# The Self-Programming Thermostat: Optimizing Setback Schedules based on Home Occupancy Patterns

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## Abstract

Programmable thermostats offer large potential energy savings without sacrificing comfort, but only if setback schedules are defined correctly. We present the concept of a self-programming thermostat that automatically creates an optimal setback schedule by sensing the occupancy statistics of a home. The system monitors occupancy using simple sensors in the home, similar to those already used in typical security systems, and the user defines the desired balance between energy and comfort using a single, intuitive knob. Our preliminary results show that this approach can reduce heating and cooling demand by up to 15% over the default setback schedule recommended by EnergyStar.

## Categories and Subject Descriptors

C.3 [**Special-Purpose and Application-Based Systems**]: Real-time and Embeded 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 air conditioning (HVAC) is the largest energy consumer in the home, accounting for 43% of all residential energy usage [8]. Programmable thermostats can substantially reduce this energy usage with a *setback* schedule that relaxes temperature setpoints at certain times of the day, typically when the home is unoccupied or the occupants are sleeping. Consumers are often advised that programmable thermostats can reduce the energy needed to heat and cool a home by 10-30% without reducing comfort [8]. However, choosing a setback schedule that achieves this goal can be challenging because people do not typically know the exact occupancy patterns of their home, especially when it has multiple occupants who come and go at different times. As a result, most people do not use optimal setback schedules for their home [8].

We present the concept of a *self-programming thermostat* that automatically creates an optimal setback schedule by sensing the occupancy patterns in a home. The system monitors occupancy statistics using a small number of cheap and simple sensors such as motion sensors in rooms and magnetic reed switches on doors, similar to those sensors used in security systems that are already deployed in many homes. These statistics are then used to define setbacks when the home is typically unoccupied.

The occupancy pattern of a typical home is not exactly the same every day, and so any given schedule must either condition an empty home on some days (which we call *waste*) or not condition an occupied home (which we call *miss time*). The self-programming thermostat allows the user to define the desired balance between energy and comfort using the *miss time knob*, which defines the maximum tolerance for miss time. As the user turns the knob, the system displays the longest possible setback schedule that achieves each miss time. This interface allows the user to choose a miss time with the desired *bang for the buck* in terms of comfort and energy savings. We expect this interface to allow the user to conserve more energy while sacrificing less in comfort than modifying the setback schedule by hand, or only modifying the temperature setpoints.

We present a preliminary analysis of the self-programming thermostat using home occupancy data for two different individuals. For one individual, the system can produce a schedule that reduces heating and cooling demand by 15% while maintaining the same average miss time as a baseline setback schedule of 8am-6pm, which is the default schedule that ships with EnergyStar compliant thermostats [15]. Alternatively, the system can reduce the miss time by 40% while maintaining the same demand as the baseline schedule. For the other individual, our system can reduce miss time by 12% while maintaining the same heating and cooling demand as the baseline schedule. Alternatively, it can reduce demand by 5% while only introducing approximately 45 minutes of miss time per day, on average.


*BuildSys'09*, November 3, 2009, Berkeley, CA, USA.

## 2 Background and Related Work

Programmable thermostats allow occupants to control an HVAC system by scheduling different setpoint temperatures at various times throughout the day. Programmable thermostats are currently one of the most cost effective ways of reducing a home's energy consumption: they cost approximately $50 and are estimated to save the average homeowner $180 per year [15]. As a rule of thumb, home owners are estimated to save 1% of their energy usage for each degree change, if the setback period is eight hours long [20]. However, these statistics are premised on the ability of the homeowner to define setback schedules that match the occupancy patterns of the home. This can be difficult, especially for homes with multiple occupants and irregular occupancy patterns. In a recent study, more than half of all homes reported not using setback schedules during unoccupied periods of the day or when occupants were sleeping [8].The goal of the self-programming thermostat is to automatically choose an optimal setback schedule for a home by empirically measuring occupancy statistics.

