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Energy Savings from Five Home Automation Technologies: A Scoping Study of Technical Potential

Final Report to the Consumer Technology Association

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Executive Summary

Home automation uses connectivity, sensing, and controls to provide consumer benefits, such as enhanced comfort, control, convenience, and security. Many applications can also reduce home energy consumption. With sales of home automation products and services projected to increase rapidly, the Consumer Technology Association (CTA) commissioned this study to quantify the technical energy savings potential[1] of home automation approaches in the U.S. and to identify their related non-energy benefits.

Based on a review of product and technical literature, we identified 17 candidate home automation approaches and selected five to study in depth. We based the selection on preliminary savings estimates and feedback from CTA TechHome Division members and energy efficiency program administrators and developers. Results, shown in Table 1, include direct energy savings less any operational energy (excluding energy used by home networks or the cloud to transmit and store data).

Table 1: Annual technical energy savings potential estimates for selected home automation approaches.

	Primary Energy		Household Savings Potential				
	quads[1]		MMBtu[2]	kWh			Relevant[**]
Approach	**Usage[3]**	**Savings**	**Heating**	**Cooling**	**Lighting**	**Electric[*]**	**Households**
Connected Thermostat	7.5	0.7-1.1	6	400	-	-1 to -30	80-90%
HVAC Zoning[3]	7.5	0.3-0.6	4	210	-	-5 to -50	60-85%
Window Covering Control[3]	7.5	0.3-1.0	5	580	±50	-90	80%
Lighting Control, Occupancy	1.5	0.4-0.6	-	-	370 to 580	-50 to -235	100%
Circuit-level Control	2.5	0.8	-	-	-	630	100%

[1] One quad = 10^{15} British thermal units (Btus)
[2] MMBtu = one million Btus.
[3] Estimates based mainly on simulations and carry higher uncertainty.
[*] Negative values indicate energy used during operation.
[**] Portion of households to which an approach is applicable.

The technical energy savings potential of these individual approaches ranges from 0.3 to 1.1 quads, or 1-5% of the total primary energy consumed by U.S. homes in 2015. Put another way, saving one quad per year is equivalent to the energy consumed by about 3 million people, the electricity produced by 250 coal-fired power plants, or 56 million metric tons (MMT) of CO_2 emissions (DOE 2012). Since several approaches address the same energy end-use (e.g., connected thermostats and HVAC zoning both affect HVAC energy consumption), the combined savings potential is somewhat less than their sum. How much of this potential could actually be realized depends on practical considerations that are not yet fully understood.

While these estimates represent current knowledge, most categories carry appreciable uncertainty due to the limited number and scope of field studies. Differences in occupant behavior, building construction, climate, and HVAC systems can all affect household-level energy impacts. For several categories, products are not yet widely available. Pursuing targeted field studies of sufficient scale, especially for approaches whose savings depend heavily on occupant behavior, could improve estimates and reduce uncertainty.

Beyond energy savings, home automation offers benefits to both consumers and utilities. For consumers, these include greater convenience, control, thermal and visual comfort, privacy, and security. For utilities, home automation could enable demand response capabilities, streamline evaluation for energy efficiency programs, and remotely diagnose and detect retrofit opportunities.

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[1] *Technical Energy Savings Potential* is the theoretical savings that could be achieved if adopted by the entire portion of relevant homes.

Key findings for each home automation approach are presented in Table 2. Potential directions for future research are highlighted in Table 3. Detailed analysis and supporting information follows in the body of this report.

Table 2: Summary of selected home automation approaches.

Approach	Value	Notes
Connected Thermostats		
Relevant Primary Energy[2]	7.5 quads	= 5.3 heating + 2.2 cooling
Technical Savings Potential	0.7-1.0 quads	= 0.7 heating + 0.4 cooling
	9-13%	reduction in relevant primary energy
Household Savings Potential	4 MMBtu	heating, typical
	300 kWh	cooling, typical
Notes	Uncertainty stems from the limited number and scope of field studies, strong dependence on user behavior, and the potential for improved features and algorithms.	
Consumer Benefits	Improved control, usability, comfort, convenience, and security.	
Utility Benefits	Demand response resource: 0.5-1.5 kW per device during DR events in hot climates. Remote identification of retrofit opportunities, HVAC diagnostics, efficiency program evaluation.	
High Value Applications	High-vacancy buildings, irregular occupancy schedules; high-load homes (poor insulation, leaky, large window area), large homes.	
HVAC Zoning Control		
Relevant Primary Energy	7.5 quads	= 5.3 heating + 2.2 cooling
Technical Savings Potential	0.3-0.6 quads	= 0.4 heating + 0.2 cooling
	4-8%	reduction in relevant primary energy
Household Savings Potential	4 MMBtu	heating, typical
	210 kWh	cooling, typical
Notes	Rooms or zones are conditioned independently to reduce unnecessary heating and cooling. High uncertainty due to lack of field studies. Results depend on compatibility with existing systems, especially single-capacity and single-speed air-based systems, the thermal isolation of rooms, and occupant behavior.	
Consumer Benefits	More precise room-level thermal control, improved thermal comfort.	
Utility Benefits	Improved/extended thermal comfort during demand response events.	
High Value Applications	Homes with frequently vacant and thermally isolated rooms; air-based HVAC systems with variable-capacity compressors and blowers; hydronic systems.	
Window Covering Control		
Relevant Primary Energy	7.5 quads	= 5.3 heating + 2.2 cooling + secondary influence on lighting energy
Technical Savings Potential	0.3-1.0 quads	= 0.5 heating + 0.6 cooling - 0.1 operational
	4-13%	reduction in relevant primary energy
Household Savings Potential	5 MMBtu	heating, typical
	490 kWh	cooling, typical
Notes	Automated window coverings control solar gains to reduce the need for heating, cooling, and/or lighting energy. High uncertainty is due to lack of field studies. Results depend on covering type, building characteristics, and operational strategy. Savings can be negative.	
Consumer Benefits	Improved thermal and visual comfort, privacy, security, higher home resale value, convenience, control, and ease of operation.	
Utility Benefits	Improved or extended thermal comfort during demand response events.	
High Value Applications	Highly glazed homes, undersized HVAC systems, windows with high solar exposure.	

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[2] Based on DOE/EIA 2015.

Approach	Value	Notes
Occupancy-based Lighting		
Relevant Primary Energy	1.5 quads	lighting
Technical Savings Potential	0.4-0.6 quads	lighting
	27-40%	reduction in relevant primary energy
Household Savings Potential	320-530 kWh	lighting, typical
Notes	Significant uncertainty due to a lack of field studies correlating occupancy and lighting use. Using lamp-based controls instead of room-based controls would reduce the savings range to 0.2-0.4 quads. A widespread replacement of incandescent lamps with LED and fluorescent lighting would significantly reduce the relevant primary energy consumption, thereby reducing overall savings potential.	
Consumer Benefits	Security and safety functions for outdoor lighting. Communicating systems offer convenience and ability to create scenes/moods.	
Utility Benefits	Communicating systems can potentially be used provide feedback on lighting usage and energy consumption and identify energy savings opportunities.	
High Value Applications	Bathrooms and bedrooms appear to have the greatest energy savings potential.	
Circuit-level Control		
Relevant Primary Energy	2.5 quads	Primary: most consumer electronics. Secondary: standby power of HVAC, white goods, ceiling fans.
Technical Savings Potential	0.8 quads	electric loads
	32%	reduction in relevant primary energy
Household Savings Potential	630 kWh	Typical
Notes	Applies to devices that draw power when not actively used and can be powered off without inconveniencing consumers. Savings opportunities will diminish as devices become more efficient in low-power mode. A majority of savings come from Tier 2 Advanced Power Supply functionality.	
Consumer Benefits	Networked, controllable circuit-breaker panels could provide greater insight into energy consumption, enhance security, and enable load management for islanded operation.	
Utility Benefits	Networked, controllable circuit-breaker panels could provide greater insight into energy-saving and demand-response opportunities, customer segmentation.	
High Value Applications	Home A-V centers, home offices.	

Table 3: Research needs.

Problem/Opportunity	Reason(s)	Research Needs
General		
Energy savings estimates have high uncertainty.	Savings can vary significantly among households, and among products within a device category. Simulation-based analyses can have high uncertainty because of oversimplified assumptions about user behavior and/or baseline conditions. Large-scale representative field studies are rare because technology adoption is still relatively low. Current users (early adopters) may not be representative of the general population. Small-scale studies provide an indication of savings potential but may not be generalizable.	Execute well-designed (randomized) long-term, large-scale field studies of energy performance across device categories, climate regions, and household types. Leverage field data sources (from home automation devices) to inform realistic simulation, specifically to better characterize impacts of user behavior.
Long-term energy savings (persistence) is unknown.	Long-term adoption is still fairly low for most product categories. Energy performance depends on how people use the technology, and this can change with time. Technology upgrades (hardware or software) can also change the energy performance of installed home automation over time.	Long-term field studies, ongoing analysis of (anonymized) user data of home automation technologies.
Consistent savings calculation methods must be developed.	Industry-standard methods do not yet exist for calculating energy performance or savings of home automation devices that depend strongly on behavior. Baseline assumptions may differ depending on what is being calculated (e.g., savings vs. performance).	Develop and validate standard methods based on industry-stakeholder process (backed by independent research).
Approach-Specific	**Key Issues**	**Research Needs**
Connected Thermostats	Savings and persistence can be highly variable. Inconsistent savings methods used across field studies, especially because of highly variable baseline behavior among homes with non-connected thermostats.	Long-term field studies, consistent methods for reporting savings or performance, and clear definitions of baselines.
HVAC Zoning Control	Zoning could *increase* HVAC energy consumption for a single-speed/capacity system. Improperly implemented zoning could create HVAC operational problems, particularly for single-speed/capacity systems.	Field study of the net energy impact of zoning for fixed- and variable-capacity HVAC systems in a range of home types and climates.
Window Covering Control	Simulation-based analyses have high uncertainty due to simplified assumptions about user behavior and/or baseline conditions that strongly impact actual savings. Lack of field studies for window covering controls.	Field studies evaluating the net energy impact in a representative sample of homes, for the main types of window coverings.
Lighting Control	Lighting usage and its correlation with occupancy by room is not well known, making it difficult to estimate savings from lights that are left on in unoccupied rooms.	Field studies in a representative sample of homes that measure coincident time-series occupancy and lighting usage by room.
Circuit-Level Control	Field and laboratory studies of Tier 2 Advanced Power Supplies (APS) have evaluated savings for periods of well under a year.	Multi-year field study to evaluate persistence of energy savings for Tier 2 APS in both media center and home office applications.

1 Introduction

1.1 Background

Home automation technologies use connectivity, sensing, and controls to provide consumer benefits, such as enhanced comfort, control, convenience, and security. These benefits reflect consumer priorities and are driving the rapid increase in adoption (Park Associates/CEA 2014, IControl 2015, St. John 2015). Collectively, networked home automation systems can enable sensor- and user-driven control of HVAC systems, appliances, lighting, outlets, home security, webcams, home energy displays, home performance analytics, and beyond. By controlling these systems, home automation technologies can strongly influence home energy consumption.

Moreover, data from multiple connected devices could enable new energy savings opportunities, such as whole-home control and performance diagnostics. Occupancy inference and activity recognition, two areas of vigorous ongoing research, seek to leverage a range of in-home data sources, including cameras, conventional occupancy detectors, radio frequency identification (RFID) tags, pressure pads, network activity, Wi-Fi or Bluetooth signals, microphones, electric power, and others (Nguyen and Aiello 2013).

Prior study suggests that home automation could address a large technical energy savings potential.[3] For example, one scoping study estimated that about 20% of residential primary energy consumption is wasted conditioning unoccupied homes and rooms, and a further 3% is wasted by electronics that draw power in off or standby modes (Meyers et al. 2010). Unfortunately, most aggregate savings estimates of this kind are based on crude assumptions and may not accurately portray realizable savings.

Home automation concepts have existed for decades, yet until recently have achieved limited U.S. adoption. As internet access, wireless connectivity, and smart-phone ownership have become ubiquitous in the last decade, many new connected devices (the “Internet of Things”) have come to market, and their growth is projected to continue (e.g., CTA 2016).

Energy management capabilities could further increase adoption, particularly as time-varying electric rates become more common, yet the energy savings potential is not well characterized for most approaches (Karlin et al. 2015, NEEP 2015). In Japan, where home energy management systems are now commonplace, adoption was driven by “a mature transmission grid, a pressing need to reduce energy demand, and the opportunity to become a world leader in a new technology market” (Bojanczyk 2012). The poorly characterized energy savings of home automation in the U.S. keeps providers from effectively marketing their energy value proposition and utility energy efficiency program administrators from fully considering these approaches for their programs. Quantifying the energy-related value of home automation could, therefore, increase consumer appeal and allow product and service providers to monetize new revenue streams, such as utility energy efficiency and demand response programs.

To address this knowledge gap, the Consumer Technology Association (CTA)™ – formerly the Consumer Technology Association (CEA)® – commissioned this study to quantify the technical energy savings potential of home automation approaches in U.S. homes.

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[3] *Technical Energy Savings Potential* is the theoretical savings that could be achieved if adopted by the entire portion of relevant homes.

1.2 Approach

This study evaluates the technical energy savings potential of selected home automation approaches. By technical potential, we mean the theoretical energy savings that could be achieved if implemented in all homes where an approach could be applied. The savings estimates include the direct energy savings less the direct operational energy (e.g., power used by the device in question), and exclude energy consumed by existing home networks and for transmitting and storing data. Unless field data suggest otherwise, we assume that people would generally use the technology to reduce their home energy consumption. This provides a reasonable (but not absolute) upper bound on possible savings.

Most approaches evaluated in this study have not yet been widely adopted and lack comprehensive field studies to evaluate their savings. Consequently, we based our analysis on the available field studies, simulations, and best estimates, which we recognize have limitations. Actual performance among homes could vary substantially because of differences in user behavior, integration challenges, or for other unforeseen reasons. These results should be viewed as approximate and uncertainty will vary depending on the available data.

Our analysis also assumes that all interoperability and adoption challenges could be overcome. Some technologies will require continued development effort before widespread adoption can take place, but most are applicable to a large portion of homes today. If the current pace of innovation continues, many of these challenges could be addressed. Major barriers are noted in the appropriate sections.

We purposely did not consider the cost of implementation or payback periods, in part because data are limited and also because prices are likely to remain fluid until the technology matures. The incremental cost is particularly difficult to properly address, since home automation technologies could be purchased for reasons other than energy savings, for instance to improve comfort, security, and convenience.

In addition to assessing the typical per-home and national (U.S.) technical energy savings potential of the approaches selected for further analysis, we also characterized several other aspects of interest to home automation stakeholders, including demand response (DR) potential, non-energy benefits to households and utilities (important drivers of adoption), and notably high-value applications (e.g., geographic location, utility service territory, and housing type).

1.3 Selecting Priority Approaches

We used the following approach to select home automation approaches to study in depth:

1. Develop a list of home automation systems, services, and devices to consider for evaluation
2. Select a subset of priority approaches for deeper analysis
3. Develop refined energy savings estimates for these priority approaches

We began by reviewing the home automation literature and commercially available products to identify the current approaches and to select several to study in more depth. To make the results of this study more generalizable, we defined product categories broadly based on the *core functionality* integral to each specific approach. In reality, competing product offerings in a single category could offer different combinations of features that could enhance (or detract from) the actual energy savings potential. For example, consumers can choose among many connected thermostat products. All connected thermostats allow users to connect and control the thermostat remotely, and this is the core feature. A subset include advanced features, such as occupancy detection or automatic setpoint adjustment. Although savings depend on which features are included and how they are used, limited data and prior research prevents us (at this time) from effectively attributing energy savings impacts to specific features.

Based on this strategy, we identified 17 home automation approaches to consider (see Table 1-1). Time and scope constraints led us to select five priority approaches where a refined analysis would yield the greatest value.

To prioritize the approaches, we developed preliminary estimates for their energy savings potential. First, we identified the annual energy consumption (AEC) by residential end-use (see Figure 1-1). For each approach, we identified the subset of AEC that it could affect. For example, connected thermostats pertain to the subset of heating and cooling energy associated with home HVAC systems that are controlled by a thermostat (excluding systems that do not normally support thermostats, such as wood stoves). Next, we estimated the approximate energy use reductions for each approach. Taken together, these provide an estimate of national technical energy savings potential for each measure, assuming that the approach is applied to all relevant households. Preliminary energy savings estimates for the 17 approaches are shown in Table 1-1. Note that many of these preliminary estimates have significant uncertainty and that savings from multiple categories may interact and are not strictly additive.

We asked CTA TechHome Division members and several utility energy efficiency program administrators (PAs) and developers for input on what home automation approaches they felt most warranted further study. Ultimately, in conjunction with CTA, we selected five approaches to analyze more deeply based on:

1. Preliminary AEC estimates (higher more likely to be selected)
2. Level of uncertainty in the preliminary energy savings estimates (higher more likely to be selected)
3. Level of interest from utility energy efficiency PAs and CTA TechHome Division

1.4 Report Organization

The remainder of this report is organized as follows:

Sections 2 through 6 present the detailed analyses for the selected priority home automation approaches. Each section includes an overview of the technology, a review of relevant literature, and discussion of key considerations, presents the energy savings opportunity calculations.

Section 7 presents the conclusions and recommendations for future research.

Table 1-1: Primary energy savings potential estimates of home automation approaches (preliminary).

Category	Approach	Energy Savings Potential (quads)	Notes
HVAC	Connected Thermostat	0.7-1.1	evaluated in this study
	Window Covering Control	0.3-1.0	evaluated in this study
	HVAC Zoning	0.3-0.6	evaluated in this study
	HVAC Diagnostics	0.4	Goetzler et al. (2012)
	Smart Ceiling Fan Control	0.02	Increase HVAC setpoints and occupancy-based control (Goetzler et al. 2012)
	Smart Ventilation System	0.0-0.03	Schedule ventilation to minimize HVAC loads; Less et al. (2014), Goetzler et al. (2012).
	Nighttime Ventilation Cooling	0.01	Goetzler et al. (2012)
	Air Conditioning Precooling	0.0	German et al. (2014)
Lighting	Lighting Control, Occupancy	0.4-0.6	evaluated in this study
	Lighting Control, Photosensor	0.3	CEE (2014)
	Lighting Control, Dimming	0.5	CEE (2014)
Electric	Circuit-level Control	0.8	evaluated in this study
	Advanced Power Strip, Tier 2	0.4	Wang et al. (2014)
Water	Domestic Hot Water (DHW), Demand Control	0.3	Based on multi-family buildings; Zhang (2013)
	DHW Temperature Modulation	0.2	Based on multi-family buildings; Zhang (2013)
Other	Home Energy Display & Feedback	0.0-0.8	Karlin et al. (2015); Sipe and Castor (2009); Kihm et al. (2010)
	Residential Commissioning	1.8	Goetzler et al. (2012)

Note: highlighted approaches were selected for in depth evaluation and reflect refined estimates.

