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Office of ENERGY EFFICIENCY & RENEWABLE ENERGY

Modeling Savings for ENERGY STAR Smart Home Energy Management Systems

July 2021

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Modeling Savings for ENERGY STAR Smart Home Energy Management Systems

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U.S. Department of Energy

July 2021

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Acknowledgments

The authors acknowledge the financial resources and valuable input provided by the National Renewable Energy Laboratory, including Stacey Rothgeb, Conor Dennehy, Lena Burkett, and Lieko Earle. The ENERGY STAR® Smart Thermostat and Smart Home Energy Management System team (Abigail Daken, Theo Keeley LeClaire, and Taylor Jantz-Sell) provided important insights that were used to guide the technical approach. Several experts on home energy management and demand response programs provided information from previous studies, including Albert Chiu of Pacific Gas and Electric, Kitty Wang of Energy Solutions, and Dr. Farhad Omar of the National Institute of Standards and Technology. We also recognize the important contributions made by other members of the Frontier Energy team, including Jon McHugh of McHugh Energy Consultants Inc., and Stephen Becker and Kate Rivera of Frontier Energy.

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Executive Summary

The objective of this study is to develop a repeatable and defensible methodology to analyze the energy savings for home energy management systems (HEMS) that meets the minimum requirements for certification under ENERGY STAR® Smart Home Energy Management System (SHEMS) Version 1 (U.S. Environmental Protection Agency [EPA] 2020a). Mandatory connected loads include a smart thermostat, two smart lights, and one smart power strip or smart outlet. Control strategies must include feedback to occupants through an in-home display, user programming, occupancy sensor-based controls, and responsiveness to utility signals such as demand response programs.

Several occupant behavior patterns were selected to quantify the range of energy savings potential for a HEMS with this basic functionality. A literature review was conducted to establish realistic room-by-room occupancy levels and usage patterns for connected devices. A series of event-driven hourly profiles were created, followed by adjustments based on application of HEMS control strategies to thermostats, interior lighting, and plug load schedules. EnergyPlus® modeling was performed using these hourly schedules in three locations (Boston, Houston, and Phoenix) to examine climate dependence of energy savings.

Total site energy savings ranged from 4.3 to 27.1 MBtu/year (7%–35%), and utility bill savings ranged from \$123 to \$670/year (6%–29%). The highest predicted savings was realized by occupants that were not energy conscious prior to HEMS installation, but highly engaged with the HEMS controls once the system was installed. The smart thermostat accounted for most of the savings, followed by the smart power strip. Smart lighting did not save a significant amount of energy in our analysis, based on an assumption that efficient LEDs with no standby power would normally be installed anyway.

1 Introduction

Home energy management systems (HEMS) are part of a quickly expanding product market that provides homeowners with the ability to control energy-consuming devices through monitoring and feedback, programmed schedules, control logic based on occupancy sensors or weather data, machine learning, and utility signals. The broad range of HEMS product combinations and the high dependence on occupant behavior make it challenging to create modeling algorithms that accurately estimate impacts on energy bills, especially under time-of-use rates. This inability to quantify the benefits of HEMS has been identified by stakeholders as a major barrier to qualifying HEMS for utility program incentives and energy efficiency credits in energy codes (Hendron et al. 2020).

For this project, Frontier Energy leveraged previous work performed by the National Renewable Energy Laboratory (NREL) in support of the Building America House Simulation Protocols (HSP) (Wilson et al. 2014), along with more recent studies of energy savings for HEMS control strategies conducted by Frontier and others, to simulate the range of expected energy and cost savings for a HEMS that minimally complies with the ENERGY STAR Smart Home Energy Management System (SHEMS) Version 1 certification requirements (EPA 2020a). The methodology developed under this project could increase demand for ENERGY STAR-certified SHEMS by increasing consumer confidence in the likely range of energy savings for a basic HEMS package. It is also an important step toward a flexible and repeatable method for predicting the energy savings of any theoretical combination of HEMS capabilities, connected devices, and occupant behavioral patterns.

1.1 ENERGY STAR Smart Home Energy Management System Requirements

The ENERGY STAR program finalized Version 1 of the SHEMS certification requirements in September 2019 following extensive collaboration and review by HEMS manufacturers, technology experts, and other stakeholders. Because we are focused on modeling systems that comply with the minimum requirements of an ENERGY STAR-certified SHEMS, it is important to identify which specific attributes are mandatory and which are optional. The relevant requirements are summarized below:

- Connected End Uses
  - Heating and cooling via ENERGY STAR Smart Thermostat (EPA 2017)
  - Two smart lights (EPA 2020b) or fixtures (EPA 2019)
  - One smart power strip/smart outlet
  - Optional control of water heaters, appliances, batteries
- Control Methods
  - Occupant feedback (energy use and recommended behavioral actions)
  - User-established rules/schedules
  - Occupancy sensor-based optimization
  - Grid signals (demand response, possible load shifting)
  - Optional use of predictive control and machine learning.

In most cases, the requirements related to connected devices and control strategies are very clear. In other cases, EPA identifies general functionality that can be difficult to quantify in a building energy model. The challenge for this project was to convert those requirements into specific modifications to thermostat settings, heating, ventilating, and air-conditioning (HVAC) availability, lighting and miscellaneous electric load (MEL) schedules and peak loads, and other modeling inputs that may be affected by the operation of the HEMS.

EPA has not published estimates of energy savings potential for SHEMS. Instead, the program emphasizes the collection of field data for a range of compliant systems to demonstrate actual savings in occupied homes. That information will be valuable in the long term, but it will likely be two or three years before useful data are available. There is also the likelihood of new technologies arriving on the market, making it challenging to obtain field test data before the results become obsolete due to the rapid evolution and turnover of HEMS products.

1.2 Building America House Simulation Protocols

The 2014 update to the HSP, combined with the Building America Analysis Spreadsheets (NREL 2011), provides much of the information needed to analyze HEMS in a consistent manner. However, the HSP is primarily focused on disaggregation of detailed end uses, along with standardized hourly and seasonal operating profiles. It does not provide guidance on how controls would impact these profiles, nor does it provide discrete event-driven schedules for individual devices or lamps. The HSP is also somewhat out of date, especially in the areas of lighting and MELs where the market has evolved rapidly over the past 5–10 years. The HSP uses constant thermostat settings of 71°F for heating and 76°F for cooling, which are based primarily on occupant comfort according to ASHRAE Standard 55-2010 (ASHRAE 2010) and are not necessarily realistic for most households. Finally, most schedules are the same on weekdays, weekends, and vacation days, which is not as realistic as we would like for detailed HEMS analysis.

2 Technical Approach

The first step for this project was a literature search to identify relevant work performed by other researchers. This helped ensure that we built upon the best information available. Detailed information about occupant behavior was sparse, but there have been several field studies evaluating various common elements of HEMS functionality, especially related to smart thermostats. There have also been a few modeling studies of the energy savings potential of various types of control logic, most often related to predictive control and machine learning. In addition, we investigated surveys of occupants regarding their attitudes toward HEMS and their likelihood of overriding grid signals or preprogrammed controls. Further details on the literature search are provided in Section 3.1.

Once we had a solid understanding of past work, we leveraged that knowledge to develop a robust methodology for modeling the energy savings potential for an ENERGY STAR-certified SHEMS. We focused on leveraging field studies that could provide direct modeling inputs, such as studies of thermostat settings with and without a smart thermostat, or a specific fraction of lights that are regularly turned off when rooms are unoccupied. In addition, we made use of studies that provide energy savings for one technology, or a bundle of technologies, as a calibration point for approximating reasonable behavioral changes that would result in comparable energy savings in our model. If no field data were available to support specific modeling inputs, we used engineering judgment to make reasonable assumptions about likely operational changes following the installation of a HEMS with specific control logic.

The starting points for all operating conditions were those documented in the HSP and associated spreadsheets. However, we needed to convert some of the smooth hourly profiles into more realistic step functions based on specific devices turning on and off at certain times of day. We also established specific occupancy levels in each room at each hour of the day, including periods with nobody at home. This use of discrete behavioral patterns in relation to the operation of specific devices was necessary to make realistic adjustments to loads based on HEMS operation and grid signals.

Modeling inputs were developed for four combinations of behavior before and after HEMS installation, as shown in Table 1. For the baseline cases without HEMS, the "Not Energy Conscious" (NEC) case represents fairly high use occupants that generally don't take actions to minimize energy use, while "Very Energy Conscious" (VEC) occupants employ thermostat set-back/set-up and usually attempt to turn off lights and electronic devices when not in use. In cases with HEMS, the "Somewhat Engaged" household makes limited use of HEMS features and sometimes overrides demand response signals. The "Highly Engaged" household uses all features and does not override demand response or other signals except in unusual circumstances, such as during a dinner party. There is also likely to be a group of "Not Engaged" households that make no use of HEMS features. Though important, we did not model this case because the energy savings would be negligible or even negative due to HEMS standby losses. Further details on the behavioral assumptions for each category are provided in Section 3.2.

Table 1. Matrix of Occupant Behavior With and Without HEMS Installed

Without HEMS	Not Energy Conscious (NEC)
	Very Energy Conscious (VEC)
With HEMS	Somewhat Engaged (SE)
	Highly Engaged (HE)

EnergyPlus was used for all modeling activity to allow maximum flexibility when implementing the HEMS analysis methodology. The HSP requirements for new construction were used for all uncontrolled end uses, along with the building envelope characteristics. A typical 2-story, 3-bedroom, 2,150-ft^2 single-family house geometry was selected for modeling, as shown in Figure 1. Because discrete occupancy levels were required at all times for the purpose of applying control logic, we assumed 3 occupants instead of the HSP default of 2.6. A summary of baseline assumptions is provided in Table 2. Refinements to occupancy, thermostat, lighting, and MEL schedules required for detailed modeling of HEMS are discussed in Section 3.2.

Figure 1. Representative house used for EnergyPlus modeling

Table 2. EnergyPlus Baseline Modeling Inputs

House Characteristic	Value
Floor area	2,150 ft^2
Orientation	East-facing
Number of stories	2
Number of bedrooms	3
Number of occupants	3
HVAC	Gas furnace, air conditioner
Location	Boston, Phoenix, Houston
Natural gas utility rate structure	Fixed national average
Electric utility rate structure	Representative time of use
Other house characteristics/schedules	HSP default

Each of the four behavioral scenarios was modeled in three different cities (Boston, Houston, and Phoenix) representing three different climate zones (cold, hot-humid, and hot-dry), resulting in 12 total modeling runs. The Boston model used a basement foundation, while Houston and Phoenix used slab-on-grade. The three locations had differing heating and cooling seasons, latent versus sensible cooling loads, lighting usage based on latitude, as well as systems interactions between internal loads and HVAC energy.

