Residential Indoor Temperature Study

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Acknowledgments

List of Acronyms

BA	Building America
BEopt™	Building Energy Optimization software
DOE	U.S. Department of Energy
HSP	House Simulation Protocol
HVAC	Heating, Ventilating, and Air Conditioning
IECC	International Energy Conservation Code
NREL	National Renewable Energy Laboratory
RITS	Residential Indoor Temperature Study

Executive Summary

The indoor temperature of homes is broadly used for many business purposes including building design, efficiency incentives, and equipment specification. Homes are simulated to assess energy costs and savings potential, risk of moisture build-up, and cost-effectiveness of improvements in construction and energy codes. Many utilities base energy efficiency incentives, at least in part, on assumptions of thermostat set points. Air conditioner manufacturers, distributors, and installation technicians design, manufacture, and select equipment for new homes, as well as equipment replacements in existing homes based on load calculations that critically rely on indoor temperature. When assessing the energy performance of heating, ventilating, and air conditioning (HVAC) systems; building insulation; and other devices such as heat pump water heaters, the heating and cooling set points are typically the most influential factors driving energy consumption (Robertson et al. 2013). In addition, the indoor temperature in any part of a house is not guaranteed to match the thermostat set point—data show temperatures can vary widely from floor to floor, room to room (Roberts and Lay 2013).

Despite their importance in our understanding of how homes use energy, and for assessing opportunities to reduce home energy consumption, home set points are generally not well-studied; notable exceptions are Roberts and Lay 2013, as well as Parker 2013. Anecdotally, there is a large variance in nearly all occupant-driven aspects of residential energy use (Seryak and Kissock 2003). Most comfort research historically focused on commercial buildings, where many people work in a common environment and effort is made to minimize any dissatisfaction across a population (Fanger 1970, Fanger 2001, ASHRAE 55). In any home, the population is comparatively smaller and occupants have direct control over the HVAC set points. Privacy is another key barrier to collecting information about occupant-driven aspects of home operation. The emergence of new technology—connected thermostats—presents an opportunity for new insights by evaluating large datasets of set points and actual indoor temperatures across climate regions, housing types, etcetera, while avoiding some of the prior barriers.

This study expands on the body of knowledge around answering the question: ***What are good assumptions for HVAC set points in U.S. homes?*** Indoor temperature data from U.S. homes were collected and analyzed using funding from the U.S. Department of Energy's Building America (BA) Program, due to the program's reliance on accurate energy simulation of homes. Simulations are used to set BA goals, predict the impact of new building techniques and technologies, inform research objectives, evaluate home performance, optimize efficiency packages to meet savings goals, customize savings approaches to specific climate zones, and myriad other uses. The BA House Simulation Protocols (HSPs) were established to standardize simulation input values (Wilson et al. 2014), and they have been adopted by a number of other local and national programs as well. It is therefore critical to ensure HSPs reflect, as accurately as possible, how U.S. homeowners actually manage comfort settings in their homes.

Detailed data were collected from 327 homes in five different BA climate zones. These data were used to guide analysis of a much larger dataset from Trane® web-connected thermostats by identifying correlations between home characteristics and temperature set points. The mean indoor temperature observed from the web-connected thermostats during the heating season was $70 \pm 0.1°F$. The mean indoor temperature observed during the cooling season was $74.9 \pm 0.1°F$.

However, the data clearly demonstrate that indoor temperatures were highly variable between homes and strongly related to climate.
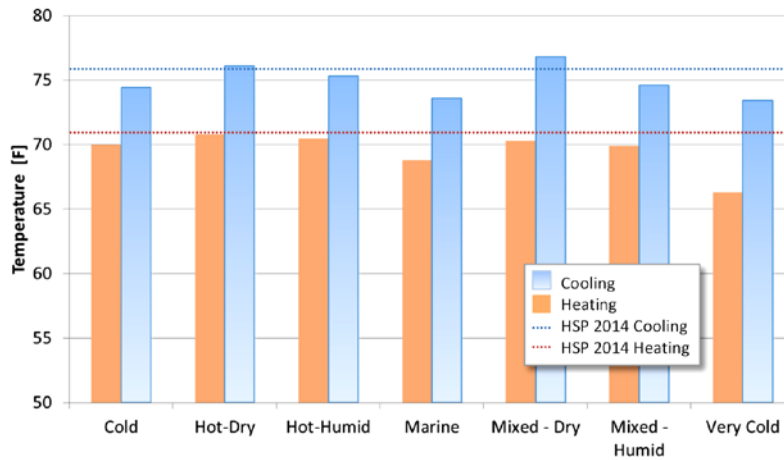
Figure E1. Variable indoor temperatures in homes strongly relate to climate zone

The high level of indoor temperature variability across homes during heating or cooling suggests that improving standard simulation protocols, such as implementing climate-dependent indoor set point assumptions, could lead to more accurate building simulations.