Several existing systems *respond* to occupancy information by turning the HVAC system on or off when the occupants leave or return to the home. For example, the Telkonet SmartEnergy control system allows the user to define a maximum *recovery time* once occupants have returned to the home. The system estimates the lag time to heat or cool the house based on home, system, and weather parameters, and automatically applies setback temperatures when the occupants leave while ensuring that the recovery time constraints can be met once they return [5]. Systems such as this one can be highly effective in spaces with unpredictable occupancy times. In most homes, however, occupancy times are expected to be predictable: most occupants sleep at night, and about half of homes with thermostats are expected to be unoccupied during working hours [20]. Another problem with systems that respond to occupancy is that they are *smart* in the sense that they are not predictable: users can predict neither their average comfort levels during the month nor their energy bill at the end of the month. Both of these values can change dramatically based on the occupancy of the space. In contrast, the self-programming thermostat has a fixed schedule and is therefore more predictable and easier to use [22].

The self-programming thermostat relies on simple sensor technology such as motion sensors in rooms [11] and magnetic reed switches on doors [25, 28] to measure the occupancy statistics of a home. Previous results by one of the authors has shown that this information is possible to extract with high accuracy [24]. Furthermore, these sensors already exist in many homes: over 32 million homes in the US already have security sensors installed on the doors and windows and motion sensors installed inside the home [19], and elderly monitoring and assisted living facilities are designing sensors to detect activity of the medicine cabinet, toilet, shower, sinks, stove, and other appliances [1, 2]. Over 5 million homes have X10 devices [7] and ZigBee devices [14] such as wireless doorbells, appliance controls, wireless smoke detectors, and wireless light switches. As homes become increasingly instrumented with wireless devices, the costs of deploying sensor infrastructure for the self-programming thermostats may be amortized or even disappear.

One distinguishing feature of the self-programming thermostat is the approach of automatically integrating information about building occupants into normal system operation. Most research and innovation in building efficiency focuses primarily on weatherization [16, 21] and equipment efficiency [17, 12, 9]. For example, a November 2006 report by the President's Council for Advice on Science and Technology (PCAST) identified building insulation and energy efficient windows, appliances, lighting, and HVAC systems as key priorities for improved building efficiency [18], but none of the focus areas identified in this report related to the interaction of a building with its occupants. Several other studies are using information about energy consumption to influence the behavior of occupants, including the energy dashboard [10], Microsoft Hohm [4], and Google PowerMeter [3], all of which aim to inform people about their own energy expenditures to empower them to change their own behaviors. Early results showed that up to 33% of energy consumption is due to occupant behaviors [23], which indicates that changes to occupant behavior can be an effective means of conserving energy. The self-programming thermostat does not aim to influence user behavior, although the information that it collects could be used toward this goal in future work.

## 3 The Self-Programming Thermostat

The self-programming thermostat is a sensing system that aims to conserve energy by sensing the occupancy of a home and optimizing the setback schedule accordingly. This system does not modify the temperate setpoints chosen by the user; it only helps the user choose the optimal times at which these setpoints should take effect. The self-programming thermostat allows the user to choose a target miss time by turning the *miss time knob*, and it displays the longest setback schedule that achieves that miss time based on all occupancy statistics previously gathered. This interface allows the user to balance energy cost and comfort, and we expect this interface to allow the user to conserve more energy while sacrificing less in comfort than if the user were to modify the schedule by hand, or were to only modify the temperature settings.

### 3.1 Problem Definition

The goal of the self-programming thermostat is to define a fixed setback schedule that minimizes miss time *on average*, given occupancy statistics. Over the course of $n$ days, the system observes the time $T_{leave}$ that the individual leaves from the home each day, and the time $T_{arrive}$ that the individual arrives at the home. From this data, the system must define a setback schedule, which is defined by two parameters: $T_{off}$ is the time at which the HVAC system is scheduled to relax the setpoint temperature, and $T_{on}$ is the time at which it is scheduled to resume the normal setpoint temperature. Most modern programmable thermostats provide four programmable parameters (to create setback periods at night), but in this study we will consider a simplified problem in which a schedule is defined by only two parameters.

