Occupancy Based Demand Response HVAC Control Strategy

Varick L. Erickson
University of California Merced
verickson@ucmerced.edu

Alberto E. Cerpa
University of California Merced
acerpa@ucmerced.edu

Abstract

Heating, cooling and ventilation accounts for 30% energy usage and for 50% of the electricity usage in the United States. Currently, most modern buildings still condition rooms assuming maximum occupancy rather than actual usage. As a result, rooms are often over-conditioned needlessly. This paper proposes an HVAC control strategy based on occupancy prediction and real time occupancy monitoring via a sensor network of cameras. This strategy shows 20.0% potential energy savings while still maintaining ASHRAE building standards.

1 Introduction

In 2003, approximately 50% of the electricity in the United states was used for heating, ventilation, and air-conditioning (HVAC) systems[2]. HVAC systems often condition rooms assuming maximum occupancy. A room could be ventilated for 30 people when only 10 people actually occupy the space. A conference room used only on Mondays could be heated and cooled needlessly. A more efficient approach is to condition rooms based on room occupancy. In order to create an efficient demand response HVAC control strategy, actual room usage must be considered.

Temperature and CO_2 levels are two main conditioning factors to consider for HVAC control strategies. Temperature only requires a binary indication if a room is occupied, which could be implemented using a Passive Infrared Sensor (PIR). However, CO_2 ventilation rates are a function of the *number* of occupants and cannot be effectively controlled via PIR. CO_2 sensors are problematic [7] for ventilation control since they may require a significant amount of time before detecting CO_2 buildup. Thus, an HVAC control strategy must utilize an occupancy monitoring system capable of detecting the *number* of occupants in *real time*. SCOPES [9] is an occupancy monitory system that detects near real time occupant movement between rooms with an accuracy of 80% [8].

While real time occupancy monitoring is important, occupancy prediction is also necessary for HVAC control. Time is required for rooms to be brought to appropriate temperatures. We must therefore be able to anticipate room usage to begin conditioning rooms beforehand. For example, if a lobby has a large number of people, then the HVAC system could know that an an adjacent conference room will be used with high probability and begin conditioning before people actually enter the room. In [8], preliminary occupancy models are created using a Multivariate Gaussian Model and an Agent Based model. These models are used for simulations but not for predictive demand response strategies. In this paper, we develop a more accurate model using a Markov Chain approach for use in a conditioning strategy.

This paper proposes a demand response HVAC control strategy that uses real time occupancy monitoring with occupancy prediction in order to achieve efficient conditioning. Section 2 defines the Moving Window Markov Chain occupancy model utilizing Markov Chains and discusses the problems inherent when using this approach and methods of overcoming the limitations. Section 4 defines an ASHRAE compliant EnergyPlus building simulation model. We discuss the building parameters and the HVAC control strategies used for the energy simulations. Section 6 evaluates the potential energy savings using the control strategies and show that 20% annual energy savings are possible. Finally, in section 7 we verify that ASHRAE standards are maintained while using the strategies.

2 Moving Window Markov Chain

2.1 Data Collection

SCOPES is a wireless sensor network of low power cameras capable of monitoring occupancy areas. Sensor nodes are placed at the boundaries between different areas and detect transitions between areas. Since the data collected by SCOPES has inaccuracies, for developing and testing the preliminary occupancy model we use five days (Mon-Fri) of ground truth occupancy data . Figure 1 shows the ten areas that data was collected at UC Merced. Simple background subtraction methods were used to first to help identify images containing people and then processed by hand to verify direction and the boundaries being crossed. More data would be preferable but processing ground truth data requires hours of time and is commonly cited as major obstacle for develop-

BuildSys 2010 November 2, 2010, Zurich, Switzerland.