Energy costs were calculated using a typical national time-of-use rate schedule developed by Frontier Energy for another project (German and Hoeschele 2014), because some of the control strategies were intended to shift load from more-expensive (4 to 9 p.m.) to less-expensive time periods rather than simply to save energy. The peak cost from 4 to 9 p.m. year-round was $0.30/kWh and the off-peak cost all other times was $0.10/kWh. A national average rate of $1.0135/therm was used for natural gas as reported by the U.S. Energy Information Administration (EIA) for 2019 (EIA 2021).

3 Project Results

The final results for this project include key findings from the literature search, the detailed methodology used to adjust modeling inputs, and the range of energy savings calculated by the EnergyPlus models.

3.1 Literature Search

The literature search revealed a range of experimental and theoretical studies that provided valuable insights into the methodology that would be needed for this project. A summary of literature search findings that we expected to use as part of the methodology, either as direct modeling inputs, adjustments to baseline assumptions, or checks on energy savings calculations, are summarized in Table 3. Further details about how these results were used are provided in Section 3.2. Many additional publications were reviewed as part of the literature search but were not explicitly used in the formulation of the HEMS analysis methodology, either because a more appropriate reference was available or because the information was not aligned with our technical approach. A more complete list and relevant summaries of these publications are available upon request from the authors of this report.

Table 3. Key Literature Results Used in This Study

Category	Attribute	Value	Source
Occupancy	Most common occupant age combination for 3-person household	Two people 25 to 34, one under 25	Mitra et al. (2020)
	Daytime occupancy (at least one person home)	44% weekdays, 65% weekends	Piper et al. (2017)
	Room-by-room occupancy	See Figure 2	Mitra et al. (2020)
Thermostat	Thermostat base comfort settings	76°F summer, 68°F winter	Based on analysis of Pang et al. (2020)
	Daytime regular or temporary vacancy setback/setup (when used)	5°F summer, 9°F winter	Based on analysis of Pang et al. (2020)
	Nighttime setback/setup (when used)	5°F summer, 9°F winter	Based on analysis of Pang et al. (2020)
	Demand response event temperature offset (when used)	+3°F summer, -3°F winter	Comparison with CEC (2019)
Lighting	Household lighting energy	~30% of 2014 HSP lighting values	Rubin et al. (2016)
	Living room lighting average operating hours	2.3 hrs/day (mix of overhead/portable)	Rubin et al. (2016)
	Bedroom lighting average operating hours	1.7 hrs/day (mix of overhead/portable)	Rubin et al. (2016)
	Living room percent portable	35%	Rubin et al. (2016)
	Bedroom percent portable	39%	Rubin et al. (2016)

Category	Attribute	Value	Source
	Lighting schedules on weekday vs. weekend	Approximately the same	Rubin et al. (2016)
	Lighting that occurs with nobody present	25% of living room lighting, 35% of bedroom	Urban, Roth, and Harbor (2016)
	Smart lamp operating hours and dimming	Field study showing increase in usage of 1 hr/day, but decrease in lumen-hours of 500 lm-hrs/day, partially due to dimming	Earle and Sparn (2019)
	Smart lamp locations	50% installed in living/family room, 33% in bedrooms	Applied Energy Group (2020)
	Occupancy sensor impact	54% lower duty cycle for occupancy sensor vs. on/off controls	Urban, Roth, and Harbor (2016)
	Potential whole-house lighting savings	212 kWh/yr in 2017, efficiency based on older EIA study	Piper et al. (2017)
MELs	Primary TV in active mode (not necessarily being watched)	7.7 hrs/day	Rubin et al. (2016)
	Time average person watches TV	2.81 hrs/day	Bureau of Labor Statistics (2019)
	Time average person plays video games	0.26 hrs/day (0.65 hrs/day for 15–24 age range)	Bureau of Labor Statistics (2019)
	Savings for Tier 2 Advanced Power Strip (APS) controlling entertainment center	148 kWh/year	Background analysis for Wei et al. (2018) derived from Valmiki and Corradini (2016)
	Potential savings for TVs/home entertainment	8%	Lamoureaux, Reeves, and Hastings (2016)
	Potential primary TV savings through circuit-level controls	131 kWh/yr savings out of 274 kWh/yr	Urban, Roth, and Harbor (2016)
	APS standby power	1 W	Background analysis for Wei et al. (2018)
	TV standby power	1 W	Rubin et al. (2016)
	TV active power	169 W	Rubin et al. (2016)
	Potential standby load reduction through optimal behavior with minimal inconvenience	30%	Lawrence Berkeley National Laboratory (2020)
	Potential plug load savings for occupancy-based controls (primarily home electronics)	341 kWh/yr with 15-minute time delay	Piper et al. (2017)

Category	Attribute	Value	Source
Cross-cutting	In-home display savings	260 kWh/yr (with HVAC), ~219 kWh/yr (without HVAC)	Herter and Okuneva (2014)
	In-home display savings (feedback to occupants about energy use)	4%–7%, declines over time	Karlin et al. (2015)
	Lighting/plug load savings impacts for demand response	Not statistically significant, but consistently positive	Applied Energy Group (2020)
	Percent of devices turned back on during demand response events	5%–20%	Applied Energy Group (2020)
	Likelihood of further participation in demand response programs based on experience with study	43%	Applied Energy Group (2020)
	Demand response events in 2020	14	Southern California Edison (SCE) (2020)
	Average number of demand response events	7.4 nationwide for behavioral programs	Smart Electric Power Alliance (2018)
	HEMS continuous power	4 W, not including thermostat	Earle and Sparn (2019)
	Savings for smart home bundle (all end uses)	1760–2150 kWh/yr, 80 therms/yr	Kemper (2019)
	Savings for smart home bundle (all end uses)	11% (net of 10% take-back effect)	Nadel and Ungar (2019)

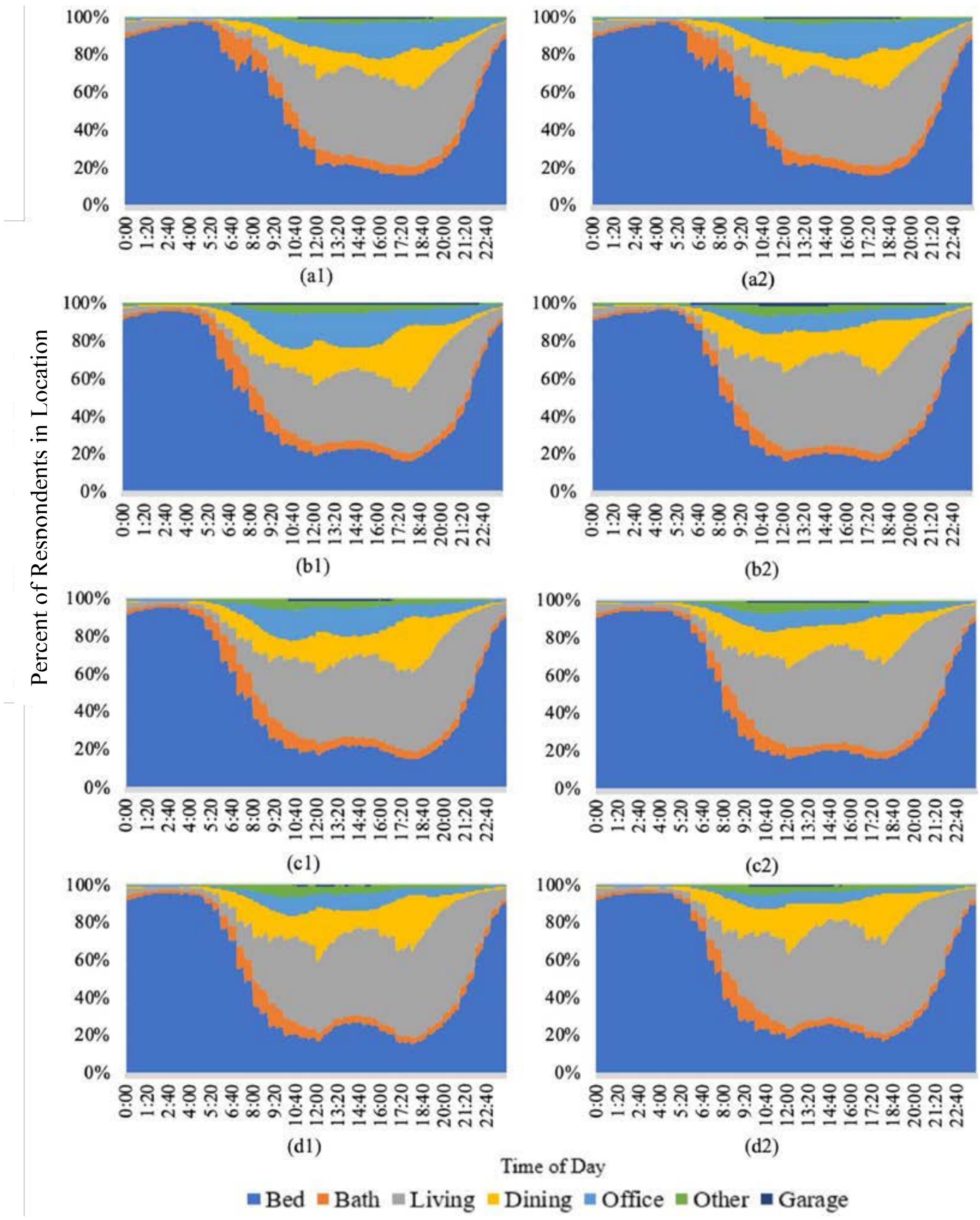


Figure 2. Spatial location of occupants (a) under 25; (b) 25–54; (c) 55–64; and (d) over 65, on (1) weekdays and (2) weekends. (Mitra et al. 2020)

3.2 Analysis Methodology

The modifications made to the baseline EnergyPlus model to reflect the event-driven energy use of HEMS-connected devices for each of the four categories of occupant behavior are described in the following sections.

3.2.1 Occupancy

The occupancy profiles were developed by creating a narrative for the three occupants of the house on weekdays and weekends, aligning occupancy as closely as possible with targeted "typical" overall occupancy levels. The targeted hourly curves were created by adjusting the HSP hourly profiles to better align with the Title 24 CASE Report on plug loads and lighting (Rubin et al. 2016) for weekends and weekdays, while maintaining the same overall occupancy levels for the week. The targeted total occupancy levels were 48 person-hours of occupancy on weekdays, 54 person-hours of occupancy on weekends/holidays, and 0 person-hours during vacation periods as defined in the HSP. Actual hourly occupancy levels (matching the targeted total person-hours) used in the HEMS modeling are shown in Figure 3. These hourly occupancy levels for modeling (dotted lines) were developed to provide more realism for the purpose of HEMS modeling than the simple target occupancy levels, which were unrealistically smooth and were expressed as fractions of people.