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1 Introduction

The indoor temperature of homes is used for many purposes including building design, efficiency incentives, and equipment specification. Homes are simulated to assess energy costs and savings potential, risk of moisture build-up, and impacts of energy code improvements. Many utilities base energy efficiency incentives, at least in part, on assumptions of thermostat set points. Air conditioner manufacturers, distributors, and installation technicians design, manufacture, and select equipment for new homes, as well as equipment replacements in existing homes based on load calculations that critically rely on indoor temperature. When assessing the energy performance of heating, ventilating, and air conditioning (HVAC) systems; building insulation; and other devices such as heat pump water heaters, the heating and cooling set points are typically the most influential factors driving energy consumption (Robertson et al. 2013). As stated by Robertson, et al., the assumed heating and cooling set points are generally the most influential simulation inputs; even a 1°F difference in a heating set point can make a 5% difference in heating energy use. Finally, the indoor temperature in any part of a house is not guaranteed to match the thermostat set point—data show temperatures can vary widely from floor to floor, room to room (Roberts and Lay 2013).

Despite their importance in our understanding of how homes use energy, and for assessing opportunities to reduce home energy consumption, home set points are not well-studied. Anecdotally, there is a large variance in nearly all occupant-driven aspects of residential energy use (Seryak and Kissock 2003). Most comfort research historically focused on commercial buildings, where many people work in a common environment and effort is made to minimize dissatisfaction across a population (Fanger 1970, Fanger 2001, ASHRAE 55). In any home, the population is comparatively smaller and occupants have direct control over the HVAC set points. Privacy is another key barrier to collecting information about occupant-driven aspects of home operation. The emergence of new technology—connected thermostats—presents an opportunity for new insights by evaluating large datasets such as set points and actual indoor temperatures across climate regions, housing types, etcetera, while avoiding some of the prior barriers.

This Residential Indoor Temperature Study (RITS) adds to the body of knowledge around answering the question: ***What are good assumptions for HVAC set points in U.S. homes?*** Indoor temperature data from U.S. homes were collected and analyzed using funding from the U.S. Department of Energy's Building America (BA) Program. Simulations are used to set BA goals, predict the impact of new building techniques and technologies, inform research objectives, evaluate home performance, optimize efficiency packages to meet savings goals, customize savings approaches to specific climate zones, and myriad other uses. The BA House Simulation Protocols (HSPs) establish standardized simulation input values (Wilson et al. 2014), and have been adopted by a number of other local and national programs as well. It is therefore critical to ensure HSPs reflect, as accurately as possible, how U.S. homeowners actually manage comfort settings in their homes.

Studies like the RITS have been performed in Europe (Johansson et al. 2013, Bagge and Johansson 2013); however, similar work in the United States has been limited (Roberts and Lay 2013, Parker 2013). The National Renewable Energy Laboratory (NREL) partnered with Trane to include data from their web-connected thermostats to increase the sample to several thousand homes. RITS provides significant valuable insights into thermal characteristics of houses and

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occupant behavior related to thermostat usage that have not previously been provided by the private sector or in previously published research.

The homes in this study were, on average, operated approximately 1.0°F cooler than current standard residential set point assumptions in the HSPs. There were also regional differences in set point behavior across the population studied. Maintaining the current practice of a set point assumption independent of climate may result in error in the prediction of energy performance up to 8–10%, and skew expectations for investment paybacks and energy costs. Details of regional and equipment-dependent thermostat trends are provided in this report.

Establishing simulation protocols such as thermostat set point assumptions, while critical to assure modeling accuracy and consistency, is generally beyond the scope of private sector research. The U.S. Department of Energy (DOE) is in a unique position to make simulation protocols for use by its programs available for adoption by other interested parties; the Residential Energy Services Network and Building Performance Institute have both adopted portions of the HSPs. The national scope and broad impact of the RITS benefits private and public research, development, and energy efficient technology deployment nationwide.

