Energy and Buildings 127 (2016) 469–478

Contents lists available at ScienceDirect

Energy and Buildings

journal homepage: www.elsevier.com/locate/enbuild

# Do occupancy-responsive learning thermostats save energy? A field study in university residence halls

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ARTICLE INFO

*Article history:*
Received 1 December 2015
Received in revised form 17 April 2016
Accepted 9 May 2016
Available online 25 May 2016

*Keywords:*
Smart thermostats
Energy savings
Occupancy
Energy efficiency
HVAC

ABSTRACT

Occupant presence and behavior can and should influence energy use in buildings. If occupancy is measured, predicted, or otherwise inferred, building controls can automatically adjust system operating parameters to use less energy without sacrificing user services. However, previous field evaluations and simulation studies appear to have overestimated the energy savings associated with this type of smart control. In this article we present results from a carefully controlled field evaluation of occupancy-responsive learning thermostats installed in every bedroom of three high-rise university residence halls. While a standard practice energy model developed prior to the retrofit estimated 10–25% savings for cooling and 20–50% savings for heating, measurements reveal that the control scheme only reduced energy consumption by 0–9% for cooling, and by 5–8% for heating for normal operation during academic periods. However, for non-academic periods when the residence halls were sparsely populated, the scheme reduced cooling energy consumption by 20–30%. We analyzed these observations in relation to occupancy patterns, room temperature records, ambient conditions, and equipment run time. The findings provide novel insight about how to improve field evaluations and refine model assumptions to better predict the impact of occupancy-responsive thermostat controls. Notably, while analysts often use fractional building occupancy trends to simulate building energy performance, this study highlights the importance of accounting accurately for both the temporal and spatial variation of vacancy events throughout a building.



## 1. Introduction

A substantial body of research has shown that simple programmable thermostats do not reliably save energy compared to traditional, manually controlled thermostats. This occurs in part because manual thermostats tend to be managed actively by occupants, whereas setpoint schedules on programmable thermostats are often set up improperly. Meier et al. and Peffer et al. reviewed numerous studies on these issues [1,2].

To overcome some of the challenges that limit the effectiveness of programmable thermostats, the buildings industry is beginning to adopt a new class of 'smart' thermostats. These emerging controls can incorporate a variety of features, including web-based or smart-phone user interfaces, energy-use feedback, networked control of multiple zones, occupancy-sensing, learning, fault detection and diagnostics, and demand response.

The present article focuses explicitly on one of the most prominent energy saving features for smart thermostats: occupancy-responsive learning setpoint control. These controls automatically relax the temperature setpoint during vacant periods, and learn about system response capabilities or occupant schedules and preferences to ensure that a room can return to the comfort setpoint for occupied periods. Fountain proposed the use of an occupancy-responsive thermostat for hotels more than 20 years ago [3]. Since then a substantial body of building science research has advanced the algorithms and functional capabilities necessary for these strategies to operate, and major advances in computing and electronics have readily enabled commercialization of numerous products.

Many authors have developed building control strategies that learn from historical trends to estimate system response parameters [4–6]. In an occupancy-responsive thermostat this capability is used to automatically choose a setback temperature that will allow for recovery to the comfort set point within an acceptable time.

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http://dx.doi.org/10.1016/j.enbuild.2016.05.024
0378-7788/

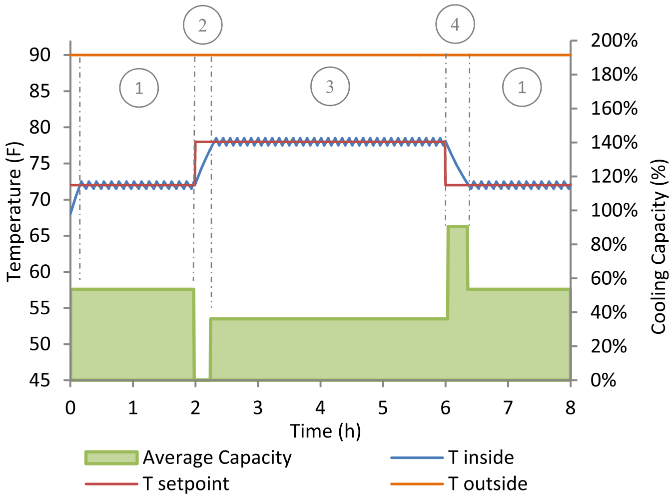


**Fig. 1.** The idealized pattern of temperature response and fractional run time for cooling before, during, and after a vacancy event. Outdoor temperature and all internal gains are assumed constant and there is no significant effect of wall thermal mass.

So as to avoid potential discomfort when occupants return, some learning thermostats employ predictive algorithms that allow systems to recover in anticipation of occupancy [7–12]. Related 'context-aware' approaches utilize opportunistic data sources – such as smart phone GPS location – to infer the likelihood of impending occupancy [13,14]. Many of these thermostat controls build from the rich bodies of research on environmental sensor networks to measure occupancy state or number [15–17], and on stochastic estimation methods to predict occupant presence and behavior [18–20].

Despite the breadth of research on occupancy, stochastic prediction, and advanced thermostat control strategies, comparably few authors have conducted building energy simulations to estimate the energy and demand savings provided by occupancy-responsive learning thermostats. Even fewer authors have conducted measured evaluations in real buildings. The simulation studies we are aware of used differing assumptions, and arrived at a variety of conclusions. Lu et al. simulated heating and cooling energy use for a home using measured occupancy data and concluded that an occupancy-responsive control scheme would reduce annual energy use by 28% [17]. Kleiminger et al. estimated that savings were only 3–10% for a well-insulated house in the heating season [8]. Erickson et al. used observed zone level occupancy data as inputs for a simulation and concluded that occupancy sensing control of HVAC in an office and laboratory environment could reduce annual energy use for heating cooling and ventilation by 42% [15]. Lo et al. used a simpler approach to estimate the energy savings potential for occupancy-responsive control of an air conditioning system that reduces air mixing between individual work spaces [21]. The authors estimated a 12% reduction in annual cooling energy use. However, they also indicated that the current standard practice for building energy simulations is not equipped to make good assessments for occupancy-responsive controls in multi-zone buildings because interior thermodynamic interactions are not properly represented [21].

