The Smart Thermostat: Using Occupancy Sensors to Save Energy in Homes

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Abstract

Heating, ventilation and cooling (HVAC) is the largest source of residential energy consumption. In this paper, we demonstrate how to use cheap and simple sensing technology to automatically sense occupancy and sleep patterns in a home, and how to use these patterns to save energy by automatically turning off the home's HVAC system. We call this approach the *smart thermostat*. We evaluate this approach by deploying sensors in 8 homes and comparing the expected energy usage of our algorithm against existing approaches. We demonstrate that our approach will achieve a 28% energy saving on average, at a cost of approximately $25 in sensors. In comparison, a commercially-available baseline approach that uses similar sensors saves only 6.8% energy on average, and actually increases energy consumption in 4 of the 8 households.

Categories and Subject Descriptors

C.3 [**Special-Purpose and Application-Based Systems**]: Real-time and Embedded Systems; H.1.2 [**Models and Principles**]: User/Machine Systems—*Human Information Processing*

General Terms

Design, Experimentation, Economics, Human Factors

Keywords

Building Energy, Home Monitoring, Programmable Thermostats, Wireless Sensor Networks

1 Introduction

Heating, ventilation and cooling (HVAC) is the single largest contributor to a home's energy bills and carbon emissions, accounting for 43% of residential energy consumption in the U.S. and 61% in Canada and the U.K., which have colder climates [1, 2, 3]. Studies have shown that 20-30% of this energy could be saved by turning off the HVAC system when residents are sleeping or away [4]. These savings, however, have been difficult to realize: typical residents will not manually adjust the thermostat several times a day, and programmable thermostats are too difficult for most people to use effectively. In fact, recent studies have found that households with programmable thermostats actually have higher energy consumption on average than those with manual controls because users program them incorrectly or disable them altogether [5, 6]. As a result, the EPA recently suspended the Energy Star certification program for all programmable thermostats, effective December 31, 2009 [7].

An important obstacle to energy conservation is the weak financial incentive for individual homeowners. A 20-30% reduction in HVAC energy would translate to a savings of about $15 per month for the average household in the U.S. [8]. For many people, this small monetary saving does not justify the difficulties of optimizing HVAC operation on a daily basis. At the national scale, however, these same savings translate to over 100 billion kWh at a cost of approximately $15 billion annually, and would prevent approximately 1.12 billion tons of pollutants from being released into the air each year [9, 10]. It is a classic *tragedy of the commons* [11]. To address this situation, a new solution must be created that "just works" and saves energy without requiring daily thought or action by household residents.

In this paper, we propose a solution called the *smart thermostat* that uses occupancy sensors to automatically turn off the HVAC system when the occupants are sleeping or away from home. Our approach uses wireless motion sensors and door sensors, which are inexpensive and easy to install; they cost about $5 each off the shelf and can be installed in minutes using double-sided tape. The smart thermostat uses these sensors to infer when occupants are away, active, or sleeping and turns the HVAC system off as much as possible without sacrificing occupant comfort.

The first main challenge of this approach is to quickly and reliably determine when occupants leave the home or go to sleep. Motion sensors are notoriously poor occupancy sensors and have long been a source of frustration for users of occupancy-based lighting systems, which often turn the lights off when a room is still occupied. For the smart thermostat, these mistakes would lead to more than just user frustration: frequently turning off and on the HVAC system can cause uncomfortable temperature swings, shorten the lifetime of the equipment, and even cause energy waste due to

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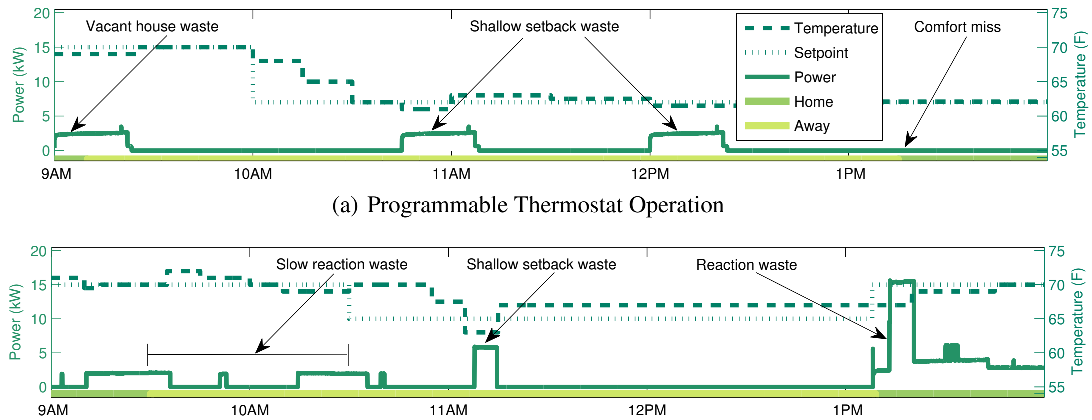


(a) Programmable Thermostat Operation

(b) Reactive Thermostat Operation

Figure 1. Both programmable and reactive thermostats cause substantial energy waste and discomfort.

frequent equipment cycling. Furthermore, a longer time-out period is not an adequate solution because it would waste energy by conditioning unoccupied spaces; the smart thermostat requires occupancy monitoring that is both quick *and* reliable. To address this problem, we use a novel algorithm that analyzes patterns in the sensor data to quickly recognize leave and sleep events, allowing the system to respond within minutes without increasing false detection rates.

The second main challenge of this aproach is to decide when to turn the HVAC system back on. Preheating the house could waste energy if the system is activated too early. On the other hand, heating only in response to occupant arrival could also waste energy because, at that point, the house must be heated very quickly; many multi-stage HVAC systems have a highly efficient heat pump that can be used for slowly preheating, but a lower efficiency furnace or electric heating coils must be used to heat the house quickly. Since the smart thermostat cannot predict exactly when occupants will arrive, it is difficult to decide which approach will be more efficient on any given day. Instead, the system uses a hybrid approach that *minimizes the long-term expected energy usage* based on the occupancy patterns of the house: it slowly preheats the house with high efficiency equipment at a time τ and, if the occupants return before that time, it quickly responds by heating the home with the lower efficiency equipment. The time τ is chosen based on the equipment efficiencies and the historical distribution of occupant arrivals, balancing the expected costs of preheating too early and preheating too late.

To evaluate our approach, we deploy sensors in 8 homes using X10 motion and door sensors that cost about $5 each [12] and can be easily installed with double-sided tape. We also collect empirical measurements of the temperature response and energy consumption of a home with a typical heating system. We construct a simulation model of this home using the EnergyPlus home energy simulation framework [13] and validate that the energy predictions match our empirical energy measurements of the home. Then, using this model, we calculate the energy cost of heating each of these 8 households using the smart thermostat algorithm and demonstrate a 28% energy saving using 12-20 sensors per home, for a total cost of less than $100. Our analysis shows that similar results would be achieved with as few as 3-5 sensors per home, a cost of about $25. For comparison, we use the same home model and weather traces to also evaluate a *reactive* algorithm that turns the system on in response to motion sensor or door sensor values, and turns the system off in response to a period of inactivity. This approach is commonly used by occupancy-based lighting systems and has recently been adopted by off-the-shelf thermostats that claim to save energy by responding to occupancy [14, 15]. However, our studies show that without our sensor analysis and control algorithms, this approach only achieves a 6.8% energy saving on average in these 8 homes. In fact, it actually increases energy usage in four of the homes due to its inability to respond quickly to occupants, as explained in Section 2.