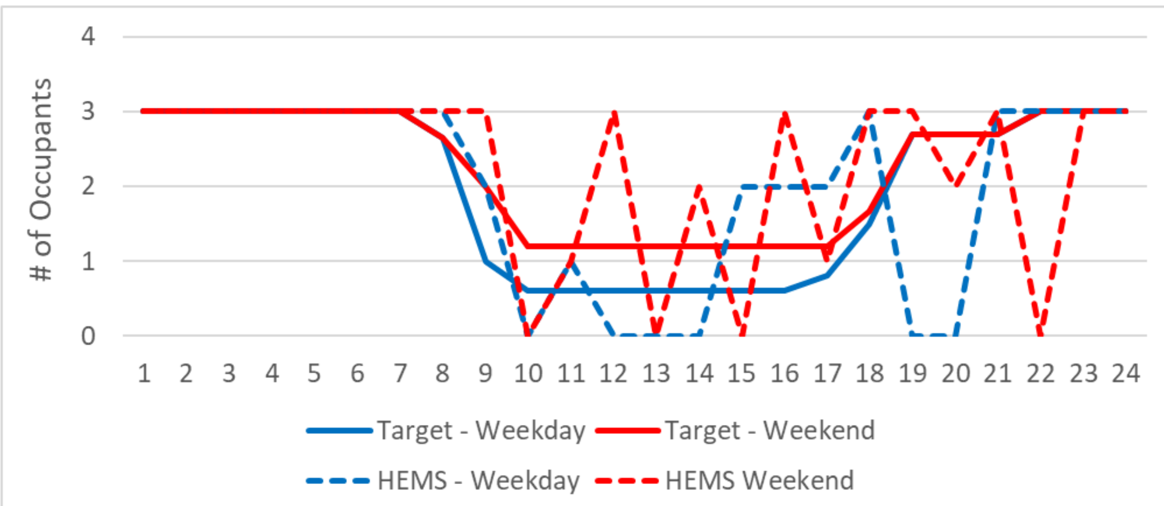


Figure 2. Hourly occupancy levels

Narratives for the three occupants on weekdays and weekends are shown in Table 4 and Table 5. A legend indicating the room in the house where each activity takes place is included below each table. Adult #1 works full time outside the home, while Adult #2 works part time. The Teenager goes to school most of the day but does some schoolwork at home in the afternoon, perhaps consistent with a freshman in college. The family has dinner together and sometimes participates in family events together, such as going out to a movie. The rest of the time, family members generally act independently.

These narratives are representative of the activities in which typical members of a household would engage, and they are the same for all four types of energy use behavior. They were carefully selected to align as closely as possible with data points from the literature documented in Table 3. For example, the amount of time spent in the living room and the number of hours watching TV are very comparable to the various field studies identified in the literature search. With only a few day-types to choose from and only three occupants, this approach can only provide "representative" savings for HEMS under realistic conditions. To add a more realistic range of behavioral patterns, the hours where nobody is home are clustered on weekdays, while on weekends they are more dispersed. For a more comprehensive study of HEMS impacts, it would be ideal to stochastically generate 365 days of activities, with probability distributions based on field studies of occupant behavior, to better represent the range of behavior both within a household over the course of a year, and across households throughout the United States.

Table 4. Weekday Occupancy Narrative

<table>
<tr><th>Hour</th><th>Adult #1</th><th>Adult #2</th><th>Teenager</th></tr>
<tr><td>1</td><td rowspan="7">Sleep</td><td rowspan="7">Sleep</td><td rowspan="7">Sleep</td></tr>
<tr><td>2</td></tr>
<tr><td>3</td></tr>
<tr><td>4</td></tr>
<tr><td>5</td></tr>
<tr><td>6</td></tr>
<tr><td>7</td></tr>
<tr><td>8</td><td>Bathroom</td><td>Breakfast</td><td>Breakfast</td></tr>
<tr><td>9</td><td rowspan="9">Work</td><td>Bathroom</td><td>Bathroom</td></tr>
<tr><td>10</td><td>Work</td><td rowspan="5">School</td></tr>
<tr><td>11</td><td>Home for lunch</td></tr>
<tr><td>12</td><td rowspan="3">Work</td></tr>
<tr><td>13</td></tr>
<tr><td>14</td></tr>
<tr><td>15</td><td rowspan="2">Cleaning</td><td rowspan="2">Homework</td></tr>
<tr><td>16</td></tr>
<tr><td>17</td><td>Reading/TV</td><td>Music</td></tr>
<tr><td>18</td><td>Dinner</td><td>Dinner</td><td>Dinner</td></tr>
<tr><td>19</td><td rowspan="2">Out to movies</td><td rowspan="2">Out to movies</td><td rowspan="2">Out to movies</td></tr>
<tr><td>20</td></tr>
<tr><td>21</td><td rowspan="2">Reading/TV</td><td rowspan="3">Reading/TV</td><td>Video games</td></tr>
<tr><td>22</td><td rowspan="2">TV</td></tr>
<tr><td>23</td><td>Computer</td></tr>
<tr><td>24</td><td>Sleep</td><td>Sleep</td><td>Sleep</td></tr>
</table>

Out of the House
Master Bedroom
Second Bedroom
Master Bathroom
Second Bathroom
Dining Room
Living Room
Office

Table 5. Weekend Occupancy Narrative

<table>
<tr><th>Hour</th><th>Adult #1</th><th>Adult #2</th><th>Teenager</th></tr>
<tr><td>1</td><td rowspan="7">Sleep</td><td rowspan="7">Sleep</td><td rowspan="7">Sleep</td></tr>
<tr><td>2</td></tr>
<tr><td>3</td></tr>
<tr><td>4</td></tr>
<tr><td>5</td></tr>
<tr><td>6</td></tr>
<tr><td>7</td></tr>
<tr><td>8</td><td>Breakfast</td><td>Breakfast</td><td>Breakfast</td></tr>
<tr><td>9</td><td>Bathroom</td><td>Cleaning</td><td>Video games</td></tr>
<tr><td>10</td><td rowspan="2">Yardwork</td><td rowspan="2">Yardwork</td><td>Yardwork</td></tr>
<tr><td>11</td><td>TV</td></tr>
<tr><td>12</td><td>TV</td><td>Bathroom</td><td>Music</td></tr>
<tr><td>13</td><td>Lunch/errand</td><td>Shopping</td><td rowspan="3">Friends/soccer</td></tr>
<tr><td>14</td><td>Reading</td><td>Cleaning</td></tr>
<tr><td>15</td><td>Soccer practice</td><td>Soccer practice</td></tr>
<tr><td>16</td><td>Nap</td><td rowspan="2">Reading</td><td>Homework</td></tr>
<tr><td>17</td><td>Long walk</td><td>Shopping</td></tr>
<tr><td>18</td><td>Dinner</td><td rowspan="2">Dinner/dishes</td><td>Dinner</td></tr>
<tr><td>19</td><td>Pay bills</td><td>Video games</td></tr>
<tr><td>20</td><td>Shopping</td><td rowspan="2">TV/video games</td><td>Music</td></tr>
<tr><td>21</td><td>Reading</td><td>TV</td></tr>
<tr><td>22</td><td>Ice cream shop</td><td>Ice cream shop</td><td>Ice cream shop</td></tr>
<tr><td>23</td><td>TV</td><td>Reading</td><td>TV</td></tr>
<tr><td>24</td><td>Sleep</td><td>Sleep</td><td>Sleep</td></tr>
</table>

Out of the House
Master Bedroom
Second Bedroom
Master Bathroom
Second Bathroom
Dining Room
Living Room
Office

3.2.2 Demand Response Events

Representative demand response events were derived from the 2020 SCE signals for the Smart Energy Program (SCE 2020). The 14 events from SCE occurred primarily on the hottest days and were often clustered together during a heat wave. We used Typical Meteorological Year (TMY) 3 data to select the hottest 14 days for each of the three sites we modeled. SCE event start times and durations were rounded off to the nearest hour, and were applied in sequence to the 14

TMY3 days, as shown in Table 6. This is a simplification of the true range of demand response events that occur under different programs for different electric utilities around the United States, which may have cold weather events and morning events. A more comprehensive analysis of demand response programs and drivers of specific demand response events would be valuable as a future research topic.

Table 6. Assumed Demand Response Events for Modeling

Event #	Start Time	End Time
1	7 p.m.	8 p.m.
2	5 p.m.	9 p.m.
3	7 p.m.	8 p.m.
4	7 p.m.	8 p.m.
5	7 p.m.	8 p.m.
6	6 p.m.	8 p.m.
7	7 p.m.	8 p.m.
8	5 p.m.	9 p.m.
9	3 p.m.	7 p.m.
10	6 p.m.	8 p.m.
11	3 p.m.	7 p.m.
12	2 p.m.	6 p.m.
13	5 p.m.	8 p.m.
14	4 p.m.	8 p.m.

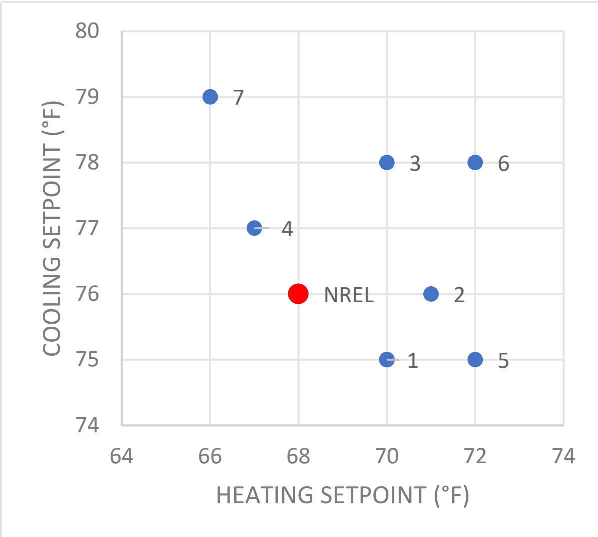
3.2.3 Thermostat

Thermostat settings vary quite a bit throughout a single day, across different day types, and for the different behavioral scenarios. To describe how temperature settings were selected for this study, temperature set points used or recommended by various sources are presented in Table 7 based upon research by Pang et al. (2020).