Several consultants and industry practitioners have published simulation studies for these thermostats, largely for the purposes of utility energy efficiency programs [22–24]. These studies focused only on single buildings, dealt only with thermostats in hotels, and used standard practice modeling assumptions, similar to Lo et al. [21]. Utilities and public agencies have also commissioned several field studies on occupancy-responsive thermostats. These studies have mainly assessed the technology applied in hotels and have yielded a wide range of results, with large variation in savings between individual rooms, and between buildings and climates. Sullivan and Blanchard reported 10–25% energy savings for heating and cooling [25]. Frey et al. observed that energy use decreased by 85% in some rooms and increased by as much as 47% in others; the authors concluded that the occupancy-responsive controls reduced energy use by 25% on average [24]. In 2008, Pistochini reported 10–70% savings for hotels in San Diego, CA [26]. Parker et al. conducted a controlled trial in several single-family residences; the authors observed that occupancy-responsive thermostats resulted in 0–6% increase in cooling energy use for some homes and a 0–4% decrease for others [27].

In this article we present novel results from a field evaluation of occupancy-responsive thermostats installed in university residence halls. This article is the first field evaluation of energy savings from occupancy-responsive thermostats within academic literature. We illustrate that standard practice building energy simulations can easily overestimate the energy savings for these thermostats, and that most previous field evaluations have made simplifying assumptions that we observed to be false for the residence halls in our study.

## 2. Methodology

### 2.1 Overview of field evaluation

This study evaluated the energy impact of occupancy-responsive learning thermostats installed as a retrofit in every bedroom of three high-rise university residence halls in Davis, California. The three buildings evaluated (named G, M, and R) were among the first of 25 residence halls at the university that were retrofit with occupancy-responsive learning thermostats—ultimately, the measure was installed in approximately 2500 individual rooms. The three residence halls studied are similar five-story concrete-steel-plaster buildings constructed in 1965. Half of the exterior envelope is composed of single pane glazing, the remainder is concrete walls with no insulation. Each residence hall consists of 110 bedrooms and various common spaces, such as corridors, meeting rooms, laundry rooms, and bathrooms. Bedrooms occupy about 50% of the total floor area. Ventilation is provided to each room by continuous central exhaust, which draws air from hallways, by infiltration, and through operable windows. A separate air handler supplies ventilation air to the central common spaces. Each bedroom has a two-pipe three-speed fan-coil unit with a local thermostat. Cooling is provided by district chilled water, and heating is provided by district heating hot water. In all cases, the new occupancy-responsive thermostats replaced unrestricted manual thermostats in each bedroom. These smart thermostats were also added to control the fan coil units in the common lounge areas on each floor. No controls revisions were enacted for the central zone air handler or exhaust ventilation systems. The thermostat installed in each bedroom uses an on-board (wall mounted) or remote wireless (ceiling mounted) infrared motion detector. The device also incorporates an on-board light sensor and logic to distinguish between vacancy and a nighttime condition where occupants are sleeping. The control scheme is reactive – not predictive. It uses a learning algorithm to select a setback temperature for vacant periods that will allow the room temperature to recover within an acceptable time when occupants return.

We evaluated cooling energy consumption in two buildings during academic periods before and after thermostat installation. Then we subjected two of the buildings to a series of controlled trials over the following year to assess energy saved for cooling and for heating. Energy savings for cooling was measured in academic periods and in non-academic periods. Heating performance was only assessed for academic periods because winter break was too short to conduct a well controlled experiment. During academic periods, each building was leased to capacity with two students in each bedroom. During non-academic periods these buildings were used irregularly for conference housing. The cooling season in Davis is characterized by hot days and cool nights. In this study, all cooling season data periods had some days with outside temperature above 95 °F (35 °C) and one cooling season period had some days with outside temperature as high as 105 °F (40.6 °C). Diurnal temperature swing during these periods was regularly larger than 35 °F (19.4 °C). The portion of the heating season analyzed was mild with minimum temperatures never below 40 °F (4.4 °C).

*2.2 Analytical Evaluation*

The analytical assessment presented in this study consists of three parts:

1. A statistical evaluation of temperature response and equipment run time in vacant rooms
2. A pre- and post-retrofit comparison to assess cooling energy savings during academic periods
3. Controlled trials to assess savings for:

(a) cooling and heating in academic periods,
(b) cooling in non-academic periods.

Thermostats were used to record data about occupancy, room temperature, comfort setpoint, active setback temperature, and fan-coil run time in every bedroom. The temperature sensor was located on board each thermostat. Users could select the comfort setpoint within a limited range specified by facilities managers. The thermostat uses a learning algorithm to automatically choose the setback temperature to ensure that room temperature can recover to the comfort setpoint within an appropriate time when occupants return. Outside air temperature, cooling energy consumption, and heating energy consumption were measured for each building through the university's energy management and control system. Water flow measurements were performed using insertion flow meters (Onicon F-1200, ±2% reading), and temperature measurements used fluid insertion thermistors (Omega TH-10, ±0.2 °C).

The pre-post assessments used a hybrid of standard methods recommended by ASHRAE Guideline 14 to compare whole building cooling energy consumption before and after the thermostat installation [28]. This method captured the combined effect of all differences between the pre and post-retrofit periods. Despite the fact that this is an industry standard protocol, the approach is disadvantaged by the fact that there is no way to ensure that other exogenous factors have not changed between the two periods compared. Following the pre-post assessment, we scheduled a series of "week ON – week OFF" controlled trials, where the occupancy-responsive and learning features of the thermostats were enabled and then disabled in alternating one-week periods. The alternating "week ON – week OFF" schedule operated continuously for 13 months. The "week OFF" periods represent baseline performance, and the "week ON" periods represent retrofit performance. This approach isolated for the effect of the occupancy-responsive features, and minimized the likelihood of confounding factors. This assessment method was used to determine savings for cooling and heating during academic periods, and for cooling in non-academic periods. Data from the baseline period in each savings analysis was used to develop a reduced-order regression model to describe cooling or heating energy consumption as a function of outside air temperature, the average temperature over the previous 24 h, and the fraction of occupancy in the building. The model structure used to represent baseline performance was adapted from the change-point or segmented-linear regression models described by Kissock and others [29,30]. Change-point models typically use outdoor temperature as the single independent predictor for cooling or heating energy consumption. However, similar to what others have shown [31–34], we found that the inclusion of other measured factors improved model prediction.

