TOWARDS ENERGY SAVINGS FROM A BIMODAL OCCUPANCY DRIVEN HVAC CONTROLLER IN PRACTICE

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ABSTRACT

Energy consumption in commercial buildings amounts to 19% of total energy consumption in the U.S., and is expected to continue increasing in the foreseeable future. Heating, Ventilation, and Air Conditioning (HVAC) systems are major energy consumers in commercial buildings, and they are usually controlled in a way that all thermal zones in a building are considered as occupied during operational hours. This control strategy, however, results in energy waste by conditioning the unoccupied thermal zones. This paper employs a bimodal demand response controller, which is based on real-time occupancy, for reducing HVAC energy consumption. The controller employs an artificial neural network based occupancy detection model to monitor occupancy in thermal zones of a building, and controls HVAC based on real-time occupancy to save energy while maintaining occupant thermal comfort. Based on real-time occupancy and time of the day, the proposed controller operates the HVAC system in three modes: occupied mode, vacant mode, and off-hour mode, each with distinct temperature settings. During the three weeks of the test, the occupancy model yielded an occupancy detection accuracy of up to 93.6%, providing reliable support to the occupancy driven HVAC controller. The daily percentage energy savings varied between -0.2% and 14.4%, with an average of 5.3%. Higher daily energy savings were observed in days when the building was less occupied. Outside temperature was found to be linearly correlated with the daily energy savings.

Keywords: HVAC, commercial building, occupancy detection, demand response, building energy reduction, energy conservation

1. INTRODUCTION

It has been widely accepted that building occupancy patterns have significant impacts on buildings' energy consumption (Lindén et al. 2006). However, centralized Heating, Ventilation, and Air Conditioning (HVAC) systems, widely used in commercial buildings, usually follow a fixed schedule, based upon buildings' design occupancy (Dong et al. 2011). Due to the lack of ability to respond to dynamic occupancy by centralized HVAC systems, energy is often wasted in maintaining a fixed temperature set point in vacant indoor spaces. Typically, operational settings are dictated according to assumed occupied and unoccupied periods of the day (e.g., occupied: 9:00 - 18:00) and do not consider when buildings are partially occupied. However, observations of actual building occupancy have found average occupancy in office buildings to represent at most a third of their design occupancy, even at peak times of day (Brandemuehl and Braun 1999). This implies that a major portion of HVAC energy is not used efficiently for maintaining desired indoor climate. The total amount of energy waste could be significant, considering the fact that HVAC systems are responsible for approximately 19% of total energy consumption in the U.S. (DOE 2011).

Motivated by the significance of such energy waste, a range of research initiatives have been undertaken to optimize HVAC controls based on occupancy information (Lo and Novoselac 2010; Zhu et al. 2000; Zhu et al. 2000). In terms of cooling and heating, prior research has reported that substantial energy savings could be achieved by not maintaining the fixed temperature set point in vacant thermal zones (Henze et al. 2004; Ma et al. 2011; Nghiem and Pappas 2011). Instead, the temperature set point could float within a certain range depending on the occupancy of the zones (Gao and Whitehouse 2009). For instance, Energystar is a self-programming thermostat that could automatically create setback schedules by sensing the presence of occupants through a motion sensor and reed switch. This thermostat was tested in residential houses and could reduce cooling and heating demand by up to 15% (EnergyStar 2013). Another example is the Telkonet SmartEnergy control system (Telkonet SmartEnergy 2010). The system allowed the temperature to vary in a wider range in vacant residential houses and, after occupants returned, the temperature was adjusted to its normal range within a lag time. The lag was determined based on tolerable recovery time set by the occupants, building type, HVAC type, and outside weather. Agarwal et al. (2010) proposed to set back the temperature set point in vacant zones. In a simulation, temperature was maintained at 22.9 ^{0}C and 26.1 ^{0}C for occupied and unoccupied rooms, respectively. The authors reported a 15% reduction of HVAC energy consumption in a mid-sized office building. Research has also been done in optimizing switch time step between occupied and vacant modes, in order to avoid too frequent system startups while maintaining comfort (Dong et al. 2011)