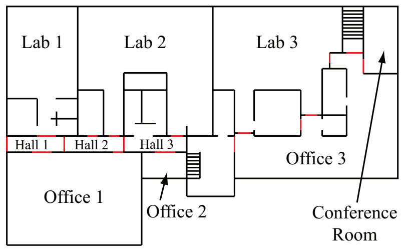


Figure 1. The ten occupancy areas and the 18 transition boundaries (red lines) that define each area.

$$\begin{array}{c|cccc} & s_0 & s_1 & \cdots & s_m \\ \hline s_0 & p_{0,0} & p_{1,0} & \cdots & p_{m,0} \\ s_1 & p_{0,1} & \ddots & & \\ \vdots & \vdots & & p_{ij} & \\ s_m & p_{0,m} & & \cdots & \end{array}$$

Figure 2. The transition matrix calculated for each hour.

ing occupancy models. However, once an occupancy model is fully developed, SCOPES data can be used for training.

2.2 Markov Chain Occupancy Model

A Markov Chain (MC) is a system of known states where the state changes probabilistically at discrete steps. This model can be used to describe how the state of a system changes over time. To model how room occupancies of a building change over time, the room occupancies can represent the state of the MC where the state changes with a certain transition probability. Let R represent the set of rooms to be modeled. For each room in R, there is a maximum occupancy. We define $S = \{s_0, \ldots, s_m\}$ to be the set of all room occupancy combinations that are possible given the maximum room occupancies of R. With the observable states S of the MC defined, we can now define the transition matrix that governs the probability of moving from one occupancy state to another. Let $p_{i,j}$ represent the probability of moving from state j to i where X_t represents an occupancy state at time t where t is measured in seconds. Let $n_{i,j}$ denote the number of times a transition is made from state i to state j. The total number of states is m. The following estimates transition matrix probabilities:

$$p_{i,j} = P(X_{t+1} = i | X_t = j) = \frac{n_{i,j}}{\sum_{k=1}^{m} n_{i,k}}.$$

It is also necessary to incorporate time into the model. Certain occupancy changes occur with greater probability depending on the time of day. Consider a person standing in a hallway at 8 am. Since it is early in the day, it is likely that the person has arrived for work and will move into either an lab or office. However, if we consider the same scenario at 8 pm, it is more likely that the person will exit the hallway in order to leave the building. To include time in the model, we define hourly transition matrices that govern the state changes for each hour. Figure 2 summarizes currently defined transition matrix used for each hour. The transition matrix used changes depending on the current hour.

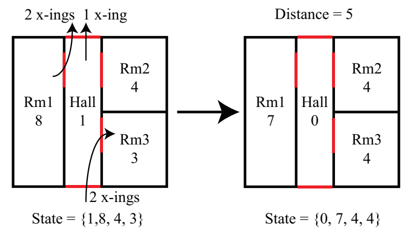


Figure 3. An example for the closest distance metric. States are represented as Hall, Rm1, Rm2, Rm3. For this example, the distance between the states is 5.

2.3 MC Limitations

There are fundamental limitations using an MC. The first is the number of states required to represent a building. For a set of four rooms each with a maximum occupancy of 20, a total of 3,840,000 states (160,000 states per hour) are needed for the complete MC model. Though transition matrices are sparse as many state transitions are impossible due to the physical constraints of the building, as more rooms are added, the number of states to manage increases exponentially. It is nearly impossible to collect data to represent all valid states. This in turn creates the presence of sink states. Suppose we are predicting occupancy and we are in state X in hour h when transitioning to $h+1$. If the transition matrix for hour $h+1$ has no probability for occupancy state X, then the prediction enters a sink state. This occurs if state X never occurs in the training data for hour $h+1$.