We developed several model formulations that included different independent predictors and used each formulation to identify regression coefficients from several weeks of hour-interval training data. We cross-validated the predictions from each model formulation to an independent data set from the same building and the same season, then compared the results. We selected the model with the best adjusted coefficient of determination ($R^2$), which also had the best root mean squared error (RMSE), coefficient of variation of the root mean squared error (CV-RMSE), and normalized mean bias error (NMBE), and used the following formulation for all subsequent assessments:

$$\dot{Q}_{CHW} = \beta_0 + \beta_1 \times T_{OSA} + \beta_2 \times (T_{OSA} - C_2)^+ + \beta_3 \times (T_{OSA} - C_3)^+ + \beta_4 \times (T_{24} - C_4)^+ + \beta_5 \times (Occ - C_5)^+ \quad (1)$$

where:

$\dot{Q}_{CHW}$ cooling (or heating) energy consumption per interval [W].
$T_{OSA}$ outside air temperature [F].
$Occ$ building occupancy rate [–].
$T_{24}$ average outside air temperature over previous 24 h [F].
$C_i$ change point beyond which $\beta_i$ is applicable.
$()^+$ term evaluated when quantity >0.

Coefficients and change points were determined for baseline periods in each building. Each baseline period consisted of 16–40 days of hour-interval data. All computations were conducted in R using Muggeo's "Package segmented" [35]. The resulting baseline models, documented explicitly in Sections 3.2.1–3.2.4, achieved adjusted coefficients of determination ($R^2$) of 0.81–0.97. This is surprisingly good fit compared to most regression models of whole building energy use. The result is helped considerably by the fact that our models only represent chilled or hot water energy consumption, and therefore avoid many exogenous factors that are usually present in whole building electricity consumption data.

We predicted the baseline energy use by feeding the environmental conditions observed in the post-retrofit periods into the baseline models. Energy savings for each assessment was calculated as the total difference between the projected baseline energy consumption trends and the actual measured energy consumption.

We cross-validated the predictions from each model to an out-of-sample data set from the same building and the same season. The cross validations resulted in somewhat lower $R^2$ values. For example, our model fit training data from one of the buildings with $R^2 = 0.944$, and cross-validation with out-of-sample data resulted in $R^2 = 0.938$. In this instance NMBE = 0.1263. Lastly, the uncertainty associated with each model prediction was calculated for 90% confidence according to ASHRAE Guideline 14 [28].

## 3. Results

*3.1. Temperature response and run time in vacant rooms*

A simplified idealization of temperature response and energy consumption surrounding a vacancy event can be broken into the following conceptual periods, and illustrated in Fig. 1 [36]:

*1. Cyclic operation to maintain comfort setpoint*. The rate of energy consumption during this period is driven mainly by the indoor–outdoor temperature difference. Temperature history, solar gains, and internal loads also play a role but are ignored in this example.

2. *Drift from setpoint toward setback temperature*. No energy is used during this period because no conditioning is needed. The rate of drift is driven by the indoor–outdoor temperature difference.

3. *Cyclic operation to maintain setback temperature*. Indoor–outdoor temperature difference is smaller, therefore thermal load and system runtime are smaller, and less energy is required to maintain the setback temperature than would be used to maintain the original comfort setpoint.

4. *Recovery from setback to setpoint temperature*. Energy consumption during this period is greater than what is required to maintain the original comfort setpoint, since capacity must be larger than the load in order to change the indoor temperature.

Expectations about the effect of occupancy-responsive thermostat controls are often based on this simple idealization. For example, previous efforts to demonstrate energy savings from these thermostats have indicated temperature drift and reduced run time as evidence of energy savings [24,25,37,38]. We approached this study with similar expectations, but found that temperature response and equipment runtime was much more complex, and that each zone in a building can respond in unique ways. Fig. 2 presents a summary of the temperature response observed in all rooms in one building over a sixteen-week period in the cooling season. These observations indicate that temperature in vacant rooms rarely drifted all the way to the setback – even when rooms were vacant for long periods.

The simple idealization presented in Fig. 1 would suggest that fan coil run time and temperature drift are correlated, but our observations show that this was not true. Fig. 3A compares the distribution of temperature measured in all rooms during vacant periods to the distribution in occupied periods. Temperature in vacant rooms did not drift far from the occupied conditions. Fig. 3B compares the distribution of fan coil run time in occupied and vacant rooms. While fan coils in occupied rooms cycled over a wide range in response to coincident thermal loads, fan coils in vacant rooms practically never operated. Fig. 3C and D present the same comparison for one of the few rooms where temperature did drift during vacant periods. While the fan coil cycled regularly during occupied periods, it did not operate during vacant periods.

Since the response for temperature and run time in the majority of rooms did not agree with the simple idealization, one must doubt the validity of assumptions about the relationship between reduced runtime and energy savings. The temperature response in vacant rooms was attenuated by something other than the room fan coil. Most likely, the thermal load for vacant rooms was transferred to adjacent occupied rooms and to the conditioned corridors. Therefore, it is not appropriate to assume that a change in fan coil run time for vacant rooms corresponds to a change in energy consumption for a building.

This observation is significant because several previous studies have assumed a simple correlation between run time and energy use. Moreover, many smart thermostats use equipment runtime patterns to self report energy savings in real time. In light of these observations, the remainder of our analytical investigation assessed energy savings in the whole building as a complete system.

### 3.2. Measured energy savings for cooling and heating

This section presents the detailed results from four energy use comparisons: a pre-post assessment in the cooling season for an academic period (Section 3.2.1), a controlled trial ("Week On – Week Off") for cooling in an academic period (Section 3.2.2), a controlled trial for cooling in a non-academic period (Section 3.2.3) and finally a controlled trial for heating in an academic period (Section 3.2.4).

The selection of which buildings were used for pre-post comparisons and which buildings were used for "Week On – Week OFF" controlled trials was based entirely on facilities construction timelines and on the availability of appropriate data for analysis. For example, there was no data for Building M preceding installation of the thermostats, so it was not used for pre-post investigation. The results from each comparison in each building are summarized in Section 3.2.5.

#### 3.2.1. Pre-post assessment of cooling energy consumption

We used cooling energy consumption data from the springtime academic period immediately preceding installation of the thermostats to develop a model (described in Section 2) for baseline cooling energy consumption in two buildings. For Building R, we developed the following equation with a least squares regression that resulted in a very good fit with adjusted $R^2 = 0.97$:

$$\dot{Q}_{CHW} = 9378 - 15.3 \times T_{OSA} + 1156 \times (T_{OSA} - 61.9)^{+} + 4290 \times (T_{OSA} - 69.4)^{+} + 1405 \times (T_{24} - 58.2)^{+} \quad (2)$$

Similar analysis for the baseline period in Building G developed a model with adjusted $R^2 = 0.96$.