2 Data Collection

This study aggregates data from multiple sources. The most detailed data, including house characteristics along with measured indoor temperatures, were collected in collaboration with the BA teams concurrent with other research studies, each with its own independent research objective separate from this work. The detailed data have the advantage of including home characteristics that could influence indoor temperatures; however, due to the cost of collecting highly detailed data, the sample size is limited. Data from web-connected thermostats augment the detailed data, providing a large sampling size. To effectively use these two disparate datasets, the detailed data are used to determine home and HVAC system characteristics, while the web-connected thermostat data are used to determine mean temperatures.

The web-connected thermostat data include temperatures measured at the thermostat itself, as well as from any remote sensors that control different zones within the home. Detailed home data are similar, though actual thermostat readings are not recorded; rather, a temperature sensor was placed next to the thermostat. If multiple temperatures are present from a given home, they are averaged to provide a single indoor temperature.

For the purposes of this study, measured temperatures equivalent to simulation model set point inputs are considered. In reality, this is not always true. Temperature variations occur throughout every house, and thermostats have a deadband within which the actual temperature at the thermostat fluctuates. DOE's primary building simulation engine, EnergyPlus (DOE 2013), assumes that the actual temperature of a building or zone is kept at precisely the set point temperature, neglecting all real-word variation within the deadband as long as the equipment has the necessary capacity. Under this paradigm, the measured indoor temperature value is a sufficient approximation to use as a simulation thermostat set point input.

2.1 Detailed Data

Detailed data were obtained from test sites coordinated by BA teams: the Florida Solar Energy Center, IBACOS, Steven Winters Associates, and the Levy Partnership and Building Science Corporation. Additional data were obtained from the Northwest Energy Efficiency Alliance residential building stock assessment (Storm et al. 2013). There are complete, detailed datasets from 327 homes as shown in Table 1 and Figure 1. All include measured temperature data from multiple rooms in the house, sampled hourly. The data include both single-family and multifamily homes across several climate zones and were typically collected with temporary data loggers such as HOBO® or with T-type thermocouples read by a Campbell Scientific® data acquisition system. Data density ranged from one to seven indoor temperature measurements within each home, plus outdoor temperature. Asset characteristics such as climate region, age, size, and HVAC system type were also collected for each home. Not every house included all relevant information; however, the data are generally quite detailed. These data were used to correlate building and HVAC system characteristics with set point temperatures.

Table 1. Locations for Detailed Data Homes

Location	Number of Homes	Months of Data	Type of Homes	BA Climate Zone	IECC Climate Zone
California	6	12	Single-Family	Hot-Dry	3B
Colorado	9	2	Apartment	Cold	6B
Colorado	7	12	Single-Family	Cold	5B
Florida	94	12	Single-Family	Hot-Humid	2A
Idaho	14	24	Single-Family	Cold	5B
Louisiana	10	17	Single-Family	Hot-Humid	2A
Maryland	28	23	Townhome	Mixed-Humid	4A
Massachusetts	11	9	Apartment	Cold	5A
Massachusetts	8	13	Single-Family	Cold	5A
New York	20	12	Single-Family	Cold	5A/6A
Oregon	40	12	Single-Family	Marine	4C
Texas	18	12	Single-Family	Hot-Humid	2A
Washington	16	24	Single-Family	Cold	5B
Washington	46	12	Single-Family	Marine	4C
Total	327				
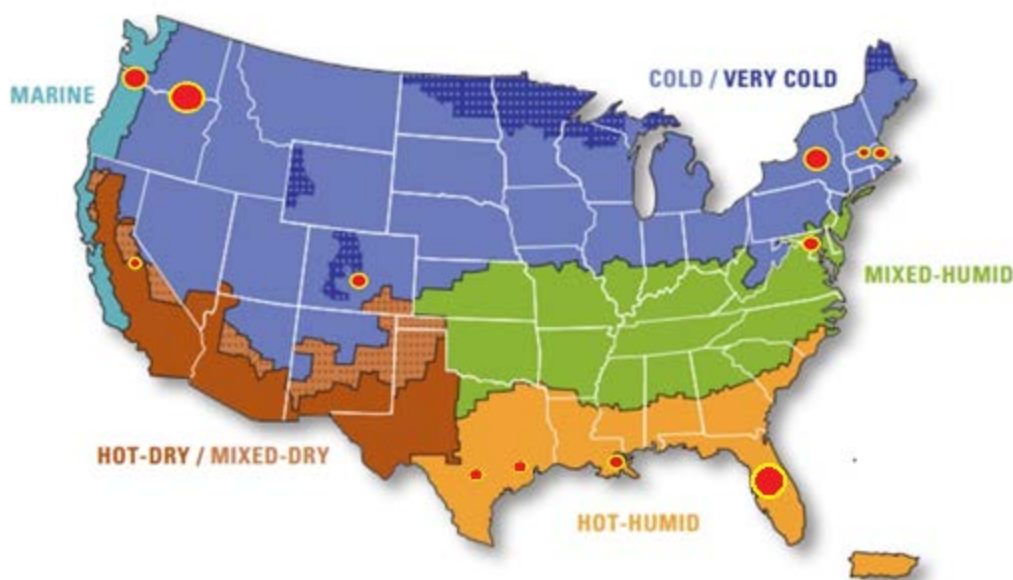
Figure 1. Locations of detailed data homes; marker size is approximately proportional to the number of monitored homes at that location

