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A Method to Generate Heating and Cooling Schedules Based on Data from Connected Thermostats

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Abstract

Internet-connected thermostats are a promising new source of temperature and operational data in homes because they record inside temperatures, setpoints, and HVAC runtimes every five minutes. Over 20 million Internet-connected thermostats have already been installed in American homes. Data from about 20,000 connected thermostats were collected and organized by climate zone, number of occupants, floor area, and day type. A method was developed to create up to 40 representative temperature schedules which, together, can more accurately capture the diversity of heating and cooling behaviors. These results are suitable for input into schedules for building energy simulation models. This information enables more realistic simulations of American heating and cooling behavior, leading to more accurate estimates of energy consumption and savings.

Keywords

building energy simulation; building codes; setpoints; thermostat; data science

Highlights

- Connected thermostats record indoor temperatures and HVAC runtime every 5 minutes
- Thermostat data from over 20,000 homes have been collected
- A tool was created to generate representative temperature schedules.
- The user can specify the number of schedules, occupants, and climate zones
- Results are suitable for input into schedules for building energy simulations

1. Introduction

1.1. Simulation of Building Energy Consumption and Its Dependence on Indoor Temperature

Building energy simulation is now an accepted practice that provides a quantitative assessment for estimating energy consumption, compliance with building codes, and determining the size of key equipment. Simulation is also used to explore the impacts of design changes and, more recently, comfort and health implications. Researchers have steadily improved techniques to model heat transfer, equipment, and controls operation (Lomas et al. 1997; Li and Wen 2014). At the same time, measurements of actual weather conditions have been refined, both in accuracy and frequency. The result has been increasing accuracy in the models' estimates of building energy consumption in actual conditions.

With the improved precision of modeling the performance of materials, equipment, and controls, the greatest uncertainty in predictions of a building's energy consumption increasingly lies in indoor temperatures. Dodoo et al. (2017) found that assumptions regarding indoor temperature were among the most important parameters in predicting energy consumption of Swedish residences. A change of 0.5°C in the indoor temperature assumption can raise or lower a typical American home's predicted heating or cooling use up to 10 percent (Booten et al. 2017). In an investigation of Swedish passive townhouses, Wall (2006) found that the space heating requirements increased three-fold when the indoor temperatures rose from 20.8°C–26.8°C.
In a study of American homes, Parker et al. (2012) showed that cooling energy use varied by a factor of 5:1 in otherwise identical homes and that proper specification of thermostat settings was critical for accurate prediction.

Actual temperatures found in buildings are important for various policy objectives beyond accurate simulation of building energy use (Hendron and Engebrecht 2010; Seryak and Kissock 2003). These policy objectives include building energy codes, health codes, and appliance efficiency regulations. For example, Huebner et al. (2018) found that many UK households are at risk of negative health outcomes because of low indoor temperatures. Garlit (2017) described the pain experienced by people suffering from multiple sclerosis (MS) when indoor temperatures rise suddenly. Mavrogianni et al. (2013) argued that weight gain by occupants is related to rising indoor air temperatures. Harrington et al. (2015) examined indoor temperatures so as to better predict in situ refrigerator energy consumption.

For simulations and code-making purposes, policymakers have generally specified thermostat setpoints based on limited measurements. In Canada, the National Building Code requires use of a 21°C heating setpoint and a 25°C cooling setpoint in living spaces (National Research Council of Canada 2015). In California, the building code requires energy model calculations to use a heating setpoint of 20°C (68°F) and a cooling setpoint of 25.6°C–28.3°C (78°F–83°F) for most conditions (Ferris et al. 2015). The problem of obtaining, and then selecting, realistic indoor temperatures and schedules becomes even more difficult when estimating regional or national benefits from improvements in building performance.

1.2. Measurements of Indoor Temperature

Actual temperature schedules inside buildings can be obtained either from direct measurements or from surveys. Each approach has advantages and limitations; these are summarized below.

Researchers have measured temperatures in individual buildings or groups of buildings for many decades. Notable studies have taken place in Japan (H. Yoshino et al. 2006), China (Hiroshi Yoshino et al. 2006), United States (Roberts and Lay 2013), Ireland (Healy and Clinch 2002), and Sweden (Johansson, Bagge, and Lindstrii 2013). These measurements are typically collected in support of other goals, such as understanding thermal comfort, health effects, or performance of building components. Temperature measurements have grown more detailed and extensive as the cost of sensors and data collection have declined. Temperature data collected through measurements are ideal for simulations because the researcher can understand the precise locations and frequency of measurements and then ensure that the simulation is consistent. The limitation of this approach is that most measurements are undertaken in small groups of buildings and for limited periods. Thus, measurements provide highly accurate temperature schedules, but they are difficult to extrapolate to larger populations or for the whole year.

Surveys are often used to collect temperature information for input to simulations. The surveys typically ask occupants to provide temperature settings in their homes during principal activities (sleeping, socializing, etc.). One of the most reputable and longest-running surveys in North America is the U.S. Residential Energy Consumption Survey, RECS (EIA 2015). The survey is repeated every four years and, in 2015, about six thousand homes were surveyed. The sample is carefully selected to represent the entire stock of U.S. homes. RECS asks survey respondents to report just six indoor temperatures: when they are home, away, or sleeping for both winter and summer. The survey provides an excellent window into national heating and cooling habits, both lattitudinally and longitudinally. The survey results are far better than no information but leave considerable uncertainty in actual temperature preferences. Like all surveys, errors and inconsistencies can arise in self-reported temperatures and schedules. For example, the survey respondent may not be the person responsible for controlling the home’s temperature. Each type of thermostat used to control the temperature—manual, programmable, Internet-connected, or no thermostat at all—has a different relationship between settings and actual temperatures. Changes in behavior during periods when the occupants are on vacation—often 10 percent of the time—are not captured. In general, the data on temperatures and schedules derived from surveys are much less precise than the other inputs used in a building simulation.

Survey results are especially problematic for simulations because these responses must be translated into hourly indoor temperatures. The researcher must further decide how to allocate the responses across weekends, holidays, and other situations. In summary, both approaches to collecting temperature data have limitations, and both cannot be used to accurately capture regionally representative temperature settings and schedules.

1.3. The Internet-Connected Thermostat

In about 2010 the first Internet-connected thermostats were offered widely to consumers. These thermostats used an Internet connection (typically through Wi-Fi) to communicate operating data to the thermostat vendor (in the "cloud") and to receive operating instructions from the vendor. The Internet connection enabled many new features to be offered to customers, such as control via smartphones and optimized operation of the homes' heating and cooling systems. Now, in 2020, we estimate that about 20 million Internet-connected (or "communicating") thermostats have been installed in North American homes. This corresponds to roughly 15 percent of stock. About four million European homes have thermostats. The North American market appears to be growing at about 15 percent per year in response to the new features the thermostats provide, incentives offered by utility companies, and the opportunity to more conveniently save energy.

Connected thermostats continuously transmit data to their vendors. Every five minutes, typical units transmit the following:

- Setpoint (or target) temperature
- Actual temperature in the home or zone
- Runtime of the heating or cooling system during the previous interval
- Occupant-selected "schedule" (that is, Home, Sleep, Away)

Many models also detect motion, humidity, and detailed operating characteristics of the HVAC system. Recently, vendors have begun offering additional temperature sensors that can be placed in other zones to assist in more precise heating and cooling strategies.[1]

Data from connected thermostats would appear to be an excellent source of temperature information. Unfortunately, most thermostat vendors have not shared these data in order to protect customer privacy (and possibly valuable market information). European (and other regions') data privacy laws may also prevent releasing this information. In at least three cases, however, vendors worked with researchers and provided them thermostat data. Woods (2006) compared data from about 100 thermostats to assumptions in California energy codes. Booten et al. (2017) analyzed thermostat data from about 12,000 homes distributed across the United States. With it, they were able to estimate temperatures by climate region. Ge and Ho (2018) used thermostat data from 27,000 American homes to study the persistence of habits in consumers' temperature setting behavior. In all cases, however, the investigators had no additional information about the homes beyond their locations, which limited the scope of their analyses.

In 2015 one thermostat vendor, ecobee, established an experimental program called "Donate Your Data (DYD)," where its customers could "donate" their data to researchers (Ecobee Inc.

[1] Most connected thermostats cannot link to electrical "smart meters" and therefore are not capable of collecting concurrent energy consumption data.

2018). Ecobee harvested limited information about the household from the set-up inputs, including the city, home's floor area, type of heating system, age of home, and number of occupants. Customer names and all personally identifiable information were removed. Purchasers of new ecobee thermostats were offered the opportunity to "opt-in" at the time of registration. The program has attracted a growing number of participants. As of September 2017, about 20,000 households have joined the DYD program in the United States. Figure 1 shows the trajectory of registrations and the major geographical locations of the DYD participants.