Table 7. Literature on Thermostat Settings, Based on Research by Pang et al. (2020)

Reference	Heating Setpoint (Setback)	Cooling Setpoint (Setback)	Note
ENERGY STAR®	<70°F	>78°F	Recommendation
Building America House Simulation Protocol (Wilson et al. 2014)	71°F	76°F	Recommendation
ASHRAE Standard 55 (ASHRAE comfort zones)	68.5°–75°F	75°–80.5°F	Recommendation
2018 International Energy Conservation Code (IECC) (International Code Council [ICC] 2018) (manual thermostat)	72°F	75°F	Recommendation
2018 IECC (ICC 2018) (programmable thermostat)	≤72°F	≥78°F	Recommendation
Florida Solar Energy Center (FSEC) (2013)	67°F	77°F	Analysis of literature review, measurements, and Residential Energy Consumption Survey
Booten et al. (2017)	70°F	75°F	Analysis of 327 North American home thermostat measurements
Huchuk, O'Brien, and Sanner (2018)	70°F	75°F	Analysis of 10,250 North America home thermostat measurements
Pang et al. (2020) ("little environmental awareness")	70°F (0)	75°F (0)	Assumption, based on past studies
Pang et al. (2020) ("acceptable environmental awareness")	70°F (-7)	75°F (+7)	Assumption, based on past studies
Pang et al. (2020) ("good environmental awareness")	70°F (-15)	75°F (+15)	Assumption, based on past studies
Pang et al. (2020) ("excellent environmental awareness")	66°F (-11)	79°F (+11)	Assumption, based on past studies

The settings used in those studies are illustrated in Figure 4, along with the assumed comfort preferences that were selected to be used in this study ("NREL").



Legend	
NREL	Assumed comfort preferences used in this study (described below)
1	Booten et al. (2017); Huchuk et al. (2018); and Pang et al. (2020) (little, acceptable, and good awareness)
2	Building America
3	ENERGY STAR
4	FSEC (2013)
5	IECC (manual)
6	IECC (programmable)
7	Pang et al. (2020) (excellent awareness)

Figure 3. Thermostat comfort set point comparisons

Most of the set points used in these other studies are aspirational rather than reflecting actual behavior. For example, Meier et al. (2011) found in a survey that almost 90% of respondents indicated that they rarely or never set a schedule on their programmable thermostat. Pritoni et al. (2015) reviewed case studies of the energy savings realized by programmable thermostats and found that only a third provided savings compared with manual thermostats, and some even increased energy use. Most of the set points from the other studies are also either recommendations or averages.

In the present study, comfort preferences were assumed to be 68°F in winter and 76°F in summer—close to the averages of the setpoints in these studies. The intent in this study was to provide set points that reflect a range of behavioral scenarios; however, all the settings assumed are based upon the same assumed *actual* comfort preferences (the temperature at which an occupant is assumed to find the best balance between comfort and energy costs). So, the base comfort preference settings of 68°F and 76°F were adjusted for each of the different behavior scenarios and throughout the day for different day types.

Smart thermostats affect the effective temperature set point at any given time in many different ways, which vary by make and model, and are often not well documented. Table 8 shows some of the functions that smart thermostats tend to use to minimize HVAC energy use or shift peak demand while maintaining comfort. These functions were analyzed to consider how they would affect the temperature set points throughout the day and combined to develop an assumed effective thermostat set point schedule for modeling the impact of the smart thermostat and what a thermostat schedule would look like if these functions were *not* used.

Table 8. Smart Thermostat Functions

Occupant Feedback	**Improved Algorithms**
• Metrics and Reports	**Predictive Control and Machine Learning**
• Interactive Charts	• Learning Schedules
• Data Download	• Learning Temperatures
User-Established Rules/Schedules	• Optimum Start
• Error-Free Schedules	• Compressor Optimization
• Flexible Schedules	• Real-Feel Temperature
• Recommended Schedules	**Improved Interfaces for Operation**
Occupancy Sensor-Based Optimization	• System Mode
• Vacancy Detection	• Accidental Permanent Holds
• Averaging Temperatures	• Vacation Holds
Grid Signals	• Temporary Holds
• Time of Use Optimization	• Efficient Default with Override
• Demand Response Event Response	• Comfort Default with Override

The assumptions that were used in developing the assumed schedules were as follows:

Not Energy Conscious (NEC):

- Comfort Setting: The thermostat settings were 72°F for heating and 72°F for cooling. This does not accurately reflect the base comfort preferences due to misprogramming. This is a worst-case assumption, but one that is probably a reality for many homes that are not paying any attention to energy conservation.

- Setback: The homeowners do not adjust their thermostats for nighttime setbacks, or when leaving the home for brief absences or vacations.

Very Energy Conscious (VEC):

- Comfort Setting: Again, the misprogrammed settings may not reflect true preferences for comfort, so the occupied period set point was 69°F for heating and 75°F for cooling.

- Setback: There is a 9°F setback for heating, and a 5°F setback for cooling at night and during vacation periods. There is no setback for either regular vacancies during the day or brief absences.

- Optimal Start: There is no optimal start function for the thermostat, so that the occupant sets the thermostat to begin an hour prior to waking or returning home (this is a simplification, and it may be more or less than an hour in a real home).

- Schedule: The thermostat time periods are not correctly set, so that the system starts an additional hour earlier in the morning and prior to returning home, and it runs an hour longer than necessary after going to bed or leaving for the day.

- Note: There are many very energy-conscious occupants who faithfully use their thermostats as "on/off" switches, and manually adjust their setpoints optimally throughout the day. These occupants can experience the lowest energy use, even without sophisticated controls. However, they also run the potential to forget to make changes and waste energy. While this behavior is not uncommon, it was not used as the definition of a Very Energy Conscious occupant for the purposes of this study.

Somewhat Engaged (SE):

- Comfort Setting: The settings are a closer reflection of true preferences for comfort, so the occupied period set point was 68°F for heating and 76°F for cooling.

- Setback: There is a 9°F setback for heating, and 5°F for cooling during nighttime, regular daytime vacancies, periodic unexpected absences, and vacations. However, the occupancy sensors only detect about half of the unexpected vacancies.

- Optimal Start: There is an optimal start function for the thermostat, so the heating or cooling system begins immediately upon waking or returning home. (Note that in reality, the system would not begin immediately when the comfort period begins. This simplifying assumption had to be made, because subhourly temperature adjustments are not possible using an hourly simulation model. A preheating or precooling period of more or less than an hour could be expected, but it is assumed to be shorter in this scenario than in the previous one).

- Schedule: The thermostat time periods are a closer reflection of actual daily schedules, but still not perfect. The system starts an hour earlier in the morning and prior to returning home, and it runs an hour longer than necessary after going to bed or leaving for the day.

Highly Engaged (HE):

- Comfort Setting: The settings reflect an attempt by the homeowner to be very energy conscious and to set the temperature a bit beyond their base comfort preference. They are able to do this because they can very readily override the temperature anytime they find themselves uncomfortable. We assume that the setting is two degrees warmer in summer and cooler in winter for most occupied hours, but that for one or two hours a day they override this setting and set the thermostat temporarily at their base comfort preference.

- Setback: There is a 9°F setback for heating, and a 5°F setback for cooling during nighttime, regular daytime vacancies, all periodic unexpected absences, and vacations.

- Optimal Start: There is an optimal start function for the thermostat, so the heating or cooling system begins immediately upon waking or returning home. (Note again that sub-hourly temperature adjustments are not possible using an hourly simulation model, so this is a simplification, and in reality, a preheating or precooling period of less than an hour would be expected).

- Schedule: The thermostat time periods are an exact reflection of actual daily schedules, due to learning algorithms and vacancy detection.
- Demand Response: Any time a demand response event is called (using the demand response event schedule described elsewhere), the thermostat set point is adjusted by 3°F, regardless of time of day, day type, occupancy, or vacation status. The resulting set points vary, but for occupied hours, tend to be 63°F for heating and 81°F for cooling. For comparison, Title 24 requires an occupant controlled smart thermostat to have a default demand response set point in cooling mode of 82°F, and heating mode 60°F (CEC, 2019).

There were no adjustments to thermostat settings based on geographic location. Heating and cooling seasons were established based on the HSP default.

The resulting adjusted set points that were used in this study are shown in Table 9 through Table 11. For these schedules, the home's occupancy matches that assumed for the other end uses (VACANT indicates that ALL occupants are absent, and OCCUPIED indicates that ANY occupant is present). In any scenarios where the temperature setting was not optimally tracking the actual activities of the occupants (for reasons described below), the temperature is highlighted. Occupant energy consciousness level (NEC, VEC) and level of smart thermostat engagement (SE, HE) are the same as defined in Table 1.

Table 9. Weekday Thermostat Settings (Nonoptimal settings are highlighted)

HOUR	Actual Activity	Thermostat Assumptions	Heating				Cooling			
			NEC	VEC	SE	HE	NEC	VEC	SE	HE
0–1	Sleep	Sleep	72	60	59	57	72	80	81	83
1–2	Sleep	Sleep	72	60	59	57	72	80	81	83
2–3	Sleep	Sleep	72	60	59	57	72	80	81	83
3–4	Sleep	Sleep	72	60	59	57	72	80	81	83
4–5	Sleep	Sleep	72	60	59	57	72	80	81	83
5–6	Sleep	Pre-heating/cooling?	72	69	59	57	72	75	81	83
6–7	Sleep	Starts too early?	72	69	68	57	72	75	76	83
7–8	Occupied	Occupied	72	69	68	66	72	75	76	78
8–9	Occupied	Occupied	72	69	68	66	72	75	76	78
9–10	Vacant	Missed vacancy?	72	69	59	57	72	75	81	83
10–11	Occupied	Occupied	72	69	68	66	72	75	76	78
11–12	Vacant	Missed vacancy?	72	69	59	57	72	75	81	83
12–13	Vacant	Missed vacancy?	72	69	59	57	72	75	81	83
13–14	Vacant	Starts too early?	72	69	68	57	72	75	76	83
14–15	Occupied	Occupied	72	69	68	66	72	75	76	78
15–16	Occupied	Occupied	72	69	68	66	72	75	76	78
16–17	Occupied	Extra comfort?	72	69	68	68	72	75	76	76
17–18	Occupied	Occupied	72	69	68	66	72	75	76	78
18–19	Vacant	Missed vacancy?	72	69	59	57	72	75	81	83
19–20	Vacant	Missed vacancy?	72	69	68	57	72	75	76	83
20–21	Occupied	Occupied	72	69	68	66	72	75	76	78
21–22	Occupied	Occupied	72	69	68	66	72	75	76	78
22–23	Occupied	Occupied	72	69	68	66	72	75	76	78
23–24	Sleep	Runs too long?	72	69	68	57	72	75	76	83

Table 10. Weekend Thermostat Settings (Nonoptimal settings are highlighted)