2.2 Web-Connected Thermostat Data

Trane web-connected thermostats from thousands of locations across the country were used as a source of large-scale set point data. These systems provide very detailed data about the HVAC systems and indoor temperatures, but lack house characteristics and provide only approximate location information. Table 2 broadly categorizes this data according to climate.

Table 2. Locations of Web-Connected Thermostat Homes

Climate	Heating	Cooling
Hot-Humid	2714	4312
Hot-Dry	445	554
Mixed-Humid	3529	4146
Mixed-Dry	29	35
Marine	593	468
Cold	3163	2592
Very Cold	38	14
Total	**10,511**	**12,121**

Only datasets including location information were included in this analysis. Some systems provided data during cooling season only, others heating and cooling. In cold and very cold climates, some locations did not have enough cooling data to be included. Note that for web-connected thermostats, each house provides one sample per year. Therefore, houses that have multiple years of data contribute more than one data point to the set.

3 Results

3.1 Temperature Dependence on Housing Characteristics

The detailed home data include home characteristics that could intuitively affect temperature and humidity. Multiple linear regressions are used to examine whether these known physical characteristics of the homes were correlated with heating/cooling set points. Results are listed in Table 3. It is not surprising that climate and equipment type are correlated with home temperature, and there was no statistically significant correlation of the detailed data temperatures to the other variables.

Table 3. Housing Characteristics' Correlation to Measured Temperatures

Independent Variable	Significant for Heating Temp	Significant for Cooling Temp
BA Climate Zone	X	X
Housing Type		
Equipment Type: Heating	X	
Equipment Type: Cooling		X
Foundation Type		
Conditioned Area		
Year of Construction		
Number of Bedrooms		
Number of Bathrooms		
Number of Floors		

Results from indoor temperature analysis are shown in the next sections, broken out using these characteristics to enable building energy analysts to select the most appropriate set point assumptions for their use case.

3.2 Mean Home Temperatures

Because the total number of detailed homes is limited and the homes were tightly clustered, these data proved insufficient for performing nationwide, statistically significant home temperature set point estimations. These limitations are overcome in this study by evaluating web-connected thermostat data, in partnership with Trane. Web-connected thermostats provide reliable information on system operation across orders of magnitude more homes with more complete coverage of the United States. Therefore, all data were leveraged throughout the remainder of this document for determining representative temperature set points.

3.2.1 Determination of Heating and Cooling Periods

Throughout the year, there are days, or even months, when a given home is not actively heated or cooled by HVAC equipment. During these times, indoor temperatures float. It was important to exclude those temperatures from any analysis as they do not drive operation of the equipment. Further, it was important to classify the other measured indoor temperatures by whether they

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influence heating equipment or cooling equipment. This allowed independent analysis of heating and cooling set points.

In cases where the detailed home datasets did not include heating or cooling equipment runtime, it was necessary to estimate periods of active heating and cooling. For this study, it is assumed that cooling occurred when outdoor temperature rose above 80°F and heating occurred when it fell below 40°F. For every hour when one of these conditions was met, the home was considered to be intentionally cooled or heated, and the measured indoor temperature was then averaged into the appropriate mean. Homes with less than 200 hours of heating or cooling data were omitted from aggregate analysis for each HVAC operating mode.

In contrast, data from web-connected thermostats include active operation of the equipment along with both actual measured temperature and set point temperature; only measured temperatures are used in this study. These data were easily filtered for operational mode (i.e., heating or cooling) and status (active or inactive). For the web-connected thermostat data, indoor temperatures are reported along with the current mode of operation (i.e., heating or cooling) and the capacity needed (i.e., the runtime calculated percent capacity needed to satisfy the demand of the zone). Periods of active heating are those times when the mode of operation indicates heating and the heating capacity requirement is non-zero (i.e., call for heat). Similarly, periods of active cooling are those times when the mode of operation indicated cooling and the capacity needed was greater than zero (i.e. call for cooling).