In terms of the energy that could be saved by efficient ventilation strategies, several bimodal controllers have been proposed and widely tested. This controller sets the ventilation rate to a minimum in vacant spaces, based on the building codes, for controlling contaminants and humidity (ASHRAE and Standard 2007), and increases it to the designed maximum rate whenever the room is occupied. An exemplary evaluation of this bimodal ventilation controller at the building level was presented in (Pavlovas 2004). The ventilation rate was kept at the maximum value when the building was occupied; otherwise it was kept at a minimum value. Up to 20% of ventilation energy was saved in an office building through simulation. This bimodal control has also proven to be a cost and energy efficient alternative to constant air volume control in a number of other research initiatives (Erickson and Cerpa 2010; Erickson and Cerpa 2010), and could reduce the ventilation energy in office buildings by up to 50% (International Energy Agency 1993).

2. MOTIVATION

The majority of prior research on occupancy driven HVAC operations was based on simulations done in building energy models. While these research initiatives have extensively explored potential energy savings by integrating occupancy in the control logic of HVAC systems, the achievability of the reported energy savings remains unclear. Various factors that are impactful on energy consumption may not be accurately modeled, simulated or exposed. There has also been a prevailing view that building energy simulations tend to overestimate consumption (Shapiro 2011). Moreover, all building energy models used in studying occupancy driven HVAC operations were calibrated with energy consumption data collected under a building's normal operations. These models do not necessarily reveal and reflect a building's energy consumption patterns under occupancy driven controllers. These limitations call for a real-world building-scale implementation to evaluate the achievable energy savings from occupancy driven HVAC controllers.

In addition, most of prior research relied on assumed or simulated building occupancy, which inevitably deviates from the actual occupancy and weakens the reliability of the reported amount of energy savings. In fact, building occupancy detection itself is an area that has seen active research in the past decade. Different technologies have been proposed for occupancy detection, such as video (Benezeth et al. 2011; Erickson et al. 2009), CO_2 sensors (Nielsen and Drivsholm 2010; Sun et al. 2011), Passive Infra-Red (PIR) sensors (Agarwal et al. 2010), communication infrastructure (Melfi et al. 2011), or a combination of different technologies (Meyn et al. 2009). Despite the exploration of these solutions, large-scale occupancy detection has remained a challenging task and has rarely been deployed at building scales for evaluating occupancy driven HVAC operations.

To address the above challenges, this paper studies the energy implications of a bimodal occupancy driven HVAC controller by implementing it in a multi-story test bed building for three weeks. The occupancy of every room in the building was monitored in real time during the test period, and used to drive the operation of HVAC system both at the thermal zone and building levels. This paper represents one of the very few efforts that integrate two active research areas, namely building occupancy detection and demand response building operations, in a single real-world implementation at a whole-building scale. The results shed light on how much energy savings can be achieved by integrating real-time fine-grained occupancy information in HVAC operations, especially in warm regions such as the Southern California. The results also highlight the complexity of various factors that may impact the achievability of energy savings in a real-world environment.

3. TEST SET UP

3.1 Test Bed Building

The test bed building modeled in this paper is a typical educational office building (Figure 1) on the University of Southern California (USC) campus near downtown Los Angeles, California. It is a three-story building with a gross area of 3,735 m^2, and contains 89 mechanically ventilated rooms including offices, classrooms, conference rooms, auditoriums and lobbies. The indoor environment of the building is monitored by 67 wired temperature sensors and 50 wireless sensor units. Each wireless sensor unit has a stand-alone single-board microcontroller with integrated support for wireless communications, and is comprised of the following sensors: a light sensor, a sound sensor, a motion sensor, a CO_2 sensor, a temperature sensor, a relative humidity sensor, a PIR sensor, and a door switch sensor. The data is automatically queried once every minute, time stamped, and stored in an SQL database. The energy consumption by various building systems such as HVAC, lighting, receptacle and mechanical is metered and recorded in a Building Energy Management System (BEMS).