Hour	Actual Activity	Thermostat Assumptions	Heating				Cooling			
			NEC	VEC	SE	HE	NEC	VEC	SE	HE
0–1	Sleep	Sleep	72	60	59	57	72	80	81	83
1–2	Sleep	Sleep	72	60	59	57	72	80	81	83
2–3	Sleep	Sleep	72	60	59	57	72	80	81	83
3–4	Sleep	Sleep	72	60	59	57	72	80	81	83
4–5	Sleep	Sleep	72	60	59	57	72	80	81	83
5–6	Sleep	Pre-heating/cooling?	72	69	59	57	72	75	81	83
6–7	Sleep	Starts too early?	72	69	68	57	72	75	76	83
7–8	Occupied	Occupied	72	69	68	66	72	75	76	78
8–9	Occupied	Occupied	72	69	68	66	72	75	76	78
9–10	Vacant	Missed vacancy?	72	69	59	57	72	75	81	83
10–11	Occupied	Occupied	72	69	68	66	72	75	76	78
11–12	Occupied	Occupied	72	69	68	66	72	75	76	78
12–13	Vacant	Missed vacancy?	72	69	59	57	72	75	81	83
13–14	Occupied	Occupied	72	69	68	66	72	75	76	78
14–15	Vacant	Missed vacancy?	72	69	59	57	72	75	81	83
15–16	Occupied	Occupied	72	69	68	66	72	75	76	78
16–17	Occupied	Occupied	72	69	68	66	72	75	76	78
17–18	Occupied	Occupied	72	69	68	66	72	75	76	78
18–19	Vacant	Extra comfort?	72	69	68	68	72	75	76	76
19–20	Vacant	Extra comfort?	72	69	68	68	72	75	76	76
20–21	Occupied	Occupied	72	69	68	66	72	75	76	78
21–22	Vacant	Missed vacancy?	72	69	68	57	72	75	76	83
22–23	Occupied	Occupied	72	69	68	66	72	75	76	78
23–24	Sleep	Runs too long?	72	69	68	57	72	75	76	83

Table 11. Vacation Thermostat Settings (Nonoptimal settings are highlighted)

Hour	Actual Activity	Thermostat Setting	Heating NEC	Heating VEC	Heating SE	Heating HE	Cooling NEC	Cooling VEC	Cooling SE	Cooling HE
0–1	Vacant	Missed vacancy?	72	60	59	57	72	80	81	83
1–2	Vacant	Missed vacancy?	72	60	59	57	72	80	81	83
2–3	Vacant	Missed vacancy?	72	60	59	57	72	80	81	83
3–4	Vacant	Missed vacancy?	72	60	59	57	72	80	81	83
4–5	Vacant	Missed vacancy?	72	60	59	57	72	80	81	83
5–6	Vacant	Missed vacancy?	72	60	59	57	72	80	81	83
6–7	Vacant	Missed vacancy?	72	60	59	57	72	80	81	83
7–8	Vacant	Missed vacancy?	72	60	59	57	72	80	81	83
8–9	Vacant	Missed vacancy?	72	60	59	57	72	80	81	83
9–10	Vacant	Missed vacancy?	72	60	59	57	72	80	81	83
10–11	Vacant	Missed vacancy?	72	60	59	57	72	80	81	83
11–12	Vacant	Missed vacancy?	72	60	59	57	72	80	81	83
12–13	Vacant	Missed vacancy?	72	60	59	57	72	80	81	83
13–14	Vacant	Missed vacancy?	72	60	59	57	72	80	81	83
14–15	Vacant	Missed vacancy?	72	60	59	57	72	80	81	83
15–16	Vacant	Missed vacancy?	72	60	59	57	72	80	81	83
16–17	Vacant	Missed vacancy?	72	60	59	57	72	80	81	83
17–18	Vacant	Missed vacancy?	72	60	59	57	72	80	81	83
18–19	Vacant	Missed vacancy?	72	60	59	57	72	80	81	83
19–20	Vacant	Missed vacancy?	72	60	59	57	72	80	81	83
20–21	Vacant	Missed vacancy?	72	60	59	57	72	80	81	83
21–22	Vacant	Missed vacancy?	72	60	59	57	72	80	81	83
22–23	Vacant	Missed vacancy?	72	60	59	57	72	80	81	83
23–24	Vacant	Missed vacancy?	72	60	59	57	72	80	81	83

3.2.4 Smart Lighting

To meet SHEMS certification requirements, two ENERGY STAR-certified smart lamps or smart fixtures must be controlled. The rooms most likely to include smart lamps and fixtures are living rooms and bedrooms (Applied Energy Group, 2020). Our assumption is that the overhead fixtures in the living room and master bedroom are connected to the HEMS. In most homes, these fixtures will have LED lamps with manual on/off controls and no dimming capability. Smart fixtures connected to a HEMS are assumed to have a small continuous standby power, dimming capability, and programmable timing for security purposes. Additional characteristics of the assumed light fixtures and controls are summarized in Table 12, along with the reference or other basis for the assumption.

Table 12. Connected Lighting Assumptions

Lighting Attribute	Without HEMS	With HEMS	Basis
Fixture type	Overhead	Overhead	Judgment
Lamp type	LED	LED	Judgment
Number of lamps	Living Room (LR): 4, Bedroom (BR): 2	LR: 4, BR: 2	EPA (2021)
Hours of useful light	3	3	Based on Rubin et al. (2016)
Fixture power	LR: 12 W, BR: 6 W	LR: 12 W, BR: 6 W	EPA (2021)
Standby power	0 W	LR: 1 W, BR: 0.5 W	EPA (2019)
Dimmed power	N/A	LR: 6 W, BR: 3 W	Judgment
Controls	On/off	Occupancy, dimming, voice activation, demand response	EPA (2020a)

Assumed operation of connected lighting in the living room and bedroom varies for each of the four categories of energy use behavior, as shown in Table 13. Key differences include how often and for how long lights are left on after leaving the room, use of dimming capability, frequency of overrides, enrollment in demand response programs, and use of programmed scheduling.

Table 13. Targeted Light Fixture Operational Behavior Before and After HEMS Installation

Behavioral Attribute	Without HEMS		With HEMS		Basis
	NEC	VEC	SE	HE	
Lights on in unoccupied rooms	1-2 hours after occupancy, 2/3 of the time	1 hour after occupancy, 1/3 of the time	Occupancy sensor override 1/2 of the time	No occupancy sensor overrides	Judgment based on Urban, Roth, and Harbor (2016)
Vacation	Always on in LR, off in BR	Always off	Always off	2 hrs/day on in LR, off in BR	Judgment
Dimming	Not available	Not available	Used 1/3 of the time	Used 2/3 of the time	Judgment
Demand response	Not available	Not available	Not enabled	Always off	Applied Energy Group (2020)

Application of these behavioral patterns to the connected lighting features in Table 12 and the occupancy schedules defined in Section 3.2.1 resulted in the hourly connected lighting energy profiles shown in Figure 5, Figure 6, and Figure 7, for weekdays, weekends, and vacation periods respectively.

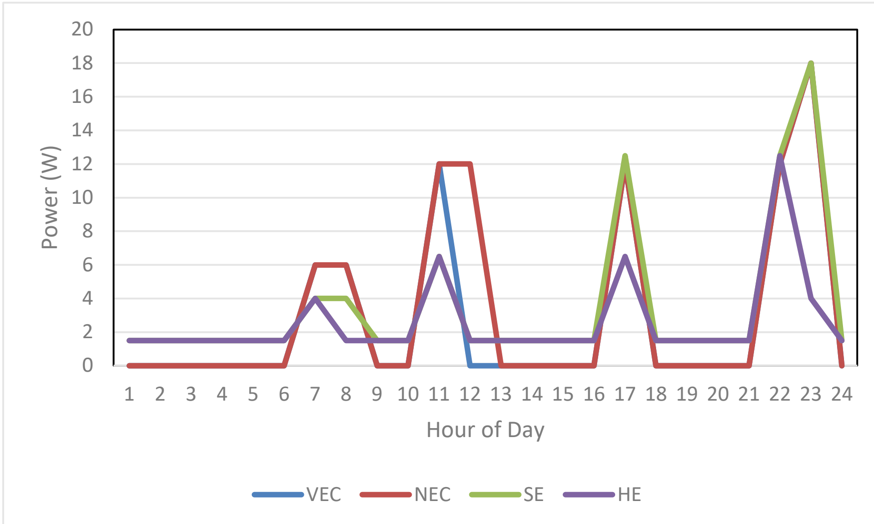


Figure 5. Weekday targeted fixture lighting profiles

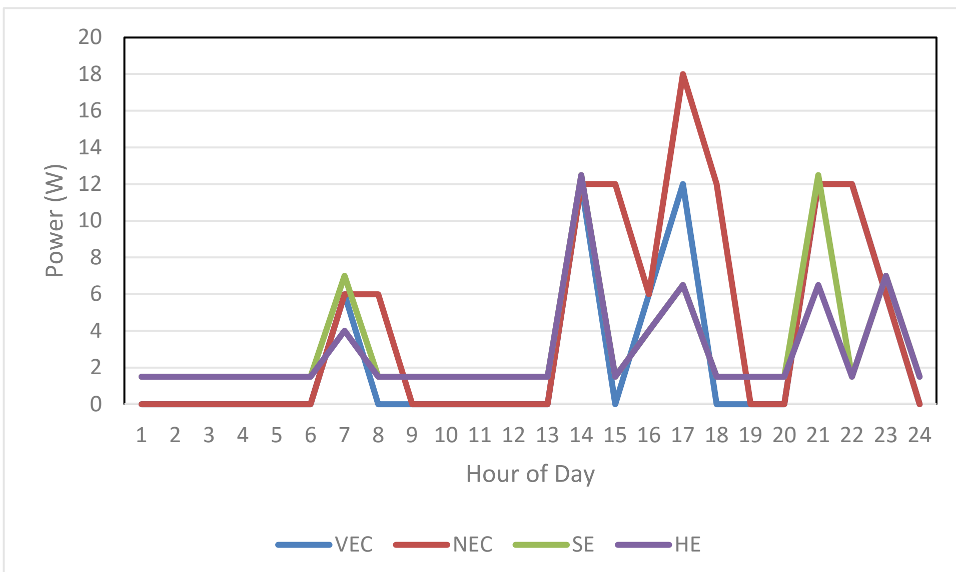


Figure 4. Weekend targeted fixture lighting profiles

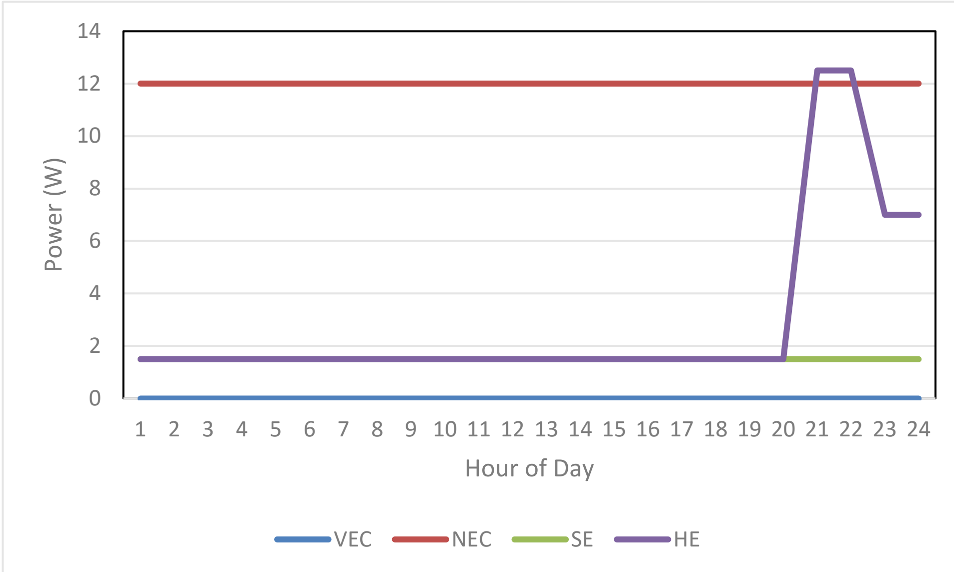


Figure 7. Vacation targeted fixture lighting profiles

To create the lighting curves for the EnergyPlus models, the total lighting energy in the HSP was first reduced by 70% based on the Title 24 CASE report (Rubin et al. 2016). Next, the connected component of the lighting energy (expressed as smooth hourly curves) in the Building America Analysis Spreadsheet (NREL 2011) was subtracted from the national average total lighting curves for October (approximately consistent with the annual average) and replaced with the event-driven lighting schedules in Figure 5, Figure 6, and Figure 7. Additional profiles were created for the 14 demand response event days, where connected lights were assumed to be turned off during peak demand periods. The monthly multipliers and latitude-specific multipliers in the Building America Analysis Spreadsheet were then applied to the hourly curves, which were then imported into the models to provide realistic annual lighting energy savings estimates for the smart lighting component of the HEMS.