The baseline observations were compared to cooling energy consumption data from the fall academic period immediately following installation of the thermostats. Fig. 4A compares measurements from the baseline period to measurements from the post retrofit period. Fig. 4B plots the time series trend for measurements in the post-retrofit period, and the time series trend for the projected baseline performance in the same period. This comparison indicates 3.4% reduction in cooling energy consumption associated with the smart thermostat installation (39.2 kWh/day ± 12.5 kWh/day). A similar analysis for Building G indicated 0.1% savings. In the second case, model uncertainty was larger than the savings observed (0.5 kWh/day ± 10.4 kWh/day).

#### 3.2.2 Controlled assessment of cooling energy consumption in high-occupancy (academic) periods

Following the pre-post comparisons of cooling energy consumption, we coordinated a series of "week ON – week OFF" controlled trials in Building M and Building G to control for confounding effects that could be present in a simple pre-post comparison. We used cooling energy consumption data from periods with the occupancy-responsive features disabled to develop a model of baseline energy consumption in two buildings during academic periods. For Building M, the following equation for cooling performance in the spring academic period resulted in adjusted $R^2 = 0.94$:

$$\dot{Q}_{CHW} = 66453 - 1312 \times T_{OSA} + 3669 \times (T_{OSA} - 51.7)^{+} + 3496 \times (T_{OSA} - 71.0)^{+} + 1300 \times (T_{24} - 62.5)^{+} + 81992 \times (Occ - 0.62)^{+} \quad (3)$$

A similar analysis of baseline data during the fall academic period resulted in an adjusted $R^2 = 0.96$. Fig. 5A compares cooling energy consumption in Building M when the occupancy-responsive features were disabled to similar measurements when occupancy-responsive features were enabled. Fig. 5B plots the time series trend for cooling energy consumption with the occupancy-responsive features enabled, and the time series trend for the projected baseline performance in the same periods. This comparison indicates 2.9% (26.2 kWh/day ± 17.5 kWh/day) reduction in cooling energy consumption associated with the occupancy-responsive controls. A similar analysis for the building during the fall academic period measured 6.2% savings (33.9 kWh/day ± 9.8 kWh/day).

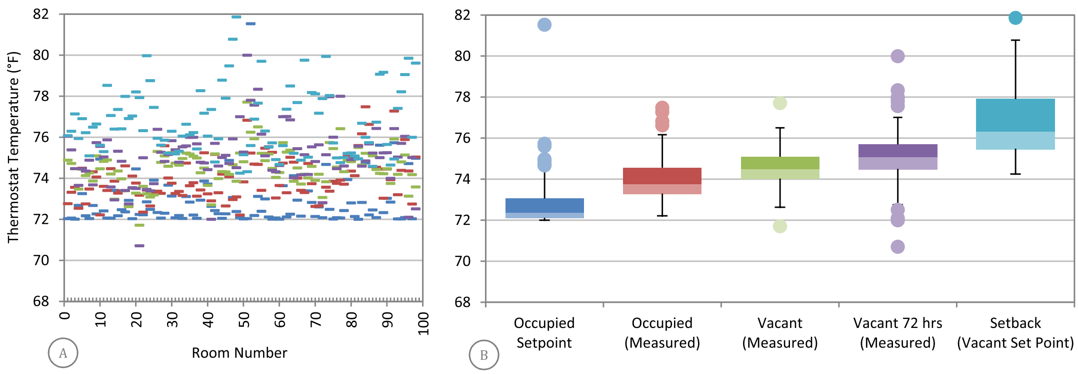


**Fig. 2.** Setpoint (blue), setback (cyan), and actual (measured) room temperatures for occupied rooms (red), vacant rooms (green), and rooms vacant for at least 72 h (purple). Values are averaged for each room across the 10 week monitoring period April–July. (A) Results for each room. (B) Boxplot of results for all rooms. The colors in (A) correspond to the colors in (B). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

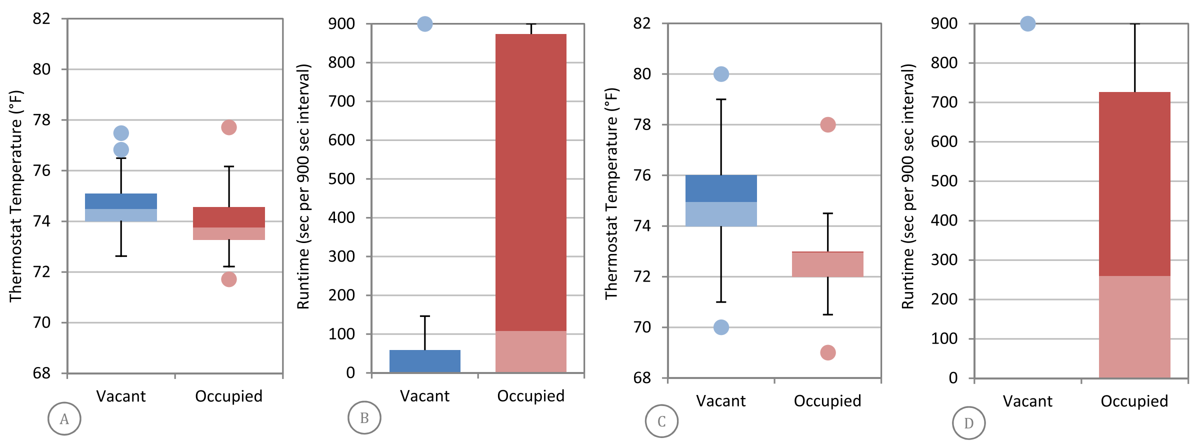


**Fig. 3.** (A) Room temperature and (B) run time for all rooms in all vacant and occupied intervals across the monitoring period April–July 2012. (C) Room temperature and (D) run time in room B204 during the same period. B204 is one of the few rooms that experienced regular temperature drift during vacant periods.

