects 48 occupancy samples each day. i.e. we have 8352 samples.

Natural questions which arise are: ?

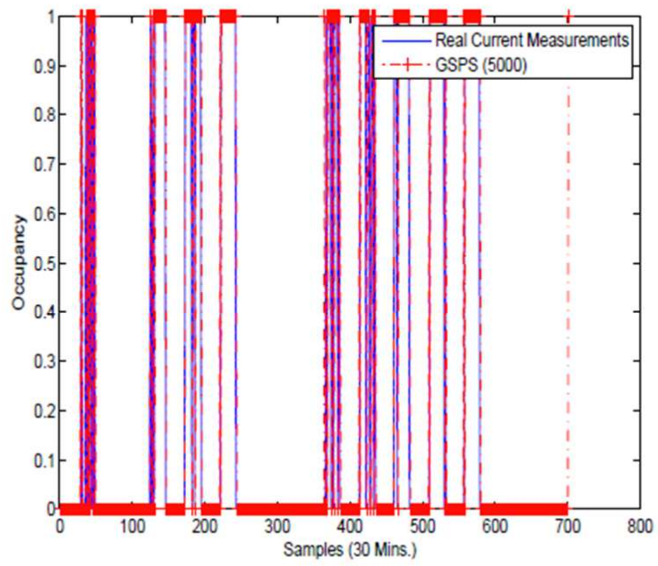
1) What is the probability for this room to be occupied? (Binary Occupancy)
2) How many people are in the room? (Detailed Occupancy)