3.2.2 Heating and Cooling Temperature Averages

The mean temperature results for the homes in the detailed home dataset and the web-connected thermostat dataset are shown in Table 4. For the web-connected thermostats, the indoor temperatures are lower than HSP 2014 for heating and cooling assumptions by 1.0 ±0.1°F and 1.1 ±0.1°F, respectively. The differences from HSPs in the detailed home datasets are even larger, specifically during the heating season. This suggests that the heating and cooling set points currently used with the HSPs may not provide an accurate representation of real-world conditions.

Table 4. Mean Heating and Cooling Values

	Heating			Cooling		
	Mean [°F]	Number of Homes	95% confidence Interval of Mean [°F]	Mean [°F]	Number of Homes	95% confidence Interval of Mean [°F]
Detailed Home Data	67.2	203	0.6	74.6	177	0.8
Web-Connected Thermostat Data	70.0	37,991	0.1	74.9	40,913	0.1
HSP	71			76		
HSP Minus Detailed Home Data	3.8			1.4		
HSP Minus Web-Connected Thermostat Data	1.0			1.1		

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Figure 2 and Figure 3 show heating and cooling temperature distribution findings. The wide distribution among heating and cooling temperature results suggest that single heating and cooling numbers may not be sufficient for an accurate representation of indoor temperature set points in building simulation. Additionally, the temperature distribution during the heating season in Figure 2 shows an unusual pattern between 67°F and 72°F. This is likely an artifact of the relatively small sample size involved and that the data are not randomly sampled throughout the population; rather, are collected through several groups of homes, each of which can have similarities to each other. The much larger sample sizes of the web-connected thermostat data help alleviate this problem. Note that there are many variables, such as demographics and occupant income, which cannot be controlled for when comparing the detailed data and web-connected thermostat data. It is possible that unknown—yet statistically significant—differences between the homes or their owners could bias results.
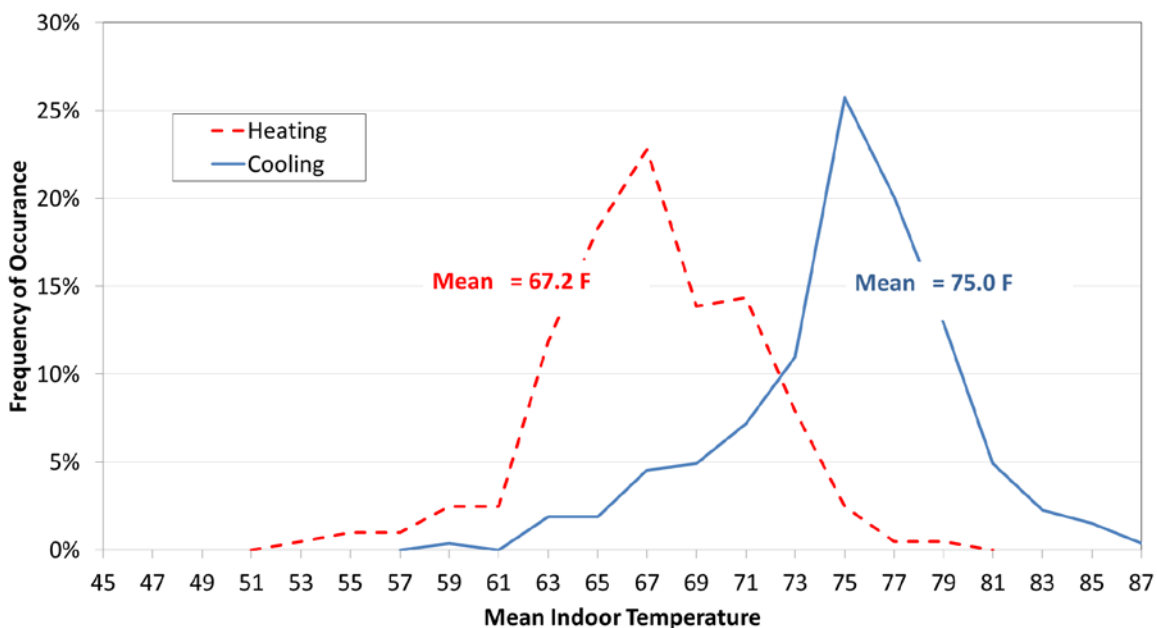
Figure 2. Mean annual indoor temperatures from detailed home data