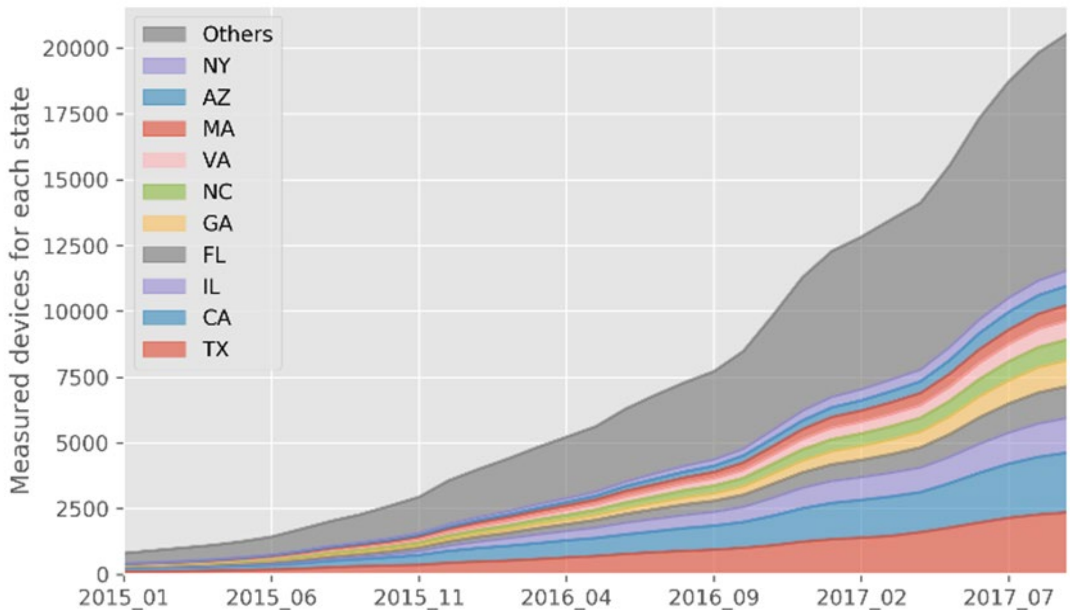

Figure 1. Growth of participants in the DYD program in the United States. The two-letter codes refer to individual states, and "Others" are the remaining states.

The richness of the DYD data are revealed in Figure 2, a heat map of temperatures for one year. The vertical axis shows one week (5 minutes x 24 hours x 7 days), and the horizontal axis shows the week of one year (52 weeks). The difference between the daytime and nighttime temperatures appear as horizontal stripes (except on weekends). The seasonal transitions appear as one moves from right to left. Data gaps appear as white spaces.

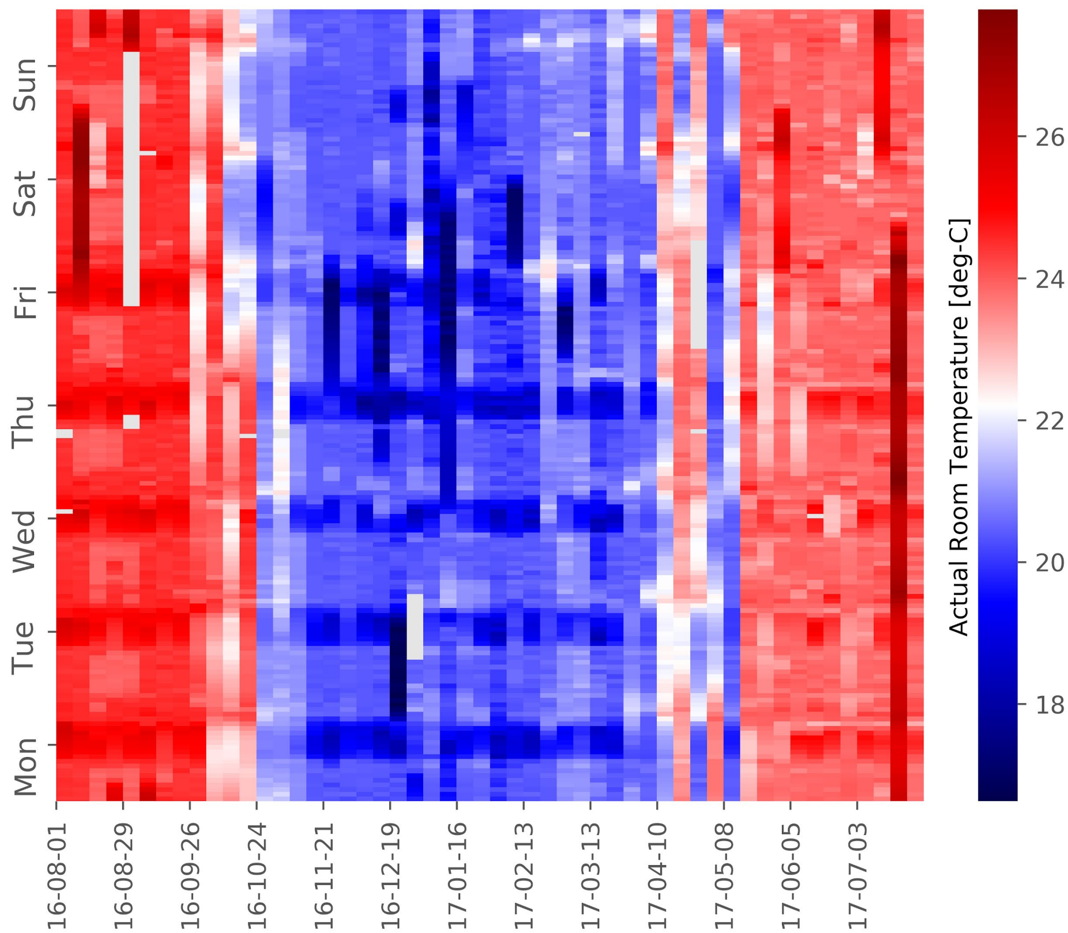

Figure 2. Temperatures in a typical DYD home for one year

Researchers have already begun to explore the DYD dataset and extract information about occupant behavior and peak demand (Meier et al. 2019), occupant temperature preferences (Huchuk, O'Brien, and Sanner 2018), occupancy prediction (Huchuk, Sanner, and O'Brien 2019), estimating energy savings from thermostats (Daken, Meier, and Frazee 2016), and using the network to track power outages (Meier, Ueno, and Pritoni 2019). However, nobody has converted the DYD data into representative temperature schedules. In this paper, we present a method to convert actual temperatures recorded in DYD homes into data suitable for building simulations of representative American homes. We begin by evaluating the representativeness of DYD homes. Then we present a method to convert DYD temperatures into a set of prototypes that capture the diversity in operating behaviors. Finally, we illustrate the method with some examples.

2. How Representative Are the DYD Homes?

Before developing representative operating schedules for American homes from DYD data, it is necessary to confirm that the participants in the DYD homes accurately reflect the diversity of homes in the United States as a whole. Each participant filled out a questionnaire; however, to avoid discouraging people from filling out the questionnaire, ecobee avoided asking standard economic and demographic questions. This made it impossible to simply compare the responses to census information. We therefore relied on indirect methods of comparison, described below.

Roughly 20,000 homes participated in the DYD program as of September 2017.[2] While this is a large number, the sample suffers from obvious biases. The DYD homes are a triply self-selected sample. First, people buying ecobee thermostats require reliable broadband Internet connections (greater than 1 megabyte/sec) and Wi-Fi networks in their homes. About 6 percent of American households lack broadband access (Federal Telecommunications Commission 2019). Most of those homes with inadequate connections are located in rural areas. Second, the connected thermostat is still a relatively new technology, so people who buy ecobee thermostats are probably early adopters and more technically proficient than the average. (This selection bias may be diluted somewhat by numerous utility programs subsidizing purchases.)[3] Finally, only a unique group of ecobee customers will choose to opt in to the DYD program and fill out the questionnaire. For all of the above reasons, the DYD sample is likely to not reflect the actual population and housing stock in the United States.

To understand the extent of this bias, we compared the DYD homes to the U.S. Department of Energy's Residential Energy Consumption Survey, RECS (see above). The RECS surveys only about 6,000 homes, but the U.S. Department of Energy rigorously ensures that the homes accurately reflect the whole population. Our approach to exploring sample bias was to compare findings from similar questions in the DYD questionnaire and RECS.

According to RECS, about 63 percent of American households are detached single-family homes. In the DYD sample, roughly 63 percent are also single-family detached homes. However, the categories in the DYD questionnaire do not map directly to the RECS categories. About 18 percent of the DYD homes are in the self-described categories of "townhouse," "condominium," "rowhouse," and "semi-detached" compared to 6 percent in the single RECS category of "single-family attached." RECS estimates that about 26 percent of American households are apartments, but only 5 percent of the DYD participants reported living in apartments. This bias towards single-family homes (detached and attached) is to be expected because ecobee thermostats are not

[2] The number of devices varies in the figures because of different filtering criteria. Figure 1 was created from the metadata as of September 2017. The values used in the subsequent analyses were reduced after removal of devices for the following reasons: measurement period of less than three months; users with three or more devices; and users in buildings other than single, detached houses. After removal, 9,925 devices remained. Some homes had heating but no air conditioning. The metadata also indicated some homes with NO "number of occupants" or NO "floor space." The number of participants increased to more than 50,000 in 2018.

[3] For competitive reasons, ecobee was not able to share with us the demographics of its customers.

compatible with most apartment heating and cooling systems. For that reason, we compared the DYD homes to RECS single-family homes (detached and attached).

We performed additional comparisons between DYD and RECS data, including: geographic distribution, floor area, number of occupants, type of heating system, and age of home. Three comparisons are presented graphically in figures 3–5.