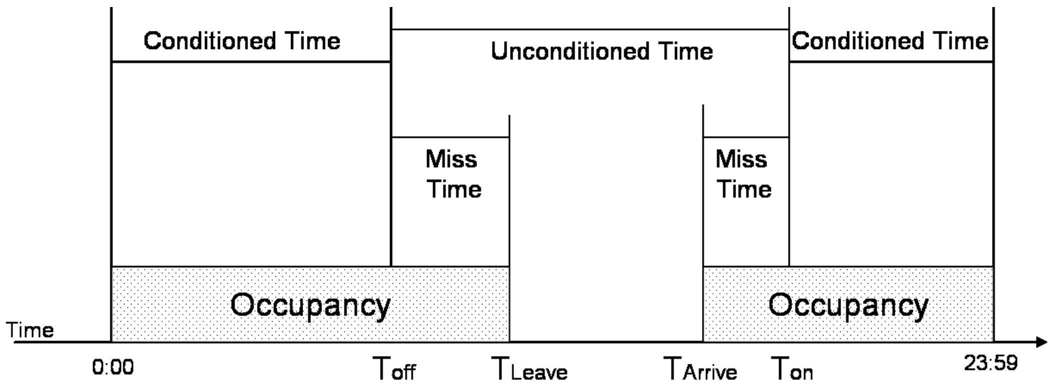


**Figure 1. Typically, a home is conditioned when it is occupied and unconditioned when it is unoccupied. *Miss time* occurs when the home is occupied and unconditioned, i.e. $T_{off} < T_{leave} < T_{on}$ and/or $T_{off} < T_{arrive} < T_{on}$.**

Let *conditioned time* (CT) be the time duration $[T_{on}, T_{off}]$ in which the home must be conditioned, and *unconditioned time* (UCT) be the time duration $[T_{off}, T_{on}]$, which is equal to $24 - CT$. Due to the unpredictable nature of home occupancy, an occupant may be home during the unconditioned time. In other words, we may have $T_{off} < T_{leave} < T_{on}$ and/or $T_{off} < T_{arrive} < T_{on}$. We call this period *miss time*. The concepts of miss time, conditioned time, and unconditioned time are illustrated in Figure 1. We define the measure of the comfort for a schedule to be the *average miss time* (MT), which is defined as

$$MT = \sum_{1}^{n} \frac{max(0, T_{leave} - T_{off}) + max(0, T_{on} - T_{arrive})}{n}$$

We evaluate the efficiency of a schedule by comparing to a baseline schedule $T^*_{off} = 8:00$ and $T^*_{on} = 18:00$. These times are the default schedule that is required to be pre-programmed onto all EnergyStar compliant programmable thermostats [15]. The efficiency of a schedule is defined as the *reduction in conditioned time* (RCT) over the baseline schedule, which is defined to be:

$$RCT = \frac{24 - (T_{on} - T_{off})}{10}$$

The baseline EnergyStar schedule is an aggressive schedule that assumes the home is unoccupied for approximately 10 hours each day. We expect this to be a conservative baseline: if people modify their setback schedules at all, they are likely to reduce the setback period from the default rather than increase it, thereby improving the relative performance of our system. In any case, survey results indicate that many people do not modify the setback schedules on their thermostats from the default values [8].

## 3.2 The Intuition

We analyzed the leave and return times from publicly-available data sets that contained home occupancy information for two individuals over the course of approximately one month. These data sets were collected by manually labeling activities such as sleeping, eating, and bathing, and leaving home. We will call these the Kasteren [26] and Tulum [13] datasets, respectively, and for the purposes of this study, we will only use the *leave home* and *arrive home* event labels. Higher efficiency could probably be attained by using information about other activity labels in these home, but that is outside the scope of this study.

The distribution of leave and return times for the Kasteren and Tulum datasets are shown in Figure 2, and clearly illustrate that these two individuals have very different departure and arrival times from each other, which indicates that any default schedule programmed into thermostats in the factory would likely not be ideal for both individuals. Furthermore, these two individuals show strong periodic patterns in their daily routines, often leaving from and arriving at the house at approximately the same times each day[1]. This indicates that the occupancy patterns of these individuals is predictable, and so the approach of using a fixed setback schedule will be effective for both individuals.