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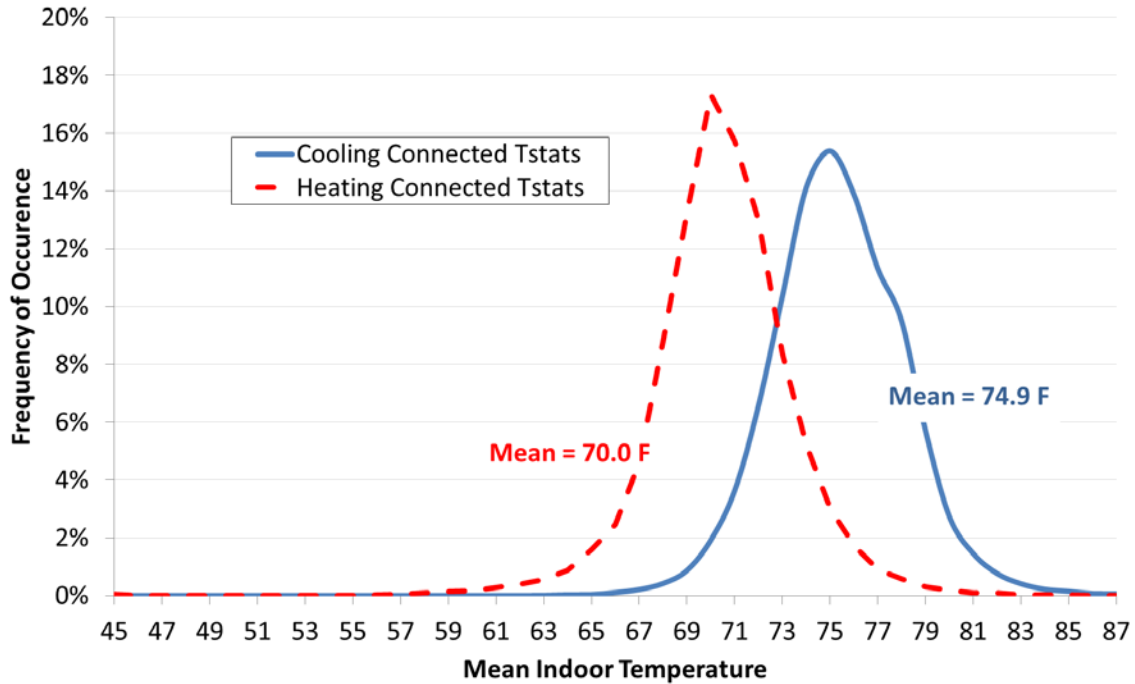
Figure 3. Mean annual indoor temperatures from web-connected thermostats

3.2.3 Heating Results by Climate and Equipment Type

Heating regression analysis showed a statistically significant effect of climate zone and space heating equipment on temperature; analysis results are provided in Table 5 through Table 7. Only web-connected thermostat data are included due to the relatively small sample size of detailed home data.

Table 5. Mean Annual Heating Temperatures by Climate

	Connected Thermostats		
BA Climate Zone	**Mean [°F]**	**Count**	**95% confidence interval of Mean [°F]**
Cold	69.4	3686	0.1
Hot-Dry	70.7	544	0.2
Hot-Humid	70.5	3590	0.1
Marine	68.9	748	0.2
Mixed-Dry	69.8	47	0.9
Mixed-Humid	69.8	4281	0.1
Very Cold	66.3	42	1.2

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Table 6. Mean Annual Heating Temperatures by Equipment Type

Heating Equipment Type	Connected Thermostats		
	Mean [°F]	Count	95% confidence interval of Mean [°F]
AS Heat Pump	69.9	18210	<0.05
Electric Furnace	71.9	1046	0.2
Forced Air Furnace	70.0	18118	<0.05

Table 7. Mean Annual Heating Temperatures by Equipment Type and Climate

BA Climate Zone	Heating Equipment Type	Connected Thermostats		
		Mean [°F]	Count	95% confidence interval of Mean [°F]
Cold	AS Heat Pump	69.3	1260	.02
	Electric Furnace	71.9	1046	0.2
	Forced Air Furnace	70.0	18118	<0.05
Hot-Dry	AS Heat Pump	70.9	167	0.4
	Electric Furnace	74.4	1	-
	Forced Air Furnace	70.6	371	0.3
Hot-Humid	AS Heat Pump	70.4	1796	0.1
	Electric Furnace	71.8	267	0.4
	Forced Air Furnace	70.5	1475	0.2
Marine	AS Heat Pump	69.0	464	0.2
	Forced Air Furnace	68.8	347	0.3
Mixed-Dry	AS Heat Pump	69.9	19	1.6
	Forced Air Furnace	69.6	26	1.2
Mixed-Humid	AS Heat Pump	69.7	2766	0.1
	Electric Furnace	67.8	4	1.7
	Forced Air Furnace	70.0	1475	0.1
Very Cold	AS Heat Pump	64.7	4	5.8
	Forced Air Furnace	67.6	27	1.2