Typically, this can be solved by introducing a small epsilon probability value of transitioning into another state. However, if we randomly choose the next state with a small epsilon value, the next state chosen may also not be represented in the transition matrix. One solution to the sink state problem is to choose the next closest state. We define the distance between two states to be the number of transitions to or from the outside world in order to account for the difference between the states. Let M_i represent the minimum number of boundary transitions that is needed for a single person to enter or exit out of a building from room i. Let $X = \{x_0, \ldots, x_n\}$ and $Y = \{y_0, \ldots, y_n\}$ represent two occupancy states where x_i and y_i are the occupancies of room i. We define distance $d_{X,Y}$ between X and Y to be the following,

$$d_{X,Y} = \sum_{i=0}^{n} M_i |x_i - y_i|.$$

Figure 3 shows an example of this distance metric. For this four room example, the distance between the states is 5. Although this method solves sink states at the hourly breaks, it does not guarantee a valid sequence of states.

2.4 Moving Window

Sink states only occur when the next transition matrix does not contain a probability for the current state. To avoid sink states, we wish to ensure that the current state exists in the next transition matrix. One way to avoid sink states is to use a transition matrix that is trained over a moving window of data. As state changes progress, the window of data that the transition matrix is trained changes.

Thus far, we have defined the MC model to have hourly transition matrices that capture the occupancy behavior for a particular hour. However, the choice to train over a specific hour is somewhat arbitrary. We can create a transition matrix for any specified window of time. Rather than define a transition matrix every hour, we instead define a transition matrix every n minutes with each transition matrix still trained with an hour of training data. Thus, each transition matrix overlaps its neighboring transition matrices by $60-n$ minutes. By having this overlap, we can reduce the likelihood of entering a sink state. Let D represent the training data. Let the function $g(D,t_0,t_1)$ return the transition matrix trained with D defined for the window of time t_0 to t_1. For example, $g(D,$ 8:00 am, 9:00 am$)$ represents a transition matrix trained with D for hour 8:00 am to 9:00 am. If $n=10$ minutes, then we get the following 140 overlapping transition matrices,

$$\begin{aligned} T_1 &= g(D,\ 00{:}00,\ 1{:}00) \\ T_2 &= g(D,\ 00{:}10,\ 1{:}10) \\ &\vdots \\ T_{140} &= g(D,\ 23{:}00,\ 00{:}00) \end{aligned}$$

Once the transition matrices are defined, we predict with the following algorithm:

$CurrState \leftarrow$ Starting state
$TransMat \leftarrow T_i$ Starting transition matrix
$Sim \leftarrow \{\}$
$w \leftarrow 0$ Window move counter
for $t=1$ to Simulation Duration **do**
  if $w > n*60$ seconds **then**
    $NextMat \leftarrow T_{i+1}$ Next transition matrix
    if $CurState \in NextMat$ **then**
      $TransMat \leftarrow NextMat$
      $w \leftarrow 0$ Reset window counter
      $i \leftarrow i+1$
    end if
  end if

  if $w < 2*n*60$ seconds **then**
    $CurrState \leftarrow RandomState(TransMat, CurrState)$
  else
    $CurrState \leftarrow$ Closest State in T_{i+2}
  end if
  $Sim.add(CurrState)$
  $w \leftarrow w+1$
end for

Once entering a transition matrix, after n*60 steps (n minutes) have past, the algorithm attempts to move to the next overlapping transition matrix. However, it only changes transition matrices if the currently defined state exists in the next transition matrix. Otherwise it remains in the current transition matrix. Though this lessens the probability of entering a sink state it is still possible to encounter. If this occurs, we use closest state of the next transition matrix.

3 Model Evaluation

Due to space limitations, we omit a full analysis of the MWMC performance and validity but include a basic metric for evaluation. When 100 days of occupancy data are generated by the MWMC and compared against a testing set of one day, we find the model has an average normalized root mean squared error (NRMSE) of 15.36% for room occupancy. While this error seems high, if we compute the NRMSE between ground truth days, we find an average NRMSE of 12.7%. This suggests that the model exhibits similar day to day occupancy variation to real world daily occupancy variation.