However, the distribution of leave and arrival times for the two individuals is very different, and this will affect the setback schedules generated by the self-programming thermostat. For example, the Tulum individual is consistently away from home for longer periods than the Kasteren individual. If both individuals were to indicate zero tolerance for miss time, the system would produce the optimal schedule $T_{off} = \max(T_{leave}), T_{on} = \max(T_{arrive})$ for both individuals, which would benefit Tulum more than Kasteren, producing 7 and 4 hours of setback duration, respectively. On the other hand, the Kasteren individual has larger variance in the leave and arrival distributions than the Tulum individual and, accordingly, can achieve more *bang for the buck* by slightly increasing tolerance for miss times. Intuitively, this is because a slight increase in the setback period will cause miss times on a smaller fraction of the days for Kasteren than Tulum. As long as $min(T_{leave}) < T_{off}$ and $T_{on} < max(T_{arrive})$, the number of increased hours of unconditioned time will be larger than the number of increased hours of average miss time, and so the derivative will be greater than one: $\frac{\delta UCT}{\delta MT} > 1$.

[1] This analysis only considers weekdays.

### 3.3 Optimization Algorithms

The self-programming thermostat defines two optimization algorithms. The first algorithm is called *Maximize UCT* and it maximizes UCT given MT. The second algorithm is called *Minimize MT*, and it minimizes MT given UCT. For brevity of the pseudocode, we define four values $A$, $B$, $C$, and $D$ that represent the minimum and maximum leave and arrival times of an individual:

$$
\begin{aligned}
A &= \min(T_{leave}) \\
B &= \max(T_{leave}) \\
C &= \min(T_{arrive}) \\
D &= \max(T_{arrive})
\end{aligned}
$$

The algorithm for Maximize UCT is illustrated in Algorithm 1. This algorithm starts with the maximum possible setback period UCT and uses a sliding window technique to calculate the minimum value of $MT$ for all schedules with that setback period. The algorithm gradually shrinks the size of the setback period and repeats until the desired value of $MT$ is achieved. The algorithm returns the first schedule that achieved the desired value of $MT$.

**Algorithm 1** Maximize UCT

**Input**: miss time $mt$, occupancy pattern $op$

**for** $UCT(T_{off}, T_{on}) = UCT(A, D) + mt$ to $mt$
    Label $A'$ with $UCT(A, A') = mt$. Label $D'$ with $UCT(D, D') = mt$;
    Slide $(T_{off}, T_{on})$ from $A'$ to $D'$
        **if** $MT((T_{off}, T_{on}), op) == mt$
            **return** $(T_{off}, T_{on})$ and $UCT(T_{off}, T_{on})$;
        **end**
    **end**
**end**

The algorithm for Minimize MT is illustrated in Algorithm 2. Given a desired value of $UCT$, this algorithm performs a single pass across the data set by increasing $T_{off}$ from 0 to $24 - UCT$, setting $T_{on} = T_{off} + UCT$, and calculating the average value of $MT$. The algorithm then returns the values of $T_{off}$ and $T_{on}$ that achieve the minimum average value of MT.

**Algorithm 2** Minimize MT

**Input**: unconditioned time $uct$, occupancy pattern $op$

Fix $UCT(T_{off}, T_{on}) = uct$;
Slide $(T_{off}, T_{on})$ within one day time
    $[(T_{off}, T_{on}), MT(T_{off}, T_{on}), op)] \rightarrow \{[(T'_{off}, T'_{on}), mt']\}$
**return** $[(T_{off}, T_{on}), mt]$ with $mt{=}{=}min(mt')$;

## 4 Experimental Results

We applied the Maximize UCT algorithm to both data sets for all values of MT from 0:00 to 24:00 at fifteen minute intervals. The result is the *Pareto optimal curve* of setback schedules: the longest duration setback period $UCT$ for every possible miss time $MT$. These curves are illustrated in Figure 3. The miss time knob allows each user to dial in to any point on this Pareto optimal curve.

Both Pareto curves are flat for very low values of MT, are curved with a slope greater than 1 for mid-level values of MT, and have a slope of 1 for high values of MT. This follows from our intuitive analysis in the previous section. For example, the size of the flat region is proportional to the time between the latest departure and the earliest arrival, i.e. $min(T_{arrive}) - max(T_{leave})$: the flat region is much longer for the Tulum dataset, which has a long period in which the occupant is consistently out of the house. The size of the curved regions are proportional to the variance in the user's arrival and departure times; the Kasterem data set has a much longer curved region than the Tulum data set due to its high variance.