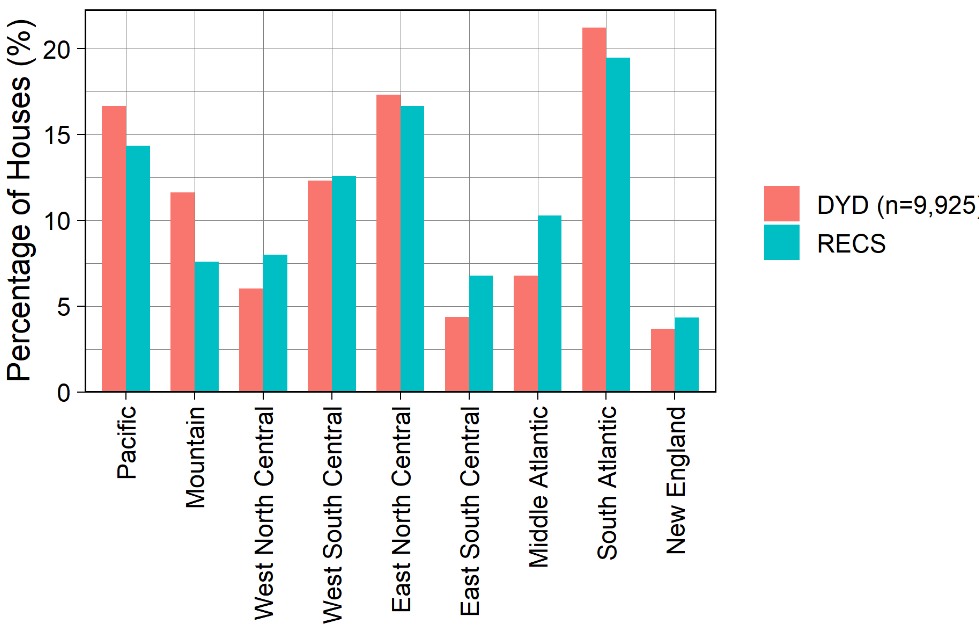

Figure 3. Geographical distribution of DYD participants compared to RECS

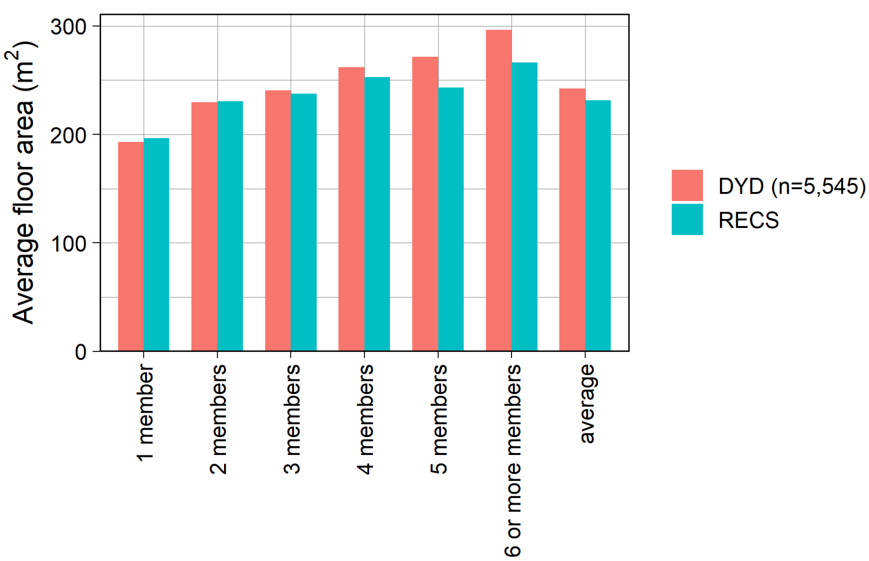

Figure 4. Distribution of floor areas with respect to number of occupants for DYD participants and RECS

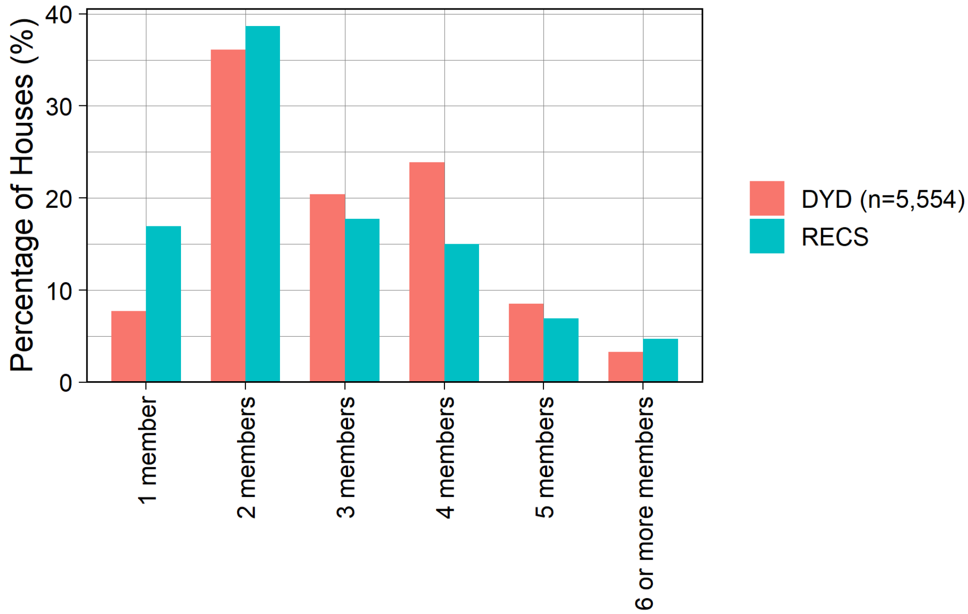

Figure 5. Distribution of number of occupants in homes for DYD participants and single-family detached homes in the RECS sample

There are some differences between the groups but fewer than one might expect. The DYD homes are geographically distributed roughly the same as RECS (Figure 3). There are relatively more DYD homes than RECS homes in the Mountain region and fewer in the Mid-Atlantic region, but the overall differences are small. Figure 4 shows the floor areas in the different regions. The DYD and RECS homes are nearly the same size—the DYD average floor area is only 4 percent larger. The relationships between the number of occupants and floor area are also similar. Figure 5 shows the distribution of occupants in DYD and RECS homes. With the exception of single-occupant homes, the number of occupants in the two groups are similar. For example, 35–40 percent of the homes in both groups have two occupants.

The age distribution of homes in the two groups is also similar (data not shown). The heating systems differ because the ecobee thermostat is not fully compatible with electric resistance heating systems and heat pumps (data not shown).

It is also possible to compare measured temperatures in the DYD homes to temperatures reported by the occupants in RECS homes. The RECS survey asks occupants to report temperature settings while at home, sleeping, and away for both winter and summer. In this comparison, the median value of the responses was used. Ecobee adopted the same terms for its primary settings (or schedules): Home, Sleep, and Away. Unlike RECS, ecobee collects both the setpoint (that is, the desired temperature) and the actual temperature. These may differ because of periods when the actual temperature floats above the setpoint or “Smart Recovery” is enabled.[4] The results of the comparison are shown in Figure 6. The figure also displays the average temperatures for the heating and cooling seasons.

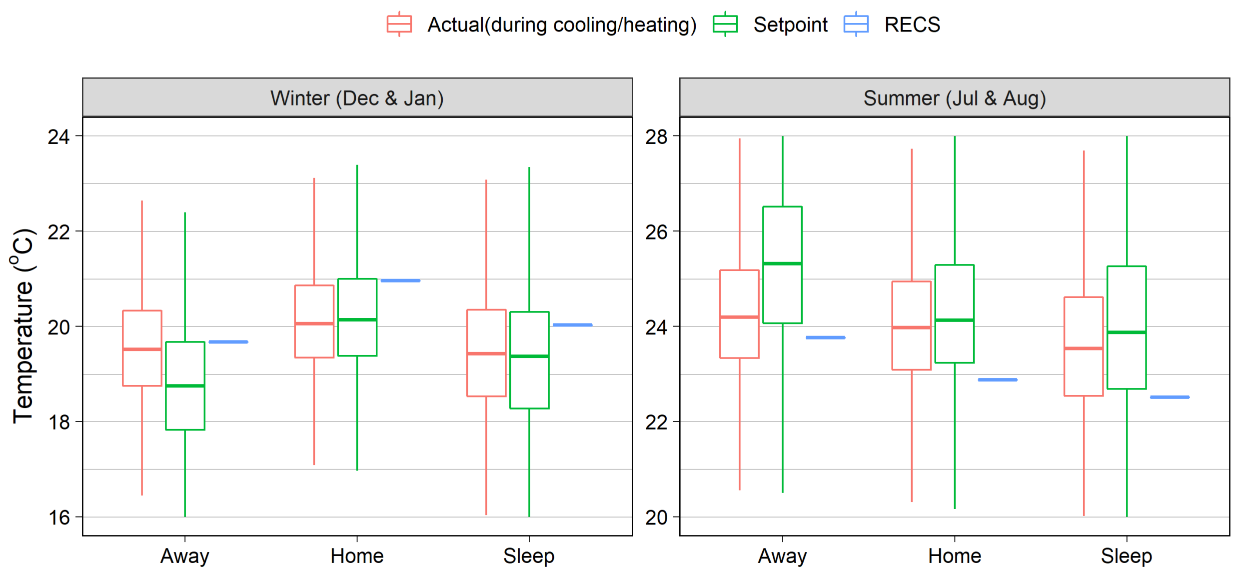

Figure 6. Comparisons of temperatures in DYD and RECS households

The temperatures follow expected behaviors; that is, in the winter temperatures are highest (warmest) when occupants are at home and lowest (coolest) when they are away. They are reversed in the summer. The impacts of floating temperatures can be observed by comparing the actual and setpoint DYD temperatures. In the winter the actual temperatures are slightly higher than the setpoints during Away and Sleep periods. In the summer, the DYD Away setpoint is significantly higher than the actual temperature, possibly because it captures cooler periods when no air conditioning was needed.