Results: Binary occupancy using GSPS model

Estimated probability of occupancy



(a) Binary occupancy using GSPS model 3000 points

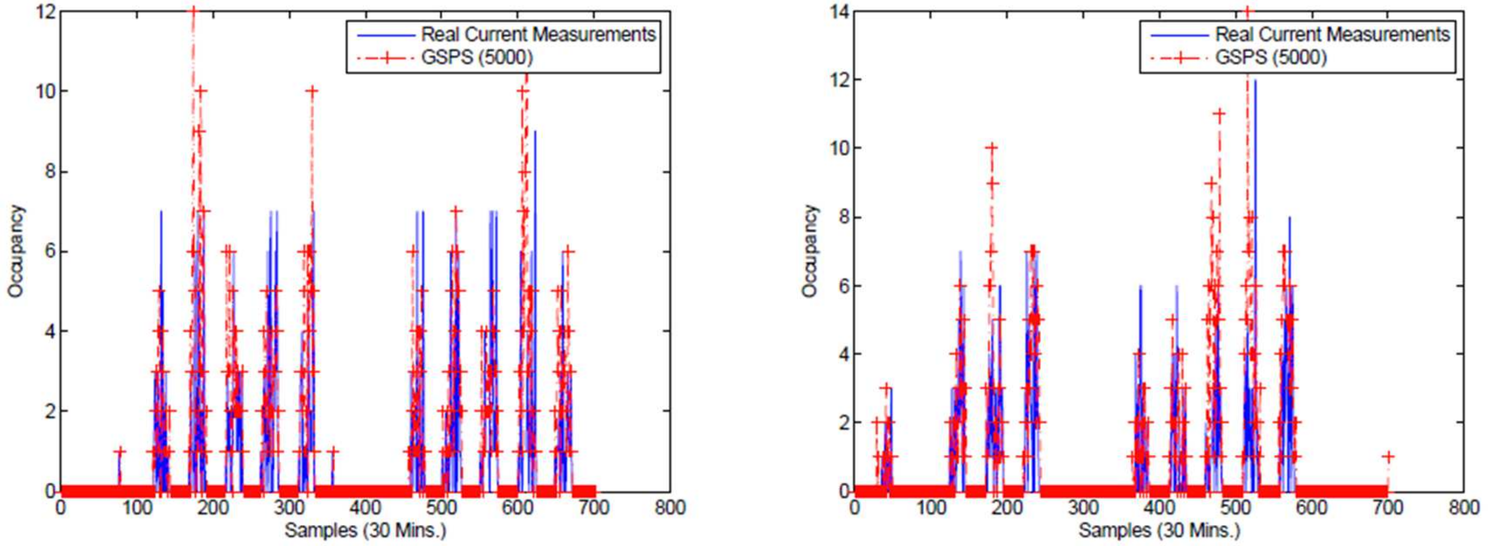


(b) Binary occupancy using GSPS model 5000 points

OAK RIDGE National Laboratory

Results: Occupancy estimation using GSPS model

Estimate detailed number of people

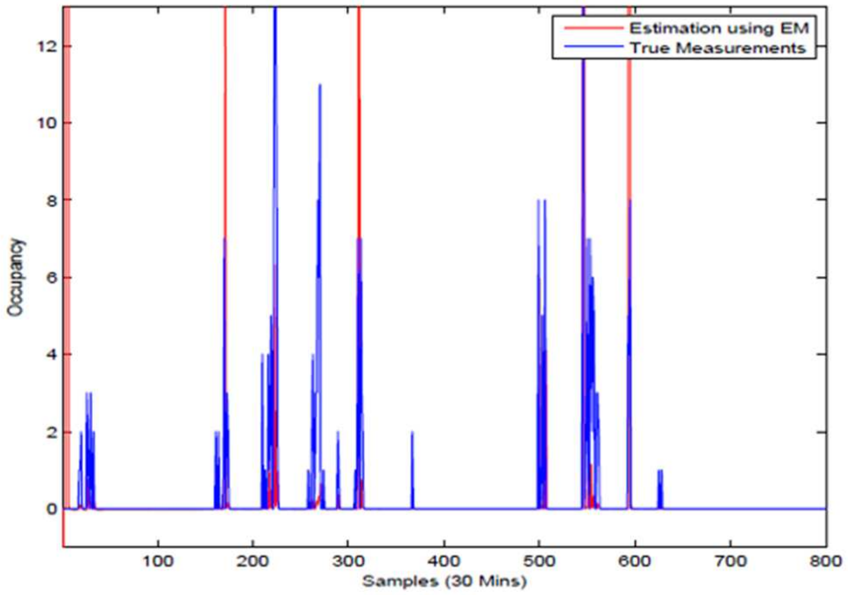


(a) Occupancy estimation using GSPS model 3000 points

(b) Occupancy estimation using GSPS model 5000 points

Results: Occupancy estimation using EM algorithm

Estimate detailed number of people



(a) Occupancy estimation using EM algorithm

Comparison of results

Root mean square error (RMSE):

$$MSE(\hat{O}) := \frac{1}{N}\sum_{k=1}^{N}(\hat{O}(k) - O(k))^2.$$

$$RMSE(\hat{O}) := \sqrt{MSE(\hat{O})}$$

Accuracy:

$$ACC\left(\hat{O}\right) := \frac{N - \sum_{k=1}^{N} \mathbb{1}\left(O(k) - \hat{O}(k)\right)}{N},$$

where O and $\hat{O}$ are true and estimated occupancy, respectively; and $\mathbb{1}\,(O(k))$ is given as:

$$\mathbb{1}\,(O(k)) := \begin{cases} 1 & \text{if } O(k) > 0, \\ 0 & \text{otherwise.} \end{cases}$$

