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

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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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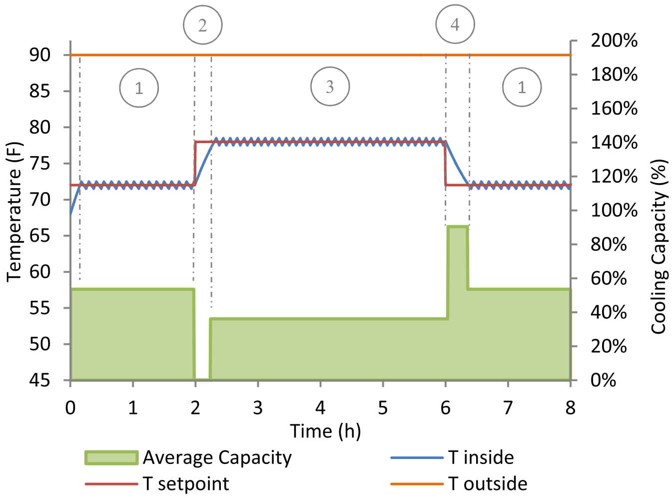


**Fig. 1.** The idealized pattern of temperature response and fractional run time for cooling before, during, and after a vacancy event. Outdoor temperature and all internal gains are assumed constant and there is no significant effect of wall thermal mass.

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 night-time 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 peri-