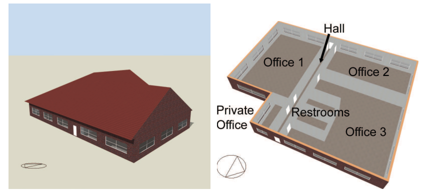


Figure 4. Floorplan of the simulated building.

EnergyPlus Building Parameters

HVAC	Single Duct AHU, VAV with terminal reheat Gas heating and cooling 7 zones
Area	Total: 7,214 ft^2 Office: 6,298 ft^2
Materials	Concrete exterior walls Metal interior walls 30% double glazed windows
Location	Fresno, CA

Figure 5. Some of the building parameters used.

4 EnergyPlus Building Simulation

With an occupancy model defined, and the availability of an occupancy monitoring system, it would be possible to implement occupancy based HVAC control strategies. In order to estimate the energy saving possible with such a system, we test HVAC strategies using EnergyPlus. EnergyPlus [3] is an industry standard tool developed by the US Department of Energy for simulating building energy taking into account many detailed parameters such as HVAC system components, occupancy, weather, and construction material.

4.1 Building Parameters

An ASHRAE Standard 90.1 [6] compliant building was created in EnergyPlus. The building geometry (figure 4) is based on the left portion of the building shown in figure 1. Since this is a preliminary analysis, the full layout of the building was not modeled to reduce simulation times. Table 5 summarizes the main parameters of the building. The HVAC system uses a single duct air handler unit (AHU) and each room has a variable air volume vent (VAV) that regulates the air supply to the room. The size of the heating and cooling plants are calculated using the steady-state methods specified by ASHRAE Standard 62.1 [5]. This method sizes the HVAC systems by evaluating the hottest and coldest times of the year along with solar gain, and room usage. This HVAC configuration is common for many office buildings.

5 Simulation Methodolgy

5.1 Occupancy

ASHRAE 90.1 and DOE-2 [1] define several occupancy profiles for office buildings daytypes and are commonly used for building simulations. These occupancy profiles are static and are based on building survey of occupants. Rather than use predefined profiles, 23 days of occupancy data are generated using a MWMC model trained with 5 days of ground truth data. The building is assumed to be empty on weekends. The 23 days will serve as the “ground truth” weekday occupancy for the simulated building. Since data was not

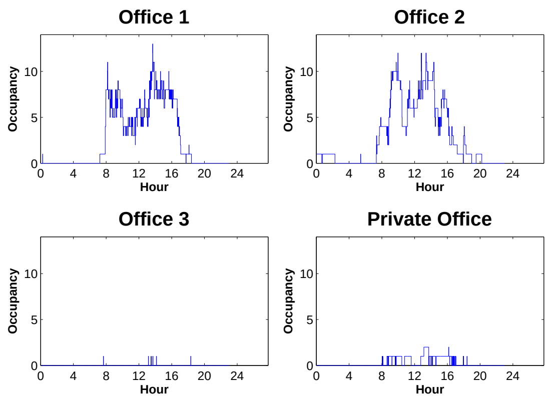


Figure 6. This figure shows a representative day for the main occupied areas of the simulated building.

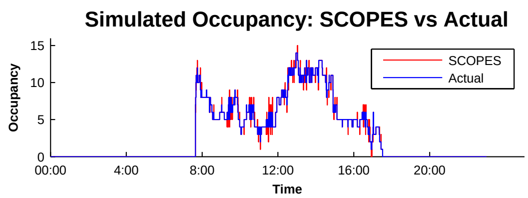


Figure 7. This figure shows the occupancy error from a system such as SCOPES for Office 1.

collected for the restrooms, a typical restroom daily occupancy schedule is used for the EnergyPlus simulations. Figure 6 shows a representative day generated from the model. Office 1 is a typical office. Office 2 is used by graduate students and exhibits different usage patterns. Office 3 is an office converted to temporary storage.