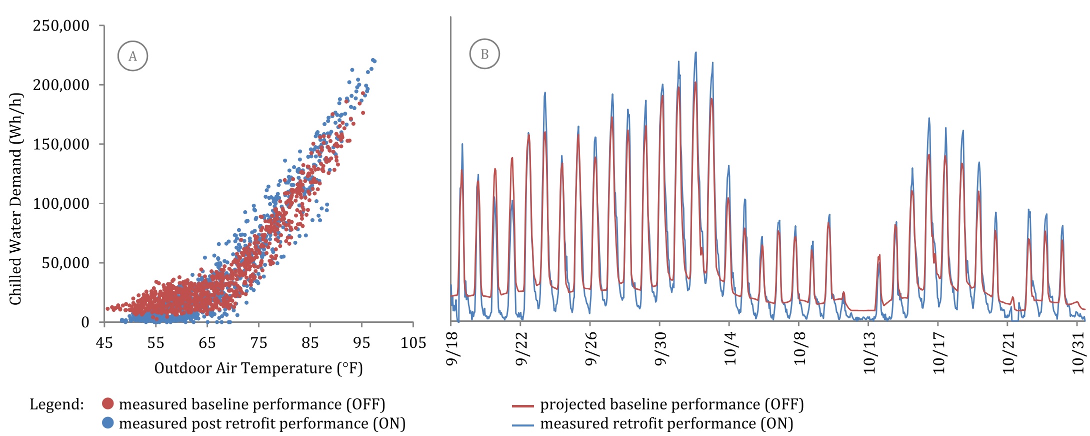


**Fig. 4.** Comparison of pre-post cooling demand during the academic period for Building R. (A) Measured 1-h increment cooling demand for the baseline (OFF) and post retrofit (ON) periods plotted against outside air temperature. (B) Measured post retrofit cooling demand and projected baseline performance for the same conditions plotted as time series. The baseline model is developed from 40 days of 1-h increment measurements. The analysis indicates 3.4% savings (39.2 kWh/day).

### *3.2.3. Controlled assessment of cooling energy consumption in low-occupancy (non-academic) periods*

The controlled trials were also used to evaluate cooling energy savings during the non-academic summer period, when the residence halls were used intermittently for conference housing. During this period, the building occupancy fraction never exceeded 21%, and patterns of occupancy were sporadic. We developed the following equation for baseline energy consumption in Building M during the non-academic period. The model represents the data nicely with adjusted $R^2 = 0.92$:

$$\dot{Q}_{CHW} = -46573 - 830 \times T_{OSA} + 3296 \times (T_{OSA} - 71.5)^{+} + 65770 \times (T_{OSA} - 99.7)^{+} + 1701 \times (T_{24} - 71.1)^{+} + 169078 \times (Occ - 0.016)^{+} \quad (4)$$

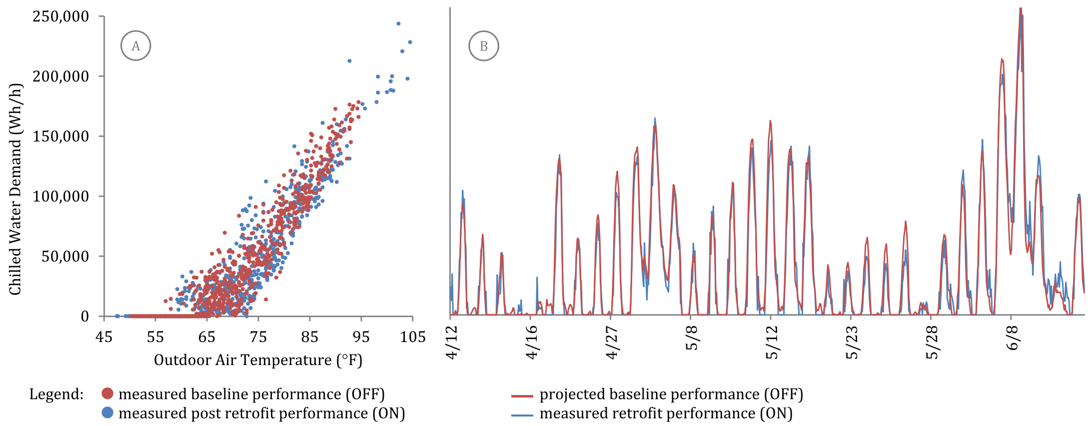


**Fig. 5.** Comparison of "week ON – week OFF" cooling demand for Building M during the spring academic period. (A) Measured 1- hour increment cooling demand for the baseline (OFF) and post retrofit (ON) periods plotted against outside air temperature. B) Measured post retrofit (ON) cooling demand and projected baseline (OFF) performance for the same conditions plotted as time series. The baseline model is developed from 30 days of 1-h increment measurements. The analysis indicates 2.9% savings (26.2 kWh/day).

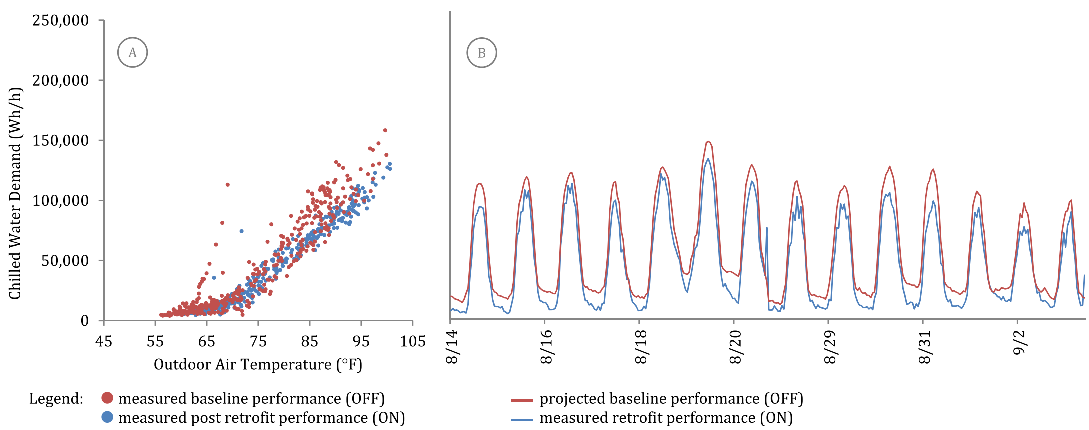


**Fig. 6.** Comparison of "week ON – week OFF" cooling demand for Building M during the summer non-academic period. (A) Measured 1-h increment cooling demand for the baseline (OFF) and post retrofit (ON) periods plotted against outside air temperature. (B) Measured post retrofit (ON) cooling demand and projected baseline (OFF) performance for the same conditions plotted as time series. The baseline model is developed from 16 days of 1-h increment measurements. The analysis indicates 20.7% savings (280.2 kWh/day).