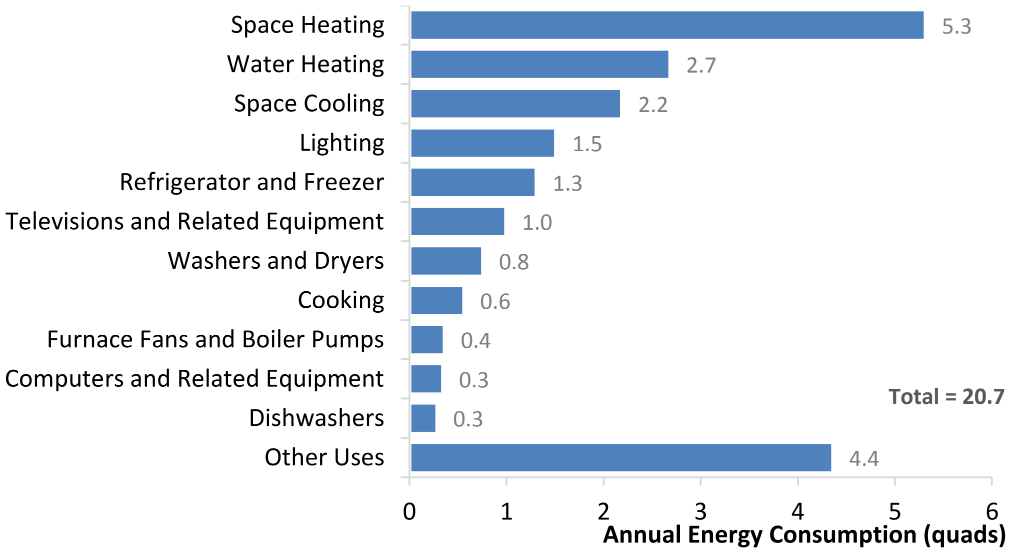

Figure 1-1: U.S. Residential primary annual energy consumption (quads[4]) by end use in 2015.
Source: (DOE/EIA 2015).

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[4] One quad equals 10^{15} British thermal units (Btus), which equals 1.055 exajoules (EJ).

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2 Connected Thermostats

2.1 Background

2.1.1 Technology Description

Connected thermostats[5] allow users to access and control their thermostat remotely over a wireless network, for instance, using a smartphone, tablet, computer, or other connected device. These features, not available in traditional unconnected manual or programmable thermostats, give users added control and flexibility that could improve thermal comfort and potentially save energy. Connected thermostats are quickly gaining market share and in 2015 comprise about 40% of the ten million units sold (Parks Associates 2015, York et al. 2015).

Smart thermostats are a special class of connected thermostats that can make automatic adjustments based on external signals that could lead to energy savings. Features like automatic temperature setbacks – driven by occupancy sensing, geolocation, or learning algorithms – aim to reduce energy used during periods of vacancy or sleeping. Other features apply behavioral feedback to encourage people to choose more energy-efficient settings.

Automated controls could also improve the efficiency of heating and cooling equipment under specific conditions. Examples include strategies to minimize the use of inefficient auxiliary electric resistance heating for heat pump systems, fan overrun for air conditioners to recover residual cooling after the compressor has switched off, fault detection and diagnostics, and the ability to respond to changes in weather or utility demand response signals. Since feature sets vary widely by product (see Urban and Roth 2014), there can be wide variation in potential and realized energy savings among products. Savings can also vary widely among users of a specific connected thermostat product, owing to differences in occupancy patterns, thermal preferences, HVAC systems, and housing characteristics.

As with traditional thermostats, one primary way connected thermostats achieve energy savings is through temperature setbacks[6] when homes are vacant or when occupants are asleep. Basic connected thermostats rely primarily on user control to implement setbacks, whereas smart thermostats rely on a combination of user control and automation. Both approaches can yield energy savings.

Poor usability has been a longstanding barrier to achieving persistent thermostat energy savings (Peffer et al. 2011). The limited space for a user interface on traditional wall-mounted thermostats, for instance, can make them difficult to program. Better interfaces on connected thermostats – made possible through the rich displays of smart phones, tablets, and computers – can be easier to use, possibly leading to higher and more persistent savings. Better usability is not guaranteed and depends on product design. People must also be motivated to save energy, or at least tolerant of energy-saving features, to realize savings.

Connected thermostats operate on a wireless network and can have multiple system architectures. Most common is a wall-mounted thermostat that can replace a traditional non-connected thermostat. Some models support communication among multiple thermostats, or other wireless sensor nodes, to provide better coverage and understanding of a home and its occupants. These can communicate directly

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[5] Some use the terms *connected thermostats*, *smart thermostats,* and *programmable communicating thermostats* (PCTs) interchangeably, however, these terms can take on different meanings. *Communicating* usually implies capability for external communication with a utility, for example, to enable demand response controls. Further discussion follows in the text.

[6] We use the term *setback* for both heating (set back) and cooling (set up).

or through a central hub. External sensors can provide information about local weather, occupancy and activity, or spatial variation in temperature to increase the sophistication of control algorithms. Virtually all devices can function to some degree without a network connection, or during a network interruption.

A second architecture adds room-level control to heating or cooling equipment that is not typically controlled by a central thermostat, such as window unit air conditioners. Some include a built-in connected thermostat. For others, an outlet-based connected thermostat can be used to turn the unit on or off according to programmed schedules or through a connected interface.

2.1.2 Control Strategies

Occupant control of thermostats accounts for a large portion of variation in household energy performance, so savings from connected thermostats must be considered relative to existing control behavior (Urban and Roth 2014).

Historically, the limited energy savings achieved by programmable thermostats has been blamed largely on poor usability and human factors (Kempton 1986, Meier et al. 2010, 2011, and Peffer et al. 2011). Even programmable thermostats that are rated as easy to use may not deliver savings if people are not motivated to select or maintain energy-efficient settings and primarily seek to maintain comfort (Sachs et al. 2012). In fact, adding a programmable thermostat to a home can sometimes increase energy consumption (Lopes and Agnew 2010, Malinick et al. 2012).

According to self-report data from the 2009 Residential Energy Consumption Survey (RECS; EIA 2011), about half (48%) of households with central air conditioning have a programmable thermostat, and of those, more than half change the setpoint while away (59%) or during sleeping hours (59%). Likewise, just less than half (43%) of households with heating have a programmable thermostat, and of those, more than half change the setpoint while away (53%) or during sleeping hours (62%). Reported setpoints vary widely among households from about 70-80°F for cooling and about 60-75°F for heating. Although self-report data on thermostat setpoints has been shown to be reasonably accurate (Sachs et al. 2012, Lutz and Wilcox 1990), it is unlikely to be sufficiently precise to detect an effect size of ±1°F. In fact, Lutz and Wilcox found average self-report temperature errors typically varied between 1-4°F depending on the time of day, and that people tend to under-report heating setpoints and over-report cooling setpoints.

These summary statistics can be misleading, however, since not all people who adjust their setpoints do so to save energy. The distribution of setback depth among RECS homes that use a thermostat, Table 2-1 and Figure 2-1, indicates that while more than 40% of all groups did not use setbacks at all, homes with programmable thermostats did so more frequently and more deeply. About 7% of heating homes and 15-22% of cooling homes used more energy intensive settings at night, reflecting diverse comfort preferences. Homes also differ widely in their preferred seasonal setup temperature, as in Figure 2-2.

These individual preferences affect savings opportunity, as people who tolerate cold temperatures in winter may already be achieving much of the possible savings even if they do not implement deep setbacks. Similarly, for homes that already implement deep setbacks, switching to a connected thermostat may yield only incremental savings. Automation could still help produce savings when real occupancy patterns do not match rigid or pre-defined schedules, and further savings could be achieved through optimized HVAC controls.

Table 2-1: Thermostat setback depth (Δ°F), percent of households with thermostat.
Positive values corresponds to energy savings (EIA 2011), n=12,082.

Time	Season	Type	-5°F or less	-3 to -4	-2 to -1	0°F	+1 to +2	+3 to +4	+5°F or more
away	heating	programmable	0%	0%	0%	43%	10%	17%	29%
		manual	0%	0%	0%	57%	6%	9%	26%
	cooling	programmable	1%	0%	0%	54%	12%	16%	17%
		manual	1%	0%	0%	65%	7%	10%	16%
night	heating	programmable	2%	2%	3%	41%	14%	15%	23%
		manual	2%	2%	3%	58%	8%	9%	17%
	cooling	programmable	5%	6%	10%	63%	8%	4%	3%
		manual	5%	4%	6%	75%	4%	3%	3%

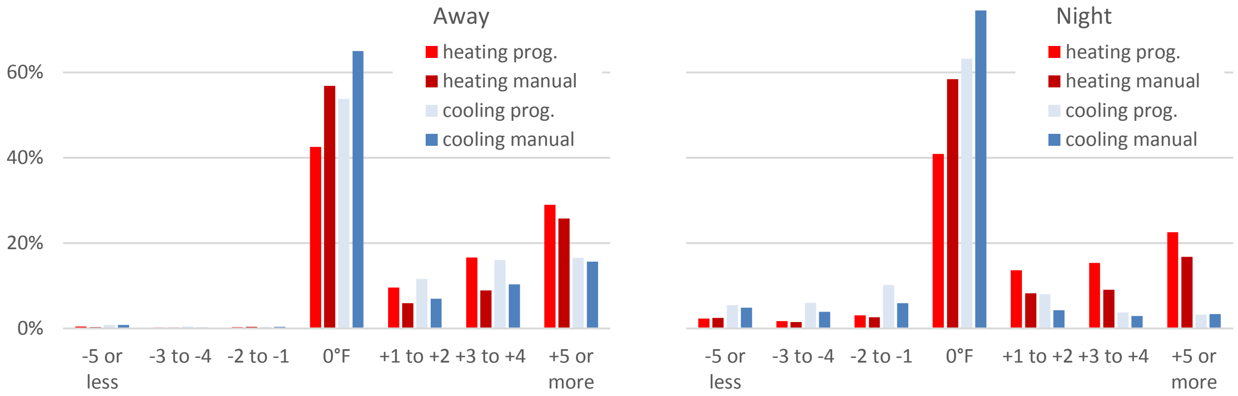

Figure 2-1: Setback depth (Δ°F) while away and at night, weighted histogram.
Positive values corresponds to energy savings (EIA 2011), n=12,082.

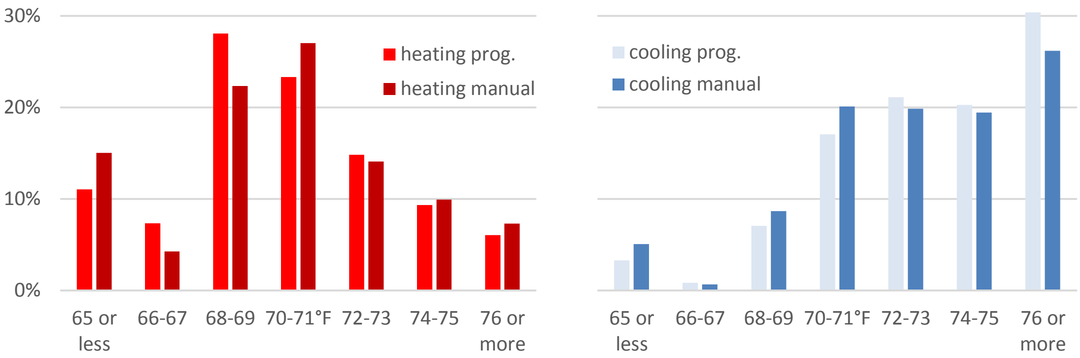

Figure 2-2: Setpoint temperature (°F) while at home, weighted histogram.
Source: (EIA 2011), n=12,082.

Persistence of savings makes evaluation challenging. Often, thermostats are shipped with energy-saving default settings that users may change over time. Setback schedule persistence for programmable thermostats has been relatively poor, at less than 70% per year (Cadmus 2012). A survey of 100 Connecticut homes found that after five years, only about half continued to use automatic setbacks (Cross and Judd 1997). If persistence is actually higher among connected thermostats, this effect could be overlooked in shorter field studies. Connected thermostats could enable various strategies for service providers to attain persistence by helping users enable, maintain, or restore efficient settings.

2.2 Energy Savings Potential

2.2.1 Heating and Cooling

Findings from recent studies on connected thermostat energy savings are summarized in Table 2-2. The discussion that follows parallels that of York et al. (2015) and leads to similar conclusions. Although many studies estimate energy savings of different thermostat products, their methods differ and cannot always be readily compared. Real-world results can vary over time because of behavior changes or software updates. The major diversity of features among connected thermostats means different products are likely to yield a range of savings. For these reasons we do not expect all connected thermostats products will yield similar or consistent savings in practice.

Prior attempts to understand, characterize, and generalize non-connected thermostat energy performance have found mixed success, and savings estimates vary considerably among studies (Nevius and Pigg 2000, RLW 2007, Michaud et al. 2009, Peffer et al. 2011, Sachs et al. 2012). This has led to some confusion among industry stakeholders. Critically, the lack of an industry-accepted method for performance assessment makes it difficult to compare thermostat products based on their expected or demonstrated real-world energy performance (Urban and Roth 2014).

Different baseline scenarios, especially, can greatly influence the results of a study, making direct comparisons difficult or impossible. Results may also pertain only to specific climate regions, demographics, thermostat products, or have other restrictions, liming how the results can be interpreted or generalized. Because not every home has the same kind of thermostat or the same setpoints to begin with, replacing an existing thermostat with a connected thermostat could yield appreciably different changes in performance from one home to the next.

Thus, to ensure a fair comparison, the baseline we use in our assessment is the existing installed base of thermostats and their current usage patterns. When possible, we have adjusted the savings estimates from the studies in the *Net Effect* column of Table 2-2 to reflect this baseline. This is important because some studies calculate savings relative to an arbitrary fixed temperature setpoint value, even though this does not reflect the average or typical savings that a customer could expect to obtain. Other studies compare their savings exclusively to homes with either manual or programmable thermostats. In some cases, professionals installed the thermostats and educated the occupants on how to use them. In others, people were on their own. These factors (and more) could skew results and lead to biased comparisons.

Even with major recent innovations, there is likely room to achieve further savings, as the savings identified are a snapshot of what is possible today. Continued innovation could address further savings opportunities beyond those stated here and also enable more users to achieve the higher end of savings reported. Existing products, however, already address the highest-value savings opportunities for the most common HVAC systems, e.g., through occupancy detection and automatic setpoint adjustment, so further improvements are likely to be incremental. That said, future communicating thermostats may also *enable* significant additional energy savings, e.g., from performance diagnostics.

All considered, we based the technical potential estimates on the highest savings achieved in larger field studies, with a small allowance for additional improvement from new or improved algorithms. Although we expect savings percentages to vary by climate, there were insufficient data to draw firm conclusions about the extent and magnitude of this variation. We emphasize the need for continued study.

Table 2-2: Energy savings studies of connected thermostats for space heating and cooling.

Study	Sample Size Enrolled (Analyzed)	State / Region	Method	Baseline	Energy Reduction	Comments	Net Effect* and Study Value
Aarish 2015a	connected thermostat 400 (238) programmable 400 (217) manual, control group 800 (469)	IN	Randomized field study, billing analysis, in home monitoring, participant surveys. Contractors replaced manual with connected or programmable thermostats in treatment households and trained participants on their usage. Pre/post period monitoring of energy and temperature were performed for treatment and control groups, and a difference-in-difference comparison was made to calculate savings.	Households with manual thermostats.	conn. (prog.) 13.4% (7.8%) heating 16.1% (15%) cooling relative to manual thermostat	Moderate attrition from outliers leads to differences in participant demographics between groups that could bias results. One climate zone.	9.6% heating 8.9% cooling High
Aarish 2015b	connected thermostat 300 (197) programmable 300 (184) manual, control group 3,845 (2,611)				conn. (prog.) 12.5% (5%) heating 13.8% (13.1%) cooling relative to manual thermostat		10.3% heating 7.6% cooling High
Apex 2014	connected thermostat 222 (174) comparison group 299 (211)	OR	Field study, billing analysis, participant surveys. Contractors installed Nest thermostats in participating homes during a site visit to households with heat pumps. Participants were matched with similar households to form a comparison group.	Heat pump households with existing unconnected thermostat.	781 kWh/yr/hh heating, or 4.7% of annual household electric usage relative to unconnected thermostat	Restricted to heat pump households in the Pacific North West.	10% heating High
Nest 2015a	connected thermostat 735 heating 625 cooling	35+ states	Field study using pre/post retrofit submetered energy data of Nest/MyEnergy customers. Pooled regression model and pre/post retrofit analysis used to identify savings.	Pre-retrofit thermostat.	9.6±2.1% heating 17.5±2.9% cooling relative to prior thermostat	Results differ slightly for households with only one thermostat: 11.1% heating 15.5% cooling Potential self-selection bias.	11.1% heating 15.5% cooling High
Nest 2015b	seasonal savings service 20,154 enrolled of 37,586 eligible	MA	Field study of a feature that tunes users' schedule for three weeks to improve savings. Eligible users were prompted to opt-in to apply the feature. Savings were calculated three ways based on pre/post weather-normalized runtime data, pooled runtime data, and average setpoint changes.	Matched Nest households in neighboring states. pre/post runtime analysis	+3.5% heating incremental improvement over existing Nest savings	Short duration (3 weeks). Savings could be impacted (reduced?) by severe 2015 winter. High opt-in rate. Large sample.	+3.5% heating incremental improvement over existing Nest savings High

Study	Sample Size Enrolled (Analyzed)	State / Region	Method	Baseline	Energy Reduction	Comments	Net Effect* and Study Value
Miller et al. 2012	connected thermostat 86 (66) heating 14 (11) cooling	MA, RI	Field study with pre/post billing analysis for heating, and self-report for cooling. Households received Wi-Fi thermostats to replace their existing unconnected manual or programmable thermostat.	Pre-retrofit programmable or manual thermostat.	8% (10%) heating 16% (16%) cooling relative to programmable (manual) thermostat	One climate zone. Small sample. Cooling results based on self-report data are unreliable.	6.6% heating 16% cooling Medium (htg.) Low (cooling)
Stewart and Jackson 2015	connected thermostat 139,945 (34,043) unconnected, baseline 12,083 (3,356)	U.S.	Field study and matched survey data. Participants were matched with similar households from RECS. Average temperature from connected thermostat UI data were compared with matched RECS self-report setpoint data. Econometric models were used to translate differences in setpoints into typical energy savings.	Unconnected thermostat setpoints represented by self-report RECS 2009 data.	8% heating 17% cooling relative to unconnected thermostat	Self-report baseline could be biased and unreliable. Average setpoints dismiss important transient effects. Artificial control group. Early adopter bias (2014). Small sample (2014).	8% heating 17% cooling Medium/Low
Ward et al. 2014	connected thermostat 1,796 (653) unconnected, baseline 12,083 (2,578)				5% heating 19% cooling relative to unconnected thermostat		5% heating 19% cooling Low
Carrier 2014 Ecobee 2013 Nest 2012, 2015 Tado 2015	not specified	U.S.	Simulation of observed customer runtime and setpoint data. Details not always normally published.	Constant avg. setpoint, e.g., 72°F.	~20-30% heating ~20% cooling Typ. relative to constant 72°F setpoint baseline	Non-representative constant setpoint baseline. Not enough detail given in simulation approach. Potential self-selection early adopter bias. Nest used customer-specific observed setpoints starting in 2012.	no viable comparison, ~8-10% higher than field studies Low

* relative to installed base of non-connected thermostats in the climate zone of the study, unless otherwise noted

2.2.1.1 Indiana Connected and Programmable Thermostat Evaluations

Two randomized controlled trial evaluations of connected and programmable thermostats were conducted on gas and electric households with manual thermostats in Indiana (Aarish et al. 2015a-b). In the first trial (2015a), contractors replaced existing manual thermostats with either a Nest connected thermostat or a programmable thermostat and trained people on how to use them. A control group received no new thermostat or training. In addition to billing and weather data, the study measured indoor temperature, air conditioner run time, and fielded surveys to identify changes in occupant behavior in both treatment groups. Savings were calculated using a weather normalized difference-in-difference pre/post retrofit design. Relative to manual thermostats, (2015a) found gas heating of about 13% (11-16%) for connected and 8% (6-10%) for programmable thermostats. Cooling electricity savings were found to be 16% (10-22%) for connected and 15% (9-21%) for programmable thermostats.