The RECS respondents report significantly higher (warmer) setpoints during the winter than setpoints measured in the DYD homes. This trend applies for Home, Away, and Sleep periods. The relationship continues during summer; that is, RECS setpoints are higher (warmer) than those measured in DYD homes. In general the RECS occupants appear to set their thermostats so they are less comfortable—colder in the winter and warmer in the summer—than occupants of the DYD homes. It is not clear if this is a difference in behaviors or an artifact of the data collection techniques. The two groups’ temperatures are more similar when the DYD temperature (rather than the setpoint) is compared to the RECS values.

[4] Smart Recovery is an algorithm that preemptively heats or cools the home in anticipation of a transition in the occupant’s schedule. The higher the difference in setpoints between these two programmed Comfort Settings, the earlier the system may engage, and the longer the system may run to reach the target setpoint.

In summary, the DYD homes are not perfectly representative of the stock of single-family homes, but they are reasonably similar with respect to location, floor area, number of occupants, and home age. It is still possible that the occupants of the DYD homes differ greatly with respect to income or education, but there is no evidence to suggest this.

3. A Method for Creating Representative Temperature Schedules

3.1. Technical Approach

No single temperature schedule can represent the wide range of temperatures and schedules. Simulations of a home's energy use based on average conditions are likely to be highly misleading. They would, for example, not capture homes operated under extreme conditions, where energy consumption might be especially high. One solution is to construct a set of schedules that captures this diversity. Ten temperature schedules would more effectively capture this diversity. The technical challenge, however, is to determine the correct weighting for the different temperature schedules so the combinations of the simulated homes reflect the national situation. The DYD data provides the necessary information to create sets of representative temperature schedules. The method of generating representative prototype temperature schedules is described below.

Our approach to generating representative temperature schedules built upon patterns observed in the DYD data. These data enabled us to identify the variables that strongly affect temperatures and schedules. As described earlier, ecobee thermostats divide the day into three schedules: Home, Away, and Sleep. The frequencies of these schedules at each hour were calculated for every hour. These frequencies were calculated separately for weekdays and weekends because the distributions are so different (see Figure 7). Annual data were used to calculate the frequencies.[5]

[5] Frequencies based on monthly (rather than annual) temperatures could be calculated, but this would require much more computation.

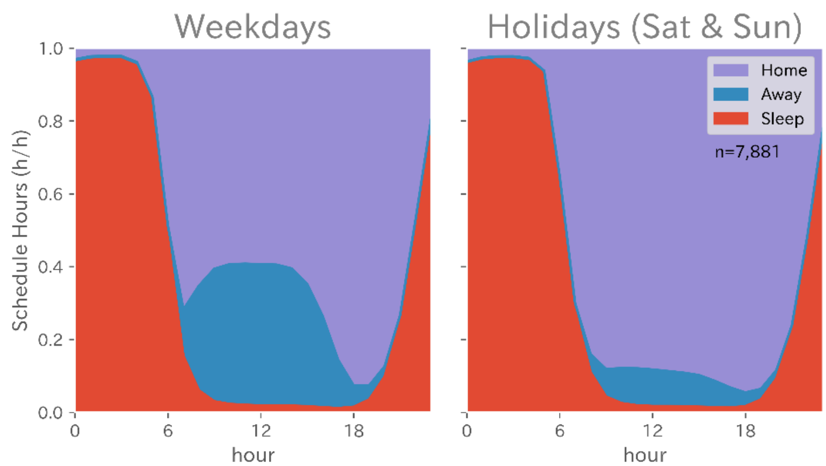

Figure 7. Frequencies of occurrence of Home, Away, and Sleep for weekdays and weekends

Figure 7 shows that on weekdays, about 95 percent of the homes are in a Sleep schedule until about 05:00 and then drop rapidly to a minimum near noon. Meanwhile, the fraction of homes in the Away schedule climbs sharply after 06:00 to almost 40 percent at noon. The maximum fraction of homes in the Home schedule occurs at about 18:00. On weekends, the Sleep schedule extends about one hour later, and the fraction of homes in the Away schedule is much less than half that of weekdays.

The number of occupants also affects the time the house resides in each schedule. Figure 8 shows the impact of the number of occupants on the occurrence of the Home schedule. Not surprisingly, the fraction of homes in the Home schedule increases with the number of occupants. This phenomenon is especially strong near 14:00 on weekdays, where single-occupancy homes are 0.5 while six-person homes are 0.75. These differences almost vanish on weekends. The DYD dataset was large enough to examine regional variations in occupancy; however, no significant differences were found.

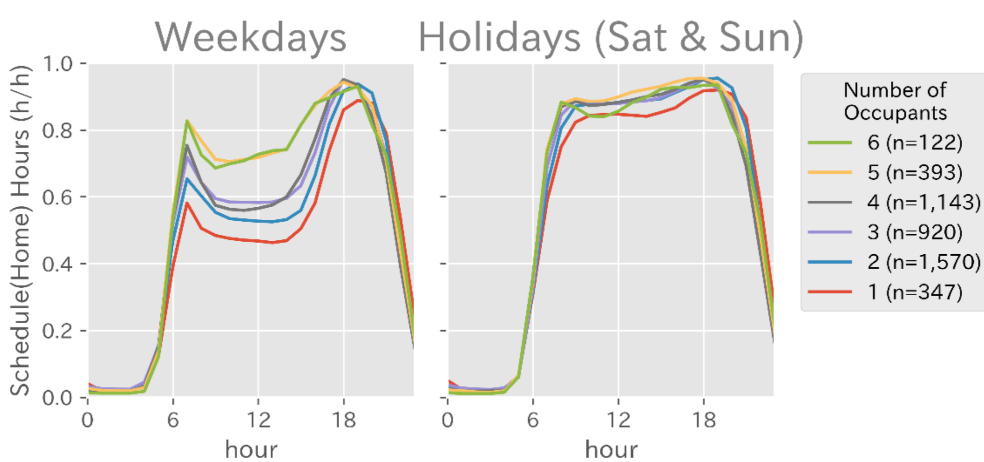

Figure 8. Influence of the number of occupants on fraction of time in the Home schedule

Figure 6 summarizes the hourly setpoints and temperatures for the entire country. However, the richness of the DYD dataset allows further disaggregation of temperatures into five separate climate zones defined by Building America for its prototypes (see Figure 9). Variations between the climate zones are easily observed. For example, during the summer the setpoints in the Mixed-Dry/Hot-Dry regions are significantly higher (warmer) than in the Hot-Humid regions. This difference probably reflects the occupants' preference for cooler air temperatures in humid climates than in dry climates so as to maintain thermal comfort. During the winter, the setpoints in all climate zones show less variation, although the homes in the Marine region have lower nighttime setpoints.

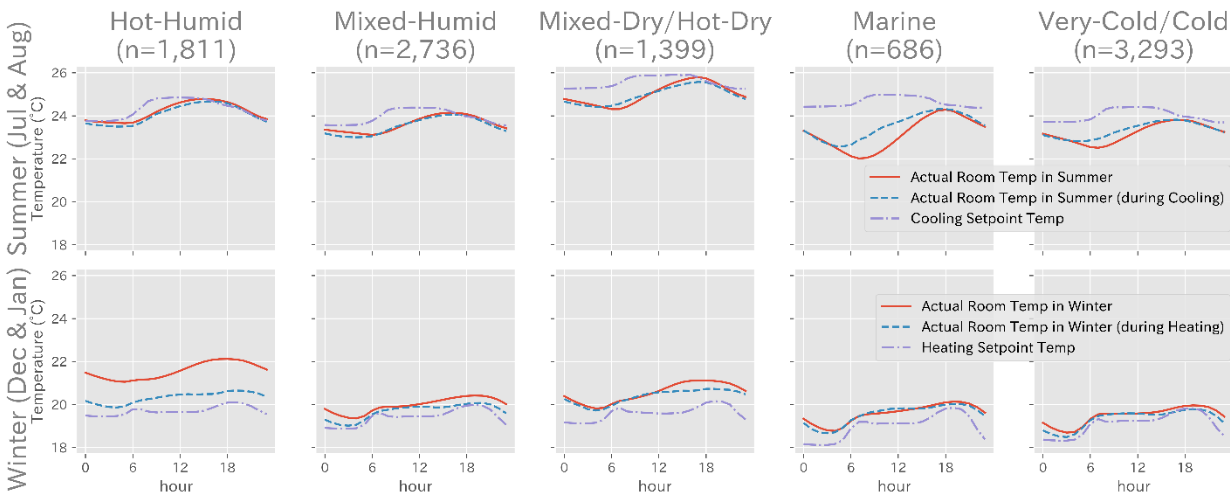

Figure 9. Room temperatures for each climate zone

The above analyses identified several variables that affect a home's heating and cooling energy consumption—temperatures, schedules, number of occupants, and climate zone. All these should be taken into account when simulating a home's HVAC use. The DYD dataset makes it possible to quantify the frequency of occurrence of these factors. In the following sections, a method is described to generate an arbitrary number of typical schedules and temperatures for inputs to simulation models.

3.2. Generating Typical Temperatures and Schedules for Simulation Model Inputs

A program was written to generate typical temperature setpoints and schedules for use in simulation models based on the DYD data. For example, if a user wishes to represent the entire range of residential temperatures and schedules in the United States with six prototypes for their simulations, what should they be? The tool provides up to 40 prototypes for conditions such as climate zones and number of occupants selected by the user. The logic behind the procedure is described below.