Similar analysis for Building G resulted in a model with adjusted $R^2 = 0.96$. Fig. 6A compares the measured cooling energy consumption with and without occupancy-sensing during the non-academic period. Fig. 6B plots the time series trend for cooling energy consumption with occupancy-sensing, and the time series trend for the projected baseline performance in the same periods. This comparison indicates 20.7% (280.2 kWh/day ± 35.0 kWh/day) reduction in cooling energy consumption. A similar analysis for Building G over the same period measured 29% savings (158 kWh/day ± 10.6 kWh/day). Cooling energy consumption is naturally lower in non-academic periods because internal gains associated with occupancy are lower, but importantly, the degree of energy savings achieved by occupancy-responsive controls is larger. Our explanation for this is discussed in Section 4.1.

### *3.2.4 Controlled assessment of heating energy consumption in high occupancy (academic) periods*

Finally, we used the controlled trials to assess savings in the heating season for an academic period. We used heating energy consumption data from periods with the occupancy-responsive features disabled to develop a model for baseline heating energy consumption in each building. The following equation represented the measured data well, with adjusted $R^2 = 0.87$:

$$\dot{Q}_{HHW} = 357860 - 5,606 \times T_{OSA} + 4149 \times (T_{OSA} - 59.2)^{+} + 2005 \times (T_{OSA} - 69.5)^{+} + 899 \times (T_{24} - 50.8)^{+} + 32280 \times (Occ - 4.46)^{+} \quad (5)$$

Similar analysis for Building G resulted in a model with adjusted $R^2 = 0.81$.

Fig. 7A compares heating energy consumption from each period as a function of outside air temperature. Fig. 7B compares the time series trends for energy use with occupancy-sensing to the projected baseline performance in the same period. This comparison indicates 5.8% (50.1 kWh/day ± 33.8 kWh/day) reduction in heating energy consumption associated with the occupancy-responsive features. Similar analysis for Building G measured 7.9% savings (84.1 kWh/day ± 24 kWh/day) over the same period.

### *3.2.5. Summary of the results for measured savings and comparison to modeled savings*

Table 1 summarizes the key results for energy savings determined through each field experiment. During academic periods, energy savings was small, but during non-academic periods the reduction in energy use was more substantial. These results conflict with many previous studies on occupancy-responsive thermostats, which have claimed larger savings for similar control strategies in a variety of applications.

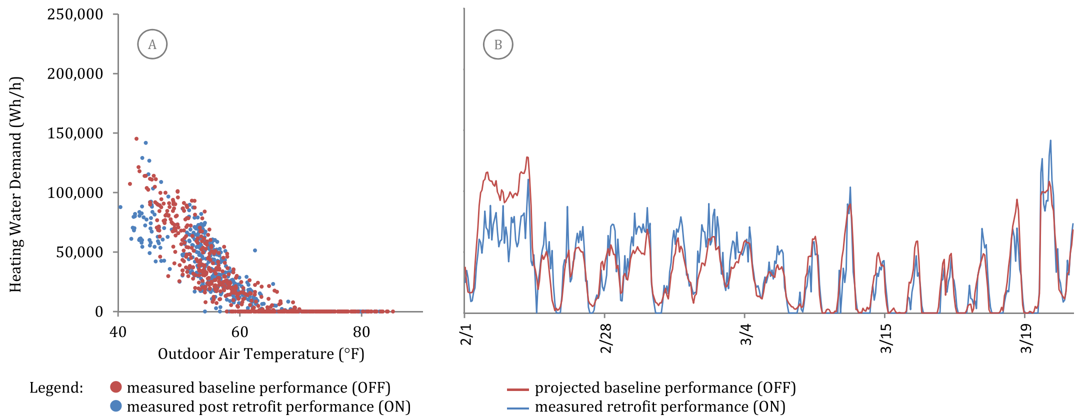


**Fig. 7.** Comparison of "week ON – week OFF" heating energy demand for Building M during the academic period in Winter 2014. (A) Measured 1-h increment heating demand for the baseline (OFF) and post retrofit (ON) periods plotted against outside air temperature. (B) Measured post retrofit (ON) heating demand and projected baseline (OFF) performance for the same conditions plotted as time series.The baseline model is developed from 22 days of 1-h increment measurements. The analysis indicates 5.8% savings (50.1 kWh/day).

**Table 1**
Summary of results for all periods analyzed to assess savings.

| Test | Building | Study Type | Mode | Activity Period | Absolute Savings ($kWh_{TH}$/day) | Uncertainty ($kWh_{TH}$/day) | Savings (%) |
|---|---|---|---|---|---|---|---|
| 1 | R | Pre-Post Comparison | Cooling | Academic | 39.2 | 12.5 | 3.4% |
| 2 | G | Pre-Post Comparison | Cooling | Academic | 0.5 | 10.4 | 0.1% |
| 3 | G | Controlled Week ON – Week OFF | Cooling | Academic | 59.8 | 15.8 | 9.8% |
| 4 | M | Controlled Week ON – Week OFF | Cooling | Academic | 26.2 | 17.5 | 2.9% |
| 5 | M | Controlled Week ON – Week OFF | Cooling | Academic | 33.9 | 9.8 | 6.2% |
| 6 | M | Controlled Week ON – Week OFF | Cooling | Non-Academic | 280.2 | 35.0 | 20.7% |
| 7 | G | Controlled Week ON – Week OFF | Cooling | Non-Academic | 158 | 10.6 | 29.0% |
| 8 | M | Controlled Week ON – Week OFF | Heating | Academic | 50.1 | 33.8 | 5.8% |
| 9 | G | Controlled Week ON – Week OFF | Heating | Academic | 84.1 | 24.0 | 7.9% |

**Table 2**
Summary of coefficients and change points (Eq. (1)) for every baseline model.

| Test | $\beta_0$ | $\beta_1$ | $\beta_2$ | $\beta_3$ | $\beta_4$ | $\beta_5$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | # of hour increments |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | 9378 | −15.3 | 1156 | 4290 | 1405 | – | 61.9 | 69.4 | 58.2 | – | 960 |
| 2 | 7806 | −164.8 | 1362 | 3882 | 520 | – | 60.2 | 75.7 | 62.5 | – | 960 |
| 3 | 1403 | −49.1 | 1328 | 5522 | 3040 | 28,700 | 62.9 | 77.4 | 77.1 | 0.51 | 795 |
| 4 | 66,453 | −1312 | 3669 | 3496 | 1300 | 81,992 | 59.7 | 71.0 | 62.5 | 0.62 | 720 |
| 5 | −10,345 | 298 | 835 | 4525 | 66,950 | 13,026 | 61.8 | 71.8 | 71.8 | 0.49 | 576 |
| 6 | −46,573 | 830 | 3296 | −65,770 | 1701 | 169,078 | 71.5 | 99.7 | 71.1 | 0.01 | 384 |
| 7 | −16,330 | 241 | 3288 | 1934 | 1886 | 14,194 | 71.3 | 82.5 | 73.7 | 0.05 | 576 |
| 8 | 357,860 | −5606 | 4149 | 2005 | −899 | −32,280 | 59.2 | 69.5 | 50.8 | 0.46 | 531 |
| 9 | 288,390 | −4134 | 2463 | 2287 | −1472 | −63,900 | 58.7 | 73.2 | 55.7 | 0.77 | 411 |