We weighted these savings results according to the current ratio of homes with manual and programmable thermostats to make them more representative (but still only to homes in similar climates) as follows. According to RECS about 93% of heating households have at least one thermostat, and of these, 43% have at least one programmable thermostat (EIA 2011). Similarly, about 98% of households with central air have at least one thermostat, and of these, 48% have a programmable thermostat. Then, the adjusted savings values for (2015a) are:

$$\text{Heating: } 13.4\% \times (57\%)_{manual} \; + \; (13.4\% - 7.8\%)\,(43\%)_{programmable} = 10\%$$

$$\text{Cooling: } 16.1\% \times (52\%)_{manual} \; + \; (16.1\% - 15\%)\,(48\%)_{programmable} = 8.9\%$$

and similarly for (2015b):

$$\text{Heating: } 12.5\% \times (57\%)_{manual} \; + \; (12.5\% - 5\%)\,(43\%)_{programmable} = 10.3\%$$

$$\text{Cooling: } 13.9\% \times (52\%)_{manual} \; + \; (13.9\% - 13.1\%)\,(48\%)_{programmable} = 7.6\%$$

Since these studies span only one year, the long-term persistence of savings is not known. Based on reported survey results, there appears to be differences in demographics and occupancy between treatment and control groups that could impact energy savings results, potentially due to limitations with the sample size. Self-selection bias could reduce the ability to generalize these results to a wider population. Households that were recruited to participate in the study were selected from those who had recently undergone a home energy audit, and those who chose to participate could behave different from those not interested in being part of an energy efficiency study.

2.2.1.2 Nest White Paper

Nest studied a subset of its users who used a service to monitor their electricity and gas consumption using a pre/post and weather-normalized regression analysis to identify energy savings relative to the period before their connected thermostat(s) were installed (Nest 2015a). Savings of about 10-11% heating and 15-17% cooling were identified. The analysis covered more than 35 states, and while not an independent study, it is likely the most geographically representative of those considered. Some self-selection bias is likely, since the sample consists of people who both purchased a Nest and previously subscribed to an energy monitoring service; however, the net impact of this bias is not clear.[7]

2.2.1.3 Nest Heat Pump Study

About 9% of homes with space heating have heat pumps (EIA 2011), and some thermostats offer features that can reduce the need for inefficient auxiliary electric resistance heat during cold temperatures. An Oregon field study evaluated the impact of Nest thermostats on homes heated by air-source heat pumps in the Pacific Northwest (Apex 2014), and found reductions in annual household electricity consumption of 781 kWh/year or 4.7% of total household electricity use. Based on average marine climate household electricity consumption (RECS 2009), this is a 10% reduction in site energy for heating.

A survey found that after the heating season over 80% of homes continued to use the energy saving features that were enabled by default during installation, including auto-away, auto-scheduler, and heat-pump maximum savings. Disabling the maximum heat pump savings setting could cause the auxiliary heater to run twice as long. More study is needed to understand the long-term persistence of features that affect energy consumption.

2.2.1.4 ecobee Pilot Study

A Massachusetts pilot study evaluated ecobee Wi-Fi thermostats and estimated heating savings of about 10% relative to manual and 8% relative to programmable thermostats, and cooling savings of 16% relative to both manual and programmable thermostats (Miller et al. 2012). Adjusted heating savings are then:

$$\text{Heating: } 10\% \times (57\%)_{manual} + (10\% - 8\%)\,(43\%)_{programmable} = 6.6\%$$

Heating savings were based on gas billing analysis, while cooling savings were based on site equipment surveys and self-report data on thermostat settings. Although the sample size was small (heating: n=66, cooling: n=11), and cooling savings imprecise, the results were similar to findings from other studies.

2.2.1.5 Honeywell Connected Thermostat Study

Two national studies estimated energy savings from a Honeywell connected thermostat based on user interface data from over 800 and 34,000 customers across the U.S. (Ward et al. 2014, Stewart and Jackson 2015). These compared seasonal average observed setpoint temperatures of users with those reported in the 2009 RECS (EIA 2009) to derive savings and used a matching procedure to identify a subset of RECS households that were similar to those in the sample to reduce bias. The baseline derived from RECS data aims to represent the regional setpoints of non-connected thermostats. Econometric models of energy consumption were then used to estimate energy savings. The 2015 study found household site energy reductions of 8% for heating, 17% for cooling, and an overall average of 9% on total heating and cooling energy, driven by differences in setpoints (-1.4°F for heating and +1.3°F for cooling).

Using average temperatures to calculate energy savings has limitations and can yield misleading results (Urban and Roth 2014). For instance, two identical homes could have the same average setpoint temperature but implement their setbacks 12 hours apart (e.g., night setbacks in one home and daytime setbacks in another), leading to very different energy consumption due to the timing and magnitude of heating and cooling loads. Furthermore, homes that overshoot their target temperature when

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[7] For example, energy conscious households could be more likely to use efficient setpoint schedules before installing a smart thermostat, and if so, would have a reduced opportunity for savings relative to the general population.

implementing setbacks, a common practice, could skew the average leading to overstated savings. For instance, if two identical households set back to 55°F and 65°F at night, respectively, and the room temperature only falls to 65°F before morning in each household, each would use the same amount of energy, but the first would get more credit for their deeper setback. Despite these limitations, this study's estimates were consistent with studies of other connected thermostats.

2.2.1.6 Simulation, Modeling, and Other Analyses

Several thermostat manufacturers have published white papers that calculate, or show energy savings potential, based on some combination of assumptions, data, and modeling. While the results of modelling studies may be valid for the strict set of assumptions used, ordinary deviations due to real-world behavior variation can produce large discrepancies with results from field studies. The lack of a common, well-defined simulation methodology makes it difficult to compare results. Often the major source of uncertainty is an oversimplified baseline setpoint temperature assumption leading to inflated savings predictions, an issue that is discussed in Nest (2015a).

Manufacturers have reported heating and cooling savings in the 20-30% range relative to a hypothetical constant and usually 70-72°F baseline (Carrier 2014, ecobee 2013, Nest 2011, Tado 2015). Nest has since updated their simulation assumptions to use customer-specific setpoint data, and notes a difference of about 8-10% between the savings it modeled relative to a constant baseline and those identified through field studies (Nest 2012, 2015a). Without more detail on the approach, sample size, and underlying data used in these studies, it is not possible to adjust findings to a relevant baseline.

Modeling against a constant setpoint can have merit; however, in such cases the term *energy performance* should be used in place of *energy savings* to avoid confusion. One approach for comparing performance of thermostats based on setpoint or temperature data is presented in Urban and Roth (2014), building on Urban et al. (2012). Other methods are still in development (see EPA's ENERGY STAR program for connected thermostats). Once a common method for computing *performance* is established and validated using field data, it may then be possible to make direct comparisons among different thermostat products in a consistent way, using appropriate baselines for the particular application.

2.2.1.7 Persistence, Algorithm Improvements, and User Engagement

The ability to achieve persistent energy savings is of great importance to energy efficiency programs, and connected thermostats have elements that could improve persistence. A common problem with manual and programmable thermostats is that savings may erode over time. Thermostats often ship with energy-saving default settings; however, in practice, people adjust or change their settings, sometimes unintentionally, and this can compromise savings (Peffer et al. 2011, Meier et al. 2011).

One important advantage of connected thermostats is that manufacturers and service providers can update software to refine existing features, add new ones, or adjust user settings. These updates can have a significant impact on energy performance. For instance, Nest (2015c) released a schedule tune-up service during the winter of 2014-15 in Massachusetts that adjusts users' setpoint schedules during a three-week period. On average, this reduced heating consumption by about 3.5% for participating homes. This high participation (>50% of eligible users) highlights the real potential to capture additional savings over time from using better algorithms and from recapturing lost savings from mal-adjusted devices.

Many connected thermostats can also show users how much energy or money they would save by using more energy efficient settings, which could further contribute to higher or more persistent savings.

2.2.1.8 Technical Potential

Technical energy savings potential, summarized in Table 2-3, is based on the savings percentage for the best-performing credible large scale field studies of Table 2-2 with an allowance for further improvements supported by the Nest tune-up example. Although there were not sufficient data from field research to derive unique savings estimates by region, we show how absolute savings could vary by climate using typical regional household energy consumption.

Table 2-3: Technical heating and cooling energy savings potential of connected thermostats.

	Household			**Households**		**U.S. Savings**	
End-Use / Climate	**Site**	**Savings**		**Conditioned**	**Thermostat**		**quads**
	Usage	**%**	**Δ**	**(000,000)**	**compatible***	**Site**	**Primary**
Heating	**MMBtu/hh**						
very cold/cold	60.5	15%	9.1	40.5	93%	0.34	0.40
mixed-humid	37.8	15%	5.7	37.1	93%	0.20	0.23
mixed-dry/hot-dry	18.2	15%	2.7	13.1	93%	0.03	0.04
hot-humid	11.9	15%	1.8	18.4	93%	0.03	0.04
Marine	26.4	15%	4.0	6.3	93%	0.02	0.03
subtotal/avg.	**38.8**	**15%**	**5.8**	**115.4**	**93%**	**0.62**	**0.73**
Cooling	**kWh/hh**						
very cold/cold	593	20%	119	31.6	98%	0.01	0.04
mixed-humid	1,906	20%	381	34.6	98%	0.04	0.13
mixed-dry/hot-dry	2,554	20%	511	11.0	98%	0.02	0.06
hot-humid	4,266	20%	853	19.2	98%	0.06	0.17
Marine	362	20%	72	2.2	98%	0.00	0.00
subtotal/avg.	**1,982**	**20%**	**396**	**98.6**	**98%**	**0.13**	**0.40**
Total						**0.76**	**1.1**

* Based on RECS data (EIA 2011), 93% of central heating systems and 98% of those with central cooling systems have at least one thermostat. We assume that standalone connected thermostats could be used to control a similar portion of non-central systems, like window unit ACs or electric space heaters.

Of the 119 million U.S. households, 97% (115 million) have and use space heating equipment and 83% (99 million) have and use air conditioning. Of those with air conditioning, 84% use central air and 31% use one or more window or wall unit air conditioners. We were unable to find energy savings evaluations of connected thermostats for window unit air conditioners, however, since these tend to be operated manually, we assume the savings percentages are similar in households with these systems.

Because we calculated savings relative to households that already have some kind of thermostat, savings will necessarily be lower than if we compared them to an average fixed temperature set point where no setbacks are possible. This is more likely to be representative of actual realized savings.

Virtually all the studies we reviewed indicate that savings can vary significantly among participating households, and in some cases, connected thermostats are unlikely to achieve any savings (Wooley et al. 2014). Studies taking place in a limited geographic region or with a small population, may not generalize to other situations, and it is unwise to give them too much weight.

2.2.2 Operational Energy

Both ordinary and connected thermostats, require power to operate. Nearly all connected thermostats are powered by wire, and power draw varies by vendor. Some use an internal rechargeable battery that draws power from the signal or common wires. Nest (2015) reports that its power consumption is less than 0.03 kWh/month or less than 1 kWh/yr, and ecobee (2015) reports power draw of less than 3.5 VA, or 31 kWh/yr. Others, like Tado, can operate from batteries.[8] While these values differ, they are still very low relative to annual heating and cooling energy savings potential, and the higher value is likely an upper-bound. Some connected thermostats can work with external hardware to gain access to additional data streams, such as additional occupancy sensors, or portable temperature sensors. These may draw power, but some, like the Nest smoke alarm, provide other primary functions. Few thermostats require a central hub, so its power requirement was not considered. Power draw of connected thermostats can be quite low and need not contribute appreciably to household energy consumption.

2.2.3 Demand Response

Beyond energy savings, connected thermostats offer households the opportunity to participate in utility demand response (DR) programs. Utilities or aggregators can signal homes during demand events to temporarily relax setpoints or duty cycle equipment to curtail demand and provide relief to the grid. Actual peak load reductions depend on program implementation details, the duration of demand response events, the portion of AC systems operating during DR events, and how often and to what extent the participating customers override the automated settings. Several programs have demonstrated success using different algorithms and approaches.

In the summer of 2013, Nest demonstrated their Rush Hour Rewards program with Austin Energy, Reliant, and Southern California Edison (Nest 2014). On average, they found that each event produced an AC load reduction of 55% or 1.2 kW per device among the more than two thousand participants. By region, average savings varied from 0.7 to 1.3 kW. Reductions were achieved with minimal or no impact on comfort for 84% of participants based on survey responses.

The 2011 Pacific Gas and Electric SmartAC program used connected thermostats and/or switches in households to limit the duty cycling of central air conditioning units during demand response events (George et al. 2012). According to the study, "When a SmartAC event is called, the control devices limit the duty cycles of central air conditioning units or adjust thermostat temperature settings, thereby reducing demand." A randomized controlled trial including thousands of residential customers was carried out to evaluate the demand response impact of this program, which produced an average of 0.5 kW per device from 4-6 PM. Average realized demand reduction varied with household energy consumption and ranged from 0.19 to 0.85 kW. No statistically significant difference in thermal comfort was identified between participants and the control group. Results represent an increase in demand response potential over the previous year's program, which the study attributes to the use of different control algorithms. Although this study relied exclusively on duty cycling, and not temperature setback adjustments, it is reasonable to believe that results for connected thermostats could be of a similar magnitude.

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[8] This low power draw is of the same magnitude as smart phones.

The 2014 San Diego Gas and Electric residential peak time rebate program rewards customers for reducing energy consumption through manual or automatic means (Hanna et al. 2014). Automatic curtailment provided an incentive of $1.25/kWh avoided, compared with $0.75/kWh for manual reductions prompted by day-ahead notifications. For the 4,000 customers participating in automated reductions, ecobee thermostats were provided and used to curtail load for four-hour periods by duty cycling central air conditioners at 50% or by implementing a 4°F setback during the same period. Consistent with the PG&E study, the average event hour load reduction was about 0.5 kW per participant. Similar demand reductions were identified by the 2011 SMUD Residential Summer Solutions Study, which compared the impacts of assorted dynamic pricing, automatic load control, and energy feedback strategies (Herter et al. 2013).

Finally, similar load reductions were reported by Lopes and Agnew (2010), who conducted a 400-participant pilot in Florida using non-communicating programmable thermostats. They found average reductions of 0.9 kW during summer peak and 0.6 kW during winter peak.[9] This suggests communicating thermostats can work at least as well as prior demand response technologies.

2.3 National Savings

Aggregate savings estimates for homes with heating or cooling systems are shown in Table 2-4. These results are somewhat higher than the 0.74 quads of primary energy estimated by Goetzler et al. (2012). Unlike the estimates for other home automation approaches in this report, which are based on simulations or other best case estimates, the values for connected thermostats have greater certainty because they are based on field studies. Future improvements to thermostat technology could yield additional savings that go beyond those found in these initial field studies. Because of the appreciable uncertainty associated with the limited number and scope of field studies and the potential for further, incremental improvements, we estimate a technical savings potential range of 0.7-1.1 quads.

Table 2-4: Annual connected thermostat energy savings potential.

	Savings (quads)		Per Household, typical	
	Primary	Site	MMBtu	kWh
Heating	0.73	0.62	5.8	-
Cooling	0.40	0.13	-	396
Total	**1.1**	**0.76**		

2.4 Conclusions

Connected thermostats offer benefits that go beyond traditional manual thermostats, helping to save energy and achieve thermal comfort. Savings arise from several mechanisms. Smart thermostats include features that can deliver deeper levels of savings and control through occupancy awareness, automatic setpoint adjustments, and optimized control of specific types of HVAC systems. The improved interfaces of connected thermostats may help users program and maintain appropriate schedules more effectively than traditional manual or programmable thermostats.

Due to the wide range of household comfort preferences and schedules, energy savings must be calculated relative to an appropriate baseline. Since many households are already achieving some portion

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[9] Surprisingly, the programmable thermostat customers in this study who used setbacks used 12% more cooling energy than those who did not.

of the available savings by implementing to manual or scheduled setbacks with their traditional unconnected thermostats, it is inappropriate to calculate savings relative to an average, constant temperature baseline. Savings may change over time, as occupant behavior and preferences can be fickle, and software updates and algorithm adjustments may impact savings for better or worse. Long-term evaluations are important for assessing these effects. Field studies of today's connected thermostats have demonstrated savings in the 5-10% range for heating and 8-16% for cooling, relative to the existing mix of unconnected manual and programmable thermostats. With new features and further refinements, it is plausible that savings could continue to increase incrementally.