2 Background and Related Work

Programmable thermostats have been a pillar of energy conservation programs since shortly after their invention in 1906, over 100 years ago. The basic idea is to control the HVAC equipment based on a *setback schedule*: the house is conditioned to a *setpoint* temperature when the occupants are typically active and floats to a more energy-efficient *setback* temperature when the occupants are typically away or asleep. The notion that energy could be saved in this manner has been part of the U.S. collective consciousness since President Carter famously donned a cardigan and turned the temperature of the White House down to 55°F at night due to the energy crisis of the 1970s. However, this approach wastes energy in several ways, as illustrated by Figure 1(a). First, the occupants leave the home shortly after 9 AM, but the system wastes energy because it is scheduled to continue heating the home until 10 AM (left side). Second, the setback temperature is well above the safety limit for the house, causing energy consumption even while the house is vacant (center). This type of *shallow setback* is typically used to reduce the risk of comfort loss, in case the building becomes occupied at that time. Third, the occupants become uncomfortable when they return shortly after 1 PM because the sys-

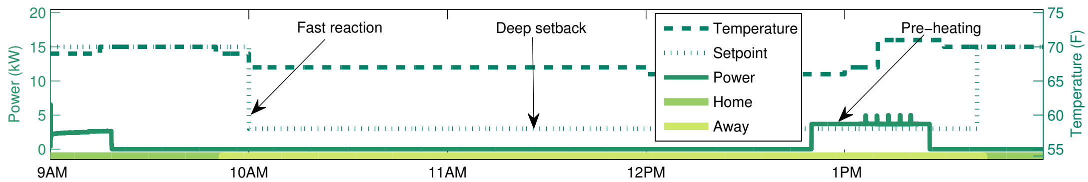


Figure 2. The goal of the smart thermostat is to automatically turn off the HVAC equipment as soon as the occupants leave, use a deep setback temperature while they are gone, and preheat immediately before the occupants return.

tem is not scheduled to heat the house until much later. On the surface, this last problem appears to be only a comfort issue, but is in fact an important cause of energy waste: the static setback schedules used by programmable thermostats cannot capture the highly dynamic occupancy patterns of most homes and will inevitably cause some loss of comfort. This risk of comfort loss causes people to reduce their use of setback schedules, or stop using them altogether. Over 50% of households that have programmable thermostats are reported to not use setback periods at night or during the day [5]. In contrast, households with the simpler dial-type thermostats can easily adjust temperature settings before going to sleep or leaving the house and, as a result, actually save more energy on average than users with programmable thermostats [5, 6]. In the preliminary work, two of the authors designed and evaluated the *self-programming thermostat* to fix this problem by automatically choosing the optimal setback schedule based on historical occupancy data [16]. However, that system still produces a static schedule and, since occupancy patterns change every day, *any* static schedule must sacrifice either energy or comfort. In this paper, we use real-time sensor data to dynamically control the HVAC system as the occupancy status of the house changes.

An alternative to the programmable thermostat is the *reactive thermostat*, which uses motion sensors, door sensors, or card key access systems to turn the HVAC equipment on and off based on occupancy [17, 15, 18, 19]. However, our preliminary studies found that reactive thermostats save less energy than programmable thermostats in residential buildings, and in 4 out of 8 households actually *increase* energy usage by up to 10% [16]. We identified three sources of energy waste, which are illustrated by Figure 1(b), collected from a home using the BAYweb brand reactive thermostat [14] with five motion and door sensors. First, the occupants leave the house at about 9:30 AM, but the system waits until 10:30 AM to stop heating (left side). This long delay is used to reduce the risk of turning off the heat while the building is still occupied (a common problem with lighting systems that use motion sensors). Second, even when the system is fairly confident that the building is unoccupied, it still wastes energy by maintaining a temperature that is well above the building safety level (middle), in order to reduce the building response time once the occupants return. Third, when the occupants do arrive shortly after 1 PM, the system must waste energy by using an inefficient stage of heating: it first responds with an energy-efficient heat pump, but after detecting that the temperature is rising too slowly it switches to a very inefficient auxiliary heater to raise the temperature more quickly. This same phenomenon has been observed in previous studies of programmable thermostats [20, 21]. In summary, the energy saving potential of reactive thermostats is limited by their inability to respond quickly to building occupants. The smart thermostat presented in this paper addresses this limitation by developing new algorithms to quickly turn off the system when not needed, and to turn on the system at a time that minimizes long-term expected energy consumption based on occupancy patterns.

3 The Smart Thermostat

The smart thermostat uses occupancy sensors to save energy by automatically turning off the HVAC when occupants are sleeping or away. The system uses cheap, simple motion and door sensors installed throughout the home (Section 3.1). Based on these sensors, the system employs three energy saving techniques, as illustrated in Figure 2. First, the *fast reaction* algorithm uses a probabilistic model to process the sensor data and quickly estimate whether occupants are active, sleeping, or away (Section 3.2). This algorithm can typically respond within minutes of the occupants leaving the house, without introducing false vacancy detections. Second, the system combines historical occupancy patterns with on-line sensor data to decide whether to preheat the home or to heat after the occupants arrive (Section 3.3). Finally, the system saves additional energy by allowing the temperature to drift further from the setpoint temperature when it is confident that the home is unoccupied. We call this a *deep setback* (Section 3.4). These three techniques allow the system to automatically save energy without sacrificing occupant comfort.

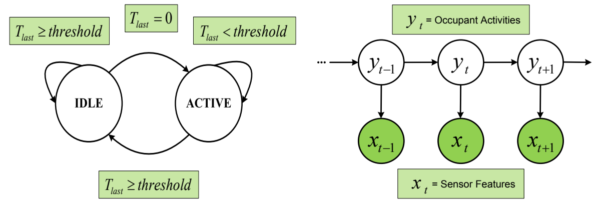
3.1 Instrumenting the Home

In order to respond to the residents, the smart thermostat requires two types of sensors to identify when occupants are in the home and when they are sleeping: passive infrared (PIR) motion sensors in rooms and magnetic reed switches on entryways. PIR sensors and magnetic reed switches are cheap and easy to install: we deploy off-the-shelf wireless X10 sensors [12] as shown in Figure 3 that can be purchased for approximately $5 each and easily installed by attaching them to the wall or door using double-sided tape. In contrast to other smart home applications such as medical monitoring and security, the domain of energy conservation can tolerate a small loss in accuracy in favor of cost and ease of use. Therefore, the smart thermostat does not require cameras or wearable tags that may be considered intrusive to the user [22, 23] or more sophisticated sensing systems used for fine-grained tracking and activity recognition [24, 25, 26].

For our experiments, we deployed more sensors than we

(a) Motion Sensor (b) Door Sensor

Figure 3. The smart thermostat uses motion sensors (left) and contact switches on doors (right).



(a) Reactive State Machine (b) HMM

Figure 4. Reactive thermostats use a state machine to switch between states based on T_{last}, the time elapsed since the last sensor firing. The smart thermostat uses a HMM to switch between states based on a probabilistic model of state transitions and sensor data.

thought necessary in order to analyze the sensitivity of our approach to the number of sensors. We installed at least one motion sensor in every room and a magnetic reed switch on exterior doorway to the home. This type of deployment would require less than 20 minutes and, at \$5 per sensor, would cost less than \$100 for most homes and about \$50 for an average home with 9 rooms and one main entrance. This is similar to the cost of purchasing and installing a typical programmable thermostat, and approximately 35% of homes in the U.S. already contain a similar set of sensors as part of a home security system [27]. Furthermore, our analysis in Section 6.3.1 shows that only 3-5 strategically placed sensors are actually needed in each home to achieve energy savings. An alternative to motion sensors would be to sense the home's electrical and mechanical systems to detect occupancy [28, 29, 30], although the effect of these systems on cost and the ability to quickly and reliably detect home occupancy has not been demonstrated.

3.2 Turning the HVAC System Off

One key challenge of the smart thermostat is to decide when the occupants have left the home so that it can turn off the HVAC system. Being too aggressive can cause the equipment to shut off too early, causing occupant discomfort, wasting energy due to rapid equipment cycling, and shortening the life of the equipment. On the other hand, being too conservative can waste energy by conditioning unoccupied spaces. In order to achieve a fine balance, the smart thermostat uses a Hidden Markov Model (HMM) to estimate the probability of the home being in each of three states: (i) *Away* when the home is unoccupied, (ii) *Active* when the home is occupied and at least one resident is awake, and (iii) *Sleep* when all the residents in the home are sleeping. Once the system detects a state transition with high probability, it responds by switching the temperature setpoint appropriately.