Table 2 documents the coefficients and change-points (for Eq. (1)) identified for each baseline data set, and the number of one-hour interval data points used to develop each baseline model. Differences in model coefficients reflect different buildings, heating or cooling modes, and academic vs. non-academic periods. For example, at Tosa = 100 °F cooling demand for Building M is approximately 200 kWh/h during the academic period, but only 150 kWh/h during the non academic period. Although this is the same building, in similar environmental conditions, the baseline data in the academic period only included high occupancy, while the baseline data in the non-academic period only included low occupancy.

To qualify for a utility rebate incentive program, an engineering consultant conducted a standard practice building energy simulation for these residence halls using DOE 2.2 [39]. To represent the effect of setback, the model lumped all vacancy events into a common zone, and then adjusted the set-point for that vacant zone. In Section 4.3 we critique these standard practice model assumptions and recommend opportunities for improvement. Table 3 summarizes the model results and compares them to the range of savings that we measured in operation. The standard practice approach overestimated savings by a factor of 2–10, with the exception of the summer non-academic period when savings were larger.

## 4 Discussion

The energy savings we observed for occupancy-responsive thermostats in three residence halls was much smaller than we had anticipated based on previous studies. In the remaining sections, we discuss the reasons for this unexpected result, based on which we formulate recommendations for methodological improvements for field evaluations, and strategies to improve simulations of occupancy-responsive thermostats in complex buildings.

### 4.1. *Vacancy is not necessarily an opportunity for energy savings*

Fig. 8 presents a boxplot distribution of the fraction of occupied rooms in each hour of the day for one building over a ten-week academic period in the cooling season. Superficially, it may seem that these residence halls would be an excellent application for occupancy-responsive thermostats. After all, daily average occu-

**Table 3**
Common practice modeled estimate of energy savings compared to measured energy savings.

| Percent Savings | Jan | Feb | Mar | Apr | May | Jun | Jul | Aug | Sep | Oct | Nov | Dec |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Space Cooling Modeled | – | – | – | 32% | 19% | 15% | 13% | 14% | 14% | 16% | – | – |
| Space Cooling Measured | – | – | – | 2.9%–9.8% | | | 20.7%–29% | | 6.2% | | – | – |
| Space Heating Modeled | 22% | 32% | 49% | 47% | – | – | – | – | – | 46% | 38% | 23% |
| Space Heating Measured | | 5.8%–7.9% | | | – | – | – | – | – | | 5.8%–7.9% | |

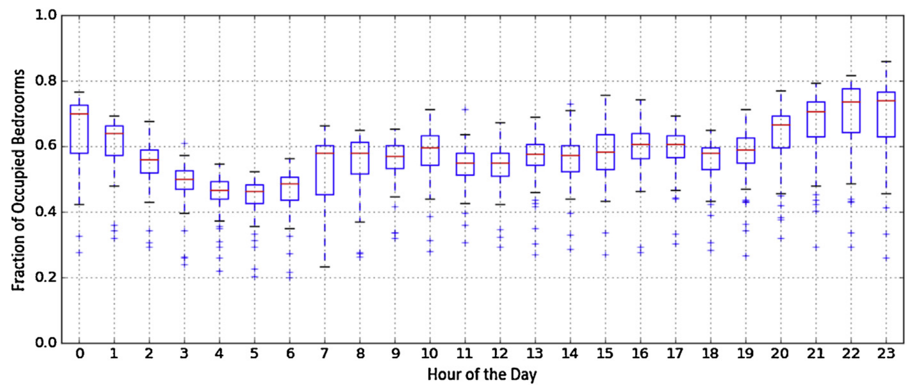


**Fig. 8.** Boxplot for fraction of occupied bedrooms for each hour during the academic period.

pancy for these buildings was only 60–70%. The hourly occupancy fraction rarely exceeded 85%, and it was sometimes as low as 25%.

However, there are other factors that diminish the potential for energy savings from setback when some rooms are vacant. Most importantly, the temporal and spatial distribution of vacancy events affects the way that thermal energy flows within a building. During academic periods, individual vacancy events in the residence halls were disaggregate and sporadic. Although some rooms remained vacant for several hours or days at a time, adjacent rooms remained occupied. When vacant zones interact thermally with adjacent occupied zones, the value of a vacant setback is limited. As noted in Section 3.1, the temperature in vacant rooms did not drift far, despite the fact that fan coil run time was reduced to zero.

The observations prompted us to conclude that individual rooms in a complex building cannot be considered independently, but the complete building must be assessed as a whole system. This conclusion is significant, because several previous studies have assumed a simple correlation between run time and energy use, and because many smart thermostats self report energy savings on the basis of reduced run time in each room. Such an approach might be acceptable in very simple scenarios, but it may not be accurate for buildings with multiple systems, or in scenarios where equipment run time is dependent on other interacting factors correlated with vacancy—such as thermal loads.

Moreover, in the academic periods many vacancy events were too short for room temperature to drift far. In these instances the energy used for recovery would mostly negate the energy saved during a brief drift period.

During non-academic periods occurrences of vacancy in each room were more temporally and physically coincident with vacancy throughout the building. This occurred because far fewer rooms were occupied, and because occupants' schedules were more aligned. As a result, the controls had more opportunity to trim energy use between occupancy events because whole blocks of vacant rooms could drift toward the setback at the same time. Furthermore, we expect that the occupancy-responsive controls would have a larger impact in higher occupancy periods if the instances of vacancy were more prolonged and more spatially coordinated. This would be difficult to accomplish purposefully in a residence hall, but might be an effective strategy for hotels. Yang and Becerik-Gerber drew similar conclusions when optimizing the mechanical system schedules for a multistory office building; the authors recommended strategic room reassignment as a method to aggregate similar workplace arrival and departure schedules in order to avoid conditioning and ventilating building zones that were only partially occupied [40].