3.2.5 Advanced Power Strip

ENERGY STAR SHEMS requires one connected smart power strip or smart outlet. For this analysis, we selected a Tier 2 APS controlling the primary entertainment system, including a TV, set-top box, and video game system. Other potential components of the entertainment system are assumed to be connected to uncontrolled outlets. The APS was assumed to have sensors that detect both occupancy and infrared signals from remote controls. It was also assumed that the APS was controlled through voice activation, programmed using the HEMS interface, and disabled in response to grid signals during demand response events. A summary of the attributes of connected plug loads is provided in Table 14, along with the reference or other basis for the assumption.

Table 14. Targeted Plug Load Assumptions

Lighting Attribute	Without HEMS	With HEMS	Basis
Connected devices	N/A	Entertainment center: primary TV, set-top box, video game system	Valmiki and Corradini (2016)
Connected load	N/A	200 W	NREL (2011)
APS standby power	N/A	1 W	Wei et al. (2018)
TV power	169 W active, 1 W standby	169 W active, 1 W standby, 0 W off	Rubin et al. (2016)
TV hours of active use	4 hrs/day weekday, 6 hrs/day weekend	4 hrs/day weekday, 6 hrs/day weekend	Bureau of Labor Statistics (2019) and Rubin et al. (2016)
Set-top box power	21 W active, 16 W standby	21 W active, 16 W standby, 0 W off	NREL (2011)
Set-top box hours of active use or DVR recording	4 hrs/day weekday, 4 hrs/day weekend, 2 hours/day vacation	4 hrs/day weekday, 4 hrs/day weekend, 2 hours/day vacation	Judgment based on NREL (2011)
Video game system power	10 W active, 2 W standby	10 W active, 2 W standby, 0 W off	NREL (2011)
Video game system hours of active use	1 hr/day weekday, 2 hrs/day weekend	1 hr/day weekday, 2 hrs/day weekend	Bureau of Labor Statistics (2019)
APS location	N/A	Living room	Judgment
Controls	On/off (active/standby)	Occupancy, remote control sensor, voice activation, demand response	EPA (2020a)

Use of the entertainment system controlled by the APS varies based on the category of operational behavior with and without the APS and HEMS, as described in Table 15. Key differences include how often and for how long devices are left on when no longer in use, whether devices are put in standby mode versus being turned off completely, frequency of APS overrides, and engagement in demand response programs.

Table 15. Targeted Plug Load Operational Behavior

Behavioral Attribute	Without HEMS		With HEMS		Basis
	NEC	VEC	SE	HE	
TV and video game system left on in unoccupied rooms after use	1 hour after occupancy, 2/3 of the time	1 hour after occupancy, 1/3 of the time	Off when unoccupied and not in use, APS override 1/2 of the time	Off when unoccupied and not in use, no APS overrides	Judgment based on Valmiki and Corradini (2016)
Set-top box left on in unoccupied rooms	Left on 24 hrs/day	Left on during the day, off at night	Programmed to turn off at night	Off when unoccupied and not in use	Judgment
Vacation	TV and video game system in standby, set-top box left on 24 hrs/day	TV and video game system in standby, set-top box on for scheduled DVR recording only	All devices off except set-top box on for scheduled DVR recording only	All devices off except set-top box on for scheduled DVR recording only	Judgment
Demand response	Not available	Not available	Not enabled	Off, including DVR recording	Judgment based on Applied Energy Group (2020)

Hourly profiles were developed for weekday, weekend, and vacation days after applying these behavioral patterns to the occupancy narratives described in Section 3.2.1 and connected plug load characteristics in Table 14. These profiles are illustrated in Figure 8, Figure 9, and Figure 10.

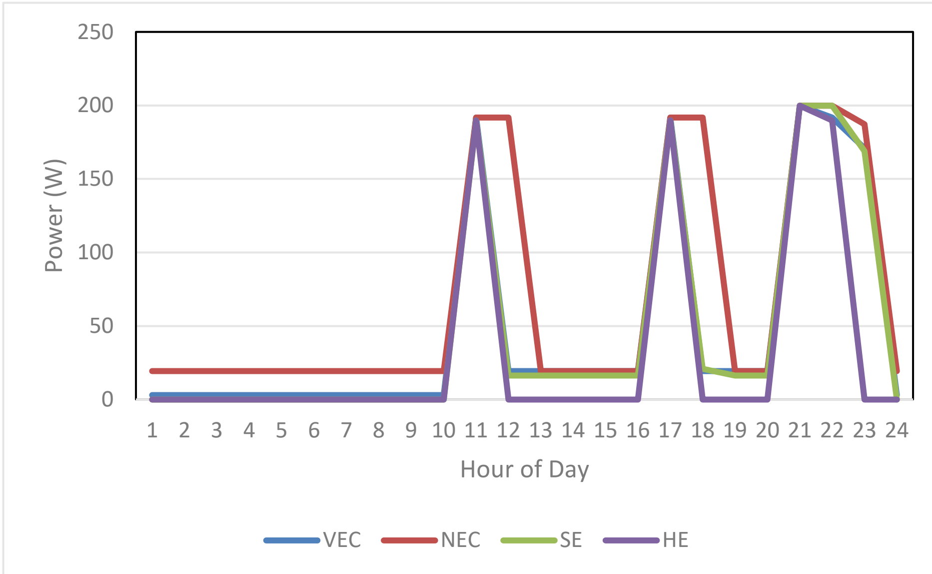


Figure 8. Weekday targeted plug load profiles

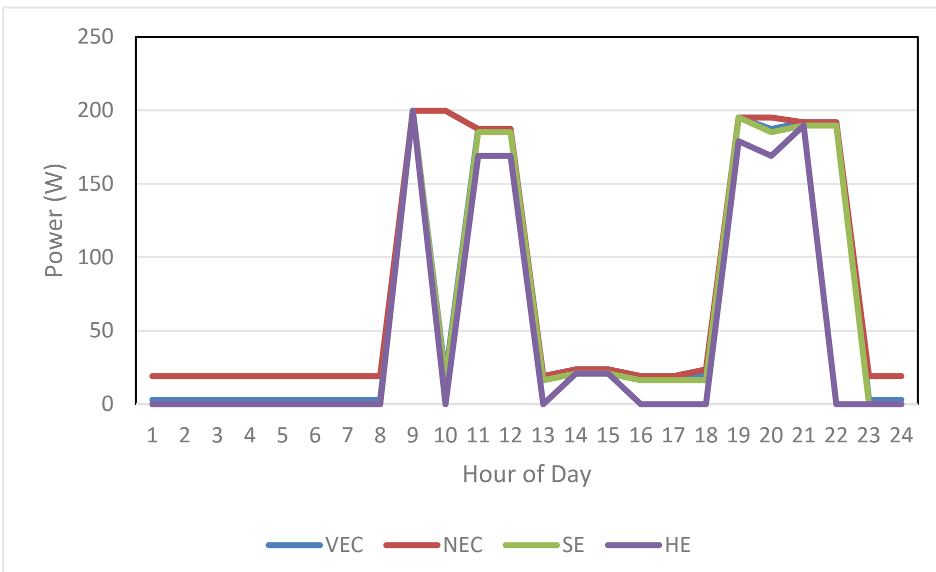


Figure 9. Weekend targeted plug load profiles

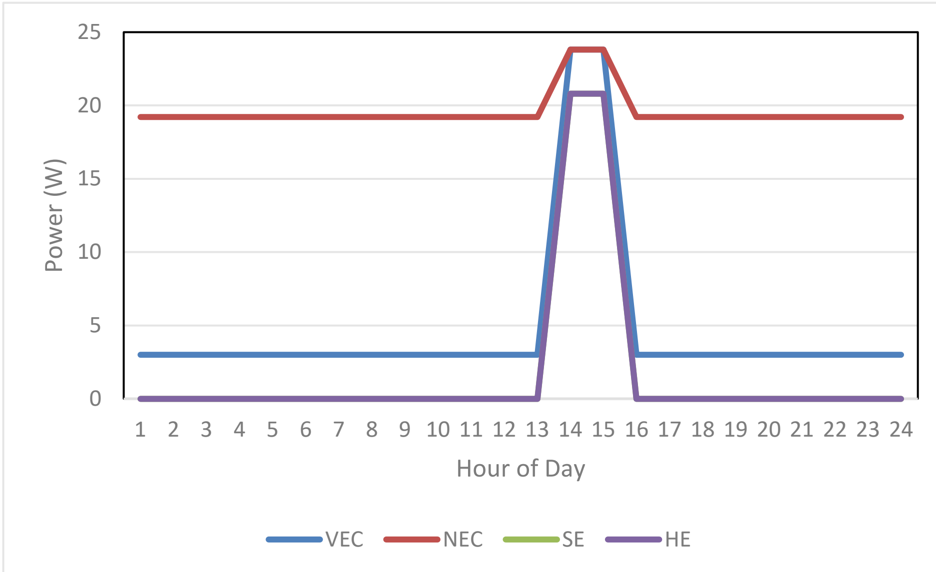


Figure 10. Vacation targeted plug load profiles

Inputs for the EnergyPlus models were developed by removing the standard HSP connected devices from the hourly curves for MELs using the Detailed MEL Analysis Worksheet tab in the Building America Analysis Spreadsheet for New Construction (NREL 2011). The discrete electricity use patterns for the connected devices were then added back in, and new hourly curves were created for the three day-types (weekday, weekend/holiday, vacation) along with 14 demand response days. Seasonal adjustments were overlaid on these curves using the monthly Home Entertainment multiplier under the Monthly Profiles tab. No adjustments were made to the plug load curves based on geographic location.