The HMM is depicted in Figure 4(b). The hidden variable (y_t) is a distribution over the home state: *Away*, *Active* and *Sleep* and the HMM transitions to a new state every five minutes. The observed variables x_t are a vector of three features of the sensor data: (i) the time of day at 4-hour granularity, (ii) the total number of sensor firings in the time interval dT, and (iii) binary features to indicate presence of front door, bedroom, bathroom, kitchen, and living room sensor firings in the time interval dT. The first feature helps the HMM use historical occupancy at each time of day to help estimate current occupancy. The second feature simply indicates whether the occupants are highly active. The third feature helps detect whether the occupants have opened or closed a door recently, and also helps filter out motion sensors with high false positives, e.g. those that are near a window.

To train the HMM using a data trace from a home with known occupancy states, these features are first calculated every five minutes. The Markov state transition probabilities $P(y_t|y_{t-1})$ and the emission probabilities for the observed sensor features $P(x_t|y_t)$ are represented using a discrete conditional probability table and are both calculated using frequency counting. However, frequency counting results in very low probabilities for several values of feature (ii) because the total number of firings per time unit has a larger domain than features (i) and (iii). Therefore, we build a generative Gaussian model for $P(x_t|y_t)$ to smooth the probability distribution for feature (ii). Additionally, we explicitly disable sleep states in the morning after contiguous hours of sleep states are detected during the night. This effectively encodes that a person has recently woken up and is unlikely to sleep again, which improves the accuracy of our HMM by correctly classifying idle periods after a person has woken up as away times.

3.3 Turning the HVAC System On

Since the occupant arrival times are not known, a key challenge of the smart thermostat is to decide whether and when to preheat the house. Preheating too early can waste energy by maintaining the setpoint for too long, while preheating too late can waste energy by increasing the chance of needing to react to occupant arrivals with an inefficient heating stage, as described in Section 2. In order to manage this delicate trade-off, the smart thermostat chooses the optimal preheat time τ that minimizes the long-term expected energy usage. It slowly preheats the house with high efficiency equipment at a time τ and, if the occupants return before that time, it uses higher capacity but lower efficiency equipment in order to quickly heat the home. Two steps are required to derive the value of τ: (i) characterize the capacity and efficiency for each stage of the home's HVAC system, and (ii) analyze historical occupancy patterns of the home.

We empirically measure the efficiency of a three-stage HVAC system that includes a 2-stage heat pump and a third stage electric heater in the house shown in Figure 9. For each stage, we preform four experiments by turning off the system, which allows the house to cool down to below 65°F, and then heating the house to a target temperature. By cor-

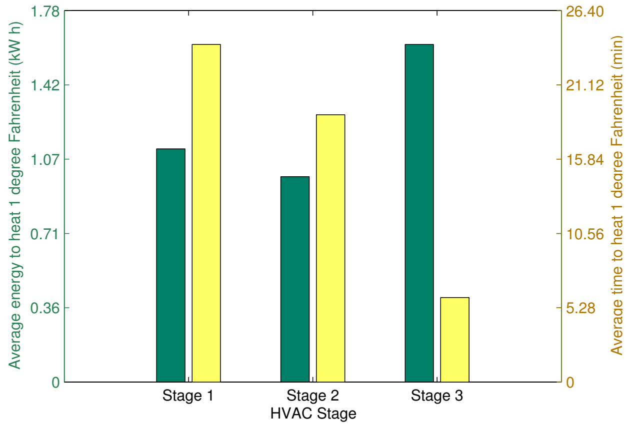


Figure 5. Energy efficiency and lag time vary among the multiple stages of HVAC. The smart thermostat uses the most energy efficient stage for preheating in order to reduce the reaction energy waste.

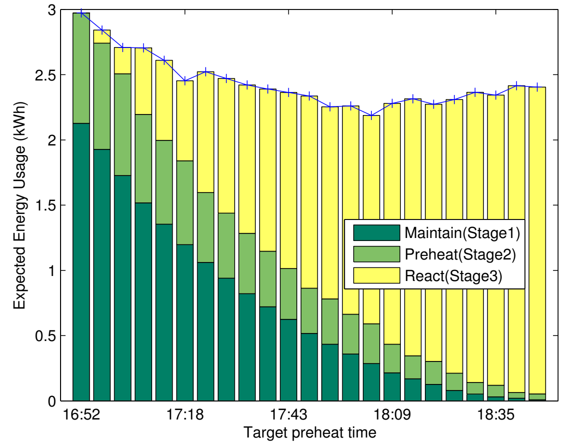


Figure 6. The smart thermostat selects the target preheat time that optimizes the long-term expected energy usage.

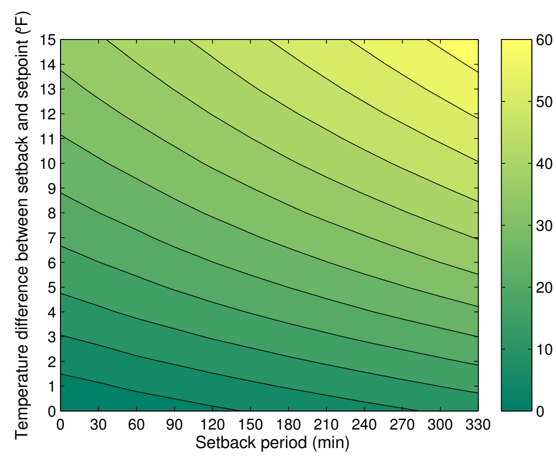


Figure 7. A deeper setback degree has a larger impact on energy savings than a longer setback period.

relating the thermostat operation logs and power measurements, we calculate the average energy used and the time taken by each stage to raise the temperature by 1°F on average, as depicted in Figure 5. The results show that Stage 2 is the most energy efficient stage, but has a long response time; at 15 minutes per degree, this stage would require 2 hours to recover from a typical 8 degree setback temperature, which would be too long for an occupied building. On the other hand, Stage 3 has the fastest response time but a very high energy cost. Note that for this equipment Stage 1 uses the same compressor and fan as Stage 2, but operates at a lower power level and speed. It is less efficient but more effective at maintaining a constant temperature.

We use these measurements to choose the optimal preheat time τ given a set $\mathbf{a}$ of observed arrival times at the home. For all possible target preheat times $t : min(\mathbf{a}) < t < max(\mathbf{a})$, we calculate the expected energy cost by averaging the waste for each arrival time $a \in \mathbf{a}$. The waste for arrival time a is defined to be the energy required to heat with Stage 3 if $a < t$. Otherwise, if $a \geq t$, the waste is defined to be the energy required to preheat with Stage 2 and then maintain the temperature using Stage 1 for time $a - t$, until the occupants arrive. Once the expected energy costs are calculated, we set τ to be the time t with the lowest expected energy cost.

To illustrate this optimization process, we calculated the optimal preheat time given the empirical arrival times found in the publicly available Tulum dataset (excluding weekends), which was created by monitoring the occupants of a home for approximately one month [31]. Figure 6 shows the expected energy cost for all preheat times between 4:45 PM and 6:45 PM. This figure illustrates that, if the system preheats too early (left side), it wastes energy due to maintaining a high setpoint temperature too long. If the system preheats too late (right side), it wastes energy because it must react with the inefficient but fast-reacting Stage 3 heating system, if occupants arrive before preheating is complete. The system can achieve the minimum energy usage by choosing a target preheating time of 6:04 PM. Preheating to this time requires 9% less energy on average than a purely reactive thermostat. It is worth noting that optimal preheat time is typically *not* the same as the expected arrival time of the occupant; it changes based on the efficiency levels of the HVAC equipment.