The program consists of two separate procedures: a method for generating temperature setpoints and a method for generating the typical schedules. Figure 10 shows the flowchart illustrating the procedure used to generate setpoint temperatures. First, the DYD data must be organized for simple computation. For each home, the distribution of the setpoint temperatures is acquired for each season (Summer/Winter), schedule (Home/Sleep/Away), and climate zone (five separate zones + all zones), and is loaded into a database. These data are similar to the “setpoint” temperatures shown in Figure 6, but are now assembled for each home.

Before generating setpoint temperatures, the user must specify the “number of desired samples (N),” that is, the number of input files to be generated. The generator then outputs a setpoint temperature schedule that can be used as an input for simulation of any climate zone, season, or schedule.

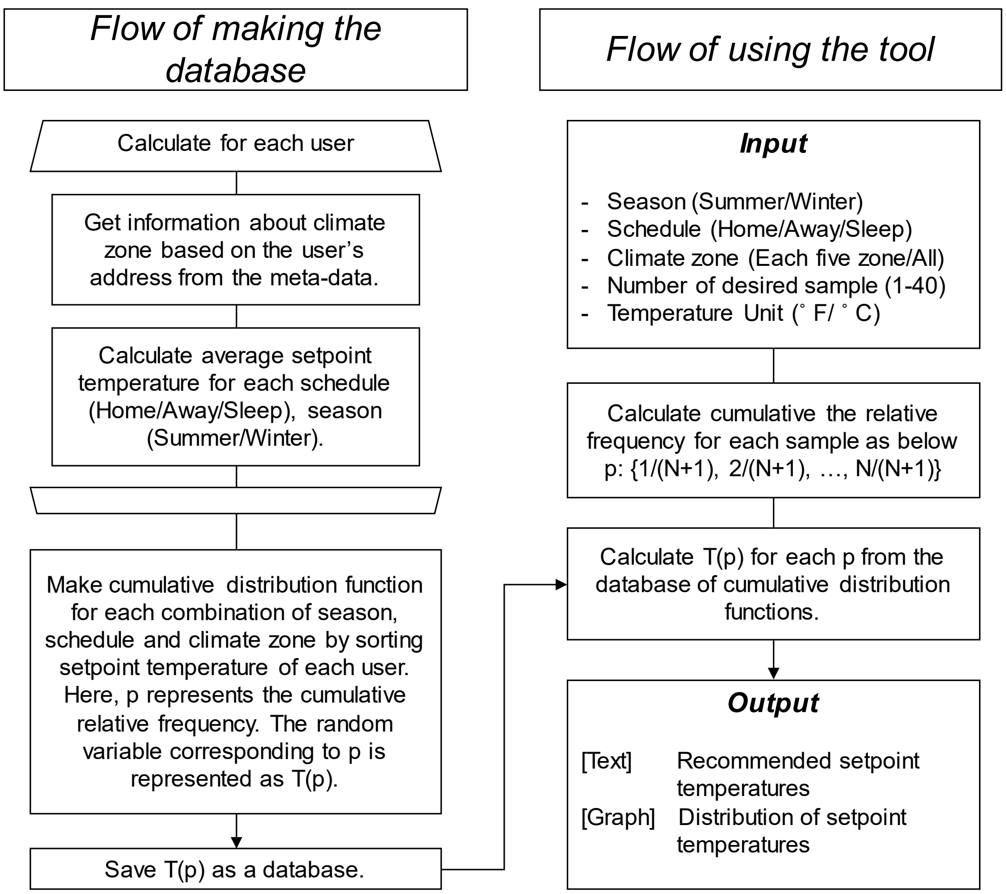

Figure 10. Flow chart showing the procedure to generate setpoints

The calculation method is straightforward. For each parameter, the setpoint temperature in the database is sorted in ascending order to create a distribution function T(p). The set of setpoint temperatures represented in Equation 1 is output,

T (k / (N + 1)) for k in 1,2, ..., N (Equation 1)

That is, the entire distribution is divided into (N + 1) digits, and the value of the delimiter is output. When N = 1, T (0.5) (the median of all distributions) is output, and when N = 4, four values of T(0.2), T(0.4), T(0.6), and T(0.8) are output. Figure 11 illustrates the setpoints calculated from this procedure for N = 4 and Figure 12 illustrates the setpoints calculated for N = 20.

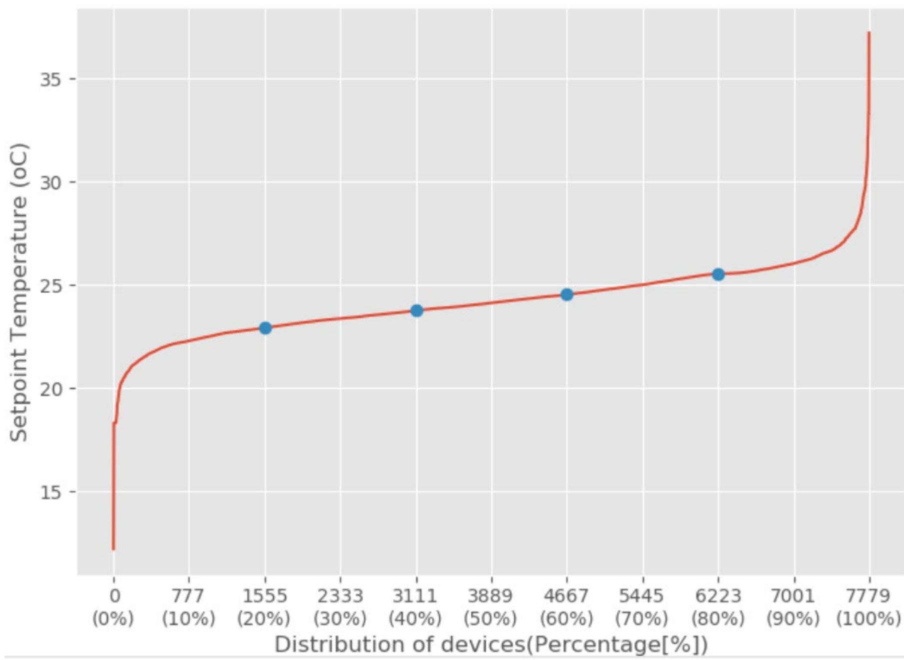

Figure 11. Distribution of setpoints in the Home schedule for all climate zones in summer with N = 4

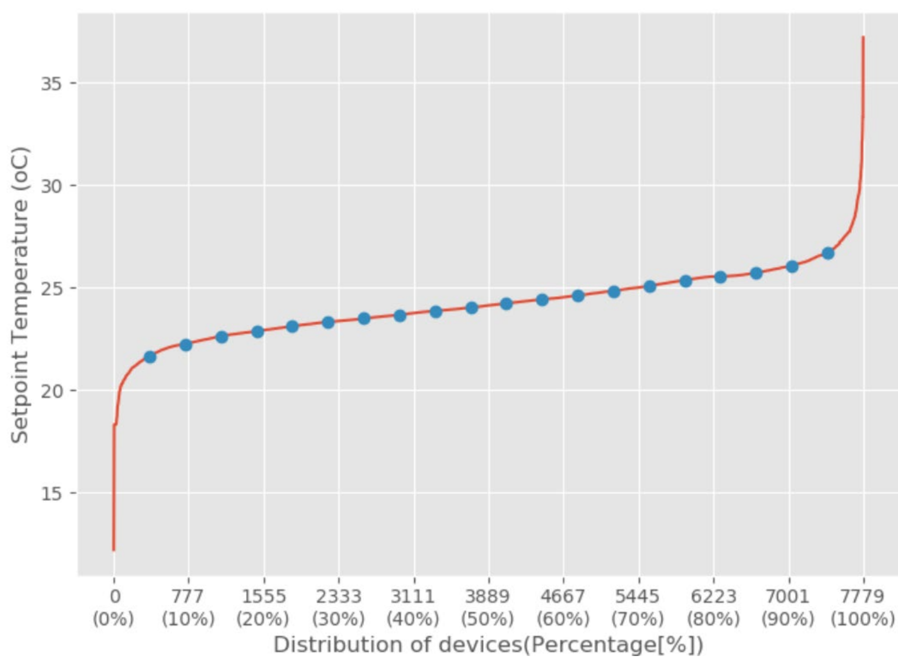

Figure 12. Distribution of setpoints in the Home schedule for all climate zones in summer with N = 20

Figure 12 shows the recommended setpoints for use in simulations during the summer while the thermostats are in the Home schedule when 20 files have been selected. The distribution is interpreted as follows: roughly 10 percent of the homes have setpoints below 22°C, 50 percent of the homes have setpoints below 24°C (the median setpoint), and 10 percent of the homes have setpoints above 26°C. Similar distributions can be generated for other schedules and, if desired, specific climate zones. It is interesting to observe that about 20 percent of the setpoints lie outside of the range 22°C–26°C.

The advantage of increasing N appears in the extremes; the fraction of homes with either very low or high setpoints are explicitly captured. These homes, for example, might be vulnerable to moisture problems.

The second component of the tool generates schedules. The methodology is summarized in Figure 13. First, the DYD schedule data must be organized for simple computation. This organization is identical to the setpoint temperatures; that is, for each home, the distribution of the setpoint temperatures is acquired for each season (Summer/Winter), schedule (Home/Sleep/Away), and climate zone (five separate zones + all zones), and loaded into a database. Next, the average number of hours [h/h] of each schedule of the day of week (Weekday/Holiday) and every hour (0–23:00) for all target households is acquired, and a database is created for each number of occupants (1–6 persons + whole). In addition to the above parameters, the generator also has a "number of desired sample(N)" of schedules to be acquired as an input, and outputs a schedule that can be used as an input of simulation for any day of the week or number of occupants. The empty boxes represent the end of the loop for each "hour," "day of week," "user," etc.