3.3 Modeling Results

The total energy and cost savings predictions for the HEMS in each of the three climates and for each of the four combinations of pre- and post-installation occupant behavior are shown in Figure 11, Figure 12, and Figure 13. Since the non-HEMS occupant behavior scenarios essentially “bracket” the range of expected non-HEMS behaviors, and there is no data on where the average home lies within this range, it is reasonable to look at the average of the two non-HEMS scenarios. Similarly, because the HEMS occupant behavior scenarios essentially “bracket” the range of expected HEMS behaviors, and there is very limited data that can shed light on where the average home lies within this range, it is reasonable to look at the average of the two HEMS scenarios. Therefore, the average savings of the four comparisons is a reasonable estimate of expected savings for our purposes.

Average site energy savings for gas and electricity ranged from 19.7% to 22.1%, and cost savings ranged from 16.2% to 17.9%. Although the savings vary by location, especially the split between gas and electric, it is noteworthy that total site energy savings is fairly consistent for the three locations we selected. The HEMS control strategies we modeled do not seem to take full advantage of the time of use rate schedules. Much of the electricity savings occurs at night and during other off-peak hours, and cost savings for gas is independent of time-of-use because a flat gas rate was used in the models. Greater use of afternoon pre-cooling could yield higher energy cost savings, but this capability is not currently a requirement of ENERGY STAR SHEMS.

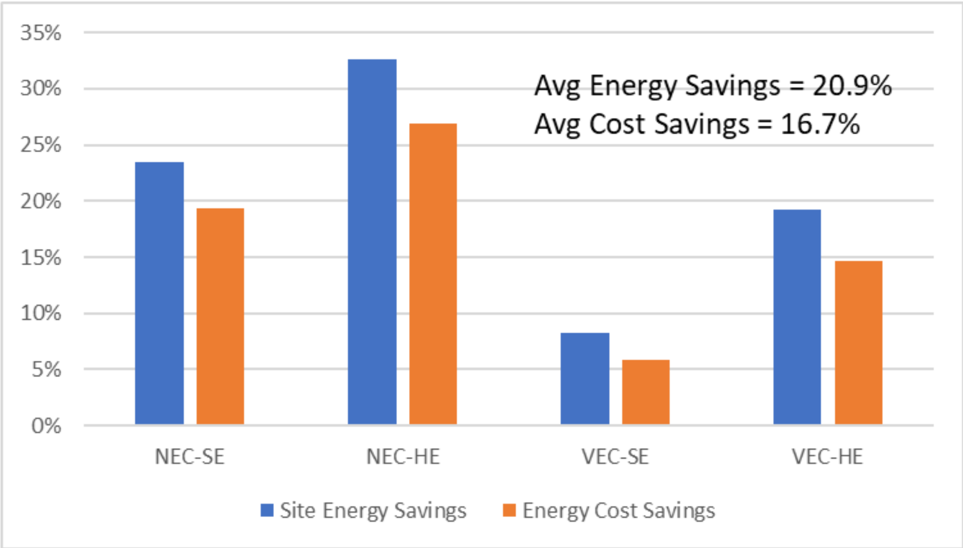


Figure 11. Total energy savings for ENERGY STAR SHEMS in Boston

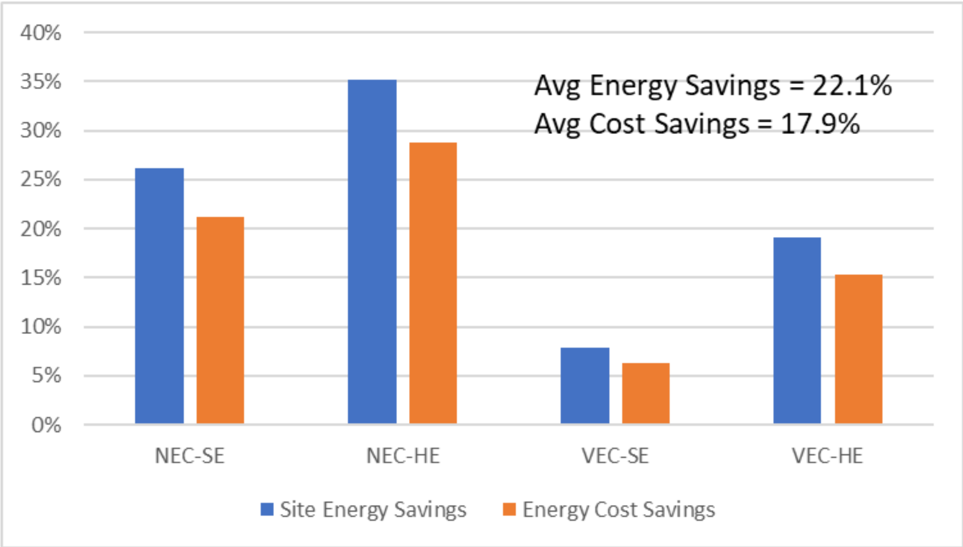


Figure 12. Total energy savings for ENERGY STAR SHEMS in Houston

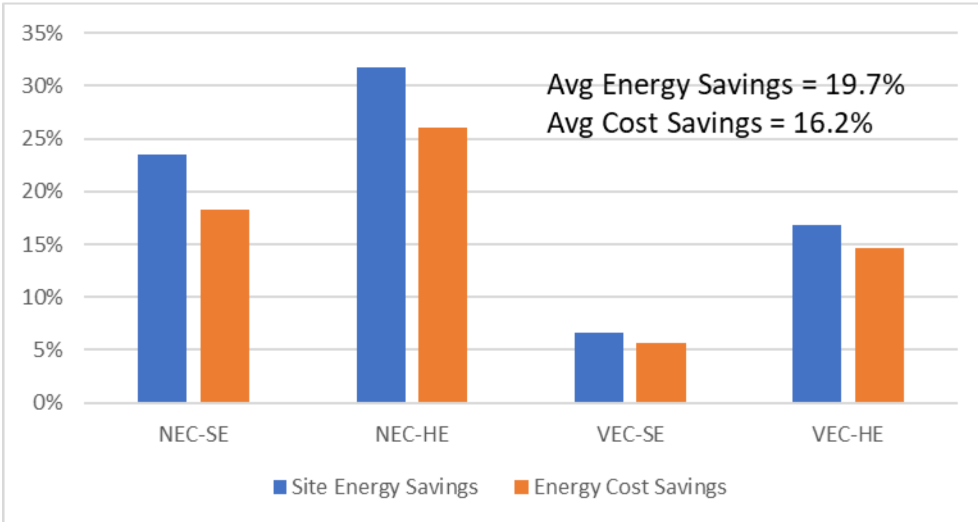


Figure 13. Total energy savings for ENERGY STAR SHEMS in Phoenix

Energy savings for each of the three relevant end uses (HVAC, interior lighting, and plug loads) are shown in Figure 14, Figure 15, and Figure 16. HVAC savings are highest in Houston, where both heating and cooling loads are significant. The predicted savings range from 12% to 60% of total HVAC energy, and depend heavily on how energy conscious the occupants are prior to HEMS installation, to what extent they use the features of the smart thermostat, and the magnitude of the heating and cooling loads.

Savings for interior lighting are much smaller because the connected lamps required for ENERGY STAR represent only a small fraction of total installed lighting, with savings ranging from -2.0% to +2.7%. There are small differences between climates because of variations in the confluence of daylight hours with occupancy and HEMS operation. There is also a risk that certain features of smart lighting (such as voice activation and home security), when combined with significant standby energy, can lead to negative savings. It should be noted that operating hours are relatively low in our analysis because the field studies indicated that living room and bedroom lights were used only a few hours per day. Some households will begin with higher usage and can expect much larger savings when the lights are controlled by a HEMS.

Savings for plug loads is unaffected by climate in our analysis, and ranges from 1% to 11% of total plug load electricity use depending on occupant behavior before and after HEMS installation. The indirect impact on heating and cooling is captured in the HVAC analysis (Figure 14). There is significant potential for higher savings by using Tier 2 APS to control additional TVs and home offices instead of focusing exclusively on the primary home entertainment system. However, field studies (Valmiki and Corradini 2016; Piper et al. 2017) indicate that the application we modeled offers the highest energy savings potential for a single APS.