3.4 Using Deep Setbacks

The typical setback temperature is 8 degrees from the setpoint, which is well above the safety limit for a house and causes energy consumption even when the house is vacant. Shallow setback temperatures are typically used to reduce risk of comfort loss, in case the building becomes occupied at that time. Because the smart thermostat responds to occupancy events, it can increase energy savings by using deeper setbacks during periods when the building is unoccupied and occupants are highly unlikely to return. Specifically, given a historical set of arrival times $\mathbf{a}$, the smart thermostat uses a deep setback as soon as the building is detected to be unoccupied, and switches to a typical shallow setback at the earliest

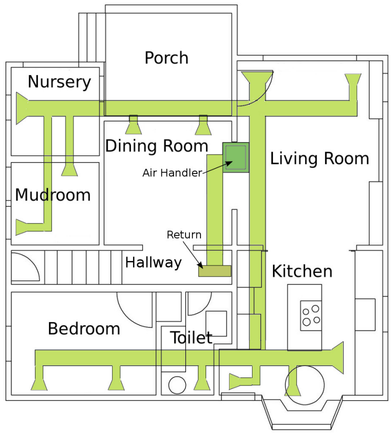


Figure 9. For realistic energy calculations and predictions, we created and empirically validated an energy model of the house and HVAC system shown here.

previously observed arrival time $min(\mathbf{a})$, which reduces the time required to recover a comfortable temperature once the occupants return.

Figure 7 illustrates that *deeper* setback temperatures have a larger impact on energy savings than *longer* setback periods: a five degree increase in setback temperature for an hour has the same effect as an additional five hours of setback time that uses the normal setback temperature, even in a moderate climate like Washington, D.C.. Since the smart thermostat either preheats the home or quickly responds to occupant arrivals, it can exploit the large energy savings made possible by deep setbacks without sacrificing occupant comfort.

To illustrate the concept of a deep setback, Figure 8 shows the distributions of leave and return times for the publicly available Kasteren [25] and Tulum [31] home monitoring datasets, excluding weekends. The individual in the Tulum study is consistently away from home for a longer period of time, and will therefore benefit more from deep setbacks. The length of a deep setback depends on the *minimum* arrival time of a household, and so the individual in the Kasteren dataset does not obtain a larger benefit from deep setbacks even though he/she sometimes returns very late in the evening.

4 Experimental Setup

In this section, we describe the data collection process and the simulation framework used to evaluate the smart thermostat.

4.1 Collecting Occupancy Data

Occupancy patterns play a significant role in the performance of the smart thermostat. To investigate the impact of occupancy patterns on the performance of smart thermostat, we use occupancy patterns collected through three means: (i) the empirical data traces from 8 instrumented homes, (ii) the occupant surveys of 41 homes, and (iii) two public smart home datasets.

We use the empirical sensor data to evaluate all three phases of smart thermostat, but cannot evaluate fast reaction using the data collected through the other two sources because they lack the sensor data required for fast reaction. Therefore, they are used to evaluate only the deep setback and preheating.

#Residents	#Rooms	#Motion Sensors	#Doors	#Door Sensors	#Weeks
1	7	7	5	3	2
1	3	3	3	2	1
1	4	4	3	1	1
1	5	4	3	1	1
2	5	5	3	1	2
3	5	5	4	2	1
3	4	4	3	1	1
2	5	5	4	2	1

Table 1. Details of the 8 homes used in deployments

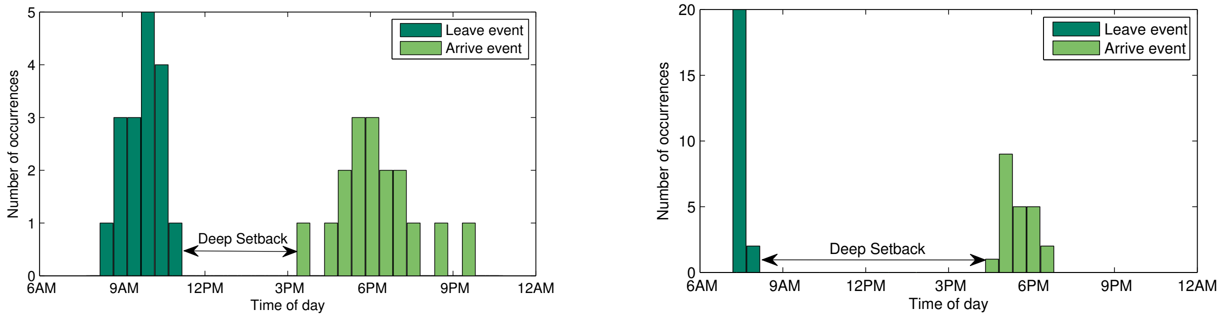
4.1.1 *Sensor Deployments*

We deploy X10 motion sensors and door sensors in 8 homes to collect occupancy and sleep information. These homes include both single-person and multi-person residences, and the people living in the home include students, professionals and homemakers. For example, one home includes a graduate student couple along with an elderly resident, two other homes include young working professionals, and another home includes three graduate students. The duration of the sensor deployments varies from one to two weeks. In general, we deploy one motion sensor in each room and one door sensor on each entryway to the home, and some inner doors. However, we do not instrument rooms or entryways that are very infrequently used. Table 1 summarizes the information about the homes.

We collect ground truth using a manual post-processing of the data and daily interviews with the residents to clarify ambiguous or questionable data. The ground truth values used for this study are best estimates by labeling user activities manually, but are not expected to be perfectly accurate. Ground truth in home monitoring experiments is very difficult to collect, and previous studies have used a wide variety of approaches ranging from self reports to video camera recordings to having a proctor physically on site to monitor home activities [32, 25, 33]. None of these schemes for creating ground truth are expected to be perfect.

4.1.2 *Surveys and Data Collection*

To augment the home deployments, we collect data from another 41 households for four weeks using surveys: each individual is instructed to write down their sleep, wake, leave, and arrive times every day, and the data are collected through periodic telephone calls. The period of the telephone calls ranges from once per day to once per week. The surveyed individuals range from students to professionals to retirees. The households comprise a variety of single-person and multi-person residences from various parts of the eastern coast in U.S.. The times collected through these surveys are expected to be precise within 15 minutes, since many residents report times in 15-minute intervals. Overall, the occupants can be categorized into five different lifestyles: retirees, students, professionals, young professionals and families.



(a) Short Deep Setback (Kasteren)

(b) Long Deep Setback (Tulum)

Figure 8. The duration of deep setback varies among different people, and depends only on the earliest observed arrival time; late arrivals do not have additional benefit from deep setbacks.

In addition to surveys, we analyze the leave, return, wake, and sleep times from two publicly-available data sets that contain home occupancy information for two individuals over the course of approximately one month each. These data sets are collected by manually labeling activities such as sleeping, eating, and bathing, and leaving home. We call these the Kasteren [25] and Tulum [31] datasets, respectively. For the purposes of this study, we only use the *leave home*, *arrive home*, and *sleep* event labels.

4.2 Simulation Framework

The practical performance of the smart thermostat can be affected by many factors such as outdoor temperature, air leakage and house insulation. Therefore, it is important to evaluate the smart thermostat with various climates and building conditions. However, large-scale experiments are extremely difficult due to resource constraints. To address this problem, we have modeled the home in Figure 9 and validated the model by comparing empirical energy measurements and energy predictions generated using the EnergyPlus simulator. This validated model allows us to evaluate the smart thermostat under various conditions, such as different climates, that cannot be easily done empirically.

4.2.1 EnergyPlus Simulator

In our experiments, we use whole-house thermal simulation modeling provided by the U.S. Department of Energy's EnergyPlus simulator as a framework to evaluate different thermostat algorithms under different housing conditions and climates. EnergyPlus is developed and distributed by the U.S. Department of Energy's Energy Efficiency and Renewable Energy division, derived from and extending the earlier DOE-2 and BLAST simulators. It has won awards for R&D, Technology Transfer and Technical Excellence, and is widely regarded as the premier baseline energy performance simulation tool in the industry.