Figure 1: Test bed building

The HVAC system in the test bed building has a Variable Air Volume (VAV) style. All spaces in the building comprise 67 thermal zones, each of which is serviced by one VAV box. A VAV box is responsible for regulating the ventilation in the thermal zone with conditioned air, and reheating the air with boiler-supplied hot water if the zone needs heating instead of cooling. The conditioned air is supplied to VAVs by Air Handler Units (AHUs) using fans and ductwork. There are two AHUs in the building, each servicing one side of the building with similar sizes of service areas. AHUs take in outside air, mix it with returned air from the building, and cool down the mixed air to 12.8 ^{0}C with chilled water supplied by chillers.

3.2 Field Test Details

A field test was carried out from March 11 - 31, 2013 on the second and third floors of the test bed, due to these floors' symmetric configurations, the diversity and representativeness in room types, and their coverage by the wireless sensor units. The baseline controller was implemented on the west side of the two floors covering 30 rooms, and the bimodal occupancy driven controller was implemented on the east side of the two floors covering 37 rooms. The west side and the east side are serviced by different AHUs, and are referred to as the control area and the test area, respectively, for the remainder of the paper. Running the two sides of the building with two operational strategies concurrently helped offset the impact of outside weather conditions and campus schedules, which impacted both areas similarly during the test.

3.3 HVAC Controllers

The baseline HVAC controller implemented in this paper works based on a fixed occupancy schedule. During the daytime (6:30 - 21:30 on workdays, and 7:00 - 21:30 on weekends), all thermal zones in the building are assumed to be always occupied, and a constant temperature set point (22.8 ^{0}C) is maintained by a Proportional Integral Derivative (PID) controller, which dynamically adjusts the airflow damper and reheating valve of each zone. The bimodal occupancy driven controller, on the other hand, is demand responsive and based on real-time occupancy. An occupancy model is developed to monitor the occupancy of each room, and the results are aggregated into the occupancy of each zone and used to drive HVAC operations. During the daytime, an occupied mode is enforced for occupied zones, where a constant temperature set point (22.8 ^{0}C) is maintained by the PID controller. If a zone stays vacant for a minimum of 15 minutes, a vacant mode is enforced, where the temperature set point is set back to 25.6 ^{0}C until it becomes occupied again. Both implemented controllers have an off-our mode, where the HVAC system is shut off during the nighttime, and no cooling, heating or ventilation services are provided.

3.4 Occupancy Modeling

In order to base the HVAC operations on reliable occupancy information, an occupancy detection model developed by the authors (Yang et al. 2013) is used. For each room in the test bed building that has a wireless sensor unit, the occupancy detection model inputs values of 12 variables sampled at a one minute-interval, and outputs an estimate of whether the room is vacant or occupied at the moment of the sampling.

The occupancy estimation algorithm is based on a multilayer perceptron neural network, in which the neurons are arranged into an input layer, an output layer and one or more hidden layers. Specifically, the inputs are readings of different ambient sensors and the output is the occupancy status. When training the model, back propagation is used, where an error function is repetitively calculated for each input and an error is propagated backwards from one layer to a previous layer. For parameter tuning, the learning rate and momentum (controlling the speed of model modification) were set to 0.3 and 0.2, respectively, using a try-and-error method. More details of the design and evaluation of this algorithm can be found in (Yang et al. 2013). WEKA v.3.7, a commonly used machine learning software, was used to implement the algorithm. After the occupancy of every room is obtained by the occupancy detection model, the occupancy of a particular zone is determined by aggregating the occupancy of associated rooms. The zone is considered vacant only if all rooms within the zone are vacant.

4. ENERGY COMPUTATION

Energy savings from the occupancy driven controller is the difference between the measured energy consumption of the zones in the test area to their expected energy consumption. This section details how measured energy consumption is computed based on building-level and zone-level meter readings and sensor readings available in the test bed, and how expected energy consumption is computed, based on an inverse approached using historical energy consumption data.