Connected thermostats can provide utilities with significant demand response resources, on the order of 0.5 kW per device during the cooling season in climates with significant cooling loads. In addition, data from connected thermostats could be used to identify retrofit opportunities, diagnose problems with the HVAC systems, or assist utilities with energy efficiency program evaluation.

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3 HVAC Zoning Control

3.1 Background

3.1.1 Technology Description

Automated zoning allows thermally isolated rooms or areas within a home to be conditioned independently. Homes using central systems for space conditioning often rely on one thermostat to control the heating or cooling of multiple rooms, and this can lead to rooms that are conditioned more than necessary. It can also lead to localized discomfort if the thermostat is located in a space with appreciably different conditions than other spaces. Simply adding more thermostats to a home may not entirely solve these problems, since most distribution systems do not offer room-level control.

Granular control of heating or cooling by room provides energy savings opportunities when individual rooms are vacant. Just as smart thermostats can use occupancy detection to set back the temperature of all zones when the *entire home* is vacant, automated zoning allows *specific rooms* to be adjusted independently. Automated zoning could allow people to condition bedrooms separately from living rooms, kitchens, and bathrooms, which may each have different occupancy patterns. Rooms that are frequently vacant, such as guest bedrooms, could be left unconditioned or partially conditioned for extended durations. To the extent that the zones or rooms are thermally isolated, energy savings may be achieved by allowing unoccupied rooms to drift outside of the ordinary comfortable temperature settings. Zoned control may also provide more uniform temperature control of the entire home and reduce overheating or overcooling certain rooms.

Until recently, if a home was not already zoned, it could be difficult to selectively heat or cool particular rooms. Retrofitting the ductwork in a home to provide customized space conditioning for individual rooms could be an expensive and invasive endeavor. Fortunately, new products are coming to market that may help overcome these challenges. Several companies are developing automated vent registers that aim to serve the market of forced-air heating and cooling systems by intelligently controlling the flow of air into specific rooms. Users may choose to control vents directly (opening or closing them as desired), or they may rely on automation driven by sensors, feedback, weather predictions, and other information to adjust the airflow to specific rooms. Similar products are available to enable automated zoning for hydronic (steam- or water-based) radiator systems. Conceivably, most existing central heating and cooling systems could be modified to enable some degree of automated zoning.

Automated zoning products typically operate with a low-power microprocessor, optional wireless radios, and a mechanical actuator to control the flow of heated or cooled air or water to a space. Vent-based control systems include a mechanical actuator that can modulate airflow to specific zones. One kind of radiator control system includes an insulating sleeve that covers the existing radiator and a small fan to actively deliver heat to rooms only when they need it. Others rely on mechanical valve adjustments, similar to thermostatic radiator valves. Integrated or external sensors can measure temperature, humidity, pressure, air flow, or other local physical parameters to provide detailed feedback and ensure proper operation and control. Zone actuation may be controlled by a central hub or through onboard controllers, and may function independently or with a connected thermostat. Vent actuators and sensor nodes can be powered by wire or may operate for years using battery power. Systems that use a fan will require a dedicated power supply. Since these systems are fairly new, it is not yet clear what architecture will be most common.

Because of limited adoption, the energy savings potential of automated zoning is not yet fully understood. As with connected thermostats, energy savings depends on many factors related to home construction, duct leakage, and especially occupant control strategy. People who adjust zone control to maximize thermal comfort, for instance, may not achieve the same level of savings as those who seek to maximize energy savings. Homes with more isolated unoccupied rooms stand to benefit more from zoning than those with few rooms or open concept floor plans. Multifamily buildings whose tenants have varied occupancy schedules may have limited energy savings potential, as heat flows between conditioned and unconditioned apartments (Wooley et al. 2014).

In the *Connected Thermostats* section, we looked at the energy impact of using better controls without zoning. Automated zoning does not require a communicating thermostat, however, these technologies could work together to achieve higher combined savings.

3.1.2 Zoning Potential and Occupancy Patterns

Zoning conditions different rooms of a home independently, so homes that heat or cool more than one room are possible zoning candidates. The number of conditioned rooms per home, Figure 3-1, is similar for heating and cooling. Since about 98% of homes with central systems condition more than one room and over half condition more than 5 rooms, the opportunity for zoning is potentially significant.

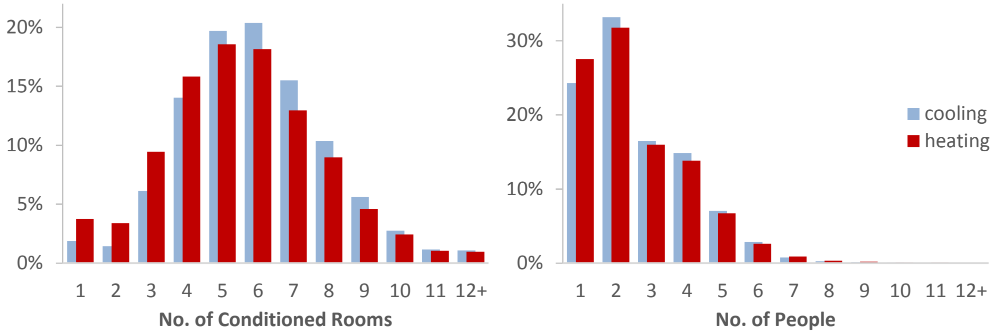

Figure 3-1: Number of conditioned rooms and people per household for homes with space conditioning.
Weighted histograms. Source: (EIA 2011).

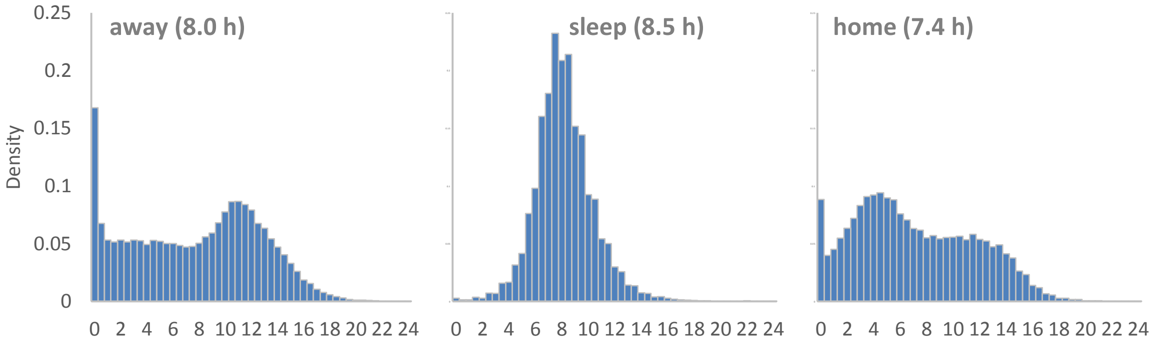

Figure 3-2: Time (avg. cumulative hours per day) spent sleeping, home, or away.
Weighted histograms, bin=30 min., n=148,345. Source: (ATUS 2015).

Occupancy plays a critical role in the extent that zoned savings can be realized. When most rooms in a home are frequently occupied, zoning is less beneficial. Conversely, when one or more rooms that are rarely used and are reasonably well isolated could consistently enable energy savings.

To better quantify the occupancy-related opportunity, we examine data from the American Time Use Survey (ATUS) administered by the U.S. Bureau of Labor Statistics. This annual survey provides location and activity data that indicate how often individuals are asleep or away from home. Microdata from 2003-2013 includes minute-by-minute activity diaries from 148,345 demographically representative participants. The distribution of time spent sleeping or away, Figure 3-2, indicates the portion of time that different rooms are vacant and, therefore, candidates for zoned energy reductions. The median daily cumulative time by activity is 8.5 h sleeping or trying to sleep, 7.5 h awake and at home, and 7.4 h away from home,[10] suggesting that up to 70% of the time there could be at least some zoning opportunity.

3.1.3 Non-Energy Thermal Comfort Benefits

Localized comfort issues can arise from under- or over-sized equipment, leaky ducts, drafts, space-specific thermal loads, or other problems. In these situations automated zoning could better direct the supply of heating or cooling to where it is needed, improving thermal comfort in priority rooms while sacrificing comfort in rooms that are used infrequently. When the existing systems cannot meet whole-building heating or cooling loads, zoning may improve comfort, but may not necessarily save energy.

3.1.4 Considerations

To be practical, automated zoning must not damage or interfere with the existing equipment. Three main areas must be addressed. First, the control strategy must not cause excessive cycling of the HVAC system, particularly of the compressor for vapor-compression systems. Second, closing vents or valves must not create excessive pressure within the ductwork. Third, closing vents must not cause insufficient airflow with fixed-capacity systems. Closing too many vents at once can increase pressure and duct leakage and damage the fan and/or the compressor (Sookoor and Whitehouse 2013). Watts et al. (2007) notes that the literature on duct leakiness indicates it is normally possible to close up to 60% of vents without incident,[11] though fan energy may increase. Bailes (2014) describes many potential problems that could arise from closing vents indiscriminately. Efficient variable-speed blowers will use more energy when vents are closed, while the air volume supplied by more common single-speed blowers will decrease as pressure increases. The latter case could lead to inadequate supply of hot or cold air to the target rooms. Moreover, insufficient evaporator airflow tends to (for a cooling cycle) depress the refrigerant saturation temperature in the evaporator, reducing the efficiency and capacity of vapor-compression cycles and potentially causing the compressor to ingest liquid refrigerant. In furnaces, this increases the temperature of the heat exchanger, also decreasing furnace efficiency for condensing furnaces. It can also prevent refrigerant from fully vaporizing before flowing into the compressor, leading to damage.

These risks highlight the importance of a technical solution that is designed to work within the constraints of existing hardware. If people apply or use the technology in a way that compromises equipment

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[10] Response data were weighted to adjust for the intentional ATUS oversampling that includes an equal proportion of weekend and weekdays.

[11] Walker (2003) conclude their study with, “Closing too many registers (more than 60%) is not recommended because the added flow resistance severely restricts the air flow though the system to the point where furnaces may operate on the high-limit switch and cooling systems may suffer from frozen coils.” See also ecovent (2014).

reliability or safety, for instance, through third-party software controls, there could be potential for damage or faster wear on the existing equipment.

3.2 Energy Savings Potential

This section calculates the average household energy savings potential of automated zone control. Primary effects include impact on heating and cooling energy. Secondary effects include the energy required to operate and control these devices and changes in fan energy consumption due to increased flow resistance. Since this category is relatively new, we note the results of some early studies on zoning potential, which have limited relevance, and follow with a more detailed estimate of technical energy savings potential based on occupant activity and room-level data.

3.2.1 Heating and Cooling

3.2.1.1 Scoping Study

Preliminary estimates of primary energy waste associated with conditioning unoccupied homes (0.86 quads), unoccupied rooms in homes (3.3 quads), and thermostat oversetting (0.50 quads), were developed in a scoping study using 2005 RECS data (Meyers et al. 2010).

Unoccupied homes refers to the kind of occupancy detection described in the Connected Thermostats section of this report and will not be considered here as a zoning measure. *Unoccupied rooms in homes* refers to the unnecessary conditioning of rooms in homes that are unoccupied for an appreciable amount of time. *Thermostat oversetting* refers to the energy wasted from using a thermostat to condition far away rooms. This can cause people to use exaggerated setpoint temperatures (e.g., higher than usual for space heating) to reach a target temperature in a room that is far from the central thermostat.

The findings of Meyers et al. and, in particular, the statements about unoccupied rooms do not consider the practical limitations of the existing HVAC systems and should be considered as optimal upper-bound estimates. Furthermore, savings derived under the category of *thermostat oversetting* may strongly overlap with those attributed to *unoccupied rooms*. For instance, even if a home had a thermostat in every room, it is not clear that savings could be addressed without de-conditioning unoccupied rooms. We derive estimates that take into account these practical issues in a later section.

3.2.1.2 Forced Air Zoning

One implementation of zoning, demonstrated by Sookoor and Whitehouse (2013), uses register-level actuation and wireless occupancy sensors to provide automatic room-level thermostat setback control. They measured a 14% reduction potential in residential heating energy consumption in a single demonstration test in a home near Virginia spanning four months. Since that study included just one home for a short duration, results may not be representative.

A laboratory and simulation study of typical California homes found that closing registers *increased* overall energy consumption under a wide range of conditions (Walker 2003). The main explanation is that savings achieved by a reduction in overall conditioned volume were more than offset by increases in duct leakage for ducts located in unconditioned space. Walker notes that duct leakage is typically 20 to 30% of total air handler flow, and that if ducts were perfectly sealed, closing vents would simply increase system pressure and reduce airflow to zones, which in turn would lower heat exchanger efficiency, negating some of the savings. Changes to system pressure as a result of closing supply registers can also affect infiltration within the home (from depressurization by the return air). As a result, the savings estimated by simpler approaches are likely to be higher than can be achieved in most existing homes.

Importantly, Walker (2003) was limited to a single-capacity compressor and single-speed blower. Homes with variable-speed or variable-capacity equipment may be able to minimize these problems with a properly controlled zoned system. Because of minimum energy efficiency standards, the installed base of single-capacity compressors and single-speed fans will likely decline in the future, potentially reducing the likelihood of these problems. The study also did not assess the impact of closing vents automatically and dynamically in response to room-level measurements, so it is possible some of these limitations could be overcome and that dynamic performance may differ by climate or building type.

3.2.1.3 Radiator Zoning

A pilot study of a fan-based radiator zoning retrofit was conducted in two multifamily buildings in New York (Radiator Labs 2015). Preliminary results for this demonstration indicate reductions in boiler runtime of about 30%. Thermostatic radiator valves (TRVs) are another type of room-level control mechanism that rely on non-powered temperature-based controls to help stabilize radiator temperature and avoid overheating. A recent field study of two apartments with billing analysis found no energy benefits (Dentz and Ansanelli 2015); however, the authors noted that conditions may not be representative and that behavior (people opening windows) and suboptimal boiler controls could have interfered. They cite prior studies that suggest heating savings of up to 12%.

Critically, when addressing a multifamily building, a sufficient portion of units must be addressed, or else heat may be lost in the distribution system and savings can go unrealized. Furthermore, the central boiler control strategy may need to be adjusted to work with a zoned radiant system to achieve savings. A common complaint in radiator buildings is overheating of specific rooms. When occupants cannot adjust the heat, people tend to leave windows open during the winter to manage space temperatures. Using a zoned approach to radiant heat delivery could reduce the magnitude and frequency of large temperature swings, reduce overheating, and maintain a more comfortable and consistent thermal environment.

3.2.1.4 New Estimates of Zoning Potential

Heating and cooling loads in different spaces in homes are driven by many dynamic factors, including solar gains, indoor-outdoor temperature difference, setpoint history, infiltration, thermal mass, insulation, and internal gains. A simple approach, and the one used here, to estimate savings potential is based on the *time-weighted occupied conditioned floor area* relative to the *entire conditioned floor area*. The complex interactions of the factors listed above makes this a fairly basic approximation;[12] however, it is the best supplemental analysis that we can complete without further information. This approach assumes that HVAC energy consumption is distributed evenly among different times of day, which could skew results, as heating loads tend to be higher at night and cooling loads higher during the daytime. Finally, a savings discount factor must be applied to account for the facts that all rooms are not perfectly thermally isolated,

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[12] For illustration, if a zoned room is not conditioned at night, its temperature may drift outside of the acceptable comfort range. Restoring temperature in the morning would initially require more energy than if the room were already at a comfortable temperature and only needed to be maintained. In this case, using a time-area method would overestimate savings, both because of this initial extra energy and because zones are not perfectly isolated. However, if the room were vacant until the afternoon, and if the room had significant daytime solar gains, it might not be necessary to supply much or any heating energy at all. As a more detailed and comprehensive simulation study over many building types, climates, and behaviors lies beyond the scope of this study, we develop estimates using with this simplified approach and note its limitations.

that rooms have thermal mass and may retain residual heating or cooling after disabled periods, the negative impact of zoning on equipment performance, and the expected increase in distribution losses.

This analysis only considers homes that use central heating or cooling systems.[13] We do not consider homes that have systems that are inherently zoned, like window or wall air conditioners, ductless minisplits, and portable or single-room heaters. Automated control can improve the energy performance of these systems, however, we consider those opportunities elsewhere in the Connected Thermostats section.

According to the 2009 RECS (EIA 2011) central heating is used in 86% of homes that use space heating equipment (83.5% of all homes)[14] and central cooling is used in 74% of homes that use space cooling equipment (61.3% of all homes). This amounts to 102.3 million homes with central heating and 72.9 million homes with central cooling for 2015.[15] Since 98% of these homes heat or cool at least two rooms, we estimate an upper limit of about 100 million heating homes and 71 million cooling homes that could benefit from automated zoning. The majority of central heating systems are forced air furnace or heat pump (81%), followed by steam or hot water systems (11%), and other (7%).

Typically, central heating or cooling systems are not zoned, and for those that are, the zoning is often coarse, for instance, an upstairs zone and a downstairs zone. Homes with multiple thermostats may have a slightly reduced savings potential if those thermostats are already being used to capture some of the zoning related potential. However, only about 17% of homes with central heating have more than one thermostat (EIA 2011). This suggests a strong untapped potential for zoning. Although RECS did not track the number of thermostats for central cooling systems, it is reasonable to assume a similar distribution. In sum, much of the granular room-wise opportunity is not currently addressed by automation linked to occupancy detection or room-level temperature measurements.

About 80% of conditioned households reported conditioning all rooms (EIA 2011); however, just because more than one room is conditioned does not mean zoning is practical or will save energy. For zoning to be effective, rooms must be thermally isolated and unoccupied to some degree.

To estimate the distribution of conditioned floor area by room type, we use RECS data for the number of rooms that are bedrooms, bathrooms (full or half), and other (kitchens, living rooms, offices, etc.). Absent square footage data by room, prior studies (e.g., Meyers et al. 2010) have weighted these rooms equally; however, this is unrealistic since bathrooms tend to be much smaller than bedrooms and living rooms. One improvement, based on professional judgment, is to use area weights (1 for bedrooms, 0.5 for full baths, 0.3 for half baths, 2 for other rooms) and apply these to the total conditioned floor area. This could better characterize savings opportunities based on occupant activity data.

We evaluated several ways that automated zoning could reduce HVAC energy consumption. Notably, our analysis does not consider periods when the home is completely vacant, as these are counted in the connected thermostat section and do not strictly depend on zoning.