Clustering techniques are applied to identify the representative schedules. The K-Means method was used to generate the groups based on the vector of the probability of each schedule for each user and for each day of week. For example, for a user (user A), and for "Weekdays," the probability for "Home," "Away," and "Sleep" for each hour (0–23:00) is calculated using the whole period. The vector has 72 elements for each user, and each element is between 0 and 1 (because it is the probability). If the number of users is 500, we have 500 data elements (each datum is a vector with 72 elements). The data are then classified into N groups using clustering analysis.

The schedules are then generated by calculating averaged probability for each group and each hour, as described in the flowchart. The number of schedules to be acquired (N) is calculated as the number of clusters, and a schedule with the maximum number of hours of schedule for each group/time is taken as the output at that group/time. K-Means is implemented using the K-Means of the scikit-learn/cluster module of Python 2.7, and the initial value of the module is used for parameters other than the number of clusters.

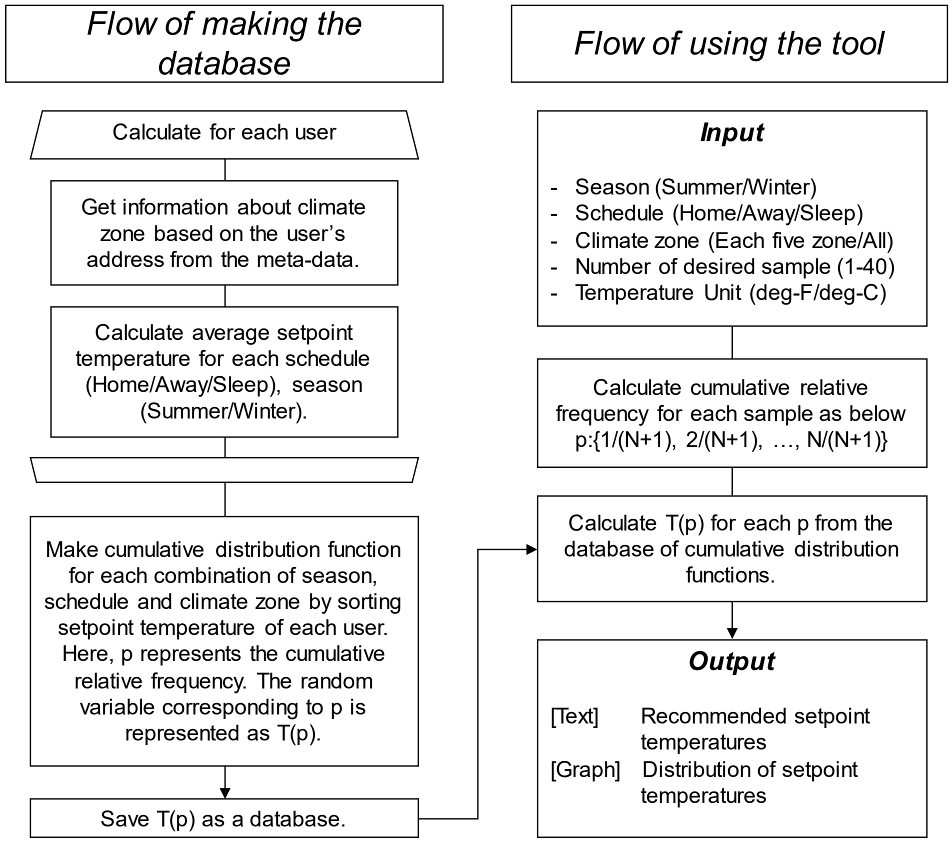

Figure 13. Flowchart of the logic used to generate schedules

Figure 14 illustrates the output for N = 4. Figure 15 displays the results in tabular form when four schedules are selected to represent the national housing stock. In two of the schedules for N = 4, there are no Away periods. These schedules with no Away time (that is, somebody is always at home) represent about 57 percent of the homes.

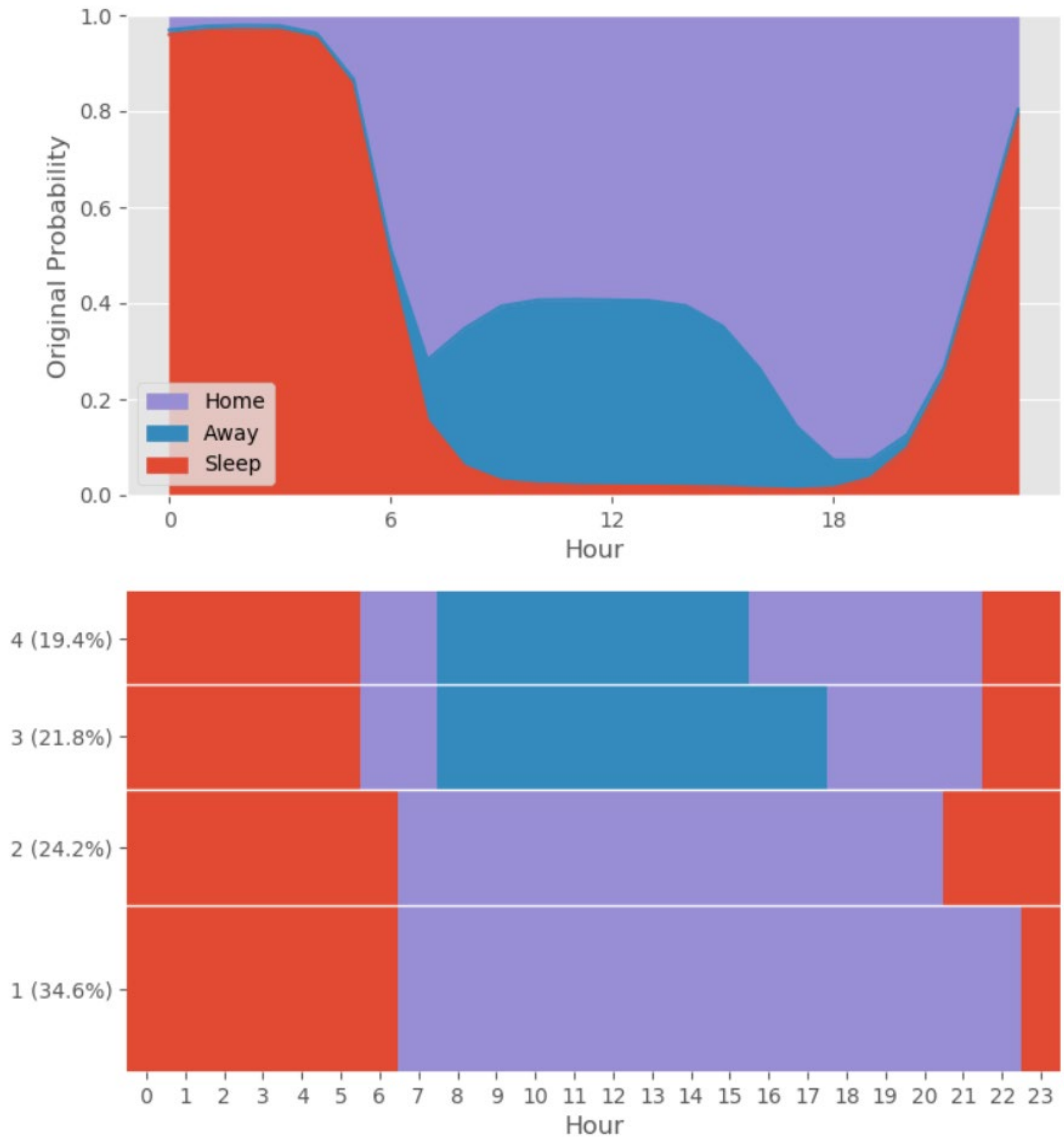

Figure 14. Schedules for weekdays, all occupants, and all regions for N = 4

Recommended 4 Typical Prototypes for Weekday, Number of Occupants: All occupants are

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S: Sleep, H: Home, A: Away

[Hour]	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1 (34.6%)	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S
2 (24.2%)	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S	S	S
3 (21.8%)	S	S	S	S	S	S	H	H	A	A	A	A	A	A	A	A	A	A	H	H	H	H	S	S
4 (19.4%)	S	S	S	S	S	S	H	H	A	A	A	A	A	A	A	A	H	H	H	H	H	H	S	S

Figure 15. Recommended schedules when four prototypes are selected (N = 4)

For N = 10, even more diverse schedules appear. Figure 16 illustrates the output for N = 10 and Table 2 displays the results in tabular form. For example, 3.5 percent of the homes have essentially all of the non-sleeping hours in the Away schedule during weekdays.