4.1 Computation of Energy Consumption

The cooling capacity, denoted as c (ton), is metered at the building level in the test bed. The embodied energy consumption is attributed to the control area (E_c^c) based on the proportion of air flow volume of control area to the total air flow within the building. The cooling energy consumption of the test area (E_c^t) is calculated the same way:

$$E_c^c = \int_t 0.75 * c * \frac{\sum_i afv_i^c}{\sum_i afv_i} \tag{1}$$

$$E_c^t = \int_t 0.75 * c * \frac{\sum_i afv_i^t}{\sum_i afv_i} \tag{2}$$

Where $\sum_i afv_i^c$ and $\sum_i afv_i^e$ are the summations of air flow volume of all VAV boxes within the control area and the test area, respectively; $\sum_i afv_i$ is the summation of air flow volume of all VAV boxes in the building. A total of 0.75 kW of power is required to generate 1 ton of cooling capacity.

The electrical power, denoted as e (kW), is metered at the building level in the test bed. The total ventilation energy consumption is divided between the control area (E_v^c) and the test area (E_v^t) following the same approach:

$$E_v^c = \int_t e * \frac{\sum_i afv_i^c}{\sum_i afv_i} \tag{3}$$

$$E_v^t = \int_t e * \frac{\sum_i afv_i^t}{\sum_i afv_i} \tag{4}$$

The heating energy consumption is calculated based on the hot water usage rate, denoted as h, metered at the VAV level. The respective heating energy consumption within the control area (E_h^c) and the test area (E_h^t) is calculated as follows:

$$E_h^c = \int_t 1.53 * \sum_i h_i^c * \Delta T * E \tag{5}$$

$$E_h^t = \int_t 1.53 * \sum_i h_i^t * \Delta T * E \tag{6}$$

where ΔT is the difference of inlet water temperature and outlet water temperature at the heat exchangers, E is the amount of energy needed to raise the temperature of 1 kg of water by 1 ^{0}C, and coefficient 1.53 is the boiler plant efficiency according to the campus facilities management services.

4.2 Computation of Energy Savings

When the HVAC system in the test bed building is operated with the bimodal occupancy control, the energy savings can be calculated by comparing the actual energy consumption with the baseline energy consumption, both associated with the test area. The actual energy consumption is metered during the test period. The baseline energy consumption is estimated based on the actual energy consumption of the control area, and a relationship between energy consumption of the test area and that of the control area. The relationship is established based on historical energy consumption data, and it is assumed that the relationship would continue to be observed if the HVAC system was not operated under occupancy driven controller during the test period. The rationale behind this assumption is that both the test area and control area are impacted similarly by various factors such as occupant schedules and outside temperature, and that there was no major retrofit in the past two years that could significantly change the energy consumption patterns of the test area or control area and hence alter the relationship between their energy consumption. It needs to be noted that while running the baseline controller and the occupancy controller sequentially in the entire building is a possible alternative approach for validating energy consumption, results from this approach would be impacted by changes in occupancy schedules or outside weather over the entire test period; therefore, this approach is not adopted in this paper.

Historical data of energy consumption in cooling, heating and ventilation is collected from the BEMS for the periods of March 11-31, 2012 and March 11-31, 2011, and organized on a daily basis. The respective relationships of cooling, heating, and ventilation energy consumption are demonstrated as follows:

$$E_c^t = 1.284 * E_c^c - 1.729 \quad (R^2 = 0.9895,\ RMSE = 3.557\,kwh) \tag{7}$$

$$E_h^t = 1.295 * E_h^c + 4.034 \quad (R^2 = 0.8965,\ RMSE = 4.219kwh) \tag{8}$$

$$E_v^t = 1.174 * E_v^c + 3.103 \quad (R^2 = 0.9374,\ RMSE = 3.209kwh) \tag{9}$$

Where E_c^c , E_h^c and E_v^c are the actual cooling, heating and ventilation energy consumption, respectively, of the control area, and E_c^t , E_h^t and E_v^t are the baseline cooling, heating and ventilation energy consumption, respectively, of the test area. The large R^2 values and small Root Mean Square Error (RMSE) values suggest high statistical significance of the above linear relationships. Therefore, if the respective actual cooling, heating and ventilation energy consumption of the test area is E_c^{t*} , E_c^{t*} and E_c^{t*} , the respective energy savings from cooling, heating and ventilation can be calculated as follows, where positive values indicate energy savings and negative values indicate energy waste.