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[13] This refers to homes with central systems and more than one conditioned room. The vast majority (96%+) meet this requirement (EIA 2011).

[14] Based on reported main heating fuel and equipment. We assume that central systems include warm air furnace, steam or hot water system, heat pump, and other equipment; this excludes built-in room heaters, pipeless furnaces, portable heaters, and wood or kerosene equipment.

[15] Based on 119 million households in 2015.

One possible source of savings comes from conditioning unused bedrooms. Assuming each person in a heated or cooled home uses at most one bedroom, Figure 3-3 shows that about half of homes have at least one extra bedroom, and possibly more if bedrooms are shared. If these extra bedrooms could be isolated and not conditioned, this represents an average reduction in conditioned floor area of 6% per household, or 14% among households with at least one extra bedroom.[16]

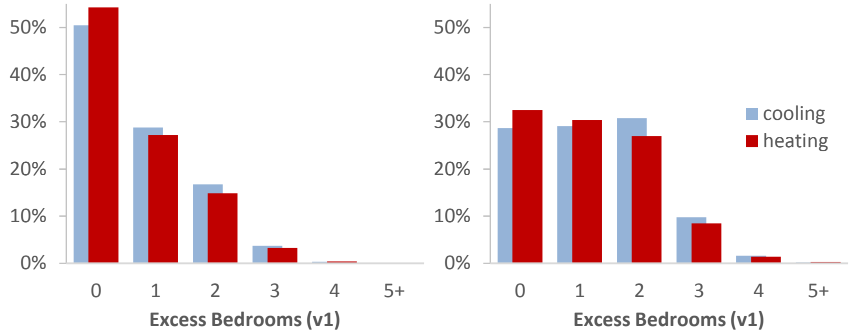

Figure 3-3: Excess bedrooms per conditioned household (bedrooms less occupants).
Weighted histograms, v1=one person per bedroom, v2=up to two people in the first bedroom (EIA 2011).

A second source of savings comes from conditioning rooms other than bedrooms unnecessarily when people are asleep. People spend a median of 8.5 hours per day sleeping or trying to sleep (ATUS 2015). Since people may not go to sleep or rise at precisely the same time, this time duration represents a reasonable upper bound for the amount of time that the remainder of a home is unoccupied at night. On average, non-bedrooms comprise about 60% of the conditioned floor area, based on the room area weights previously defined. Eliminating conditioning for these zones during the 35% of the day when people are asleep could yield a further 21% reduction. Some portion of these savings are already being addressed by households who implement nighttime setbacks in the entire home; however, zoning may capture a larger portion of these savings. Because of this potential overlap, savings may not be strictly additive with those obtained from multi-zone programmable or connected thermostats.

A third source of savings comes from conditioning rooms (other than empty bedrooms) when people are awake and at home. Even though a person can be in only one room at a time, during active hours people may move from room to room more frequently and expect these rooms to be comfortable. This makes it harder to identify what portion of the home can be left unconditioned during active hours. Leaving unoccupied rooms unconditioned for brief periods is unlikely to yield much savings. To estimate this potential, we consider homes that have more conditioned non-bedrooms than people, and assume that for 7.5 hours (about 30% of the day) these rooms may go unconditioned. For about 40% of homes, there is no excess of non-bedrooms. On the average, excess non-bedrooms amounts to 19% of conditioned floor area for both heating and cooling. This has the potential to save up to an additional 6%.

Taking these three sources together, an upper bound for savings based on not conditioning unoccupied rooms is about 30% (essentially reducing the effective conditioned floor area by 30% and assuming no

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[16] If we instead assume that one master bedroom per home sleeps up to two people, these reductions become 11% and 19%.

thermal transfer between spaces). In practice, however, the achievable portion will likely be far less for reasons already discussed, so we discount[17] the achievable savings to about 10% for heating or cooling.

3.2.1.5 Technical Potential

3.2.2 Operational Energy

Most automated zoning technologies, including sensors, can operate with very low energy consumption. Systems can be powered either through electrical outlets or through battery power, meaning that operational energy can be negligible for most applications. Devices that require fan power, as with the radiator retrofit technology, will require a dedicated power source. However, in that case, the fan would run only periodically during the heating season. Assuming a power draw of 5 W, a duty cycle of 50%, and seasonal duration of half a year, the average annual energy consumption for these systems could be on the order of 10 kWh per radiator (or about 53 kWh per home, assuming the average of 5.3 heated rooms per radiator household [EIA 2011] and one radiator per conditioned room), which is far less than the household savings potential in the cold climates that have these systems. With about 11 million radiator households, this amounts to about 0.005 quads, which is negligible compared to the savings potential.

Zoning impact on fan energy can be more pronounced. In a controlled laboratory study in California, Walker (2003) found that the power draw of a single-speed air handler dropped gradually from 570 to 460 W as ten registers were closed in sequence. The effect depends on the distance of the registers from the blower, with farther registers having a smaller impact. If this relationship holds generally, the magnitude of the effect is on the order of 10 W per closed register for similarly sized fans. Following the same logic described for radiator systems, this will likely have a small impact on electricity consumption.

Table 3-1: Technical heating and cooling energy savings potential from HVAC zoning control.

	Household Site Usage	Savings		Households w/ central systems	U.S. Savings quads	
End-Use / Climate		**%**	**Δ**	**(000,000)**	**Site**	**Primary**
Heating	**MMBtu/hh**					
very cold/cold	60.5	10%	6.0	35.6	0.22	0.25
mixed-humid	37.8	10%	3.8	32.9	0.12	0.15
mixed-dry/hot-dry	18.2	10%	1.8	10.2	0.02	0.02
hot-humid	11.9	10%	1.2	16.4	0.02	0.02
marine	26.4	10%	2.6	3.8	0.01	0.01
subtotal/avg.		**10%**	**3.9**	**98.9**	**0.39**	**0.45**
Cooling	**kWh/hh**					
very cold/cold	593	10%	59	19.9	0.00	0.01
mixed-humid	1,906	10%	191	26.5	0.02	0.05
mixed-dry/hot-dry	2,554	10%	255	8.9	0.01	0.02
hot-humid	4,266	10%	427	16.4	0.02	0.07
marine	362	10%	36	1.2	0.00	0.00
subtotal/avg.	**2,135**	**10%**	**213**	**72.9**	**0.05**	**0.16**
Total					**0.44**	**0.61**

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[17] As an alternative approximation, if it were possible to allow the room temperature to float between reasonably wide temperature setpoints (e.g., 60-84°F), this yields a savings of about 30% (EPA Energy Star programmable thermostat savings calculator) applied to 30% of the home's floor area, or about 9% savings. The actual uncertainty is appreciable.

The estimated technical potential of automated zoning on homes that use central heating or cooling equipment is shown in Table 3-1. Although there were insufficient field data to derive region-specific savings estimates, we show how absolute savings could vary by climate using typical regional energy consumption values. Additional savings estimates and discussions about behavioral considerations can be found in Rohde et al. (2012) for homes in the European Union. We assume that automated zoning is compatible with existing central heating and cooling systems.

3.2.3 Demand Response

Zoning could complement demand response programs with connected thermostats by reducing the number of spaces conditioned by the HVAC system. In practice, zoning could either increase or decrease loads. If a room is unconditioned for a large part of the day, the recovery period could require more energy than if the room had been conditioned continuously. Consequently, the impact of zoning on demand response is not the same as relaxing temperature setpoints across the entire home. It is plausible that using zoning to disable one or more rooms during a demand response event could achieve improved local comfort in priority spaces, or moderately improved demand response resources during an event.

3.2.4 National Savings

Aggregate savings for homes with central heating or cooling systems, in Table 3-2, are well below the 3+ quads of primary energy estimated by Meyers et al. (2010), mainly because we considered only homes that use central systems, and because of the technical limitations of zoning. Indeed, zoning by closing off vents haphazardly could increase energy consumption, so these values should be taken as optimistic technical potential, and not endorsements for existing products, particularly for single-speed blowers and single-capacity heating or cooling systems. The uncertainty of these values is high because few systems have been installed to date. To compensate, we adjust our technical savings potential estimate to 0.3-0.6 quads.

Table 3-2: Annual HVAC zoning energy savings potential.

	Savings (quads)		Per Household, typical	
	Primary	**Site**	**MMBtu**	**kWh**
Heating	0.45	0.39	3.9	-
Cooling	0.16	0.16	-	213
Total	**0.61**	**0.55**		

3.3 Conclusions

Residential zoning for central HVAC systems is uncommon and most homes that currently have some degree of zoning lack the granular room-level control needed to address a significant portion of the energy savings potential. Automated zoning could address these opportunities using readily adapted hardware control-based retrofits. The extent of savings depends on several factors, including typical occupancy patterns, how the devices are controlled, and the number of conditioned rooms in a home that are or can be thermally isolated. Uncertainty about achievable savings is high, as some laboratory studies and simulation suggest that closing registers could increase household energy consumption under a range of typical conditions, particularly for homes with distribution systems located outside of conditioned spaces. Automation may be able to overcome some of these challenges.

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4 Window Covering Control

4.1 Background

4.1.1 Technology Description

Window coverings,[18] such as blinds, shades, and curtains, influence heating, cooling, and lighting energy consumption of homes by altering the transmission of solar gains, natural light, and to some extent, heat transfer through windows. The effect on these end-uses depends on control strategy, together with many building-specific parameters. Automated window covering control could improve the energy performance of complex and interrelated building systems relative to manual control.

Most window coverings in the U.S. are installed on the interior-facing side of the window.[19] More advanced active window systems, such as electrochromic windows and windows with coverings sandwiched between panes (Rheault 1989, 1990, Bilgen 1994) could also benefit from automated controls; however, these will not be considered since they are less common, generally must be integrated into the window hardware, and are not yet easily adopted as an aftermarket retrofit.

Automated window covering systems typically include a motorized device that can adjust position (blind slat rotation and tilt angle, retraction). Some can be installed with existing shades or blinds. Architecture varies from standalone, self-contained units to systems with wireless mesh networks that are controlled centrally or through a server. Adjustments can be made through an interface (wall switch, remote control, smart phone, tablet, computer, etc.), automatically through software or rule-based controls, or manually through physical adjustment. Devices can be hard-wired, battery powered, or even solar powered.

Devices that rely on wireless communication often require supporting hardware, such as a central hub, access nodes, or signal boosters. While some systems can operate using industry standard home network hubs, others use proprietary communication and control networks, and these require independent network hardware, hubs, and nodes.

The energy impact of window coverings depends strongly on many complex and interrelated variables, including climate; window covering material, properties and geometry; amount and type of windows; building properties; thermostat settings; and especially the covering control strategy. Energy savings also depend on how precisely the coverings are installed. A gap of a few inches around the window perimeter, for instance, could compromise savings. The vast combination of variables leads to a higher uncertainty when estimating the potential energy impact.[20]

4.1.2 Control Strategies

Today most window coverings in homes are controlled manually and lack automated capabilities; however, automated control can help occupants achieve specific goals such as increased energy performance, thermal comfort, visual comfort, privacy, and security. Some systems may increase the resale value of the home. Energy savings is rarely the highest customer priority, so it is unlikely that people will optimize energy savings at the expense of these other benefits. Still, automation can help people achieve energy savings while respecting their preferences.

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[18] *Window Coverings* or *Window Treatments* refer to all kinds of window shading devices.

[19] Exterior window coverings, more prevalent in Europe, can block a higher portion of solar gains than interior coverings.

[20] The Attachments Energy Rating Council are developing certifications to enable credible energy comparisons. See: http://www.aercnet.org.

Although there are many possible control strategies, these are common high-level approaches:

1. **Manual Control**: physically adjust coverings at will
2. **Scheduled Automation**: adjust coverings at pre-determined times to programmed levels
3. **Feedback Automation**: coverings and/or lights respond to sensors, external data (weather, occupancy, etc.), or utility demand response programs
4. **Scenes**: user defines one or more settings and controls multiple actions at once (e.g., all coverings open and lights dim; all coverings open and lights turn on, adjust coverings in all rooms, etc.)

Most automated window coverings can be programmed with user-defined schedules, allowing each unit to change states at designated times. Coverings can be grouped together into "collections" to be controlled simultaneously or according to similar rules. Various criteria can be used, depending on what information or sensors are available and on the user's goals or preferences. For instance, thresholds can be set for incident light intensity, solar flux, or blind slat temperature, controlling deployment, retraction, and/or adjusting blind angle. This feedback could originate from sensors that measure occupancy, space temperature, solar intensity, or light levels, or it could come from a third-party software or control hub that provides access to data about weather, HVAC, and lighting systems.

Users may select rule-based "if-this-then-that" methods or more sophisticated algorithms that attempt to optimize energy, comfort, and privacy settings within the constraints of user preferences. Some systems allow for integrated control of lighting or HVAC systems. Many advanced control algorithms[21] have been explored to further optimize performance, with the focus primarily on office applications and daylight optimization. For more detailed discussion see Van Den Wymelenberg (2012) for a literature review of blind use patterns, control strategies, and thresholds, based on surveys and field studies covering both residential and commercial buildings.

Products may offer or implement many different algorithms, and occupants are free to reprogram or override these automated controls, making it impossible to know with great certainty how these devices will really be used. Even if the window covering control strategies and thermal properties were known, the actual energy savings in a given household depends on the control strategies of other devices, such as heating and cooling equipment. Closing window coverings to mitigate solar gains may increase the required lighting energy consumption, for instance, while optimizing for natural light may affect solar heat gain, for better or worse, depending on the situation.

4.1.3 Considerations

This analysis evaluates the incremental benefit of adding automation to existing window coverings. This is different from comparing shaded and unshaded windows, or shaded windows with insulating blinds. Instead, we estimate the potential energy impact of automation relative to the existing stock of manually-

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[21] Koo et al. (2010) developed an algorithm to optimize daylight penetration while protecting user-defined zones from direct glare. In contrast to simpler algorithms that may be overly conservative in closing entire banks of blinds at once to protect large zones from glare, this method instead shades only the designated areas using more granular control of individual blinds. Hu and Olbina (2011) developed an artificial neural network approach for dealing with the special challenges of controlling split-blind systems whose upper and lower sections can be adjusted independently. Genetic algorithms that can learn and adapt to sometimes conflicting occupant preferences were developed to make the task of programming and managing blind settings less arduous and more effective at achieving savings (Guillemin and Molteni 2002).

operated window coverings. The impact primarily affects residential heating and cooling energy, with secondary impacts on lighting energy and energy required to power the motors and controllers.

Because of the complexity and relatively low adoption, most research on window covering control technologies comes from small-scale field or laboratory tests and computer simulation studies, primarily focused on commercial building applications. Energy models require detailed information to accurately simulate a system's thermal performance. Heat transfer through window coverings depends on factors such as color, slat angle and geometry (in the case of blinds), spacing from the window, material thickness and density, room geometry, and other factors. Airflow through and around coverings also affects heat transfer and is difficult to predict. Still, models continue to evolve and improve (Curcija et al. 2013), and reasonable savings impacts may be estimated based on simplifying assumptions.

Crucially, actual energy savings depends on motivations and behaviors of occupants that are not yet well characterized. As more data become available about typical usage patterns, we may better estimate what fraction of users can realize the technical potential. Because energy savings in this category are highly sensitive to many factors, our analysis considers a realistic best-case scenario. It assumes that people use the automated features primarily to save energy. Since actual savings depends on how the technology is used, and since automated coverings are not prevalent enough to determine typical usage scenarios, the energy savings estimates in this category could have significant uncertainty.

4.2 Energy Savings Potential

This section calculates the average household energy savings potential of automated window covering control for several climate regions.

4.2.1 Heating and Cooling

To evaluate the heating and cooling impact, we first characterize the baseline control behavior. D&R International (2013) provides a detailed picture of residential window coverings and control patterns based on a demographically representative Internet survey of over 2,000 households. They found that 72% of windows in Northern climates and 88% in Southern climates had window coverings of some kind. Blinds were the most common type (62%, half of which are metal or vinyl), followed by curtains (19%), shades (17%) and shutters (2%). Light colored coverings were most common (73%), followed by medium (19%) and dark (8%). Metal and vinyl blinds had the largest portion of light colored coverings (83%) vs. curtains and draperies (49%). For this analysis, we assume control systems could apply to the 80% of households with coverings of some kind.[22]

About half of window coverings in the survey were always closed and about 75% were not adjusted daily. That residential occupants rarely adjust window coverings is consistent with findings from studies of commercial buildings. For more detail on occupant control, see Mavrogianni et al. (2013) and Bennett et al. (2014). Both studies note the scarcity of field data on this topic.

Based on the extensive D&R survey results, Curcija et al. (2013) performed detailed parametric simulations of the energy savings impacts of different window coverings, with 16,486 combinations spanning 12 climate zones, four building types, three baseline windows, coverings (e.g., horizontal and

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[22] Although some shade systems are incompatible with automated controls, it is possible for households to replace them as part of a retrofit, e.g., switching curtains for automated blinds.

vertical louvered blinds, cellular shades, roller shades, surface applied films, and interior fixed panels), qualities (defining the solar and thermal performance levels), and deployment states (opened, half-opened, and closed; 0, 45°, -45°, 90° slat angle). They did not model sheer shades, window quilts, Roman shades, and drapes; however, those types comprise a smaller portion of the market as noted above, and fewer automated products currently address them. The study found that coverings can increase or decrease annual energy consumption depending on a wide range of variables.

A similar follow-on study (Firlag et al. 2015) focused specifically on the energy impacts of different covering control algorithms using residential building simulations in four U.S. cities representing different climate zones. This study identified space conditioning site energy savings potential in the range of 11.6-13.0%, depending on strategy and climate. Several algorithms were considered, including:

1. **Fixed schedule (x3):** shades that are either (1) always fully opened, (2) always fully closed, or (3) always half opened.
2. **Manual control**: schedule-based control where shades can be open, half-open, or closed during morning (6am-12pm), afternoon (12pm-6pm), and night (6pm-6am). The schedules are the same as those used by Curcija et al. (2013) and are based on the D&R International (2013) survey results.
3. **Heating/cooling system state**: if cooling is on, shades are fully opened, otherwise fully closed.
4. **Simple rules**: shades are fully opened unless there is any solar radiation (daytime) or outdoor temperature is below 63°F (likely need for heating).
5. **Perfect citizen**: fully automated control to optimize HVAC energy consumption based on an algorithm using external temperature, solar radiation, internal temperature, and thermostat setpoints (70°F for heating and 79°F for cooling in this case).
6. **Heat flow**: maximizes heat gains or losses depending on whether or not the system requires heating or cooling, based on assumed wall and window thermal properties.
7. **Predictive weather-forecast**: based on future weather data, the system can attempt to pre-heat or pre-cool the conditioned space by making adjustments to the shade position.