Figure 4 calculates the MT and reduced condition time (RCT) values for six schedules that the self-programming thermostat might recommend to each user. These schedules are called:

1. **baseline:** the 8:00-18:00 schedule, for which $RCT = 0$ by definition
2. **base-CT:** minimizes MT while maintaining the same CT as the baseline schedule
3. **base-MT:** minimizes CT while maintaining the same MT as the baseline schedule
4. **5% RCT:** minimizes MT while reducing the baseline CT by 5%
5. **10% RCT:** minimizes MT while reducing the baseline CT by 10%
6. **15% RCT:** minimizes MT while reducing the baseline CT by 15%

The results show that our approach can reduce miss time over the baseline schedule by 40% and 15% for the Kasterem and Tulum data sets, respectively, as seen by comparing the first and second sets bars. Furthermore, it can reduce the conditioned time by 15% for the Kasterem data set without affecting the miss time, as seen by comparing the first and third sets of bars. Thus, without any input from the user, the self-programming thermostat can produce substantial energy savings simply by shifting the times of the default setback schedule to best match each user's daily patterns. This approach cannot reduce conditioned time for the Tulum dataset, however. This is because the user rarely leaves or arrives during the baseline schedule's conditioned time, and therefore produces little waste.

The second set of three schedules show that the self-programming thermostat could reduce energy costs by 5% for the Tulum dataset while only causing an average of 45 minutes of miss time per day. This amount of unconditioned time is likely to be tolerable since the temperature will be approaching that of a conditioned state.

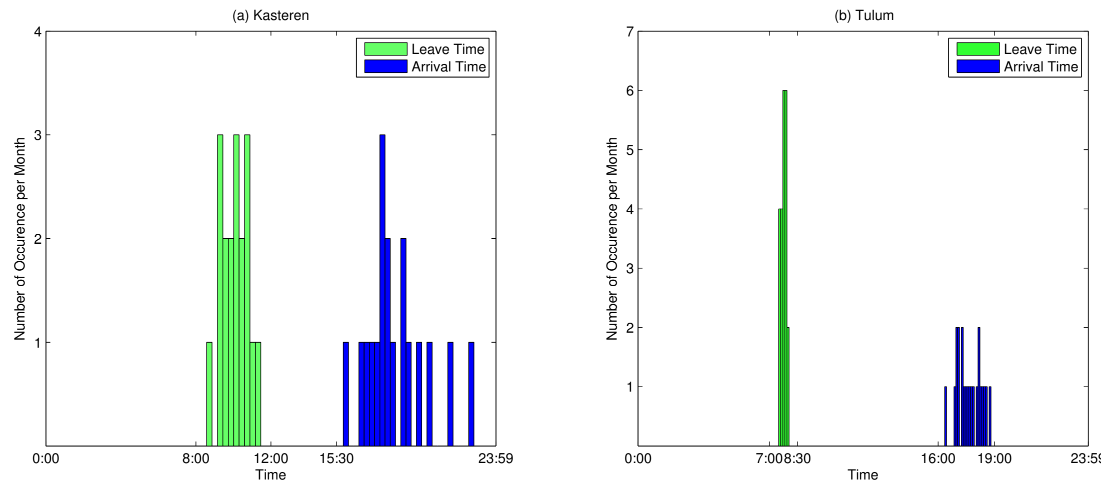


**Figure 2. The departure and arrival distributions are very different for both users, in terms of both mean and variance.**