$$E_{c,savings}^t = E_c^t - E_c^{t*} \tag{10}$$

$$E_{h,savings}^t = E_h^t - E_h^{t*} \tag{11}$$

$$E_{v,savings}^t = E_v^t - E_v^{t*} \tag{12}$$

5. TEST RESULTS

5.1 Occupancy Modeling Results

In order to validate the performance of the occupancy detection model, the ground truth occupancy data was collected in three rooms within the test area during the test period. These rooms were located on both south and north sides of the building, had different sizes, and were occupied by occupants who had distinct occupancy patterns. These rooms were purposefully selected to represent all rooms within the test area. The occupancy of these rooms was monitored by digital cameras. Images taken from these rooms were hand-labeled by the authors to obtain the ground truth occupancy data. The estimated occupancy for these three rooms, which was reported by the occupancy detection model also at one-minute intervals, was then compared to the ground truth to analyze the accuracy of occupancy detection. The results are summarized on a daily basis and shown in Table 1.

Table 1: Daily accuracy of occupancy detection model

Week	Room A (%)			Room B (%)			Room C (%)		
	max	min	mean	max	min	mean	max	min	mean
1st	97.9	91.6	93.4	100	87.6	94.3	100	91.6	94.3
2nd	97.3	88.9	93.0	100	90.7	98.5	100	78.4	93.8
3rd	92.7	89.4	91.1	93.4	88.6	90.7	100	82.2	93.0

The results indicate that the estimated occupancy in the three rooms well matched the actual occupancy. The daily accuracy varied between 78.4% and 100%, with an average of 93.4%. For each room, on average, the daily accuracy was over 95% for 33.3% of the time. From a weekly perspective, the mean accuracy for all rooms during the entire test period was always higher than 90%. Moreover, the accuracy was generally comparable between the three rooms. Considering the representativeness of the three rooms, it is reasonable to believe that the accuracy of the estimated occupancy in those non-camera-monitored rooms was consistently high during the test period.

The mean occupancy was 50%, 41%, and 54% at the room level and 69%, 61% and 61% at the zone level for the three consecutive weeks. From a daily perspective, the mean zone-level occupancy varied between 47% and 80%. From a zone perspective, the mean occupancy varied between 23% and 100%. The cooling period of a zone, when the 22.8 ^{o}C set point was enforced, was directly determined by the zone's occupancy. Average cooling period and average occupied period were highly correlated, as can be seen in Figure 2. The difference between these two values was due to the 15 minutes delay for the system to switch from the occupied mode to the vacant mode. A larger difference between these two values indicates more frequent changes between occupied/vacant modes.

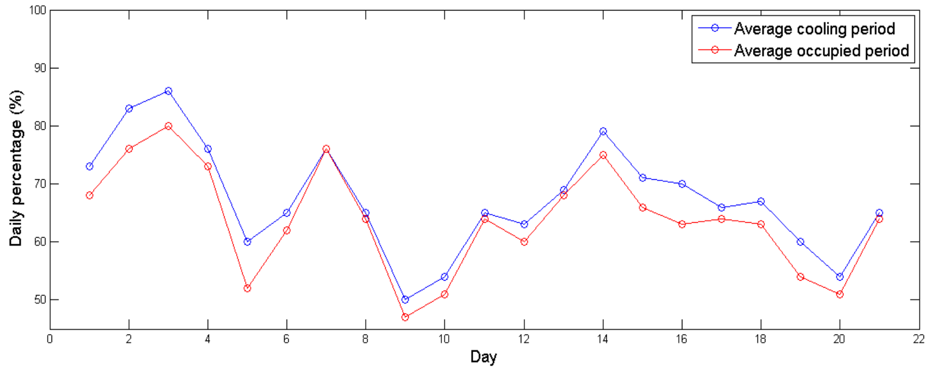

Figure 2: Average cooling and occupied periods for 21 test days

5.2 Energy savings

The baseline cooling, heating and ventilation energy consumption of the test area during the test period was calculated using equations (1-3), and compared with the actual energy consumption of the same period. The energy savings are calculated using equations (4-6). The results are summarized in Table 2.