We also wish to simulate the error observed an occupancy monitoring system such as SCOPES, which was shown to observe room transitions with 80% accuracy. 20% of the time, the system either inverts the direction or detects a false positive/negative transition. Both errors occur with roughly equal frequency. To simulate the error SCOPES, for each of the 23 simulated days, we introduce error in 20% of the transitions. Figure 7 shows one day of the simulated ground truth data along with the corresponding simulated SCOPE data. Even with 80% accuracy, the observed occupancy is very close to ground truth occupancy since the directionality errors occur with roughly equal frequency and thus self compensate. The impact of this error is addressed in section 6.

5.2 Ventilation Strategy

ASHRAE Standard 62.1 uses the following to calculate outdoor air ventilation rates:

$$V_{bz} = R_p P_z + R_a A_z \tag{1}$$

where z denotes the zone, V_{bz} is the ventilation rate, R_p is the minimum CFM/person, P_z is the number of people, R_a is the minimum CFM/ft^2, and A_z is the floor area. Typically, maximum estimated zone occupancy, determined by floor area, is used for P_z. The other constants are determined by ASHRAE Standard 62.1. For our ventilation control strategy, we will use the data observed by the occupancy monitoring system. Note that this data contains simulated errors similar to the

	Heating	Cooling
T_{tg}	76°F	72°F
T_{ASH}	82°F	69°F

Figure 8. Temperature setpoints used by the HVAC.

errors observed in SCOPES. In order to account for possible under-counting of occupants, the occupant estimates are increased by 10%. Since the monitoring system is capable of observing changes at the resolution of seconds and EnergyPlus is only able to schedule occupancy at the resolution of minutes, we approximate system observed occupancy by using the maximum room occupancy for each minute.

5.3 Heating and Cooling

Since room temperature requires longer periods of time for adjustments, the heating and cooling makes use of the MWMC to determine beforehand when to turn on or off conditioning. A comfortable target temperature (T_{tg}) and an ASHRAE temperature (T_{ASH}) is used for conditioning that depends if the HVAC is heating or cooling. The T_{tg} is a comfortable temperature for an area. T_{ASH} is a more extreme temperature but still meets ASHRAE Standard 55 [4]. The Table 8 shows values for these setpoints. Let O_t represent the observed room occupancies at the point of time t. Let the function $MWMC(O_t,t)$ return a one hour prediction using the MWMC given the starting state O_t and time t. Let $P_i = MWMC(O_t,t)$ for $i = 1 \ldots n$ where n is the number of predictions to perform. Let PD_i denote the number of seconds the rooms are occupied for P_i. For each hour h, the following determines conditioning level:

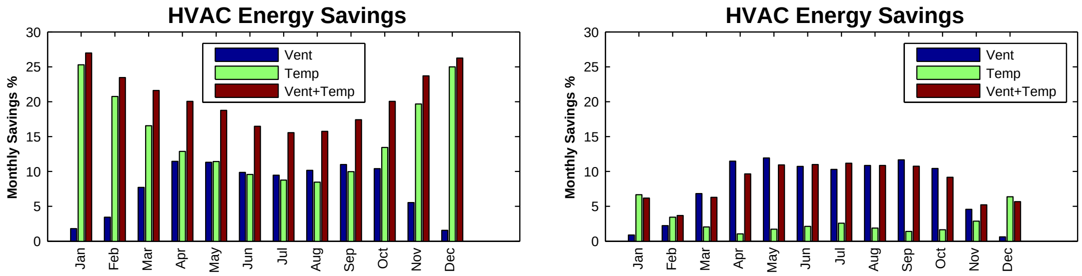
$CondTemp_h \leftarrow$ Conditioning Temperature Setpoint for h
$avgOccDur \leftarrow \frac{1}{n}\sum_{i=1}^{n} PD_i$
if $avgOccDur > 10$ minutes **then**
  $CondTemp_h = T_{tg}$
else if $6 < h \leq 24$ **then**
  $CondTemp_h = T_{ASH}$
else
  $CondTemp_h = 0$
end if

This strategy aggregates multiple predictions to find the likelihood of a section to be occupied. The comfortable T_{tg} temperature is used only if the area is occupied at least 10 minutes. During all daylight hours, the temperature is always kept at minimal levels. This is to ensure ASHRAE standards are met, and to take advantage of thermal momentum. We found less energy is expended overall if a minimal temperature is maintained until midnight.