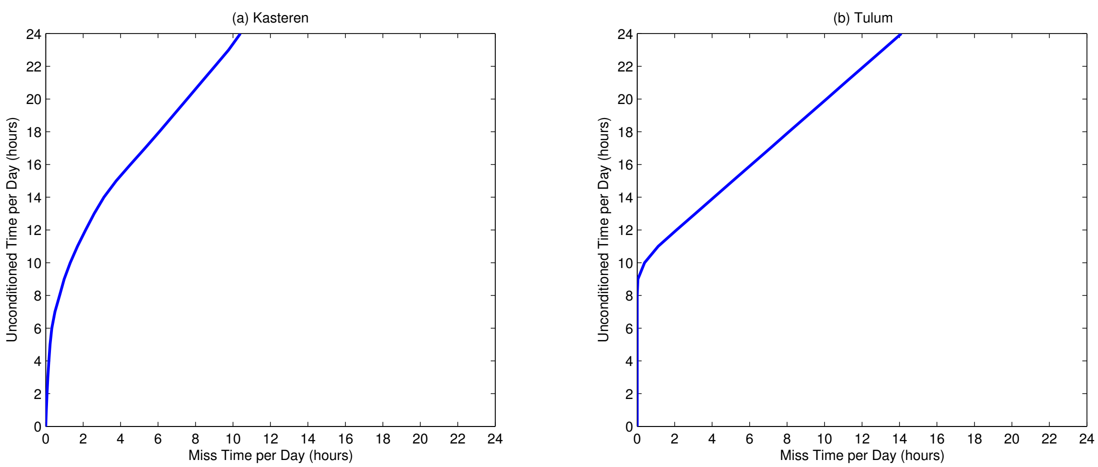


**Figure 3. These Pareto optimal curves illustrate the longest possible setback duration for any given miss time.**

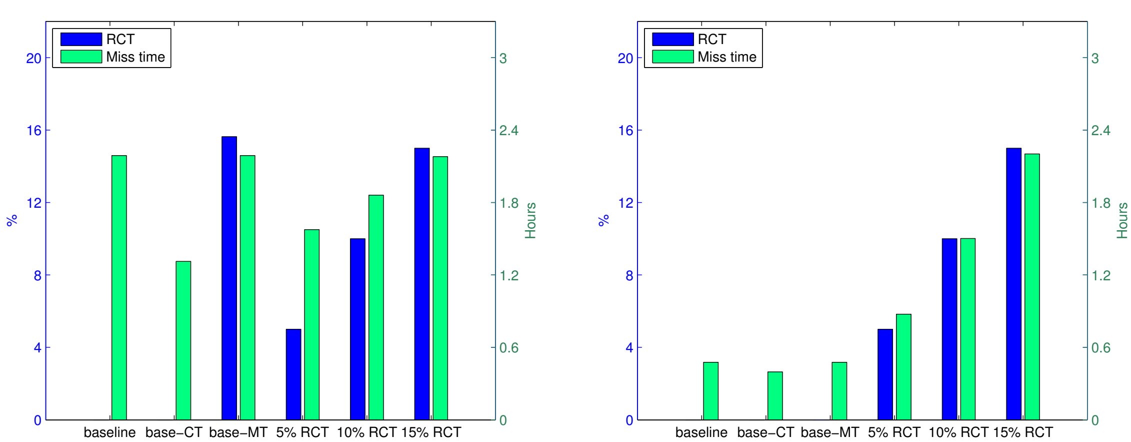


**Figure 4. The miss time (MT) and the reduction in conditioned time (RCT) are shown for six different schedules. The baseline setback schedule recommended by EnergyStar is on the left. Kasterem could reduce CT by 15% without increasing MT, and Tulum could reduce CT by 5% while only introducting about 45 minutes of miss time per day.**

## 5 Conclusions

In this paper, we present the concept of a *self-programming thermostat* that senses occupancy statistics in a home in order to optimize the setback schedule. We present a preliminary analysis of two empirical data sets that provides strong support for our hypothesis that substantial HVAC waste can be reduced by monitoring the occupants of homes and automatically optimizing setback schedules. The strength of this conclusion is limited by the small number of users studied, and our inability to convert reduced waste into concrete energy conservation statistics. However, these preliminary results demonstrate that this approach warrants further study, and that it likely to succeed.

The approach presented here is the most simplistic version of the self-programming thermostat, and more sophisticated techniques could provide better results. For example, the departure and arrival times of users could be more predictable based on the day of the week, the day of the year, or personal schedules and appointments available online through an electronic calendar. Similarly, previous work by the authors has demonstrated that simple sensors such as those required by the self-programming thermostat can be used to recognize activities of daily living such as sleeping, cooking, showering, and grooming [25]. These activities could also be used to improve prediction about arrival and departure times. As these predictions are improved, the conditioned time can be decreased without increasing the miss time.

A current nationwide goal is to improve energy efficiency of existing buildings by 25% [27], and the American Recovery and Reinvestment Act of 2009 has already allocated $5 billion dollars for retrofitting low-income homes and $4.5 billion dollars for federal buildings [6]. However, retrofitting homes with improved weatherization and equipment upgrades can cost thousands of dollars per home. The self-programming thermostat requires approximately $100 in new sensor hardware per home, and therefore has the potential to have a larger impact on the overall national energy budget that existing approaches, given the same number of investment dollars.

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