The same study identified both site and source energy consumption for heating, cooling, and fan energy for each scenario. For each climate, we considered the double-glazed low-emissivity window simulations as most representative, and we used results for manual control as the baseline and the *Perfect Citizen* scenario as the automation case. According to Firlag et al. (2015), for the different idealized automated control strategies simulated, there was not much difference in energy performance.

To find the average household and total national site and primary (source) energy savings potential of window covering automation, we applied the end-use percent savings from Firlag et al. (2015) to the regional end-use consumption data[23] from the 2009 Residential Energy Consumption Survey (RECS, EIA 2013). We matched the simulated cities to RECS regions as described in Table 4-4. The total heating and cooling energy savings, shown in Table 4-1, ranges from 11-20% depending on the climate.

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[23] We evenly scaled the number of U.S. households in the RECS data by region to reach the current total of 119 million. This method produced end-use estimates for heating and cooling that came within 0.02 quads (primary) of the 2015 EIA values used elsewhere in this report.

Table 4-1: Annual site energy savings of automated window coverings relative to manual control.
Simulated for a typical home of 2,400 ft^2 with low-e windows (based on Firlag et al. 2015).

	Heating (MMBtu)				Cooling (kWh)				Fan (kWh)				Total (MMBtu)			
Climate	Manual	Auto	Δ	%	Man.	Auto	Δ	%	Man.	Auto	Δ	%	Man.	Auto	Δ	%
very cold/cold	63	57	6	9%	560	330	220	40%	690	580	110	16%	67	60	7	11%
mixed-humid	32	27	5	15%	860	610	250	29%	670	530	140	21%	37	31	6	17%
mixed-dry/hot-dry	4	3	1	21%	4,300	3,830	470	11%	1,310	1,140	170	13%	23	20	3	13%
hot-humid	16	13	3	19%	1,390	1,060	330	24%	670	530	140	21%	23	19	5	20%
marine	32	27	5	15%	860	610	250	29%	670	530	140	21%	37	31	6	17%

Since RECS did not report fan energy separately for heating and cooling energy, we assumed that applying the heating and cooling savings percentages (from Firlag et al.) to the aggregate regional values (from RECS) inherently includes the appropriate fan energy savings.[24]

The heating and cooling savings potential, summarized in Table 4-2, represents the savings across the 80% of homes that already have window coverings of some kind. On average the technical potential is about 0.6 quads site and 1.1 quads primary energy.

To check the validity of this estimate, we reviewed a separate bottom-up analysis that simulated and disaggregated the heating and cooling load components for 80 single-family and 66 multi-family prototypical building models (1986-1992) intended to represent about 70% of the housing stock (Huang 2000). This study alternately adjusted individual building model parameters to zero (wall U-Value, window U-Value, window SHGC, etc.) and used regression to isolate load components. Overall, Huang found that conduction losses through windows accounted for 26% of the heating load while solar gains reduced heating loads by 8%. For cooling, solar gains through windows accounted for 32% of the cooling load and conduction gains through windows only 1%. Windows, then, account for about 1.5 of the 7.5 quads (about 20%) of residential heating and cooling, see Table 4-3.

If the analysis from Table 4-2 represents the actual technical potential, this implies window coverings could reduce window-driven loads by up to 60% for heating and 84% for cooling. This seems a higher portion of the net window contribution than may be warranted, suggesting that the simulation assumptions (in either Huang [2000] or Firlag [2015]) may not be applicable or representative of the entire housing stock. However, the load components from windows in Table 4-3 do not represent strict upper limits on savings potential. For instance, in heating season, shade control could provide increased beneficial solar gains, potentially even surpassing conduction losses.

As noted earlier, it could be especially challenging to reach the technical potential in practice, since occupant behavior may not be aligned with energy savings. To reflect this uncertainty, we extend the lower-bound savings estimate at 0.4-1.1 quads.

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[24] This is justified, since the simulated percent fan energy savings always lies between the heating and cooling savings percentages, and they are likely to be strongly correlated.

Table 4-2: Technical heating and cooling energy savings potential from window covering automation.
Based on Firlag et al. (2015)

	Household Site					U.S. Savings	
	Usage	Savings		Households	% with	quads	
End-Use / Climate		%	Δ	(000,000)	covering	Site	Primary
Heating	**MMBtu/hh**						
very cold/cold	60	9%	5.7	40.6	80%	0.19	0.22
mixed-humid	38	15%	5.8	37.1	80%	0.17	0.20
mixed-dry/hot-dry	18	21%	3.8	14.8	80%	0.04	0.05
hot-humid	12	19%	2.3	20.0	80%	0.04	0.04
marine	26	15%	4.1	6.6	80%	0.02	0.03
subtotal/avg.			**4.8**	**119.0**	**80%**	**0.46**	**0.54**
Cooling	**kWh/hh**						
very cold/cold	593	40%	237	40.6	80%	0.03	0.10
mixed-humid	1,906	29%	553	37.1	80%	0.07	0.21
mixed-dry/hot-dry	2,554	11%	280	14.8	80%	0.01	0.04
hot-humid	4,266	24%	1,024	20.0	80%	0.07	0.21
marine	362	29%	105	6.6	80%	0.00	0.01
subtotal/avg.			**582**	**119.0**	**80%**	**0.19**	**0.56**
Total						**0.65**	**1.10**

Table 4-3: Window heating and cooling load components (quads) vs. technical potential of covering automation.
Based on Huang (2000).

	Total Primary	Window Contribution						Estimated Savings	
	Energy (quads)	Conduction		Solar Gain		Net		% of Net	Primary
Heating	**5.3**	26%	**1.38**	-8%	**-0.42**	18%	**0.95**	57%	**0.54**
Cooling	**2.2**	1%	**0.02**	32%	**0.70**	33%	**0.73**	77%	**0.56**
Total	**7.5**	17%	**1.30**	3%	**0.25**	22%	**1.68**	65%	**1.10**

4.2.2 Lighting

Automated window coverings have a second-order effect on lighting energy consumption. Drawn window coverings can reduce access to natural light and increase the need for artificial light. Depending on how they are used and the baseline behaviors without automation, this could either increase or decrease lighting energy requirements. People in offices tend to cover windows to mitigate glare, frequently leaving them covered long after the offending conditions have passed (O'Brien et al. 2012, O'Brien 2013). Automation can help overcome this tendency, increasing the amount of available daylight.

Lighting optimization in conjunction with window covering control is more common in commercial buildings that require consistent daytime lighting levels. In this context, automation has demonstrated lighting energy reductions of 16-70% (Park et al. 2011), and normally depends on integrated lighting control systems that can dim or switch off lights in response to available light levels.

Lighting optimization in homes is rare. Heating and cooling normally comprise a much larger fraction of household energy consumption than lighting. People also tend to have more control over their lighting in homes than in commercial or office environments. Without an integrated lighting control system, lighting savings would depend on occupant adjustment of lights, which is unreliable and difficult to predict.

Additionally, lighting energy use in homes tends to correlate with occupancy, which is higher in the early mornings and evenings (NREL 2010). Since natural light levels are often lower or nonexistent at these times of day, this reduces the duration that shades can influence lighting energy consumption.

Daylight access – the fraction of daylight hours that shades remain open – depends on the chosen control strategy. Firlag et al. (2015) estimated these impacts for various control strategies using simulation and compared the results with survey-based values for manual control. Results for low-solar gain windows, shown in Table 4-4, indicate that adding automated control would tend to increase access to daylight compared to the baseline case, but only slightly.

Table 4-4: Fraction of daylight hours that shades are opened.
Source: (Firlag et al. 2015).

Climate	Representative City	Manual	Automated
very cold / cold	Minneapolis, MN	43%	48-55%
mixed-humid	Washington, DC	38%	44-51%
mixed-dry / hot-dry	Phoenix, AZ	31%	19-24%
hot-humid	Atlanta, GA	31%	34-40%
marine[25]	Washington, DC	38%	44-51%

Even if automated window coverings do affect access to daylight, the subsequent impact on actual lighting usage in homes remains uncertain. The primary energy used for lighting in U.S. homes in 2015 was 1.5 quads. If lighting automation changes daylight availability by 10% (up or down), this could increase or decrease lighting energy consumption by up to ±0.15 quads. Since a majority of lighting energy consumption occurs during non-daylight hours in homes (Wilson et al. 2014), the actual impact on lighting would likely be appreciably smaller than this, e.g., ±0.05 quads.

4.2.3 Operational Energy

Window covering controls require energy to operate the motors, sensors, microprocessors, and communication components of the automated controllers. How much energy depends on the adjustment frequency, the type and frequency of communication, and the number of coverings controlled. Many systems operate according to the hub and node model, where each covering or bank of coverings represents a node (radio-controlled motor) that is managed centrally through a hub that supports external control through a remote user interface.

Normally, standby radio power dominates the energy consumption of wireless window covering motors. To be ready and responsive, individual nodes cannot power down fully. Standby power varies among products: for instance, one model draws about 0.36 W (20-30 mA @ 12V DC), while a more efficient model uses an ultra-low standby power radio receiver and draws only 0.03 mA (Rollertrol 2015). Motors require more power to adjust window coverings; however these adjustments occur infrequently and briefly. One estimate is about 2 W during operation for cellular shades, and under 1 minute of adjustments per day (Firlag et al. 2015). Even with hyper-active control (5 minutes of adjustments per day), and higher motor

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[25] No marine climate was modeled in Firlag et al. (2015), however, the simulated end-uses for Washington, DC were the closest available. Less than 6% of the total U.S. housing stock is in marine climates, so this should have a minor impact on aggregate results.

power requirements for heavier coverings (5 W active), the standby power would still dominate the overall energy usage in all but the highest-efficiency case.

Low-power nodes can be powered using batteries that last for a year or more, depending on usage, or small solar panels and rechargeable batteries. Hard-wired systems, more commonly seen in high-end, new construction, and commercial applications, may draw more power. These tend to have home-run wiring to central power supplies. *Rated* power is higher (around 240 W for a panel serving 5 motorized shades [Automated Shade 2015]), and limited field data exist for average power draw. Most residential coverings can be operated with small DC motors using low voltage wires (12/24 V).

Hubs must also remain on to support communication. One Wi-Fi capable node is rated at a maximum of 0.1 A at 110 V AC, or about 1 W, and can control up to five shades (Somfy 2015). Multiple hubs of this kind can be linked together to allow remote control of many shades. Larger homes may require more hubs to communicate across greater distances.

Table 4-5: Window shade control power draw and energy consumption.

	Power (W)		(hr/yr)	Energy (kWh/device)		
Node	**Standby**	**Active**	**Active**	**Standby**	**Active**	**Total**
High Efficiency	0.0004	2	30	0.0	0.06	0.1
Med Efficiency	0.36	5	30	3.2	0.15	3.3
Low Efficiency	1.00	10	30	8.8	0.30	9.1
Hub						
High Efficiency	-	1	8760	-	8.8	8.8
Low Efficiency	-	4	8760	-	35	35

Other wireless nodes may provide add-on features, such as measuring light or solar intensity. Add-on nodes typically use low-power wireless communications. One sensor node, for example, is rated at 450 mA at 24 V DC, or about 10 W (Somfy 2015). These items are more common in commercial applications and are not essential, so we neglect their impact.

Considering the above values, we assume that each node and hub draws an average of 1 W. Thus, a system with eight controlled shades and two hubs draws about 10 W, consuming 90 kWh/yr.[26] The household energy penalty of about 0.3 MMBtu/yr site or 0.9 MMBtu/yr primary, amounts to 0.09 quads nationally.

4.2.4 Demand Response

Demand response programs can temporarily cycle or turn off the air conditioners of participating customers to curtail peak loads. This can cause buildings to become less comfortable or overheated during the events. Simulation suggests that, with proper control, thermal comfort could be improved during demand response events (Bennett et al. 2014), possibly by automatically adjusting window coverings. More research is needed to quantify these benefits.

4.2.5 National Savings

Aggregate savings for the 80% of homes with window coverings are shown in Table 4-6. To reflect the high uncertainty of these simulation-based results, and because many assumptions have yet to be

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[26] Firlag et al. (2015) estimates that 8 controlled shades could consume less than 1 kWh/year, however, this estimate does not appear to include communication or hub requirements, and assumes highly efficient electronics.

demonstrated and validated in the field, we estimate net technical savings potential of 0.3-1.0 quads. Real savings could be lower or even negative in particular cases, depending on actual conditions.

Table 4-6: Annual window covering control energy savings potential.

	Savings (quads)		Per Household, typical	
	Primary	**Site**	**MMBtu**	**kWh**
Heating	0.54	0.46	4.8	-
Cooling	0.56	0.19	-	580
Lighting Penalty	±0.05	0±0.03	-	±50
Operational Energy	-0.09	-0.03	-	-90
Total	**1.0**	**0.6**	**4.8**	**490±50**

4.3 Conclusions

The annual technical energy savings potential of window covering automation is about 0.3-1.0 quads primary energy. This assumes deployment in the 80% of homes with window coverings and that the systems are automated to optimize heating and cooling energy consumption. Effects are driven primarily by reductions in heating energy in cold climates and cooling energy in warm climates. Impact on lighting energy is expected to be small, and could increase or decrease consumption. Plug loads associated with shade control could be very low, but this depends on the technology.

Automation offers potential for overcoming the behavioral barriers that limit energy savings – specifically, the tendency for people to cover windows when it is too bright and leave them covered later. It is unclear how consistently people will adhere to energy-saving schedules, even if automation makes this simple. This adds to the uncertainty of estimates, which is already large based on the wide range of present building configurations. We know from the history of other automated or schedule-based devices, such as thermostats, that the majority of occupants may not be good at programming or adhering to schedules strictly to save energy. Some people may install automated window coverings for other reasons and not save any energy, or even increase their energy consumption. Nevertheless, the technology offers the potential for significant savings if used appropriately to reduce energy consumption.

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5 Occupancy-Based Lighting

5.1 Background

Light fixtures in the average U.S. home contain more than 50 lamps[27] (Ashe et al. 2012, Gifford et al. 2012) that account for just over 10% of residential electricity consumption (EIA 2015). Automated lighting control aligns lighting usage with occupant presence in one of two ways. Occupancy-based control senses when a space becomes occupied and automatically turns on the lights in response. In contrast, vacancy-based control relies on people to turn on the lights when they enter a space and subsequently turns off the lights when occupancy is no longer detected (CEE 2014). In practice, we believe that occupants would prefer using vacancy-based lighting control systems in most interior spaces because it is more aligned with how people typically operate lights in the home (i.e., manually turning on lights when they enter a space). In several applications, occupancy-based control would clearly be problematic. For instance, bedroom and hallway lights that turn on when people awaken in the middle of the night. For the remainder of this section, we use the term "occupancy-based control" to refer to both approaches.

Before automatically switching off the lights, both approaches typically implement a minimum time-out period to avoid inadvertently turning off lights when occupants are not detected for brief periods, and to prevent excessive lamp cycling, which could reduce lamp lifetime.

Three primary types of sensors are used for occupancy-based lighting control (CEE 2014, Roth et al. 2005):

1. Passive Infrared Sensors (PIRs) detect occupancy within a room based on changes in infrared emission of objects within the sensor's field of view.
2. Ultrasonic Sensors emit inaudible sound signals and evaluate changes in the reflected sound patterns to detect motion and, hence, occupancy.
3. Acoustic sensors infer occupancy by detecting sound waves emitted by sources in the space.

Hybrid Sensors (HS) or Dual-technology Sensors use multiple sensor types, typically, PIR and ultrasonic, to improve the accuracy of detecting occupancy within a space. In addition to these well-established approaches, numerous emerging approaches are being developed to detect or infer occupancy, presence, and proximity that could be integrated with controllers to supplement or replace occupancy sensors. Some use algorithms that consider inputs from one or more networked sensing systems, such as cameras, RFID tags, pressure pads, network activity, Wi-Fi or Bluetooth signals, microphones, and power draw (Nguyen and Aiello 2013; see also Li et al. 2012, Ting et al. 2013, Conte et al. 2014, Martin et al. 2014).

5.2 Energy Savings Potential

Fundamentally, occupancy-based lighting controls save energy by turning off lights when spaces are not occupied. To evaluate energy savings potential requires comparing lighting usage patterns to occupancy patterns in different household spaces. Importantly, both of these variables and total lamp power vary as a function of space type (Ashe et al. 2012, CEE 2014, Gifford et al. 2012).

Several studies have evaluated the energy savings opportunities of occupancy-based lighting controls in *commercial* buildings, including a meta-study for the U.S. (Williams et al. 2011). Unfortunately, a literature search revealed a dearth of similar studies and data for the residential sector. Light use duration by household space is reasonably well understood thanks to multiple field studies and other studies

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[27] A lamp refers to a single light bulb of any kind (e.g., incandescent, fluorescent, LED, etc.).

extrapolating their findings to a national scale (Ashe et al. 2012, Gaffney et al. 2010, Gifford et al. 2012, NMR Group 2014, Stum 1992; see Figure 5-1). Except for a two-home study in CA (see CLTC 2012), we did not find field studies that *simultaneously* measured both occupancy and lighting use in the same space.

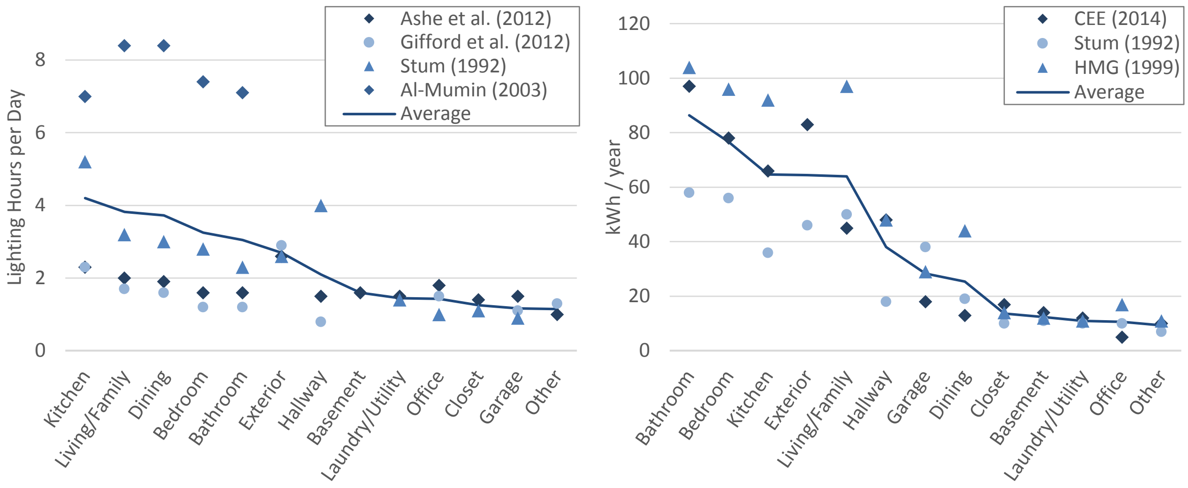

Figure 5-1: Estimated average lighting usage, and estimated savings potential per household by space for 2015.