6 Energy Savings

In this section we examine the energy results of HVAC conditioning strategies. We examine a typical static schedule, the venting strategy, the temperature control strategy, and the venting and temperature strategies together. In particular, we examine the energy consumption of the major HVAC components; the fans, pumps, heating (gas), and cooling (gas). In addition to evaluating the energy consumption, we also examine how well the strategies are able to meet actual building demand and keep occupants comfortable.

Figure 9(a) shows the impact the occupancy based ventilation and temperature control has on energy usage. The occupancy driven ventilation strategy alone is able to reduce total energy usage by 8.1%. The ventilation strategies save more energy (10.4%) between the months of Apr-Sep. The



(a) Normal Usage

(b) Forced Full Office Usage

Figure 9. This figure shows the monthly energy of the HVAC fans and pumps and the gas required for heating and cooling. 9(a) shows the energy usage when Office 3 is used mainly as storage. 9(b) shows energy when all areas are used.

temperature strategy shows a reduction of 14.4% annually and 21.9% from Nov-Mar. Combined, both strategies reduces total energy consumption by 20.0%. During the coldest months of the year, the savings are 26.6%. Note that savings are not additive when combining strategies because ventilation can affect energy used for temperature control. Cooling takes place in the air handler loop. During the summer, optimal venting reduces the amount of outside air introduced into the AHU allows increased recirculated air. We see optimal venting savings increase during the warmer months. Heating, however, partially takes place at the VAV level. The AHU has coils pre-heating air, which is then re-heated at the VAVs. Since VAVs contribute as a heating source, reducing the temperature of a zone will decrease pre-conditioned air in the AHU and thus increases the pre-heat load. For cold months, optimal venting at the VAV level reduces heated air flow into the AHU and decreases pre-heating efficiency.

We show these strategies significantly reduce energy for buildings with areas of light usage. However, in some instances, all spaces could be utilized reducing the potential for energy savings. To verify that savings are still achievable, Office 3 occupancy is forced to have the same occupancy schedule as Office 1. Since Office 3 has a larger area than Office 1, occupancies for Office 3 are scaled with respect to room area. Figure 9(b) shows HVAC energy usage for this scenario. Heating and cooling savings are reduced to 2.8% savings annually, but 6.5% is still saved for Dec-Jan. A significant savings of 8.1% yearly is still achieved using optimal venting. Both strategies together yield an annual energy savings of 8.8%. During the fall and spring, venting alone outperforms a combined strategy. Because outside temperatures are close to target indoor temperatures for these months, it is more efficient to maintain room temperatures than to cool down rooms heated by solar gain. For Dec-Jan, optimal temperature control outperforms a combined strategy. Though baseline ventilation increases conditioning of outside air, increased ventilation at the VAV level also increases pre-conditioned air to the AHU, which decreases the pre-heat load. This reduction of the pre-heat load offsets the increased cost of conditioning additional outside air.

These results show that in buildings with all rooms are utilized the majority of the day, only slight savings are possible through optimal temperature control alone. Thus, an HVAC system relying solely on binary models of occupancy derived from PIR sensing would only be able to achieve minute savings. Under uniform room usage, savings though ventilation are more significant and underscores the usefulness of an occupancy sensing platform. The results also suggest conditioning within the AHU have greater potential for savings.