Table 2: Daily HVAC energy savings

Week	Cooling (%)			Heating (%)			Ventilation (%)			Overall (%)		
	max	min	mean	max	min	mean	max	min	mean	max	min	mean
1st	18.4	3.1	10.2	14.4	-78.9	-33.0	15.2	0.3	7.9	14.4	-5.4	4.1
2nd	16.1	2.3	10.4	0.0	-59.1	-29.8	14.3	2.4	8.5	11.3	1.0	5.1
3rd	19.6	4.0	11.9	6.1	-98.1	-30.7	16.4	2.0	9.7	13.7	-0.2	6.7

It can be seen from the results that the occupancy driven HVAC control led to an average saving of 10.8% and 8.7% in cooling related energy and ventilation related energy, respectively. The amount of savings was generally consistent on a weekly basis, but varied significantly on a daily basis. In addition, an average increase of 31.1% in heating energy was observed. This increase was due to the fact that when the temperature set point was set back in a vacant zone, the difference between the current temperatures and desired temperatures increased. This increased difference sometimes caused the VAV reheating valve to switch its status from closed to open, resulting in unintended waste of heating related energy. The analysis on heating energy related data also agrees with this conclusion. The 25.6 ^{o}C temperature set point was used for 31.7% of the time, when averaged over all zones and the entire test period. This figure, however, was almost negligible for the year of 2011 and 2012. It indicates that the controller has forced the system to stay at a higher temperature set point for much longer than it normally does, and this has caused a significant increase in heating energy consumption.

The relationship between the daily energy savings and the daily occupancy is plotted in Figure 3. All data points are divided based on the occupancy, namely group 1 (occupancy < 0.55) and group 2 (occupancy>0.55). Using unpaired right-tailed t test, the results show that, at a confidence level of 99%, the mean energy savings in days with occupancy less than 0.55 are statistically larger than the mean energy savings in days with occupancy higher than 0.55. However, the impact of occupancy on energy savings is not statistically significant within each group. Given the occupancy, the daily energy savings can vary within a wide range and therefore are unpredictable. This suggests that there existed other factors that exerted impact on the energy savings resulting from the occupancy driven controller.

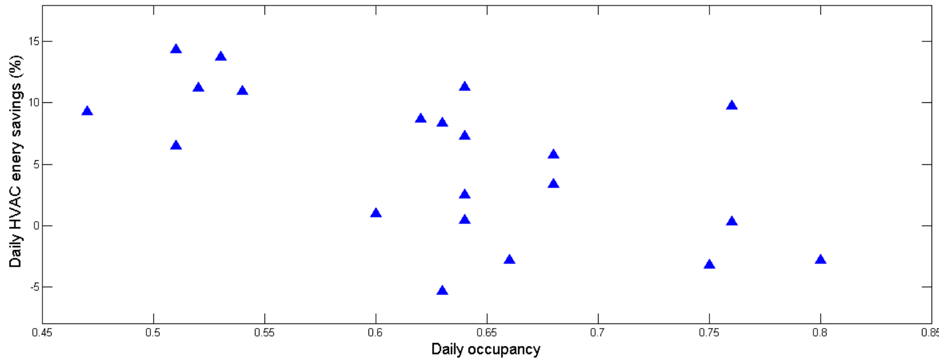

Figure 3: Relationship between occupancy and daily energy savings

Among these factors, a major one is the outside temperature. The outside temperature is sampled once an hour at AHUs. The relationship between the mean outside temperature and the energy savings is plotted in Figure 4. The higher energy savings during warmer days partly resulted from the fact that when the temperature set point was set back to 25.6 ^{0}C in a zone, the temperature in the zone was generally higher than cooler days, leading to less heating energy consumption triggered by the increased set point. This relationship, coupled with the variance in outside weather temperature, also explains the variance in daily energy savings, which varied between -0.2% and 14.4% on a daily basis.