In the simulation, a model is described which integrates the physical description of a building (including walls, floors, roofs, windows and doors, each with associated construction properties such as R-Value of materials used, size of walls, location and type of windows) with the descriptions of mechanical equipment (heating and cooling), mechanical ventilation schedules, occupancy schedules, other household equipment, and so on. The simulation applies

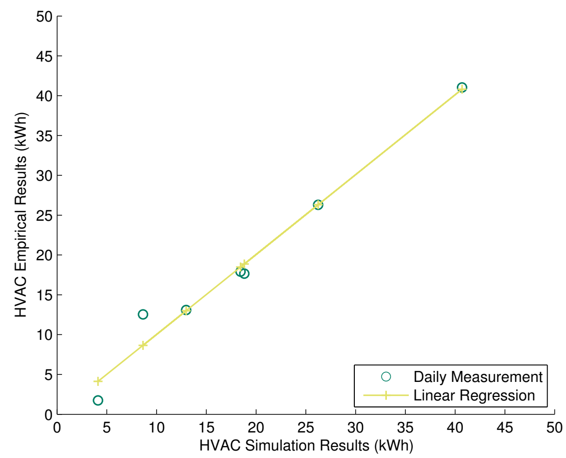


Figure 10. The observed energy usage closely matches the values predicted by our model.

this model to a time-series thermal calculation using well-known thermal transfer equations and aggregate climate and weather data from local airports and weather stations. The calculations output interior and exterior air temperatures, energy consumption, heating and cooling loads and indices for human comfort, among numerous other results. The simulation is performed for extreme heating and cooling periods to establish mechanical equipment sizing and performance response, and can be carried out for a full year or part of the year to obtain comprehensive or specific results.

4.2.2 Simulation Model Validation

To create realistic energy calculations and predictions, we instrumented and modeled a two-story, 1700 square foot residential building equipped with a three-stage HVAC system, as illustrated in Figure 9. The building contains over 100 sensors to monitor building operation and response, including 80 temperature and 40 humidity sensors, 15 motion sensors, 7 door sensors, electric power metering, and a Web-enabled thermostat that provides both control and operational logs. We create a detailed model of the system that includes the building location, construction properties and multistage op-

	Wall Insulation R-value (ft$^{2\circ}$Fh/BTU)	Air Infiltration Air Changes per Hour (ACH)
Poor	3.6	1.5
Moderate	13.2	0.8
Well	25.7	0.25

Table 2. Building conditions using in our analysis

Climate Zones	Locations
Zone 1	Minneapolis / St. Paul, MN
Zone 2	Pittsburgh, PA
Zone 3	Washington, D.C. / Stirling, VA
Zone 4	San Francisco, CA
Zone 5	Houston, TX

Table 3. Weather conditions used in our analysis

erations of the HVAC system.

In order to validate the fidelity of our model, we run the same control and operational logs of the real system in the simulation and compare the results with the empirical measurements. In order to perform the simulation under the same weather conditions, we collect the actual weather records of the week when the data collection took place from the local airport weather station that provides hourly data resolution. Also, to increase the credibility, we pick a week in the winter with fluctuating outdoor temperature that causes the HVAC system to react in different ways. We perform a regression analysis on the simulation and empirical results, as shown in Figure 10, and find that the average daily error of HVAC energy usage is 1.80 kWh, smaller than the accuracy of the power meter. Therefore, these results indicate that the simulation accurately represents the empirical energy consumption as observed in our real testbed.

4.2.3 Simulation Configurations

Using the validated model, we evaluated our system using all sets of occupancy measurements under multiple different building conditions and climate zones. Table 2 lists three types of building insulations, each of which is decided by the combination of wall construction and air leakage. Table 3 lists the locations that represents the five climate zones in the U.S., ranging from cold Minneapolis, Minnesota to hot Houston, Texas.

In these simulations, we focus on the energy usage of HVAC. Any additional internal loads from artificial lights, appliances, and radiant heat from occupants are intentionally excluded, as they would render results of time and temperature setback studies ambiguous. Natural and artificial air ventilation are also intentionally excluded to keep results focused on changes in thermostat. All the simulation output are tabulated at a one-minute time step.

5 Evaluation

In this section, we first describe the baseline algorithms and the evaluation metrics that are used for evaluation and comparison. Then, we present the performance of the smart thermostat.

5.1 Baseline and Optimal Algorithms

We compare the smart thermostat against the reactive thermostat described in Section 2 that infers three occupant states from sensor data, as shown in Figure 4(a). The reactive algorithm switches to the *Active* state whenever it senses motion firings from a home. The algorithm then waits for a silent period (T_{last}) at least *threshold* minutes long before switching to the *Idle* state. The *Idle* state is classified as *Away* during the day, and as *Sleep* during the night from 10 PM to 10 AM (fixed time interval). The reactive thermostats on the market use proprietary algorithms that are not publicly available, so we created a best-effort replica of the system based on marketing literature and empirical observations of a real system in action [14, 15]. As a standard, we use the EnergyStar setpoint temperatures whenever the occupant wakes or arrives, and the EnergyStar setback temperature whenever the occupant leaves or sleeps [34].

Programmable thermostats do not react to occupancy at all, and so they always achieve the same energy savings, but the comfort sacrifice changes per home. This makes the energy savings difficult to interpret, because it is unclear how much of the energy saving is due to eliminated waste and how much is due to sacrificed comfort. For this reason, we do not include the programmable thermostat in the comparison.

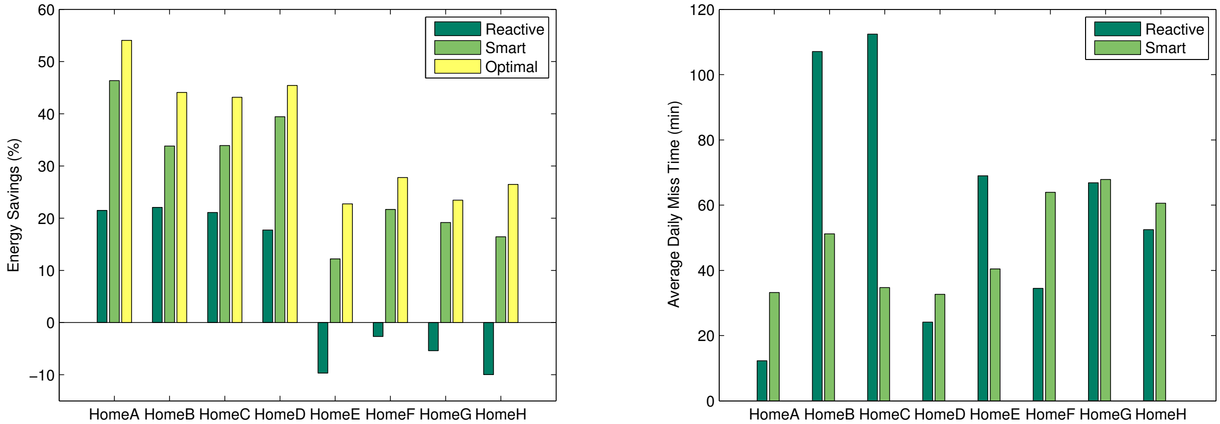
In our comparison with the reactive thermostat, we use a *threshold* of five minutes because it produces a similar comfort sacrifice to the smart thermostat, which makes the energy savings more comparable. As mentioned in Section 3.2, the HMM in our *fast reaction* technique also uses a five-minute time interval with which to decide state transitions. In actual commercial products, such as the BAYweb reactive thermostat [14], a larger threshold such as 60 minutes is usually used by default [35]. Our comparison with five-minute threshold is conservative, because using higher threshold values would only decrease energy savings.

We compare our system with an optimal algorithm that provides the theoretical upper bound on energy savings. We assume that the optimal scheme knows the states of the home at all times, and that there is no lag time in the temperature adjustment at the state switch. This implies that the miss time of the optimal scheme will always be zero. The optimal algorithm applies deep setback whenever the home is unoccupied, and uses the same temperature settings as EnergyStar whenever the home is occupied. Thus, no algorithm could achieve higher energy savings than the optimal algorithm without sacrificing comfort.

The smart thermostat runs over the data traces of either the home deployments or the surveys and other datasets. In order to maintain the validation with limited number of data, we perform leave-one-out cross validation over the number of days of the deployment when training the HMM of online inference algorithm in the smart system. For example, given n days of deployment, we test the HMM on each day using the remaining $n-1$ days of labeled ground truth data as training data.