CLTC (2012) concurrently monitored both occupancy and lighting usage in different spaces in two homes in the Davis, CA area for 8 and 22 days, respectively. Based on that study and industry expertise, CEE (2014) developed estimates for the energy savings potential from occupancy sensors in different spaces.

To estimate the energy savings of occupancy-based controls in homes, HMG (1999) used data from the Tacoma Public Utility (TPU) field study. The TPU study logged total operating time (by space) for most fixtures in 161 homes over 4-12 months. Some fixtures had typical on-off control and some had occupancy control. On average, the indoor fixtures with occupancy-based control had a 54% lower duty cycle than those with on-off control. In contrast, outdoor lamps with motion sensors had a 14% *higher* duty cycle. The authors clearly note the significant uncertainty due to small sample sizes, and state that correlation does not imply causation: other factors (besides the controller) could affect motion sensor duty cycle.

At least two studies obtained survey-based estimates of lighting usage and occupancy for different spaces. Stum (1992) developed estimates for the unintended on-time of lights in different spaces, based on a prior survey of 90 homeowners in the Northwest. Based on professional judgment and a desire for a conservative estimate, the unintended on-time values used were 50-90% of the survey values. The values were combined with total lighting usage estimates for different spaces that were developed based on a regional lighting metering study, a survey-based study, and expert judgment. This yields the estimates for energy savings for different spaces shown in Table 5-1. Self-reported estimates likely have high uncertainty, as people may have difficulty accurately recalling how long lights remained on when they were not in a space (HMG 1999).

Table 5-1: Percent of residential lighting usage while spaces are unoccupied, by space.

Space	Al-Mumin (2003) Time-out = 0/6 min.	CEE (2014)	CLTC (2012)	Stum (1992)
Basement		60%		48%*
Bathroom	79% / 71%	50%	51%	30%
Bedroom	39% / 36%	44%	41%	31%
Closet		64%	41%	39%
Dining	50% / 45%	16%		23%
Exterior		50%		28%
Garage		33%		71%
Hallway		53%	53%	20%
Kitchen	76% / 69%	39%		21%
Laundry/Utility		60%		48%
Living/Family	50% / 45%	25%	24%	28%
Office		17%		33%
Other		46%		34%**

* Assuming basement savings equals laundry/utility

** Assuming other savings equals average percent savings for all spaces.

A more recent study performed in Kuwait used surveys to estimate both occupancy and appliance usage patterns for 30 Kuwaiti households; it also collected data on light fixtures, types and power characteristics recorded (Al-Mumin et al. 2003). A look at the context of this study reveals major issues applying its findings to the U.S. First, the (heavily subsidized) cost of electricity was less than $0.01/kWh. Likely as a consequence, the average usage per space is approximately 3 to 5 times greater than the U.S. studies as shown in in Figure 5-1. Second, the homes are very large, on average comprising an average of seven bathrooms, seven bedrooms, 3.3 living rooms, and 2.4 kitchens. To estimate energy savings, we subtracted the average hourly estimates for occupancy from those for lighting use, and summed the total for all hours where lighting use exceeded occupancy. This estimated energy savings potential assumes no time-out period, i.e., once a space is unoccupied, the lights would immediately turn off. Assuming a six-minute time-out period[28] reduces the estimated savings potential by approximately 5%.

Our household-level energy savings estimates are based on the room-by-room usage and lighting power estimates of Ashe et al. (2012), combined with the per-room energy savings estimates of Stum (1992), HMG (1999), and CEE (2014). To address the spaces from Ashe et al. (2012) that are not explicitly covered in Stum et al. (1992), we assigned the energy savings for similar spaces to those spaces, i.e., Basement = 48% (same as laundry/utility), Other = 34% (simple average of percent savings for all spaces evaluated). We then normalized the kWh saved values to the 2015 average lighting kWh/household value from EIA (2015).[29] This yields average per-household energy savings of 30% (370 kWh; Stum 1992), 47% (580 kWh; HMG 1999), and 41% (510 kWh; CEE 2014). For the sake of comparison, a meta study of the energy savings of occupancy-based lighting controls in *commercial* buildings found an average savings of about 24%.

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[28] This time is subtracted from the difference between estimated portion of households with lights on in each space and estimated portion of households with each space occupied in each hourly bin. Put another way, the time-out is a once an hour event that affects every hour equally.

[29] Ashe et al. (2012) estimates a national average of 1,550 kWh/hh/year (=175TWh/113.1 million households) for lighting in 2010, whereas DOE/EIA (2015) estimates 1,225 kWh/HH/year. Based on the increased penetration of CFLs and LED lamps over that period, we assume that a decrease in average lamp power accounts for the decrease and that lighting usage and the number of lamps per household did not change.

Taking into account parasitic energy consumption from fixture-level control (see below), the net savings estimates equal 320, 460, and 530 kWh per household.

As noted earlier, the expected annual energy savings varies significantly by space, with almost an order of magnitude difference in energy savings among spaces (see Figure 5-1). Given the large variability in the *actual* magnitude of unoccupied lighting usage in different spaces, these estimates have significant uncertainty. A rigorously designed and executed field study that measures this value in a representative sample of households is needed to improve this estimate.

5.2.1 Operational Energy

The occupancy sensing and control elements also consume power, which decreases the net energy savings from occupancy-based lighting control. In this instance, the granularity of control does have a significant impact on the magnitude of the parasitic energy consumption. We evaluated two different cases, control of individual lamps and control of one or more fixtures (fixture-based control). Table 5-2 summarizes the average number of indoor and outdoor fixtures and lamps per household, as well as their power draw characteristics for fixture-based and lamp-level control. The power draw characteristics are based on data for commercial-sector fixture-level occupancy sensors (PG&E 2006) and new connected lamps (including one communication gateway per household; IEA 2014).

Table 5-2: Lighting control units (CU) and lamps (L) per household, and power for control.

			Power (W)		UEC (kWh)		
Location	**Control Units**	**Lamps**	**CU**	**L**	**CU**	**L**	**Sources for Power**
Indoor	15.0	47.4	0.2	0.4			CalPlug (2016a,b), Kofod (2015)
Outdoor	2.7	4.1	0.9	0.4			IEA (2014), PG&E (2006), CalPlug (2016a)
Total	**16.7**	**51.5**	**5.5**	**27****	**48**	**235**	**IEA (2014)**

* Includes 1.9W for communications bridge, 8 interior occupancy sensors, and 2 exterior occupancy sensors.

Clearly, the energy consumed by the control system for lamp-level controls is more than three times greater than that for fixture-based control. That said, it is important to note that the connected lamps that have recently entered the market are almost all light-emitting diode (LED) lamps, so that replacement of incandescent lighting sources with connected lamps would still realize significant energy savings relative to a typical home that still has many incandescent lamps (CEE 2014). In addition, the connected lamps offer households additional non-energy benefits that fixture-based occupancy sensors do not.

As compact-fluorescent lamps (CFLs) and LED lamps replace existing incandescent lamps, both per-household and national residential lighting energy consumption will decrease further (EIA 2015). This will reduce the absolute kWh savings potential of occupancy-based lighting controls, but should not appreciably alter the percent of lighting energy consumption saved. It will, however, magnify the importance of operational energy consumption of any sensors and controls relative to that of the lamps.

5.2.2 National Savings

The lighting end use accounts for just over seven and ten percent of residential primary energy and electricity consumption in 2015, respectively (EIA 2015). Since occupancy sensor-based lighting control is applicable to most spaces in homes and the current penetration of occupancy-based lighting control in homes is negligible for most household spaces, with the limited exception (7%) of exterior lighting (CEE 2014), the technical energy savings potential would apply to almost all current residential lighting energy consumption. Taking into account the energy consumption of fixture-based controls, we estimate that occupancy-based lighting control could reduce household lighting energy consumption by about 0.4 to 0.6 quads. Lamp-level controls would reduce this value appreciably, to 0.2 to 0.4 quads.

5.3 Other Factors

Fully networked lighting control systems also have the potential to monitor lighting usage and energy consumption, which can be used to provide feedback on energy consumption and identify energy savings opportunities. Connected systems also increase customer convenience (i.e., remote wireless control of lighting) and can enable households to create and implement different mood or scene settings that enhance the indoor environment (CEE 2014). This functionality could also be used to mimic an occupied home while the home is unoccupied, providing a security function. Occupancy-based control of exterior lights can also provide security benefits by triggering lights when motion is detected, potentially deterring would-be thieves or vandals. It may also enhance personal safety by ensuring that outdoor areas are lit when people are present, likely reducing the risk of injury (falls, sprained ankles, etc.; Meier 2016).

The demand response potential of occupancy-based lighting controls in homes is very limited because, by definition, the technology only turns on – or, in the case of a vacancy sensor, keeps the lights on – in spaces when they are occupied. Moreover, only about 2% of daily lighting energy consumption occurs in each of the hours during peak demand periods, i.e., typically noon to 6PM, in June, July, and August, yielding an average lighting power draw of approximately 50 W[30] (Wilson et al. 2014). Consequently, turning off unneeded lighting left on or dimming (if possible) connected lighting during peak demand periods would achieve a very modest peak demand reduction.

5.4 References

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[30] The Building America Benchmark finds that about 2% of daily residential lighting energy consumption occurs in each hour between 2 and 6PM in the months of June, July, and August. Given that an average of ~6% of annual residential lighting energy consumption occurs in these months (Wilson et al. 2014), that yields a peak demand of ~50W per household (= 1,225 kWh/hh*6%*2%/30).

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6 Circuit-Level Control

6.1 Background

Many electric devices consume power when they are in idle, sleep, standby, or off modes. In addition, people sometimes leave devices on (in active mode) when they are not being used, such as leaving a television on while no one is watching or listening. With an appropriate sensing system, circuit-level controls can intelligently disable the circuits powering these devices to save energy without compromising ordinary functionality.

Commercial building codes have taken the lead in requiring automated control of individual power receptacles. Notably, ASHRAE 90.1-2013 requires automated control for controlled power receptacles in several different building spaces, including office work spaces. *Automated receptacles* can be controlled based on occupancy (e.g., from existing occupancy sensors used for lighting control) or a time clock (Halverson et al. 2014), while *uncontrolled receptacles* are available for devices that cannot simply be powered off without adversely affecting functionality, such as computers. One assessment of a similar system for the residential sector assumed that a controller similar to a programmable time switch for lighting control would operate the system (California Utilities 2011).

Tier 2 advanced power strips (APS) include sensing and intelligence that can power down more sensitive loads without using a set schedule and without compromising functionality or convenience. For example, several Tier 2 APS products can monitor a room for infrared (IR) remote control signals. When no signals are detected for at least an hour, the device infers that nobody is watching and powers down the TV and other controlled loads. To avoid unintentionally switching off the TV while it is actively being used, the APS has a blinking light to alert viewers of an impending power-down event and prompts them for input to avoid the power down. A similar notification could be provided through a smart phone app.

A variant of the same Tier 2 APS is designed to work with computers and their peripherals to sense when the computer (the controlling device) is no longer being actively used. After 30 minutes without active use, the APS puts the PC into sleep mode and powers off the controlled peripherals. As with the ASHRAE 90.1 systems, devices that must always remain on can be plugged into the appropriate APS socket so they are not affected by the power down (Valmiki and Corradini 2015, Wang et al. 2015). Plug-level controllers also exist with ability to remotely control individual devices on a schedule or on command, as well as to monitor electricity consumption (Karlin et al. 2015, NEEP 2015).

In addition to these existing products, numerous emerging approaches are under development to detect or infer occupancy, presence, and proximity in the built environment that could be integrated with controllers to supplement or replace occupancy sensors. These use algorithms that consider inputs from individual or multiple networked sensing systems, such as cameras, conventional occupancy detectors, RFID tags, pressure pads, network traffic, Wi-Fi or Bluetooth signals, microphones, and power draw (Nguyen and Aiello 2013; see also Li et al. 2012, Ting et al. 2013, Conte et al. 2014, Martin et al. 2014).

Both occupancy- and time-based approaches could be implemented with web-based user interfaces and controllers that, in turn, integrate with networked and controllable circuit-breaker panels that switch on and off individual circuits (e.g., LynTec 2015).

6.2 Energy Savings Potential

We evaluated the impact of circuit-level controls for groups of devices that could be controlled using similar strategies: consumer electronics, white goods, and HVAC equipment. Separate analyses for each group follows.

This analysis assumes that people effectively implement and do not override the circuit-level control functionality. In practice, human factors could significantly compromise real-world savings. For example, if a TV is plugged into the "always on" circuit instead of the control circuit of a Tier 2 APS, TV energy consumption will not be reduced. To avoid this situation, it is critical for products to include simple and clear labels, e.g., an APS with a plug marked "Television," and to ensure that the control systems do not compromise user experience and convenience. To cite another example, if a control system disrupts the functionality of a set-top box when a person wants to watch TV, the user may become frustrated and plug it into an always on circuit, eliminating potential savings. Powering off an older video game console that is unable to save and resume a paused game could result in the same frustrating outcome.

6.2.1 Consumer Electronics

Circuit-level controls could reduce consumer electronics (CE) energy consumption in the same ways as Tier 2 APS. First, they could turn off CE that are in a sleep or standby power mode, reducing the power draw of the devices connected to each circuit to that of the standby power draw of the circuit-level controller. Second, they could turn off devices that have been unintentionally left on after a period of time without user input. Field and modeling studies suggest that this second functionality dramatically increases the energy savings potential by about 350%, most notably by reducing the on time of computers and televisions. Overall, Tier 2 APS functionality appears to reduce the energy consumption of a typical home entertainment center or home office set-up by approximately 51% (Wang et al. 2014). With the exception of televisions, video game consoles, and pay TV set-top boxes (STBs), we apply the 51% savings estimate to the residential CE unit energy consumption (UEC) and installed base values for 2013 (from Urban et al. 2014). That said, the *persistence* of the savings from Tier 2 APS has not been well characterized.

Our assessment of televisions takes into account the fact the 51% energy savings estimate is most relevant to the most-used television in homes. For less-used televisions, the potential percentage savings decreases because the one hour time-out period represents a larger portion of total TV usage time. Wang et al. (2014) uses an average daily usage t_u of 4.9 hours a day and estimates that about 1.9 hours (~40%) are user-absent t_{ua} (occur after the one-hour time-out period without user input). Since the time-out period equals one hour, this yields a similar value for the user-engaged period t_{ue} (the time when the user is actively watching the TV). For all the television usage groups, we evaluated the potential user-absent period for two cases:

1. The portion of total on time t_u that is user-engaged t_{ue} is constant:

$$t_{ue} = (1 - 40\%)t_u - 1;\ t_{ua} > 0$$

2. The portion of total on time t_u that is user-absent t_{ua} is constant:

$$t_{ua} = 40\% \cdot t_u - 1;\ t_{ua} \geq 0$$

Both calculation approaches, shown in Table 6-2, yield similar total energy savings estimates of 43-44% of total TV energy consumption.

One Tier 2 EPS manufacturers does not recommend using their products to power down video game consoles (EmberTec 2015), while another only recommends applying it to game consoles that do not have a hard disc drive (HDD; TrickleStar 2015). Thus, we only consider savings for game consoles without an HDD. In the future, a control algorithm similar to that for PCs could be developed for game consoles; assuming the same 51% savings, that would yield a UEC reduction of 45kWh and a national energy savings potential of 5.7 TWh.

Similarly, for satellite and telco STBs,[31] we assume that units with a DVR cannot be powered off because they must remain on to receive pre-positioned content from providers and record content requested by subscribers. Non-DVR satellite STBs powered up after being off for more than a few minutes may have a start-up period of about five minutes to read channel assignments and update the electronic program guide (Langille 2015). Thus, to provide an acceptable customer experience, any control system should turn the STB back on about 15 minutes before the TV would be viewed. We assume that STBs can be powered off outside the average viewing time of the most-watched TV, i.e., for 17 hours per day.[32]

We estimate that, on average, CE accounts for a large majority (~73%) of circuit-level controls, excluding potential additional savings from occupancy-based lighting control and thermostats.

Table 6-1: Circuit-level control, consumer electronics savings potential.

Device	Stock (000,000)	UEC kWh	Savings kWh	AEC TWh	Notes
Television	301	166	73	22	See Table 6-2
Set-top box: Satellite	75	112	65	4.9	non-DRV STBs only, calculated for “on” hours >7, all off hours
Set-top box: Telco	22	106	24	1.3	Assumed similar to Satellite STB
Set-top box: Digital Media Player	40	36	18	0.7	51% savings*
Set-top-box: Digital TV Adapter	13	30	15	0.2	51% savings*
Video Game Console	72	61	31	2.2	51% savings for Wii, PS2, Xbox (Wang et al. 2014)
Compact Audio	64	75	38	2.4	51% savings*
DVD player	142	24	12	1.7	51% savings*
A-V Receiver	48	65	33	1.6	51% savings*
Home Theatre in a Box	20	89	45	0.9	51% savings*
Soundbar	16	82	42	0.7	51% savings*
VCR	43	34	17	0.7	51% savings*
Blu-ray Player	52	14	7	0.4	51% savings*
Computer: Desktop	88	186	95	8.3	51% savings*
Computer: Notebook	93	51	26	2.4	51% savings*
Monitor	97	58	30	2.9	51% savings*
Computer Speaker	64	52	21	1.3	51% savings*
Printer	93	12	6	0.6	51% savings*
Total			**465**	**kWh/hh**	**Averaged over 119 million households**

* Tier 2 APS studies

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[31] As described at the end of the Circuit-Level Control section, customer and provider convenience would likely be compromised if cable STBs are cycled off for many cable TV systems, so we did not include those in our assessment. This may change as more cable systems become IP based.

[32] This would just accommodate the most-used TVs as well as less-used TVs.

Table 6-2: Calculations for television savings opportunity.