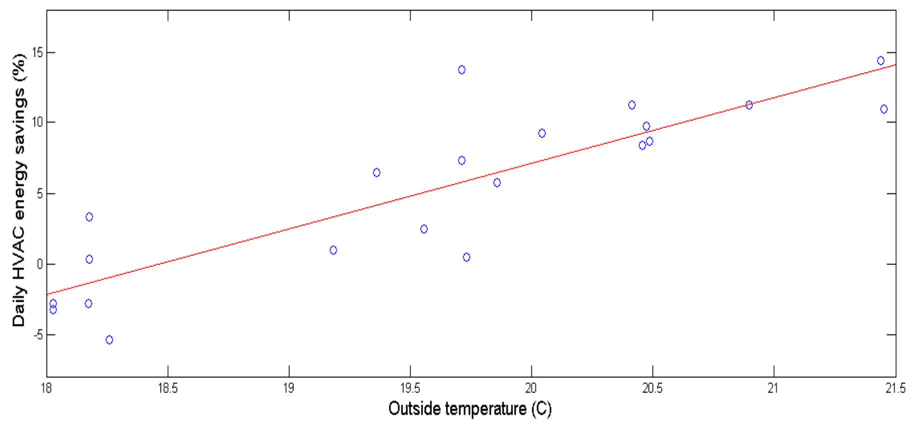

Figure 4: Relationship between outside temperature and daily energy savings

6. DISCUSSION AND CONCLUSIONS

This paper presents one of the few recent efforts to examine the energy savings of a bimodal occupancy driven demand response HVAC controller achievable in a real-world environment. A building-scale implementation is carried out, and is supported by an ambient sensor-based real-time occupancy detection model that feeds the controller with real-time room-level occupancy information. This paper explores how much energy savings could be achieved in a building, where energy savings are impacted by various uncontrolled factors, such as occupant schedules and outside weather conditions, in addition to the HVAC controller. A test was done for three weeks. Mean energy savings were 5.3%, varying between -0.2% and 14.4% on a daily basis. It is worth noting that the temperatures in occupied rooms were maintained within the range specified by the building codes and standards. There was no complaint submitted by occupants to the building managers or campus facilities management services about thermal discomfort caused related to the test.

The occupancy conditions had a direct impact on the amount of daily energy savings. Higher energy savings were observed in days when zones in the test area were less occupied. Meanwhile, the energy savings were impacted by the weather conditions as well. A higher outside temperature could cause an increase in the energy savings when the occupancy driven controller was implemented. These findings are complementary to related findings reported from building energy simulations. The energy savings achieved in the test were lower than those reported in the majority of the prior research (Bauman et al. 1994; Chen et al. 2008; Goyal et al. 2012), which reported savings between 15-50% in simulations. This difference partially resulted from one limitation of the evaluated bimodal occupancy driven HVAC controller, that it does not prevent the VAV boxes from reheating air in vacant zones. This limitation has unnecessarily resulted in a significant increase in heating energy, and lowered the overall energy savings. The lower energy savings also resulted from constraints that are usually not modeled in simulations. For example, the 15 minutes delay for the system to switch from the occupied mode to the vacant mode is not considered in simulations. Enforcing this delay reduces energy savings, however, it is necessary in the real-world test in order to reduce too frequent system startups and maintain occupant comfort. In addition, HVAC services in public spaces within the test area, such as lobbies, corridors and restrooms, were always under the occupied mode during the test. These spaces were included in energy saving calculations, and hence reduced the overall percentage energy savings of the test area.

One fact that needs to be emphasized is that the test was done in the warm Southern California region, where cooling and ventilation are dominant energy consumers in HVAC systems. In regions where heating energy consumption is higher, the bimodal controller needs to be redesigned to avoid heating vacant zones, and the resulting energy savings are likely to vary.

The absolute amount of daily HVAC energy savings was 12.0 kWh on average during the test. Considering the fact the test area accounts for about one third of the total area of the building and HVAC energy consumption in spring is below yearly average, the annual HVAC energy savings, if the occupancy driven controller is implemented in the entire test bed building, are estimated to be roughly 16,000 kWh. However, if the reheating valves are disabled under the vacant mode, the estimated annual savings will increase to 23,000kWh. In future research, the controller will be improved to address this issue by enabling it to control the positions of reheating valves, which will mitigate reheating energy related wastes and further reduce HVAC energy consumption. The controller will also be operated and evaluated during summer time, which represents the conditions that contribute most to HVAC-related energy consumption in the Southern California area.

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