5.2 Evaluation Metrics

We evaluate the trade-off between energy efficiency and user comfort in the experimental results with two quantitative metrics: energy saving and miss time. *Energy saving* is defined as the percentage of saving by the scheme over the cost of continuously maintaining the setpoint tempera-



(a) Home Energy Savings

(b) Home Miss Time Benchmark

Figure 11. Based on data collected in 8 homes, the smart thermostat saves more energy than reactive systems and sacrifices less comfort.

ture. *Miss time* is defined as the total time when the home is occupied but the temperature has not reached the setpoint temperature. In order to address small temperature fluctuations, our metric tolerates 1°C (1.8°F) temperature difference between the actual temperature and the setpoint. This value is within the bounds of sensor noise.

5.3 Home Deployments Evaluation

We evaluate the smart thermostat against the baseline and optimal algorithms in the 8 home deployments using our validated house model. In the simulation, we run 14 days in January and July using the climate in Charlottesville, VA to evaluate both cooling and heating. We set the deep setbacks to 10°C (50°F) for heating and 40°C (104°F) for cooling, which are safe temperatures that do not cause damage to a house in real life. To further improve the credibility, we randomly map each day of occupancy data traces to each day of weather data traces. These simulations are used to calculate the average of heating in the middle of winter and cooling in the middle of summer.

Figure 11(a) shows the results of energy savings of the 8 homes using sensor deployments. The smart thermostat outperforms the reactive thermostat in all the 8 homes. Homes A-D have regular occupancy patterns so that our system achieves more energy savings, with an average of 16.3 kWh (38.4%), while the reactive thermostat saves 8.7 kWh (20.6%). In contrast, homes E-H are typically occupied for most of the day. The average energy saving of the smart thermostat decreases to 7.4 kWh (17.4%). However, the reactive thermostat wastes energy due to the frequent reactions, which are costly because they must use the higher capacity but lower efficiency stage of HVAC operation. The average energy waste is -2.9 kWh (-6.9%) and the maximum waste is close to 4.2 kWh (10.0%). On average, the reactive thermostat saves 2.9 kWh (6.8%) while the smart thermostat saves 11.8 kWh (27.9%), which approaches the optimal saving at 15.2 kWh (35.9%). Thus, the smart thermostat can reduce energy consumption in a wide range of homes that have different occupancy patterns.

Figure 11(b) shows the miss time of the same three schemes in the 8 homes. Compared to the reactive thermostat, the smart thermostat is better with three homes (B, C and E), the same with one home (G), and slightly worse with four homes (A, D, F and H). The miss times of reactive thermostat, however, are much more variable than those of the smart thermostat. On average, the smart thermostat has 48 minutes of miss time, while the reactive thermostat has 60 minutes. Thus, the smart thermostat actually reduces miss time by 12 minutes on average. We conclude that the two approaches are roughly comparable in terms of miss time, since this is a small average daily improvement that would not likely be noticed in most homes. On the other hand, extreme cases such as Homes B and C probably would be noticeable: the smart thermostat decrease their daily miss times by 55 and 80 minutes, respectively.

6 Analysis

In this section, we analyze how much each component of the smart thermostat algorithm contributes to its energy savings. We also discuss the impact of the number of sensors, climate zones, and building types on the performance of the smart thermostat. Finally, we use a combination of census data, weather data and housing data to weight each of these parameters to generate a weighted sum of expected energy savings if the smart thermostat were applied across the entire U.S..

6.1 Inference Accuracy

We evaluate the accuracy with which our HMM approach tracks occupancy of the home and compare it to the commercial reactive algorithm described in Section 5.1. We expect the HMM approach to outperform the naive reactive algorithm, since the HMM incorporates rich semantic information from the deployment, in contrast to the commercial reactive algorithm that only uses the *number* and *timing* of sensor firings.

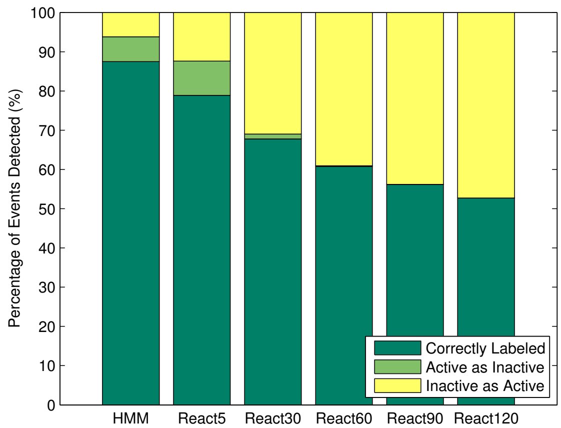


Figure 12. Our HMM has higher accuracy of on-line occupancy inference than baseline approaches.

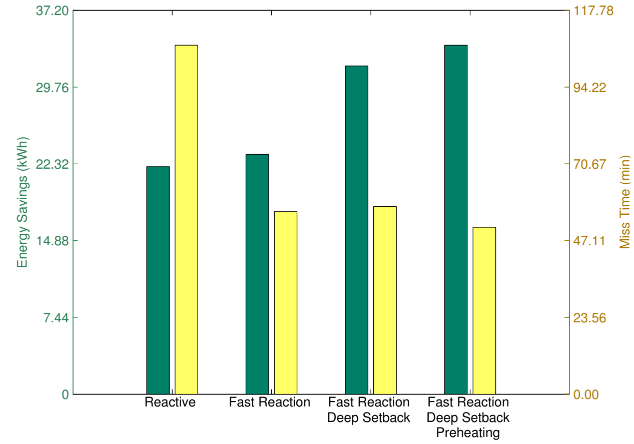


Figure 13. All components of the smart thermostat contribute to the reduced energy usage and miss time (data is from Home B).

Figure 12 shows the accuracy of our HMM approach in inferring the states in the home deployments, in comparison to the naive reactive algorithm. As parameterized by *threshold*, we evaluate the reactive algorithm with different values of *threshold*, ranging from 5 to 120 minutes. Lower *threshold* values result in aggressive implementations with faster reaction to *Away* events, but also increases the probability of idle *Active* events being classified as *Away*; higher *threshold* values result in more conservative implementations. To be fair to the reactive algorithm, we group *Sleep* and *Away* events together as the *Inactive* state, since the reactive scheme uses a simple fixed time window to differentiate *Sleep* from *Away* events. We observe that the reactive algorithm's accuracy was lower when *Sleep* and *Away* are *not* grouped together. We show three evaluation metrics, namely, percentage of events correctly labeled, percentage of events where *Active* is classified as *Inactive*, and vice versa.

The results in Figure 12 show that the HMM approach (88% correctly labeled) outperforms the best reactive algorithm (React5 with only 78% correctly labeled). We see that the HMM classifies fewer active events as inactive and fewer inactive events as active, leading to lower miss times and higher energy gains for the smart thermostat. Thus, our HMM approach is able to achieve higher accuracy than reactive schemes because it is able to automatically incorporate semantic information about which sensors are being fired in the home (living room, bathroom, kitchen or bedroom), and other useful context not currently used in commercial implementations. We also observe that, as *threshold* increases, the reactive algorithm is able to reduce or eliminate the number of active events that are labeled as inactive, by essentially waiting for a longer silence period to ensure high confidence in the *Inactive* state prediction. However, increasing the threshold also leads to more *Inactive* events being classified as *Active*, since the algorithm has to wait for a longer *threshold* period in the *Active* state, before changing the state to *Inactive*.

6.2 Effect of Each Component

The smart thermostat consists of three main components: fast reaction, deep setback, and preheating. To investigate the effect of each component, we run the experiments while adding these components in an accumulative fashion, starting from fast reaction, then adding deep setback and finally adding preheating. We use data from home B for this analysis, and the energy saving and miss time are shown in Figure 13.