3.2.4 Cooling Results by Climate and Equipment Type

The following tables show the mean temperatures sorted by cooling equipment type and climate zone location of the homes. Tables 8–10 show mean temperature results by equipment type and climate. All of the data point to climate as being an important characteristic for mean temperatures. Only web-connected thermostat data are included due to the relatively small sample size of detailed home data.

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Table 8. Mean Annual Cooling Temperatures by Climate

BA Climate Zone	Connected Thermostats		
	Mean [°F]	Count	95% confidence interval of Mean [°F]
Cold	74.3	2885	0.7
Hot-Dry	76.4	614	0.8
Hot-Humid	75.3	5058	0.7
Marine	74.0	565	0.8
Mixed-Dry	76.0	46	1.1
Mixed-Humid	74.4	4668	0.7
Very Cold	73.4	17	1.6

Table 9. Mean Annual Cooling Temperatures by Cooling Equipment Type

Cooling Equipment Type	Connected Thermostats		
	Mean [°F]	Count	95% confidence interval of Mean [°F]
AS Heat Pump	74.8	19622	<0.05
Central AC	75.0	19197	<0.05

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Table 10. Mean Annual Cooling Temperatures by Equipment Type and Climate

BA Climate Zone	Cooling Equipment Type	Connected Thermostats		
		Mean [°F]	Count	95% confidence interval of Mean [°F]
Cold	AS Heat Pump	74.1	1181	0.1
	Central AC	74.3	1336	0.1
Hot-Dry	AS Heat Pump	76.8	179	0.5
	Central AC	76.3	420	0.3
Hot-Humid	AS Heat Pump	75.4	2419	0.1
	Central AC	75.3	2575	0.1
Marine	AS Heat Pump	73.7	376	0.3
	Central AC	75.0	129	0.6
Mixed-Dry	AS Heat Pump	76.8	18	1.3
	Central AC	75.9	23	1.2
Mixed-Humid	AS Heat Pump	74.5	3046	0.1
	Central AC	74.4	1567	0.1
Very Cold	AS Heat Pump	74.5	3	5.0
	Central AC	73.1	11	1.9

3.2.5 Heating and Cooling Trends

Figure 4 shows the mean temperatures across climates for both heating and cooling seasons. The trends are similar across climates; higher cooling temperatures correspond to higher heating temperatures and vice versa.
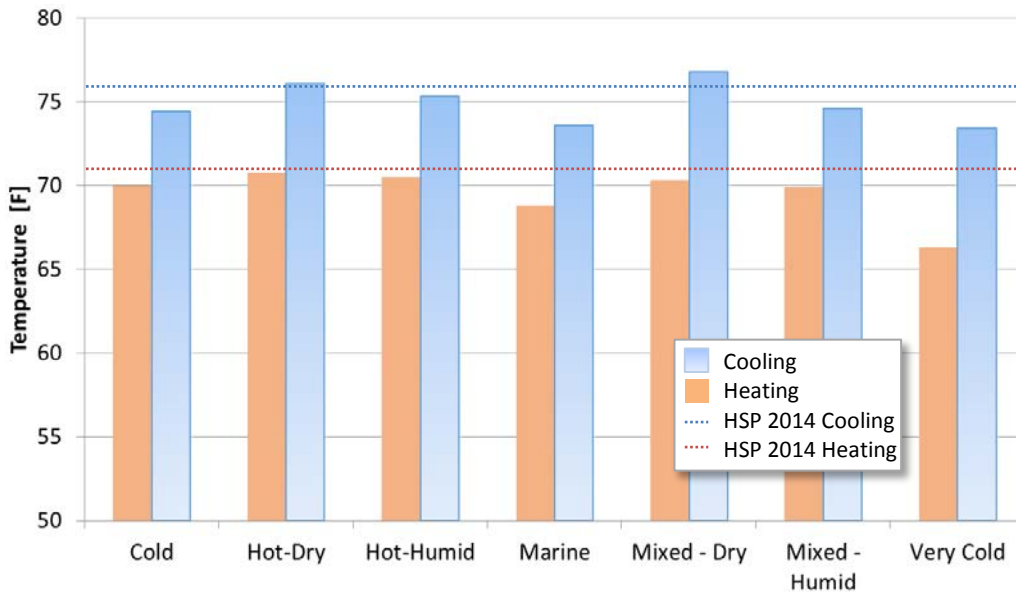
Figure 4. Mean annual indoor temperatures during heating and cooling for each climate