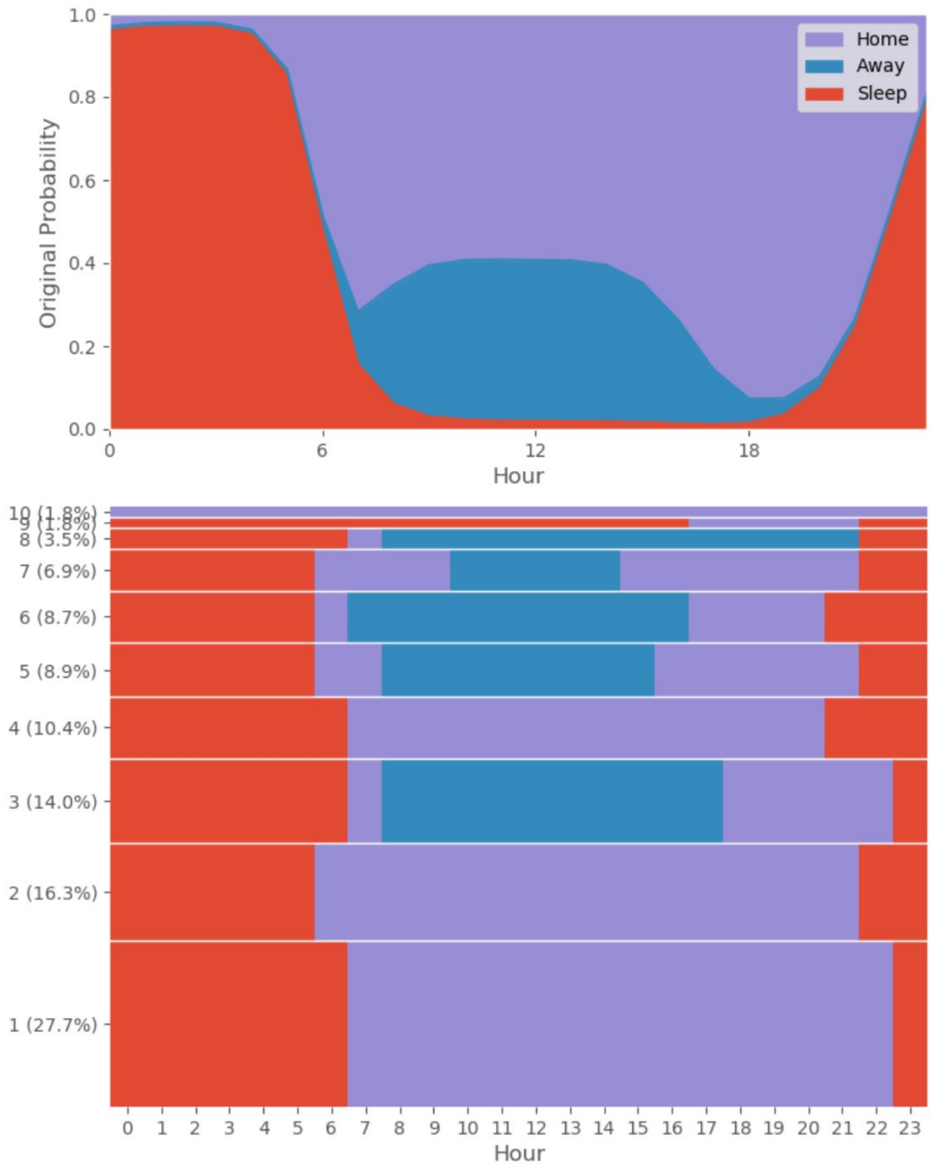

Figure 16. Schedules for weekdays, all occupants, and all regions for N = 10

The power of this method and the underlying data are illustrated in the example below. In this case, three schedules were generated for each climate zone (N = 15). A further distinction was made between homes with a single occupant and those with four occupants. Tables 2 and 3 show the temperatures, schedules, and fraction of housing stock represented by each schedule. Table 1 shows the temperatures for the prototypes in each climate zone, schedule, and season. Note that the temperatures of prototypes in the same climate zone differ by as much as 3°C for the same schedule.

Table 1. Temperature settings for the prototypes in each climate zone, schedule, and season

Season	Summer	Winter

Climate zone	Schedule / Sample number	Sleep	Away	Home	Sleep	Away	Home
Hot-Humid	1	22.7	24.4	23.5	18.5	17.9	19.5
	2	23.7	25.4	24.4	19.7	18.9	20.3
	3	25.0	26.5	25.3	20.7	19.8	21.2
Mixed-Humid	1	22.3	23.8	22.9	17.9	17.5	19.3
	2	23.4	25.0	23.7	19.1	18.5	20.0
	3	24.7	26.5	24.7	20.1	19.4	20.9
Mixed-Dry/ Hot-Dry	1	23.9	25.3	24.3	17.9	17.2	19.3
	2	25.2	26.5	25.3	19.4	18.5	20.3
	3	26.4	27.9	26.1	20.6	19.9	21.3
Marine	1	23.3	24.8	23.5	16.8	17.0	19.1
	2	25.0	26.5	24.8	18.5	18.2	19.9
	3	26.6	27.7	25.6	19.7	19.4	20.6
Very-Cold/Cold	1	22.5	24.1	22.9	17.3	17.2	19.1
	2	23.7	25.4	23.9	18.8	18.4	20.0
	3	25.1	26.9	25.0	19.9	19.4	20.8

Table 2 shows the hour-by-hour schedules for the schedules and the percentage of DYD homes represented by the prototype. Separate timings are also generated for weekdays/holidays and for the number of occupants (one or four). The percentages attributed to each prototype vary widely. For example, in the Weekday schedule there are three prototypes with one occupant. About 95 percent (51 + 44) of the homes are represented by two prototypes and about 5 percent are represented by Sample 3. Sample 3 also has a complex schedule because it has two periods while in the Away schedule.

Table 2. Hour-by-hour schedules and the percentage of DYD homes represented by the prototype

Day of week	Number of occupants	Sample number	Percentage of DYD homes	Sleep	Away	Home
Weekday	1	1	51	0-6, 22-23	8-16	7, 17-21
		2	44	0-6, 23	-	7-22
		3	5	0-12	13-15, 19-23	16-18
	4	1	43	0-5, 22-23	8-15	6-7, 16-21
		2	29	0-5, 23	-	6-22
		3	28	0-5, 21-23	-	6-20
Holiday	1	1	50	0-5, 23	-	6-22
		2	34	0-7, 23	-	6-22
		3	16	0-7, 22-23	8-17	18-21
	4	1	47	0-6, 23	-	7-22
		2	43	0-6, 21-23	-	7-20
		3	10	0-6, 22-23	9-16	7-8, 17-21

This information is sufficient to create temperature schedules for each prototype and to weight the resulting simulations so as to create a national average heating and cooling energy consumption.

4. A Schedule Generator Tool

The above examples were generated for homes located in all climate regions, with all numbers of occupants, during weekdays. Other schedules can be generated for specific climate zones, days of the week, number of occupants, and floor area. However, each schedule requires access to the sorted data, as described in Figures 10 and 13. To enable wider access to the results, we developed a tool to generate temperature schedules. Figure 17 is a screenshot of the user interface.

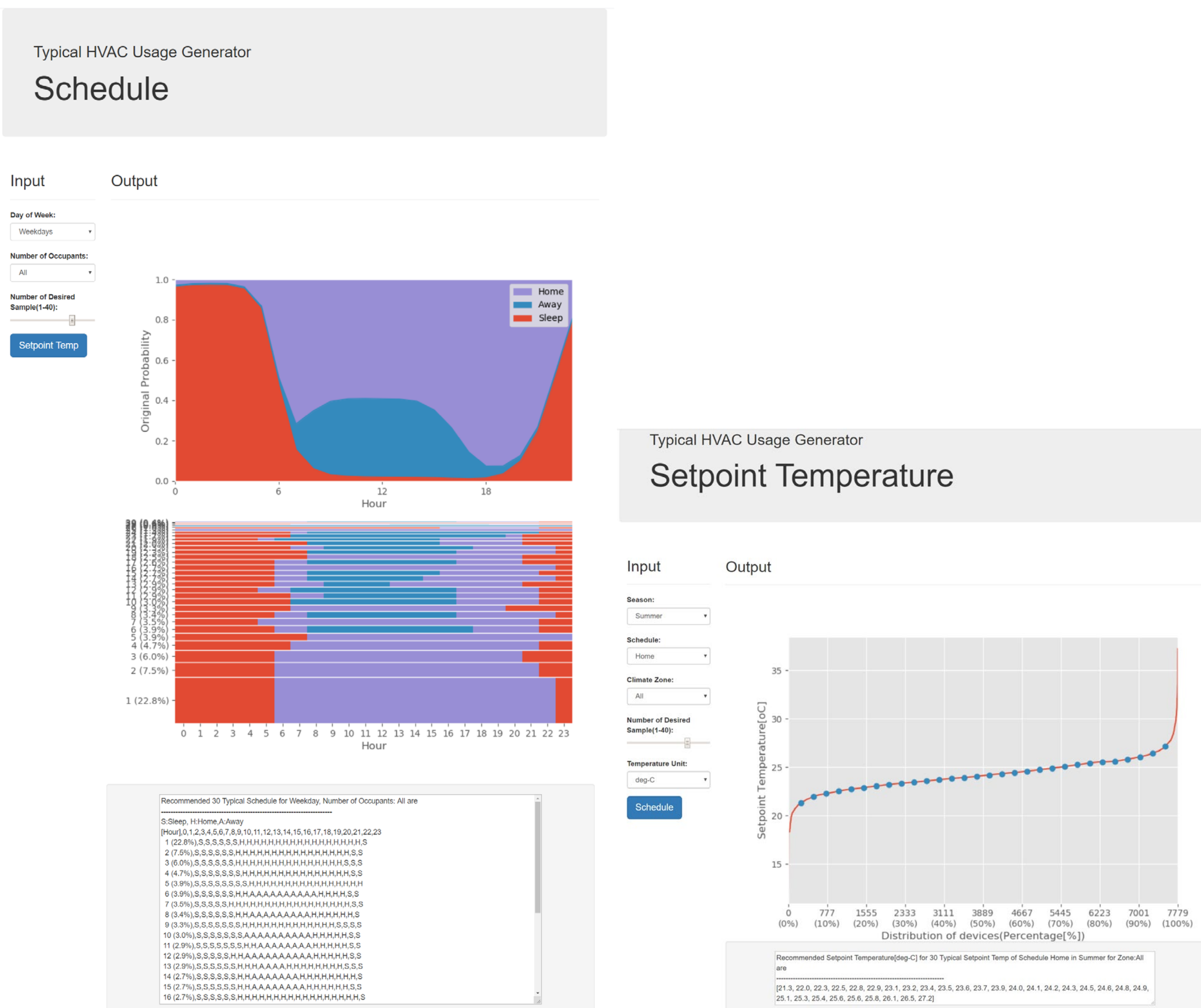

Figure 17. A screenshot of the user interface for the schedule generator tool

The user can specify the number of schedules (up to N = 40), climate zone, and number of occupants. The tool returns graphical displays of the results and tables similar to those presented earlier. These results are suitable for input into schedules for building energy simulation models. The tool makes it possible to identify quickly temperature schedules that may cause unusual energy consumption or performance issues and estimate the fractions of homes falling into those categories.