7 Conditioning Effectiveness

While the strategies are able to reduce energy usage, we must also examine how well the strategies are able to condition the building. Due to space limitations, we omit analysis of predicted mean vote metrics of thermal comfort and instead focus on the ability of the system to meet ASHRAE temperature and ventilation standards.

7.1 Temperature Effectiveness

To measure temperature performance, we examine the temperature range of the rooms during the times room are occupied and check whether temperatures fall within the range specified by ASHRAE Standard 55 (30% humidity, winter clothing 1.0 clo, summer clothing 0.5 clo). For this analysis, we focus on Office 1, which is consistently occupied and Office 3, which is more sporadically occupied. Figure 10 shows Office 1 room temperatures for representative winter and summer days. From the figure, we can see that the predictive strategy reduces conditioning sooner than the baseline strategy. Over the course of a year, the baseline strategy has a root mean squared deviation (RMSD) of 3.46^{o}F from the target temperature during occupied hours. The prediction strategy has an RMSD of 3.75^{o}F from the target temperature. At all occupied times, Office 1 temperatures complied with ASHRAE standards and has comparable performance to the baseline strategy for consistently occupied spaces. Similar results were found for Office 2, Hall, and the Private Office.

Next we examine how the strategy performs for an inconsistently occupied space. The baseline strategy and predictive strategies have RMSD's of 3.0^{o}F and 6.4^{o}F respectively from the target temperature. While the room may be uncomfortable, the temperatures still fall within the acceptable range established by ASHRAE. In figure 10, we see this larger deviation from the target temperature when using the predictive strategy. This is because the prediction strategy anticipates very low occupancy in this space and thus conditions the space using the more minimal temperature setpoints. However, the strategy still makes an effort at 11 am to reduce the temperature since Office 3 was likely to be occupied. For the summer and winter days shown for Office 3, the space is occupied less than 10 minutes per day spread

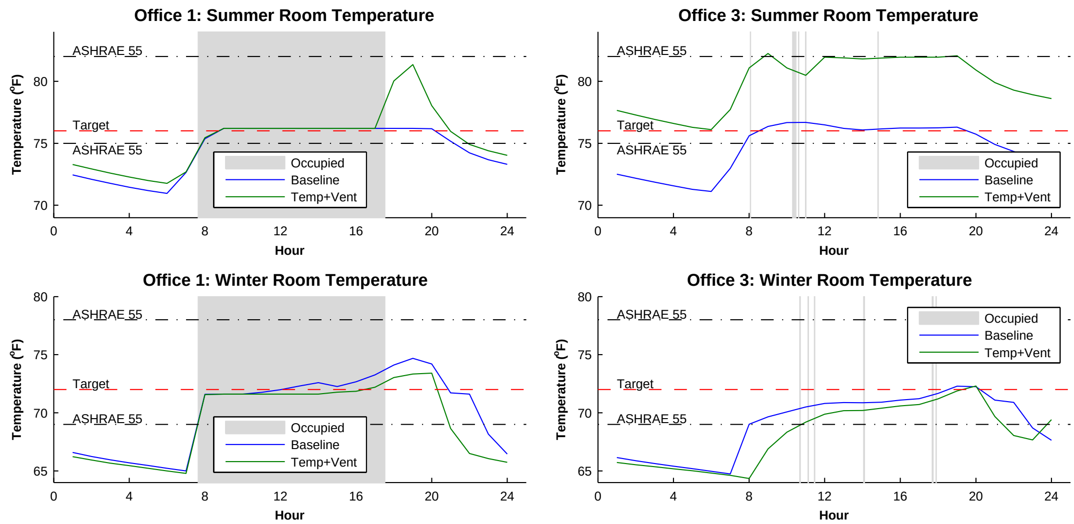


Figure 10. This figure shows the room temperature for a representative winter and summer day of Office 1 and Office 3.