The results indicate the effect of each component on total energy saving and miss time. First, we see that fast reaction outperforms the reactive thermostat in energy saving, from 22.0% to 23.2%, and miss time, from 107 minutes to 56 minutes. This is because our on-line inference algorithm is much more effective than the simple threshold used in the reactive algorithm in both responsiveness and accuracy. Once the deep setback is added, the smart thermostat saves 8.6% more energy while the miss time increases slightly by 2 minute due to the larger temperature offset in the reactions. Finally, by preheating when possible, the smart thermostat can achieve energy saving of 34.0% and improve miss time of 51 minutes.

6.3 Sensitivity Analysis

We perform a sensitivity analysis to identify how sensor deployments, occupant types and climates affect the performance of the smart thermostat.

6.3.1 Sensitivity to Number of Sensors

The evaluation of our on-line HMM inference algorithm in Figure 12 uses data from all the sensors installed in our 8 homes. This includes more sensors than shown in Table 1, and includes sensors on daily use objects such as the fridge, microwave, stove, sink, and shower, deployed for activity recognition purposes [36]. In this section, we perform a simple analysis of how many sensors are *actually* required for our proposed smart thermostat.

In particular, we consider two sets of sensors: (i) the full set of sensors (12-20 sensors) including motion sensors, door

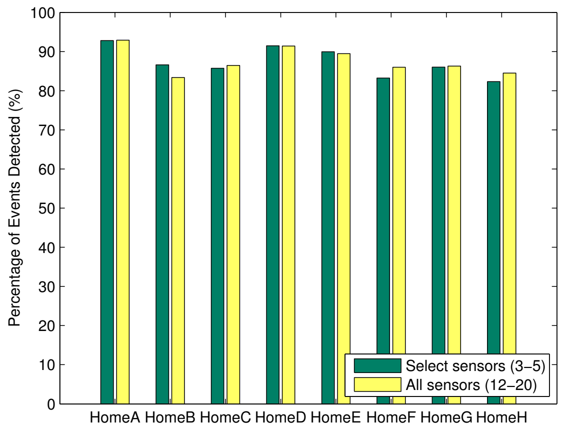


Figure 14. The HMM event detection accuracy is robust even with only a small number of sensors.

sensors and reed switches on everyday objects, and (ii) the *select* set of sensors (3-5 sensors), including *only* the motion sensor in the living room, bathroom, bedroom, and kitchen, and the front door switch sensor, for all our 8 homes. The *select* set is chosen based on intuition about which areas in the test homes would be most indicative of the three activity states, and the same analysis could be done on-site by a trained technician at the time of installation. We only chose the *select* set once for each house, and did not choose and evaluate multiple sets or use post-facto optimization.

Figure 14 shows the percentage of resident states correctly identified by the HMM for our two sensing choices. We observe that the difference in inference accuracy for these two schemes is almost negligible for all homes. Our *selected* sensor set sufficiently captures resident activity in our 8 homes for the purpose of accurately inferring occupancy and sleep information. Figure 15 illustrates how the smart thermostat performs for the 8 households with two different sensor sets. The results indicate that the smart thermostat, for both sensor sets, provides similar energy saving and miss time. The selected sensor set saves energy by 28.9% on avarage, while the sening choice with all sensors achieves the average energy saving of 23.6%. The average miss time of the selected sensors is 54 minutes, while the set of all sensors has 48 minutes of miss time on average. Thus, using our deployments in 8 homes, we show the potential of using a small set of 3-5 sensors at low costs (less than $25) to accurately infer resident state for energy monitoring purposes.

6.3.2 Sensitivity to Occupancy Patterns

We divide the occupants of surveys into homes with *periodic* and *aperiodic* schedules by analyzing the occupancy patterns in each case. For each category, we use the validated house model and run the simulation for heating and cooling for 14 days in January and July, respectively, using the same weather file of our city. Also, for each simulation day, we randomly pick one day out of the deployment days and use its occupancy data for the simulation. When the simulation finishes, we sum the results of all simulation days and then get the average value for energy usage and miss time.

Figure 16 illustrates how the smart thermostat performs for occupants with two main different occupancy patterns. The results indicate that, for both occupant types, the smart thermostat provides much higher energy saving and lower miss time than the reactive thermostat. For aperiodic people, smart achieves 26.4% energy saving and 44 minutes for miss time, while reactive provides 20.0% energy saving and 60 minutes for miss time. For periodic people, smart achieves 32.4% energy saving and 38 minutes for miss time, while reactive provides 23.0% energy saving and 65 minutes for miss time. We observe that the smart thermostat benefits "periodic" more than "aperiodic". This is because the occupancy dynamics of "periodic" is lower than "aperiodic", making it easier to preheat for these people. In general, the smart thermostat is better than the reactive scheme across different categories of occupancy patterns, in both energy saving and miss time.

6.3.3 Sensitivity to Climate Zones

We evaluate the smart thermostat algorithm in each of the five typical climate zones across the U.S.. For each climate zone, we use the validated house model and run the simulation for heating and cooling for 14 days in January and July, respectively. Also, we randomly map the days of deployments to the simulation days. All the results are averaged by the number of simulation days.

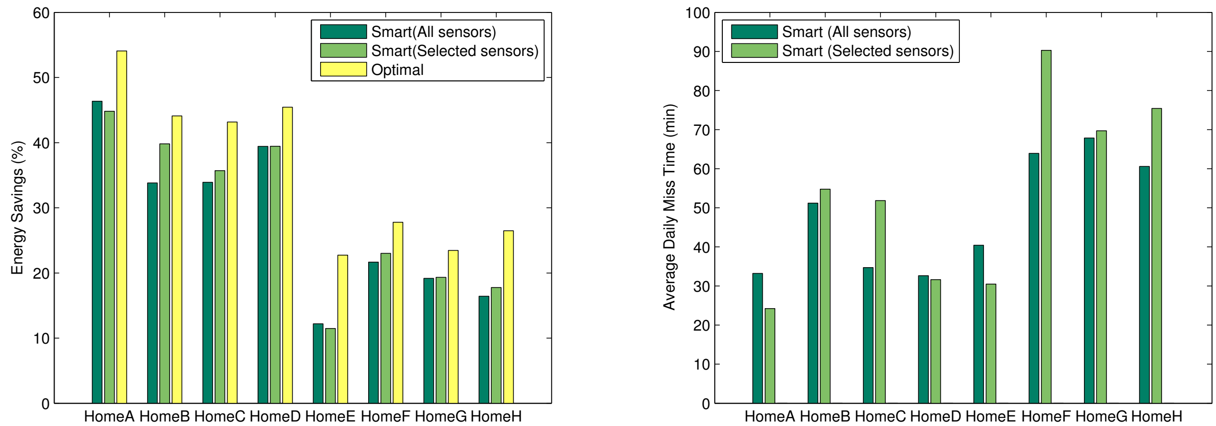
Figure 17 shows the effect of climate on the performance of the smart thermostat, when used with professional occupants. These results indicate that the smart thermostat provides higher energy saving and lower miss time than the reactive thermostat. Another observation is that as the climate becomes warmer from MN to TX, the smart thermostat approaches the optimal scheme in terms of percent energy saving. This is due to two reasons. First, the deep setbacks used by the smart thermostat are beneficial during the day, but are not used at night when the occupants are sleeping. This helps warm climates more, where peak loads are typically mid-day. In contrast, cold climates have peak loads at night. The second reason why the smart thermostat helps more is that the total energy used is higher in cold climates, but the energy saved by the smart thermostat remains roughly constant: in a warm climate, lowering the setpoint temperature by 5-8 degrees may be enough to get the home's heat to turn completely off, saving 100% of the energy. In a cold climate, on the other hand, lowering the setpoint by the same 5-8 degrees will only reduce the energy bill by a fraction.