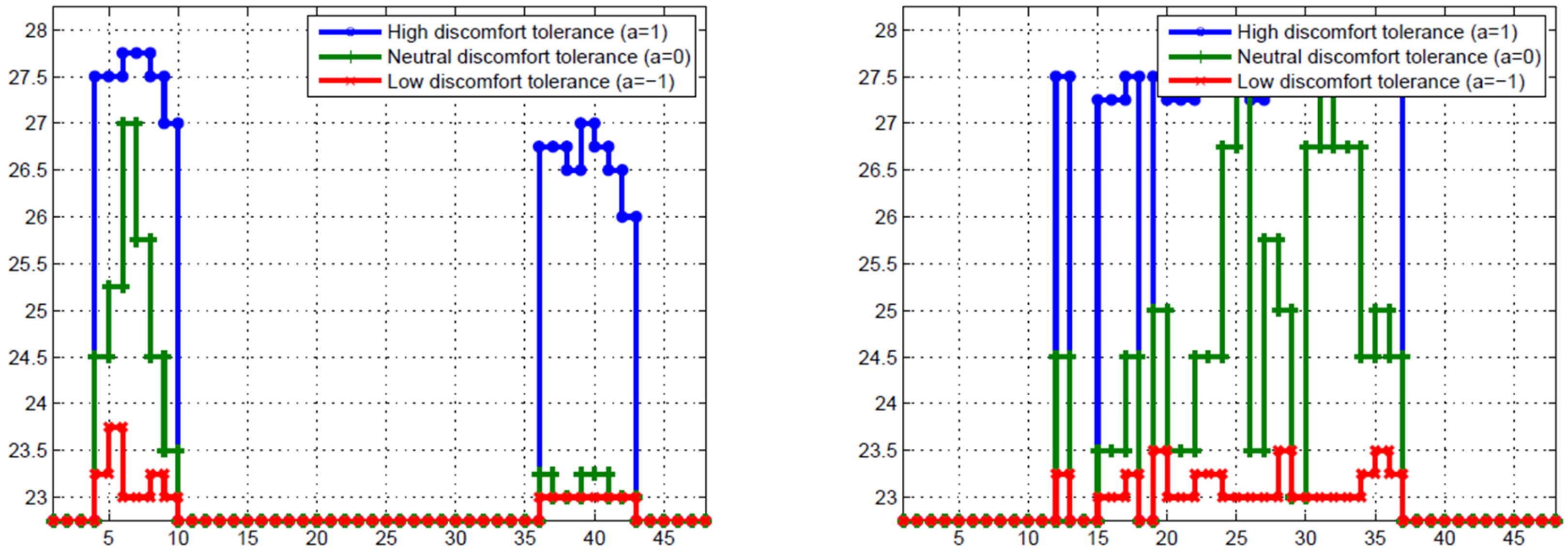
Comparison of binary estimations

Methods	Estimation RMSE	Accuracy
Probability counting	0.206	0.683
GSPS (3000)	0.094	0.889
GSPS (5000)	0.086	0.912

Comparison of detailed occupancy estimation

Methods	Estimation RMSE	Accuracy
GSPS (3000)	3.078	0.700
GSPS (5000)	2.646	0.715
EM	3.715	0.615

Results: Detailed temperature set-points



(a) EM

(b) GSPS model 5000 points

Summary

- Proposed method based on FSA and EM achieves high accuracy occupancy estimation.
- Also:
- Provides an effective algorithm to automatically assign reference temperature set-points based on the occupancy information.
- FSA needs big training data while EM does not.
- Uses real occupancy data to estimate binary (on/off) as well as detailed occupancy amount.

- Future work:
- Incorporate with advanced occupancy detection/tracking algorithm
- Apply the proposed occupancy estimation and temperature setting strategy into control design problem

References

- [1] Dong, J., Ma, X., Djouadi, S., Li, H., and Liu, Y. (2014). Frequency prediction of power systems in fnet based on state-space approach and uncertain basis functions. *IEEE Trans. Power Systems*.
- [2] Dong, J., Ma, X., Djouadi, S. M., Li, H., and Kuruganti, T. (2013). Real-time prediction of power system frequency in FNET: A state space approach. In Smart Grid Communications (SmartGridComm), 2013 IEEE International Conference on, pages 109–114. IEEE.
- [3] Klir, G. (1969). *An Approach to General Systems Theory*. Van Nostrand Reinhold.
- [4] Klir, G. (2013). Architecture of systems problem solving. Springer Science & Business Media.
- [5] Erickson, V. L., Carreira-Perpiñán, M. Á., and Cerpa, A. E. (2011). Observe: Occupancy-based system for efficientreduction of hvac energy. In Information Processing in Sensor Networks (IPSN), 2011 10th International Conferenceon, pages 258–269. IEEE.

Thank you!
Questions?

OAK RIDGE
National Laboratory