### 4.2. Opportunities to improve field evaluations

In light of what we have observed in our study, it appears that some of the methods used in previous field evaluations could lead to disputable results. Namely, some previous studies have not controlled for interactions between rooms, and some have assumed that equipment run time is proportional to energy use. We recommend the following improvements to current practice for future field assessments of occupancy-responsive thermostats:

1. Do not assume that changes in equipment runtime can represent energy savings.
2. Consider the ways that spatial and temporal diversity in occupancy influence energy performance
3. Assess the impact on the whole building by measuring energy consumption of all mechanical systems. Reduced energy consumption in a vacant room may be offset by increased consumption for adjacent occupied rooms, thus changes for individual rooms may not represent the whole.
4. Do not compare rooms with occupancy-responsive controls to adjacent rooms without the controls. Since zones interact thermally, this method could inflate the differences in energy use.
5. Structure the study as a controlled trial to minimize the effect of exogenous variables such as changes in weather, building operations, room occupancy, and user behavior.

We are only aware of one publicly available study that conducted this type of controlled trial to assess energy savings of occupancy-responsive thermostats. The study – conducted for single family homes in Florida – reported 0–6% increase in energy use for some homes and a 0–4% decrease for others. The differences were attributed to the ways that people used their thermostats prior to retrofit with the smart device [27].

### 4.3. Opportunities to improve simulations

The common practice for building energy simulations may not properly capture the effects of occupancy-responsive thermostats. The main shortcoming is the inaccurate representation of temporal and spatial diversity for vacancy events. Modeling error can be compounded by simplification of the mechanical systems controlled by these thermostats.

In many packaged simulation tools, complex building layouts are represented as a few major perimeter zones, and a single interior zone. Each of these model zones may group what are in reality many independently controlled rooms. Usually, occupancy in these grouped zones is described by predefined scheduled coefficients that represent the fractional occupancy in each zone at each time step. ASHRAE 90.1-2004 [41] and others [42–44] provide standard occupancy coefficients for various building types to guide practitioners in the building design phase. While this model approach does account for the thermal gains associated with occupants in each major building zone, it does not capture the local thermodynamic interactions that occur between smaller individually controlled rooms in complex buildings. In particular, it does not allow for set point changes associated with local vacancy events, since vacancy in a particular room is only described as a reduced occupancy fraction for the whole building. In scenarios where occupancy-responsive thermostats rely on local set point changes in each room – such as residence halls and hotels – the level of detail employed by common modeling practice is not adequate. Despite the shortcoming, several studies have applied these simplified modeling assumptions to estimate energy savings for occupancy-responsive thermostats in complex buildings [22–24].

We recommend the following improvements to current practice for future simulations of occupancy-responsive thermostats:

- Represent all individually controlled rooms as independent thermal zones, and do not group large areas into single thermal nodes.
- Use accurate occupancy schedules for each individually controlled room, and ensure that the group of schedules has temporal and spatial diversity that matches the application modeled.

More accurate information about building level occupancy fraction would not be sufficient; simulation of occupancy-responsive thermostats in complex buildings requires room-level occupancy information and appropriate physical detail. State of the art building energy simulation engines are capable of accommodating models with this level of detail, but unfortunately the information to populate such models is rarely available to practitioners.

Feng and Hong recently published a compelling approach to model occupancy that combines multiple stochastic methods to simultaneously generate schedules for occupancy fraction in the whole building, occupancy state for each individual zone, and location for each building occupant [20]. This method is more advantageous than standard approaches to modeling occupancy because it generates a probabilistic representation of both temporal and spatial distribution of occupancy states in a complex multi-zone building. If it were coupled with a sufficiently detailed physical model, this type of method could provide an excellent path to predicting the impact of occupancy-responsive controls in complex multi-zone buildings. However, the method requires significant knowledge about mean occupant tendencies, and the probabilistic distribution of occupant behaviors, factors that are currently not well documented.

## 5. Conclusions

The buildings industry is beginning to adopt a new class of 'smart' thermostats that provide a variety of advanced features including occupancy-responsive and learning algorithms to automate temperature setback during vacant periods. In this study we facilitated a controlled trial to assess the extent to which this type of thermostat reduced heating and cooling energy consumption in three high-rise residence halls. For operation during the academic period energy savings was much smaller than what many previous studies have suggested. However, energy savings during the non-academic period was more substantial.

We discovered that in complex buildings such as residence halls, reduction in equipment runtime for vacant rooms does not necessarily result in energy savings for the whole building. This is significant because a number of commercially available thermostats rely only on equipment run time information to infer energy savings. Many previous field evaluations have also assumed that these parameters are correlated. We recommend that future field evaluations should measure energy use in carefully controlled trials.

A standard practice building energy simulation prepared for the buildings evaluated in this study overestimated savings by a factor of 2–10, for the academic periods. Our observations explain why it has previously been difficult for practitioners to accurately model the impact of occupancy-responsive thermostats. Most importantly, common modeling practices do not properly represent the temporal and spatial diversity of vacancy events in buildings with many individually controlled zones. Further, these building models often simplify geometry and mechanical systems in ways that would affect energy use estimates associated with occupancy-responsive thermostats.

Researchers have recently advanced stochastic modeling tools that can generate a probabilistic representation of the temporal and spatial distribution of occupancy states in a complex multi-zone building. Coupled with a sufficiently detailed building model, these methods could improve the accuracy of energy simulations for occupancy-responsive learning thermostats. However, these techniques require a level of specificity that is not readily available to practitioners.

As the capabilities for modeling tools progress, we also note the need for further research about user behaviors. Smart thermostats could easily increase energy use for end users that actively manage manual or programmable thermostats. The energy savings achieved by these new devices will also depend on the ways that smart thermostats affect user behavior.

Although energy savings for the buildings we evaluated was smaller than anticipated, we expect that occupancy-responsive controls could have much larger impacts in other scenarios. The savings results during the non-academic period are compelling and suggest that occupancy-responsive thermostat controls could play a valuable role for energy efficiency in buildings that experience long periods of low occupancy. Also, there are many buildings where controls are currently unconstrained, poorly managed, or set to maintain a constant temperature, or constant ventilation rate, at all times regardless of occupancy. The strategy would offer substantial energy benefits in those applications.

## Acknowledgments

We would like to thank California Institute for Energy and Environment for funding this work and for providing visionary leadership for the research. The endeavor would also not have been possible without generous help from UC Davis Student Housing and the UC Davis Energy Conservation Office.

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