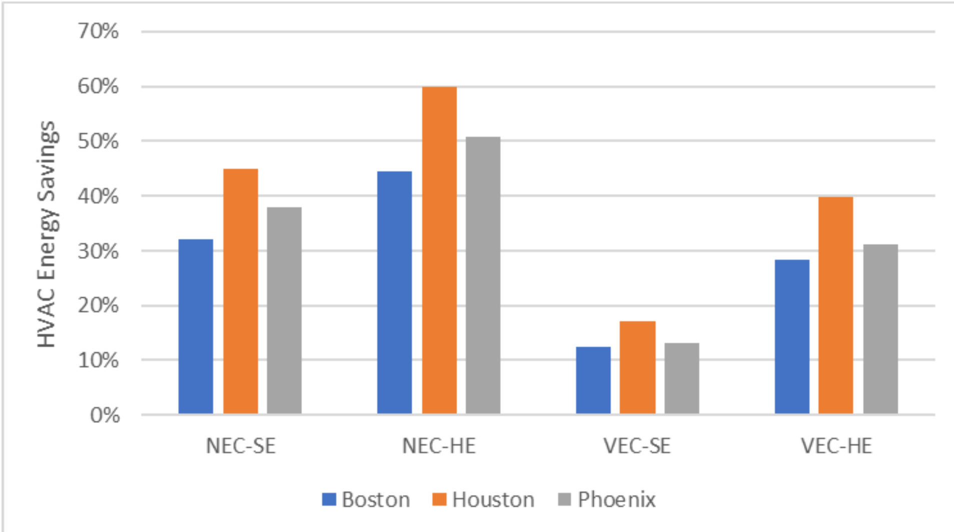


Figure 14. HVAC energy savings for ENERGY STAR SHEMS

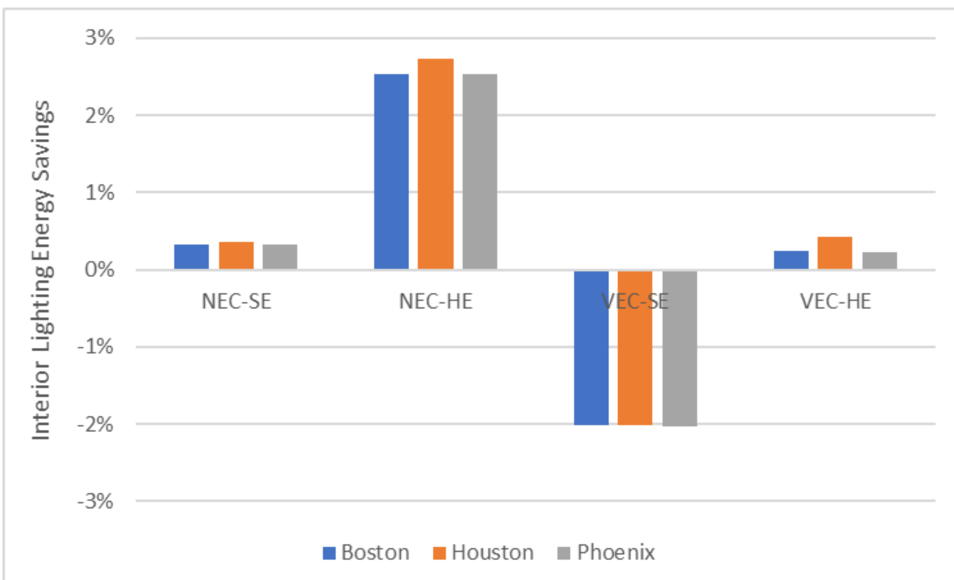


Figure 15. Interior lighting energy savings for ENERGY STAR SHEMS

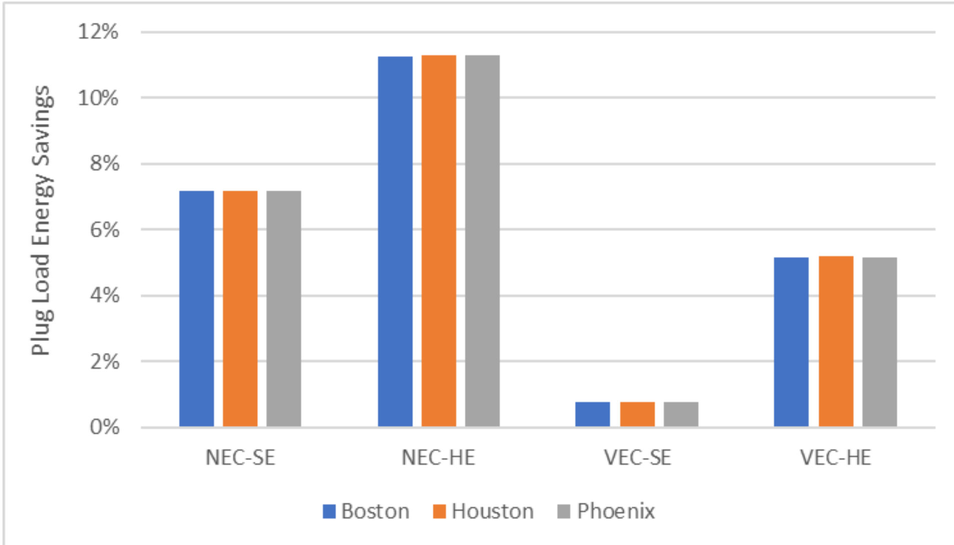


Figure 16. Plug load energy savings for ENERGY STAR SHEMS

A complete summary of modeled electricity and gas use for each occupant behavior, connected end use, and geographic location is provided in Table 16. These more detailed results provide easier comparison to existing field studies, to verify that the range of modeled savings is reasonably consistent with savings measured in actual homes. It is clear that energy savings for lighting and plug loads are relatively independent of climate, but HVAC energy and cost savings vary significantly based on space conditioning loads and utility rate schedules. Using the data in Table 16, energy savings can be analyzed in a variety of ways, depending on the objectives of the analyst.

Differing assumptions can lead to very different results, which is why we have documented our assumptions in detail. Spreadsheets illustrating the application of our assumptions to the behavioral narratives are available from the authors upon request. These spreadsheets have been automated to the extent practical, allowing relatively straightforward generation of new results using different assumptions.

Table 16. Predicted Annual Energy Use for ENERGY STAR SHEMS

Behavioral Attribute	Without HEMS		With HEMS		Savings (Avg. HEMS vs. avg. non-HEMS)
	NEC	VEC	SE	HE	
Boston					
HVAC Electricity (kWh)	2,187	1,428	1,184	864	43.3%
HVAC Natural Gas (therms)	944	742	651	536	29.6%
Interior Lighting Electricity (kWh)	351	343	350	342	0.3%
Plug Load Electricity (kWh)	2,756	2,578	2,558	2,445	6.2%
Whole House Electricity (kWh)	7,861	6,916	6,730	6,289	11.9%
Whole House Natural Gas (therms)	1,137	937	847	733	23.8%
Whole House Site Energy (MBTU)	141	117	108	95	21.5%
Whole House Electricity Cost ($)	1,268	1,126	1,095	1,028	11.3%
Whole House Natural Gas Cost ($)	1,153	950	859	743	23.8%
Whole House Total Energy Cost ($)	2,421	2,076	1,954	1,771	17.2%
Houston					
HVAC Electricity (kWh)	6,294	4,622	4,000	3,157	34.4%
HVAC Natural Gas (therms)	223	133	104	68	51.7%
Interior Lighting Electricity (kWh)	348	340	346	338	0.6%
Plug Load Electricity (kWh)	2,756	2,578	2,558	2,444	6.2%
Whole House Electricity (kWh)	11,965	10,107	9,542	8,576	17.9%
Whole House Natural Gas (therms)	362	272	243	206	29.2%
Whole House Site Energy (MBTU)	77	62	57	50	23.1%
Whole House Electricity Cost ($)	1,963	1,684	1,589	1,450	16.7%
Whole House Natural Gas Cost ($)	367	276	247	209	29.1%
Whole House Total Energy Cost ($)	2,330	1,960	1,836	1,659	18.5%
Phoenix					
HVAC Electricity (kWh)	9,838	7,882	7,137	6,020	25.8%
HVAC Natural Gas (therms)	135	68	48	26	63.5%
Interior Lighting Electricity (kWh)	354	346	353	345	0.3%
Plug Load Electricity (kWh)	2,756	2,578	2,558	2,445	6.2%
Whole House Electricity (kWh)	15,515	13,374	12,686	11,447	16.5%
Whole House Natural Gas (therms)	251	184	165	142	29.4%
Whole House Site Energy (MBTU)	78	64	60	53	20.4%
Whole House Electricity Cost ($)	2,596	2,283	2,162	1,965	15.4%
Whole House Natural Gas Cost ($)	255	187	167	144	29.6%
Whole House Total Energy Cost ($)	2,851	2,470	2,329	2,109	16.6%

4 Conclusions and Recommendations

This study applied behavioral data gathered from published field studies to model the range of expected energy savings for a HEMS that meets the minimum certification requirements for ENERGY STAR SHEMS. The following key conclusions were drawn from this study:

- Whole-house site energy savings ranged from 7% to 35% depending on location and occupant behavior before and after HEMS installation. This translates to 4.3 to 27.1 MBtu/year.
- Energy cost savings ranged from 6% to 29% of total utility bills, or $123 to $670/year, depending on location and occupant behavior patterns.
- The vast majority of savings potential was driven by the smart thermostat, followed by the Tier 2 APS. Savings for smart lighting was very small given the baseline assumption of energy-efficient LEDs with no standby power. In modern homes it is difficult to achieve significant savings in the lighting category unless occupants operate the lights more than a few hours per day.
- Energy-conscious behavior is beneficial in and of itself. Over half of the difference between the energy use of the highly engaged HEMS-using homeowner and that of the not-energy-conscious, non-HEMS homeowner is captured by becoming a very-energy-conscious user. Simply using an existing thermostat efficiently and turning off end uses when not in use can result in very significant savings. This suggests that other behavioral interventions might have promise when used instead of or in addition to installing HEMS.
- HEMS with additional connected end uses (appliances, hot water system, electric vehicles) or additional devices in the plug load and lighting categories would yield much higher savings. This study was designed to provide a conservative estimate of HEMS potential with a limited number of connected loads.
- The lack of a meaningful “average” occupant behavior pattern made it challenging to estimate average energy savings. Instead, a range of savings was provided based on energy consciousness and engagement with HEMS features. For specific households, it would be necessary to estimate savings using the behavioral patterns that are most consistent with the actual occupants or rerun the analysis with different assumptions and occupant narratives. The methodology used for this analysis may be useful to others as a starting point.
- Because different control strategies are often interrelated or have similar effects (such as voice activation and occupancy sensors, either of which can be triggered when an occupant enters the home), we did not attempt to quantify savings for individual control methods. Energy savings were calculated for all control strategies combined.

Recommendations for further study include the following:

- The magnitude and range of savings suggest further research is warranted. 35% of whole-house energy savings is a very large opportunity, which should be enthusiastically pursued by energy efficiency programs and codes and standards developers. However, since the range of savings is so large (from 7% to 35%) and mostly attributable to differences in the behavior of occupants with and without HEMS, this influence must be better understood before having confidence in expected program savings.
- There is a need for analysis of a greater variety of occupant behavior, derived statistically and based on realistic distribution seen in field studies. It is difficult to match energy savings observed in field studies across many houses using a very limited number of events with only two behavior types before and after HEMS installation. While this study bounded the range of savings, it would be valuable to estimate savings across a large number of houses by applying stochastic methods to create modeling inputs that represent the true day-to-day and family-to-family diversity in HVAC, lighting, and plug load usage. This more sophisticated analysis would have to be based on a much richer understanding of the behavior of HEMS users, as well as the behavior of non-HEMS users. Accurate assumptions for both baseline and improved cases are critical to estimating savings.
- Expected savings for additional connected end uses should be analyzed. By including hot water, appliances, Internet-of-Things-enabled devices, and distributed energy resources, a more realistic upper limit for HEMS savings can be evaluated. This study focused on HEMS capabilities that are somewhat modest relative to the true potential savings for this technology.
- Potential savings for expanded control logic should be studied. More advanced controls than required by ENERGY STAR SHEMS can begin to approach the theoretical maximum energy savings potential without occupant inconvenience. Such controls could include predictive controls, machine learning, tracking of occupant locations inside and outside the house, fault detection and diagnostics, and more advanced energy savings recommendations through in-home displays. Field studies that correlate realized energy savings with the operational behavior of end users are needed to identify which control algorithms are responsible for most of the potential savings from HEMS. This would be critical for development of energy efficiency programs or codes and standards that aim to provide credit for installation of HEMS that utilize specific beneficial control algorithms.
- More detailed analysis of demand response events is needed. This study focused on one typical year of demand response events in SCE service territory. Other utilities in other locations may use very different criteria for issuing grid signals to curtail electricity use. This is an evolving area of research beyond the scope of the current study, but it could provide greater insights into the potential for improving grid resilience through the use of HEMS.

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DOE/GO-102021-5538 ▪ July 2021