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3.3 Impact on the House Simulation Protocols

The findings of this study have the potential, if adopted by BA through the HSPs, to significantly change energy-use predictions. As an example of this impact, four 1980s vintage houses with construction features and HVAC equipment types matching the most common practice in the four different climate zones were simulated, with the only variation being temperature set point assumptions. Table 11 provides the results from these simulations.

Table 11. BEopt Energy Impact of Using Web-Connected Thermostat Temperature Findings Compared to HSP 2014 Assumptions

Location	Change in energy from *lowering* heating set point by 1.0°F		Change in energy from *lowering* cooling set point by 1.1°F	
	Heating	Whole Home	Cooling	Whole Home
Seattle, WA	-8%	-3%	8%	0.2%
Chicago, IL	-5%	-2%	5%	0.3%
Atlanta, GA	-8%	-2%	4%	0.7%
Houston, TX	-11%	-1%	3%	1%

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4 Conclusions

The purpose of this study was to collect residential indoor temperature data and analyze it, adding to the body of knowledge regarding simulation assumptions for thermostat set points across the United States. Data were collected from across all U.S. climate regions in two ways: (a) by performing a detailed survey which measured indoor temperatures in one or more indoor locations including adjacent to thermostats, for 327 homes, and (b) by collecting data from web-connected thermostats in more than 12,000 homes. The authors believe this is the most complete U.S. housing set point survey performed to date.

Due to limited geographic coverage in the detailed data homes and limited housing characteristics in the web-connected thermostat data, both of these datasets were used to create a more comprehensive understanding of HVAC set point trends than either would make available on its own. Analysis of the detailed data clearly show that, among locational and physical home characteristics, only climate region and HVAC equipment type influence homeowner set points. Other potentially influential characteristics (i.e., insulation level, vintage, and size) were found independent from this control variable. Fortunately, the web-connected thermostat data include location and equipment type, and the large sample size enables higher statistical confidence in the results.

The measured mean indoor temperature observed from web-connected thermostats during the heating season was $70 \pm 0.1°F$. The mean indoor temperature observed during the cooling season was $74.9 \pm 0.1°F$. These are 1.0°F and 1.1°F lower, respectively, than HSP 2014 set point assumptions for heating and cooling. The mean temperatures can be further disaggregated based on climate and equipment type based on the results in Tables 5–10.

It is acknowledged that a sampling bias could result from the data collection sources that were available during the study. Occupants of BA "detailed data" research homes are typically more engaged in energy efficiency and the environment than the average American, and they were aware that their homes were being monitored. These factors could result in selection bias among the occupants and/or cause an observation bias since the homeowners knew the researchers were watching their energy performance. Further, if equipment or other systems are found to malfunction in BA homes, it is highly likely they will be repaired to facilitate the research goals of the project, leading to different thermal and energy outcomes than the general population of U.S. homes. As with other HVAC manufacturers, Trane web-connected thermostats are only available to homeowners who purchase higher-end Trane HVAC systems. Only more affluent-than-average homeowners are likely to purchase such systems, and those homeowners are expected to be less sensitive to utility costs, and thus may use HVAC set points that make them more comfortable than the overall population would select. Overall, these potential biases are understood; however, they could not be independently controlled for within the data means available.

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Future Work

In addition to temperature, humidity can play a substantial role in how HVAC systems operate in homes and how much energy they use. It is important to understand temporal fluctuations in humidity and how those can be categorized to better determine whether certain homes are likely to have air quality and/or durability problems. It is also important to understand what data are needed to quantify the air quality and durability risk of other homes and how this type of data can be used to help predict those problems so they can be remedied. A large humidity dataset of similar size and detail was collected in parallel with the temperature data from Trane, which can help answer some of these questions.

As noted previously, we hope to perform additional data collection and analysis to explore the potential data biases, revising our recommendations accordingly. Further, a longitudinal study could show how set point decisions are influenced by other factors such as climate change, higher-efficiency HVAC equipment, changing utility rates, or code-driven improvements in home construction. Increasing availability of data from "Internet of Things" devices promises to greatly accelerate our understanding of how homes are operated.

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