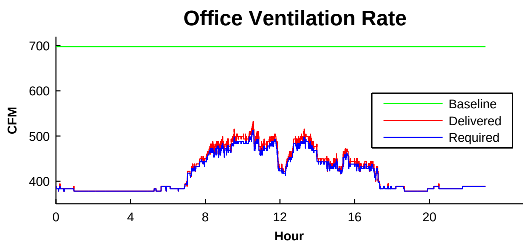


Figure 11. Office ventilation rates derived from equation 1 using maximum, estimated, and actual occupancy.

across multiple trips. It seems reasonable to reduce the conditioning when occupants only stay a few minutes each day.

7.2 Ventilation Effectiveness

In order to meet ASHRAE standards, we must meet the ventilation requirements dictated by equation 1. Figure 11 show the delivered, required, and baseline ventilation rates. The delivered ventilation uses the occupancy observed by the system with a 10% safety margin. The baseline strategy uses maximum estimated occupancy. It is apparent that the baseline ventilation strategy, common for most buildings today, over ventilates the building. For the 23 days used for the simulation, the RMSD between the estimated and the required ventilation rates is 4.86 CFM (normalized RMSD of 3.6%). The system ventilation only falls below the required CFM 0.001% of the time. This suggests that the 10% additional occupants is a sufficient safety margin for a system similar to SCOPES to provide adequate ventilation.

8 Conclusion

We develop a new model of occupancy based on Markov Chains trained with ground truth data. Using this model, we define occupancy based ventilation and temperature control strategies and implement them in an EnergyPlus model. We show with these strategies there is a potential of 8.8% energy savings for typical office buildings while still maintaining HVAC services that comply with ASHRAE standards. When a building has underutilized areas, the 20.0% annual savings can be achieved with 26.5% savings for months Dec-Jan. This implies even greater savings for colder areas. In the future, we plan to investigate predictive strategies that accounts for other factors such as AHU temperature and solar gain. We also are currently deploying a new occupancy monitoring system to collect longer traces of data to develop improved occupancy prediction models and plan to only rely on system collected data.

9 References

[1] Doe-2 - building energy analysis tool and cost analysis tool. `http://www.doe2.com/DOE2`.

[2] EIA - energy information administration. `http://www.eia.doe.gov/`.

[3] Energyplus - building energy analysis tool. http://apps1.eere.energy.gov/buildings/energyplus/.

[4] ASHRAE standard 55: Thermal environmental conditions for human occupancy. American Society of Heating, Refrigeration and Air-Conditioning Engineers,Inc., 2004.

[5] ASHRAE standard 62.1: Ventilation for acceptable indoor air quality. American Society of Heating, Refrigeration and Air-Conditioning Engineers,Inc., 2007.

[6] ASHRAE standard 90.1: Energy standard for buildings except low-rise residential buildings. American Society of Heating, Refrigeration and Air-Conditioning Engineers,Inc., 2007.

[7] S. J. Emmerich, A. K. Persily, N. I. of Standards, T. U. S.), and A. E. Corporation. *State-of-the-art review of CO2 demand controlled ventilation technology and application*. U.S. Dept. of Commerce, Technology Administration, National Institute of Standards and Technology, [Gaithersburg, Md.] :, 2001.

[8] V. L. Erickson, Y. Lin, A. Kamthe, R. Brahme, A. Cerpa, M. D. Sohn, , and S. Narayanan. Energy efficient building environment control strategies using real-time occupancy measurements. In *Proceedings of the 1st ACM Workshop On Embedded Sensing Systems For Energy-Efficiency In Buildings (BuildSys 2009) in conjunction with ACM SenSys 2009*, Berkeley, CA, USA, Nov. 2009. ACM.

[9] A. Kamthe, L. Jiang, M. Dudys, and A. Cerpa. SCOPES: Smart cameras object position estimation system. In *In the Proceedings of the 6th European Conference on Wireless Sensor Networks(EWSN 2009)*, pages 279–295, Cork, Ireland, Feb. 2009. Springer-Verlag.