6.4 Projected Nationwide Savings

Based on the percentage of energy saved by the smart thermostat in each climate zone (Figure 17(a)) and the U.S. Energy Information Administration's data (Table 4) on the amount of energy used for heating [37] and cooling [38] by residences in each zone, we estimate the amount of energy that could be saved if the smart thermostat were deployed in all homes with HVAC systems across the United States. We estimate the energy saved, E_z in zone z as:

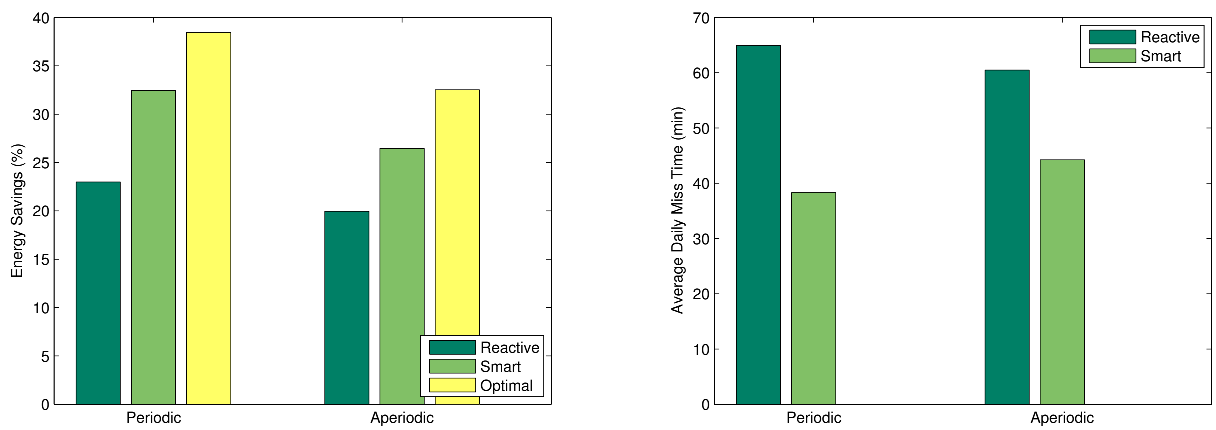
$$E_z = (H_z + C_z) * P_z \quad (1)$$

where H_z is the energy used for heating, C_z is the energy used for cooling, and P_z is the percentage saved by using the smart



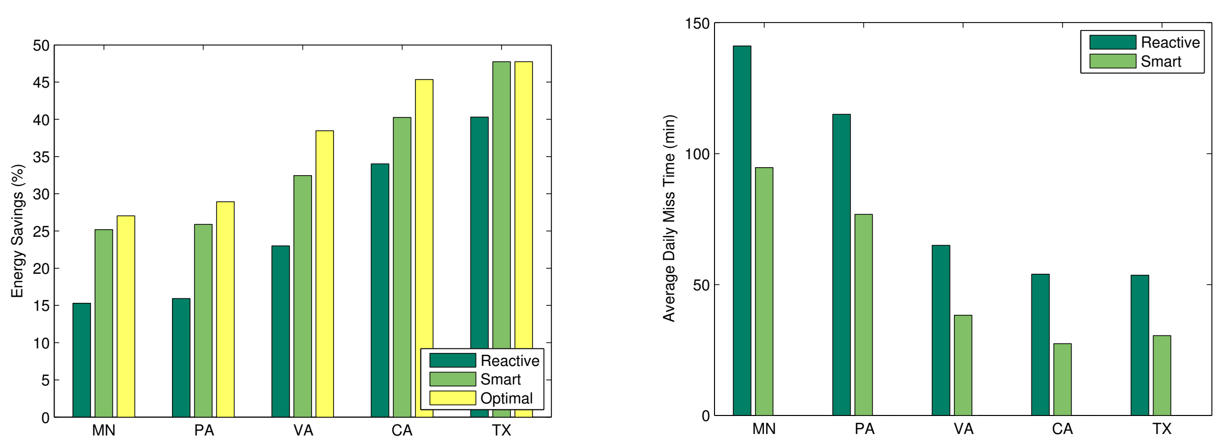
(a) Energy (b) Miss Time

Figure 15. Sensitivity to Number of Sensors



(a) Energy (b) Miss Time

Figure 16. Sensitivity to Occupancy Patterns



(a) Energy (b) Miss Time

Figure 17. Sensitivity to Climate Zones

Climate Zone	Heating (billion kWh)	Cooling (billion kWh)	energy saving (%)
1	9	6	25.1919
2	24	25	25.8860
3	34	33	32.4408
4	23	31	40.2601
5	25	88	47.7498
Total	115	183	

Table 4. Energy usage for heating and cooling in each of the five climate zones.

thermostat in that climate zone. The projected energy saved nationally, NE, is:

$$NE = \sum_{z=1}^{5} E_z \tag{2}$$

and the percentage of energy saved nationally, PE, is:

$$PE = \frac{NE}{\sum_{z=1}^{5}(H_z + C_z)} \tag{3}$$

These calculations give the projected nationwide savings to be 113.9 billion kWh or 38.22% of the electricity used for heating and cooling.

7 Limitations and Future Work

In the current work, we assume that there are no pets or plants in the building. However, the existence of pets and plants would make a difference in the system design. For example, we need to take the requirements of pets and plants into consideration when deciding the setback temperatures, and would need to account for pets when analyzing occupancy sensor data. In the future work, we will provide an interface to allow users to set customized setback temperatures. Future improvements will also be needed to differentiate between pets and people for occupancy sensing.

Another limitation of the current work is that we only evaluate a single type of equipment; different equipment types has different efficiencies, and will offer different risks and benefits for preheating and precooling. In future work, we plan to investigate more equipment types to do a sensitivity analysis, which will give us a more precise vision of the potential impact of the smart thermostat if deployed at large scale.

We plan to extend the smart thermostat and further improve the energy efficiency with the use of zoning. Zoning systems have long been used to stabilize the temperatures in different parts of a home, such as the first and second floor, but these systems are all thermostatically controlled. In preliminary analysis, we find that only half of the rooms are used for up to 60% of the time that a home is occupied, and these rooms are somewhat predictable based on ongoing activities and the time of day. This indicates the potential for substantially more savings by combining the smart thermostat with zoning systems.

8 Conclusions

In this paper, we present the concept of a *smart thermostat* that senses occupancy statistics in a home in order to save energy through improved control of the HVAC system. This system uses a combination of long-term occupancy and sleep patterns with real-time sensor data to control the HVAC system. We evaluate the smart thermostat by analyzing 51 data sets, 8 of which were generated by deploying a real sensor network in homes to collect the wake, leave, arrive, and sleep times of the occupants. Our results indicate that the smart thermostat can provide larger energy savings and more comfort than existing baseline solutions. This approach has a very low initial cost of less than $25 per home, and can save 28% of residential HVAC energy consumption on average, without sacrificing comfort. This solution serves an important need for low-cost energy consumption.

This project has the potential for a large impact because of its low cost. The impact of many otherwise effective energy-saving technologies is limited by high initial cost, because they can take years or even decades to produce a positive return on investment. Studies have shown that energy-saving technologies should produce a return on investment within two years in order to achieve widespread adoption [39]. In the U.S., the average expenditure per household for space heating and electric air-conditioning is $677 [8] annually or $56.42 per month. Therefore, our system should cost about $230 to be financially viable, including the costs of hardware, installation, configuration, and maintenance. Our analysis shows that the sensing-based solutions presented here can be effective with a cost of less than $25 per home in off-the-shelf hardware, and it will also be easy to retrofit to existing homes and buildings. Recently, the American Recovery and Reinvestment Act of 2009 allocated $5 billion toward helping low-income families improve the weatherization of their home. However, this money is only expected to achieve a small percentage of the national target for energy reduction, and achieving the actual targets will require many billions more. The cost profile of the smart thermostat would give more *bang for the buck* to federal stimulus money: we expect a cost of less than $10 billion in hardware to equip all 130 million homes in the U.S. with our system, saving an estimated 113.9 billion kWh nationwide per year. Due to its low cost, this research will help propel the nation towards its goal of a 25% improvement in the energy efficiency of existing buildings across the country by 2030, as defined by the Architecture 2030 Challenge [40] and reiterated by President Obama [41].

9 Acknowledgements

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