	Stock (000,000)	Total On Time, t_u h/day	Power W		Reduction in On h/day		New Off hours/day		UEC Savings kWh		UEC kWh	AEC Savings TWh	
TV Priority			**On**	**Off**	**Case1 (C1)**	**Case 2 (C2)**	**C1**	**C2**	**C1**	**C2**	**Base**	**C1**	**C2**
1	115	7.0	105	1.1	3.2	2.8	20.2	19.8	131	114	274	15	13
2	81	3.8	81	1.6	1.29	1.50	21.5	21.7	51	57	125	4	5
3	48	2.6	78	1.9	0.6	1.0	22.0	22.4	31	45	89	2	2
4	24	2.4	80	2	0.4	1.0	22.0	22.6	29	44	84	1	1
5	11	1.6	81	2.4	0.0	0.0	22.4	22.4	20	20	65	0	0
6+	23	1.1	84	2.6	0.0	0.0	22.9	22.9	22	22	57	0	0
								Wtd. Avg.	**73**	**72**		**22.1**	**21.7**

6.2.2 White Goods

Many appliances have controls, power supplies, and displays or clocks that draw 2 to 3 W continuously. In an aggressive case, circuit-level control would power off these devices when they are not running, i.e., typically all but one or two hours a day. A manual wall controller would be used to turn back on the circuit as needed to operate different appliances.

Table 6-3: Circuit-level control, white goods savings potential.

Device	Stock (000,000)	Power Draw W	UEC Savings kWh	AEC Savings TWh	Notes
Cooktop or Stove	119	2.6	21	2.5	Ownership rate from DOE/BT (2012), scaled to 2015 hh; assumed same standby power (2.6W) as over-the-range microwave ovens (DOE 2013); assumes off outside of 2 operating hours/day.
Dishwasher	73	2.0	17	1.2	Usage from DOE/BT (2012); assumed similar power draw as other white good; installed base from Goetzler et al. (2013)
Clothes Washer	113	2.0	17	1.9	Usage and saturation from DOE/BT (2012); power draw from Korn and Dimetrosky (2010)
Clothes Dryer	98	2.3	19	1.9	Power draw from EPA (2011); saturation and run time from DOE/BT (2012)
Total			**63**	**kWh/hh**	**Averaged over 119 million households**

6.2.3 HVAC Systems

Measurements made as part of DOE rulemakings found the controls and power supplies of central HVAC systems have a standby power draw on the order of 8 to 11 W.[33] Circuit-level control can save energy by powering off the dedicated HVAC circuit during times of year when the system does not typically run. This could be achieved in practice, for example, by using outdoor temperatures to predict whether or not the system will run. As an initial estimate, we assume that all central residential air-conditioners, furnaces, and boilers run half of the year and can be turned off the other half. In contrast, central heat pumps are assumed to have very limited savings potential because they will, on average, operate in either heating or cooling mode most of the year.

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[33] An ECM furnace fan draws about 3 W more (DOE 2011b).

The savings potential for window air conditioners is much lower than central units due to a lower (about 1W) power draw (DOE 2011b) in units with electronic controls, and negligible (about 0.03W) power draw in off mode for units with electromechanical controls.

Table 6-4: Circuit-level control, HVAC savings potential.

Device	Stock (000,000)	Standby Power W	UEC Savings kWh	AEC Savings TWh	Notes
Central AC	62	12*	53	3.2	Power draw and saturation (51.8%) from DOE (2011a)
Window AC	69	1.0	5.3	0.4	Saturation (29%) from DOE/BT (2012); assumed 2 units/hh; 1.0W (DOE 2011b)
Central Heat Pump	15	38**	0	0.0	No savings, assumed to operate most of year; power draw and saturation (12.8%) from (DOE 2011a)
Furnace: Gas+LPG	52	8	35	1.8	Power draw and saturation (12.8%) from DOE (2011a)
Furnace: Oil	3	9	39	0.1	Power draw and saturation (12.8%) from DOE (2011a)
Boiler: Gas	7	8	35	0.3	Power draw: (DOE 2011a), saturation (DOE/EIA 2009)
Boiler: Oil	4	9	39	0.2	Power draw: (DOE 2011a), saturation (DOE/EIA 2009)
Total			**50**	**kWh/hh**	**Averaged over 119 million households**

* DOE (2011a) assumes that 10 percent of central air conditioners have a crankcase heater that draws 40W.

** DOE (2011a) estimates that two-thirds of central heat pumps have a crankcase heater that draws 40W.

6.2.4 Other Devices

Ceiling fans appear to have the greatest energy savings potential of common “other” loads, specifically from occupancy-based power-down of fans when the spaces they condition are unoccupied. Although some ceiling fans do have occupancy sensors,[34] it appears that most do not. Unfortunately, we did not find any field studies that correlated ceiling fan usage and occupancy in different rooms. Kantner et al. (2013) fielded an Internet survey to evaluate what portion of ceiling fan usage occurs when rooms are unoccupied. Based on the survey responses, it appears that approximately 39% of ceiling fan usage occurs when rooms are unoccupied. Interestingly, this is similar to our estimate for the energy savings potential of occupancy-based lighting controls in homes (see Section 5).

We also evaluated the potential savings from powering off coffee makers, toasters, and toaster ovens when not in use. Only a portion of these products draw power when not in active use, and the analyses take this into account. Of these devices, coffee makers may be able to realize significant additional savings by eliminating some portion of the energy consumed in idle (warming) mode when they draw about 70 W (Roth et al. 2008). It is not immediately clear, however, how detection of excess warming energy consumption would be implemented and integrated with circuit-level control.

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[34] For example: http://www.gossamerwind.com/content/what-so-special-about-these-fans-0, http://www.techrepublic.com/article/haiku-ceiling-fan-for-the-smart-home-owner/.

Table 6-5: Circuit-level control, other devices.

Device	Stock (000,000)	UEC kWh	UEC Savings kWh	AEC Savings TWh	Notes
Toasters and Toaster Ovens	174	N/A	1.5	0.3	16% of time in low-power mode, average power = 1.1W (Greenblatt et al. 2013)
Coffee Maker	72	N/A	7	0.5	50% of time in low-power mode, average power = 1.7W; (Greenblatt et al. 2013)
Ceiling Fan	239	99	39	9	Kantner et al. (2013); off-mode savings much smaller[35]
Total			**84**	**kWh/hh**	**Averaged over 119 million households**

6.2.5 Devices Unsuitable or Not Considered

Several devices were intentionally excluded from the analysis because they are not likely to be suitable for circuit-level control for practical compatibility reasons, or because they have low impact on overall savings. These are summarized in Table 6-6.

Table 6-6: Devices not suitable or not considered for circuit-level control.

Not Suitable	Reason / Considerations
small network equipment	always on for connectivity
microwave oven	always on to maintain clock
clock radio	always on to maintain clock
docking station	always on for clock or for charging
power tool chargers	many require maintenance charging
cordless vacuum	many require maintenance charging
fish tank heater and pump	always on and required for fish
security system	always on
cordless phone	always on
refrigerators and freezers	always on
cable set-top box	always on, shutting off can compromise convenience to customers or providers
air purifiers	operation not tied to occupancy
hair dryer	usually unplugged when not operating
iron	usually unplugged when not operating
garage door opener	may not be feasible to shut off circuit shared with garage lights ~4.5W (Meier and Aillot 2015)
Not Considered	
lighting	considered separately in Section 5
space heaters	unclear energy savings potential
pool pump	small installed base of variable frequency drive pumps
mobile phone	low annual energy consumption
tablet computer	low annual energy consumption
waterbed heater	small installed base (~4 million) and lower standby power (~2W; Roth et al. 2008)
irrigation system controller	modest installed base (~14 million; EPA 2011) and power draw (~1.8W; Meier and Aillot 2015)

6.2.6 Operational Energy

The sensor and control systems required to implement circuit-level control typically do consume additional energy. The estimated incremental power draw depends upon the sensors and controller used,

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[35] Estimated 0.3W average ceiling fan standby power based on remote controlled units (1.4 W, 17% market share DOE 2014).

as well as the granularity of control implemented. Table 6-7 summarizes power draw estimates for different potential sensing and control system components that can be purchased today.

To evaluate the approximate additional power consumption from circuit-level control, we defined the room-by-room controllers required to implement circuit-level controls for the systems evaluated in earlier in this section, excluding ceiling fans.[36]

Table 6-7: Energy consumption characteristics of circuit-level control components.

System Type	Power W	UEC kWh	Source
Networked controllable circuit-breaker panel	~9*	79	Tschirner (2015); greatest flexibility in control algorithms implemented
Time-based lighting controller	0.2	2	California Utilities (2011); limited CE savings relative to Tier 2 APS
Occupancy sensor (per space)	0.2	2	CalPlug (2016)
Tier 2 APS	~0.9	8	Wang et al. (2014), Tricklestar (2015)

* In practice, the circuits do draw additional power when switching, but the duration of switching events (~25 ms; Tschirner 2015) minimizes the energy impact from switching. For example, 1,000 switching events/day would have a total duration of 25 s/day.

Table 6-8: Energy consumption characteristics of a prototypical circuit-level control system.

Room	Controller(s)	Power W	UEC kWh
Kitchen	Timer Controller (2) – Plug Loads; Dishwasher and stove top	0.4	4
Living Room	Tier 2 APS – CE; STB on timer; Ceiling fan occupancy sensor	1.3	11
Dining Room	None	0.0	0
Bedroom – 1	Tier 2 APS – CE; STB on timer; Ceiling fan occupancy sensor	1.3	11
Bedroom – 2	None	0.0	0
Bedroom – 3	None	0.0	0
Laundry	Timer Controller	0.2	2
Mechanicals	Seasonal Timer Controller (2)	0.4	4
	Total	**3.6**	**32**

6.2.7 National Savings

Taking into account the energy consumed by a circuit-level control system in a prototypical household, circuit-level controls could reduce electricity consumption in an average household by about 630 kWh per year. Applied to all U.S. households, this equates to a technical energy savings potential of about 75 TWh, or 0.8 quads. Both estimates exclude potential savings from occupancy-based control of lighting systems.

6.3 Other Factors

Circuit-level control devices that also measure circuit-level power draw have the potential to provide multiple benefits beyond direct load control. Indeed, some plug-level controllers and APS already have this functionality. All are based on the ability to use the detailed electricity consumption profiles to obtain much more detailed insight into how individual homes consume electricity than conventional electricity bills or smart-meter data.

First, circuit-level electricity consumption data can be used to provide very specific feedback on energy consumption to households. As noted by Armel et al. (2013), the energy savings obtained from feedback

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[36] Ceiling fans have quite limited energy savings potential and only occupancy-based control would make sense to apply.

increases when it is delivered in real time and is provided for specific devices or energy end uses. Moreover, the ability to provide actionable energy-saving behavioral recommendations customized to the electricity-consuming devices and context of individual households has the potential to further increase realized energy savings. Similarly, utility energy-efficiency and demand-response programs could use the data to perform remote audits to identify energy efficiency (EE) and demand response (DR) retrofit opportunities and potentials for individual homes, as well as customized estimates of the energy savings potential and payback period of retrofits. The same data could also be used to help segment different customers, potentially increasing the effectiveness of customer outreach and retrofit uptake rates. Subsequently, post-retrofit data could be used to confirm that the retrofit had been successfully completed and provide remote evaluation, measurement and verification (EM&V) of actual energy savings and demand reduction. Measurements at sufficiently high sampling rates also have the potential to provide device-level performance diagnostics, e.g., for HVAC systems (Armstrong et al. 2006).

Control implemented through networked and controllable circuit-breaker panels could also facilitate implementation of load management capability for demand response and for load prioritization in homes operating independent of the grid (e.g., islanded operation during power outages).

Finally, circuit-level whole-home controls could provide a security function by automatically turning on and off different lights and devices to mimicking household usage patterns when a home is vacant.

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7 Conclusions

7.1 Overview of Findings

Home automation technology offers the potential to achieve substantial energy savings if they are used for that purpose. In this study, we evaluated the technical energy savings potential of five home automation approaches relative to the baseline of household energy consumption in 2015. The results in Table 7-1 include the direct energy savings of the approaches, less any operational energy required (e.g., to power wireless radios or sensors). They do not, however, take into account any additional energy consumed by home networks or the cloud to transmit and store data. The approaches evaluated – and their potential savings – are relevant to a large majority of U.S. homes.

Table 7-1: Annual technical energy savings potential estimates for selected home automation approaches.

	Primary Energy		Household Savings Potential				
	quads[1]		MMBtu[2]	kWh			Relevant**
Approach	**Usage[3]**	**Savings**	**Heating**	**Cooling**	**Lighting**	**Electric***	**Households**
Connected Thermostat	7.5	0.7-1.1	6	400	-	-1 to -30	80-90%
HVAC Zoning[3]	7.5	0.3-0.6	4	210	-	-5 to -50	60-85%
Window Covering Control[3]	7.5	0.3-1.0	5	580	±50	-90	80%
Lighting Control, Occupancy	1.5	0.4-0.6	-	-	370 to 580	-50 to -235	100%
Circuit-level Control	2.5	0.8	-	-	-	630	100%

[1] One quad = 10^{15} British thermal units (Btus)

[2] MMBtu = one million Btus.

[3] Estimates based mainly on simulations and carry higher uncertainty.

* Negative values indicate energy used during operation.

** Portion of households to which an approach is applicable.

The technical energy savings potential of individual approaches ranges from 0.3 to 1.1 quads, or 1-5% of the total primary energy consumed by U.S. homes in 2015. Put another way, saving one quad per year is equivalent to the energy consumed by about 3 million people, the electricity produced by 250 coal-fired power plants, or 56 million metric tons (MMT) of CO_2 emissions (DOE 2012). Since several approaches address the same energy end-use (e.g., connected thermostats and HVAC zoning both affect HVAC energy consumption), the combined savings potential is somewhat less than their sum. How much of this potential could actually be realized depends on practical considerations that are not yet fully understood.

These estimates do contain some important sources of uncertainty, largely driven by the limited scope and number of field studies. Case studies and simulation-based studies provide important groundwork for estimating energy savings potential of several categories; however, they are often based on assumptions that do not always capture the complexities observed in the field. In particular, variability in occupant behavior can yield large differences in observed savings on a household level. Additionally, differences in building construction, climate, and HVAC systems can affect household-level energy impacts. When field studies are available, it is often challenging to generalize findings because of differences in methods and experimental bias. For several categories, products are not yet widely available or adopted. Despite these limitations, our figures represent the best current knowledge of credible savings estimates. Future studies will continue to shed more light on the actual savings opportunity.

Beyond energy savings, home automation offers benefits to both consumers and utilities. For consumers, these include greater convenience, control, thermal and visual comfort, privacy, and security. For utilities, home automation could enable demand response capabilities, streamline evaluation for energy efficiency programs, and remotely diagnose and detect retrofit opportunities.

While the home automation approaches we evaluated all have appreciable energy savings potential, several hurdles must still be overcome for this technical potential to be realized at a large scale. Currently, energy savings is often not the primary driving force behind consumer adoption (or the usage) of most home automation technologies. As more field studies are completed, the case for energy savings may become clearer for specific technologies, which could lead consumers to better appreciate and assess the economic case. Alternatively, if consumers continue to adopt home automation products for benefits besides energy savings, we must recognize that not everyone will use the technology in a way that reduces home energy consumption. Thus, the realized energy impact will depend strongly on how the products implement these features.

Current federal regulations for lamps are projected to significantly reduce residential lighting energy consumption over the next several years. This will, in turn, reduce the potential savings from lighting controls. Similarly, as the standby (and on-mode) power draw of devices declines with better technology, the opportunity for circuit level control savings will also diminish with time. Conversely, we identified an energy penalty associated with the automation hardware for several approaches. As lower power standby options for sensing, communication and control become more widely available and less costly to integrate, these penalties would be expected to decline.

7.2 Recommendations for Further Study

Most categories, except for connected thermostats, have major gaps in empirical data to inform estimates of real-world savings opportunities. Consequently, well-designed field studies are needed to refine the energy savings potential estimates of home automation technologies. Recommendations for future study, specific to the approaches evaluated here, are provided in Table 7-2.

Table 7-2: Research needs.

Problem/Opportunity	Reason(s)	Research Needs
General		
Energy savings estimates have high uncertainty.	Savings can vary significantly among households, and among products within a device category. Simulation-based analyses can have high uncertainty because of oversimplified assumptions about user behavior and/or baseline conditions. Large-scale representative field studies are rare because technology adoption is still relatively low. Current users (early adopters) may not be representative of the general population. Small-scale studies provide an indication of savings potential but may not be generalizable.	Execute well-designed (randomized) long-term, large-scale field studies of energy performance across device categories, climate regions, and household types. Leverage field data sources (from home automation devices) to inform realistic simulation, specifically to better characterize impacts of user behavior.
Long-term energy savings (persistence) is unknown.	Long-term adoption is still fairly low for most product categories. Energy performance depends on how people use the technology, and this can change with time. Technology upgrades (hardware or software) can also change the energy performance of installed home automation over time.	Long-term field studies, ongoing analysis of (anonymized) user data of home automation technologies.
Consistent savings calculation methods must be developed.	Industry-standard methods do not yet exist for calculating energy performance or savings of home automation devices that depend strongly on behavior. Baseline assumptions may differ depending on what is being calculated (e.g., savings vs. performance).	Develop and validate standard methods based on industry-stakeholder process (backed by independent research).
Approach-Specific	**Key Issues**	**Research Needs**
Connected Thermostats	Savings and persistence can be highly variable. Inconsistent savings methods used across field studies, especially because of highly variable baseline behavior among homes with non-connected thermostats.	Long-term field studies, consistent methods for reporting savings or performance, and clear definitions of baselines.
HVAC Zoning Control	Zoning could *increase* HVAC energy consumption for a single-speed/capacity system. Improperly implemented zoning could create HVAC operational problems, particularly for single-speed/capacity systems.	Field study of the net energy impact of zoning for fixed- and variable-capacity HVAC systems in a range of home types and climates.
Window Covering Control	Simulation-based analyses have high uncertainty due to oversimplified assumptions about user behavior and/or baseline conditions that strongly impact actual savings. Lack of field studies for window covering controls.	Field studies evaluating the net energy impact in a representative sample of homes, for the main types of window coverings.
Lighting Control	Lighting usage and its correlation with occupancy by room is not well known, making it difficult to estimate savings from lights that are left on in unoccupied rooms.	Field studies in a representative sample of homes that measure coincident time-series occupancy and lighting usage by room.
Circuit-Level Control	Field and laboratory studies of Tier 2 Advanced Power Supplies (APS) have evaluated savings for periods of well under a year.	Multi-year field study to evaluate persistence of energy savings for Tier 2 APS in both media center and home office applications.