Schedules and temperatures for some common situations were calculated, and the input files were created for building simulations. These are available in the Appendix. A user can download them and easily incorporate them into simulations. Alternative prototypes, that is, with different N, number of occupants, or specific climate zones are available from the authors. The results will be updated as more DYD become available.

5. Discussion

5.1. Overview of the Contribution

The DYD database provides insights into the temperature preferences and schedules in homes that were never before available. Previously, national estimates could only be formed from surveys based on guesses by occupants, with a few temperatures representing behavior through a season and in different types of occupancy. In contrast, the DYD data are based on actual measurements in thousands of homes taken every five minutes. They therefore represent a transformation of our knowledge of heating and cooling preferences from point values to patterns and cycles. This information enables more realistic simulations of American heating and cooling behavior, leading to more accurate estimates of energy consumption and savings. It also can be used to improve government and utility recommendations for energy-saving thermostat settings. Further, the DYD database has applications not directly related to temperatures, such as HVAC sizing or improving estimates of energy consumption of heat pump water heaters.

5.2. Limitations of the DYD Data

It is essential to understand the DYD's limitations before generalizing the findings to the entire U.S. housing stock. First, the overwhelming majority of participants are single-family homes. Second, the database contains relatively few homes equipped with heat pumps. Several sources of bias in the participants were also identified, such as self-selection and early-adoption. The participants provided some socio-demographic information but not income, precise location, and other key indicators. Nevertheless, the DYD homes were surprisingly similar to the single-family homes in the RECS with respect to location, floor area, and number of occupants.

Another unknown factor is the manner in which people use their thermostats. We cannot exclude the possibility that DYD participants heat and cool their homes differently than other homeowners because their thermostats have additional features. One unique feature is remote control (via smartphone or the web), which gives DYD participants the ability to pre-heat or pre-cool their homes. Another feature is that ecobee can adjust temperatures and schedules to reduce HVAC energy consumption (if allowed by the participant). Finally, we have no direct information that the participants are correctly operating their thermostats and are satisfied with the thermostat's performance. Earlier studies of programmable thermostats found that a large fraction of occupants incorrectly programmed them, with many users selecting the long-term Hold feature (Meier et al. 2011). The ecobee thermostat also allows the user to switch the thermostat to Hold. This feature overrides schedules for two hours, four hours, until the next schedule change, or indefinitely. A small group of homes were frequent users of the Hold feature. About 25 percent of the homes were responsible for 75 percent of the Hold hours.

Sometimes the occupant-selected setpoints are overridden by utilities with demand response programs. Those temperatures were included in the analysis because only a small percentage of homes participate in demand response programs, and the programs affect temperatures only a few hours each year.

The DYD data provides insights into conditions in homes that significantly depart from the average. For example, it is possible to estimate the fraction of homes maintained below 16°C in the winter or cooled to above 28°C in the summer. Homes can have very different schedules of occupancy; the DYD data show that about 2 percent of the homes keep their thermostats in a single schedule (and therefore a single temperature). Figure 8 illustrates the variation in schedules for homes with single occupants. On weekdays, for example, still about 50% of the homes are occupied all day and then jump to nearly 90 percent on weekends. Future investigations could examine the extent that schedules for Fridays are beginning to more closely resemble Saturdays and Sundays rather than weekdays.

The DYD database is expected to keep growing and exceed 100,000 participants in 2021. This will provide much more detailed insights into temperature behaviors. Newer thermostats are often equipped with multiple temperature sensors, so researchers can explore the intra-home temperature variations. Unfortunately, the value of a larger sample will be constrained by the poor metadata about the participants. So an important goal will be to improve the quality of information about the occupants—floor area, demographics, etc.—to complement the rich temperature and HVAC operation data.

A final limitation is the absence of homes where both temperature and energy data are available. This is mostly an institutional problem—thermostat vendors and utility companies refuse to share their data—but it is understandable to protect privacy and security. The failure to share energy and temperature data makes it impossible to perform some of the most fundamental explorations, such as the relationship between indoor temperatures and energy use.

5.3. Limitations of the Methodology

The method of generating temperature schedules described above has several important limitations, some of which are described below.

The method assumes that occupant behavior in each schedule is independent. The drawback of this approach is that dependency information is lost; for example, the method cannot capture situations where homes with low Sleep temperatures also have low Home temperatures. We adopted this approach of decoupling schedules to enable easier calculation of temperature schedules for different categories of homes.[6] A method based on Monte Carlo simulations might capture dependencies across schedules. These insights would come at the cost of much more computation and a less flexible tool for generating temperature schedules.

This paper explored only the temperature aspects of the DYD data. The ecobee thermostats—and nearly every other connected thermostat—also collect runtimes of the HVAC equipment. Here, too, new insights into residential heating and cooling operation can be obtained. For example, homes with heat pumps may adopt different schedules from those heated with natural gas. Operational data will also help verify the performance of HVAC systems in simulation models in ways that were never before possible. These results will be reported in future communications.

The K-means clustering method was used to divide the schedule data into the desired number of groups. These results can be influenced by the random seed value. To assess the impact of different seeds, we compared the results of the tool with three different numbers of prototypes (N = 4, N = 10, and N = 20) and two seed values. Changing the seed did not affect the results for small values of N. On the other hand, a new seed applied to a large N did appear to affect the makeup of the prototypes. We inspected the results and found that the characteristics were still similar. For example, the daytime “Away” rate was approximately 57 percent, which was close to the original probability. We concluded that the value of a seed does not significantly affect the overall makeup of the input files generated for simulations.

6. Conclusions

A new type of thermostat, which is connected to the Internet, collects temperature and operating data every five minutes from millions of homes in North America and in a growing number elsewhere. This paper explored the application of these data to simulations of energy residential building energy use. The goal was to create more realistic temperatures and schedules in the simulation models than those used today. The approach assumes that a portfolio of simulations,

[6] We investigated the independence of the setpoints for Home, Sleep, and Away for a representative sample of 200 homes. Indeed, there appears to be a correlation between, for example, a low Home setpoint and a low Sleep setpoint. However, we believe that this correlation becomes less significant when a group of homes within a similar climate is considered.

each capturing one set of temperatures and schedules, will provide more insights than a single simulation with average temperatures and schedules. The analysis relies on a unique dataset: the approximately 20,000 owners of ecobee thermostats who opted to share their thermostat's performance information with researchers through the Donate Your Data Program.

The first step was to determine if the homes in the program were representative of the stock of homes in the United States. A series of comparisons were made between the limited metadata available from the participants and a national survey of representative homes. The DYD dataset generally matched the survey results for single-family homes with respect to location, floor area, and other characteristics. Thus, we concluded the DYD homes were reasonably representative of the U.S. single-family homes.

A method was developed to generate temperature schedules based on the DYD data. The goal was to create a flexible program that could generate 1–40 different temperature schedules for simulations. The program generates distributions of indoor temperatures in each of the three operating schedules (Home, Sleep, and Away) and under different conditions, such as season, day of week, and number of occupants. The user must select the number of simulations desired. The program then searches for the temperatures that best reflect the shape of the distribution for the desired number of simulations. Next, the program generates distributions of time that the homes spend in each operating schedule, both with respect to actual time of day and the durations. The program then searches for the schedules that best reflect the shape of the distribution for the number of simulations selected. It outputs hourly temperature profiles suitable for inputs to building energy simulation programs. The program also calculates the fraction of housing stock to which each profile applies. Thus, a user can assign a weight to the results of each simulation so as to estimate average heating or cooling energy consumption for the entire stock of homes.

The tool also can identify the fraction of homes operated with less-common temperatures or schedules. These situations are difficult to capture when simulations only use average conditions, yet may be important because they may be associated with unique technical or health problems. When the methodology matures and the number of homes increases, the tool can be transferred to a website. A web-based tool will allow users to select the number of prototypes and generate input files as required.

The Donate Your Data database has important limitations, but this study shows the applications of big data and the insights that these analyses can provide into technical, health, and behavioral issues. The DYD data are based on actual measurements in thousands of homes taken every five minutes and represent a transformation of our knowledge of heating and cooling preferences from a few point values to detailed patterns and cycles. Further insights are likely as the dataset grows and other characteristics are investigated.

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Appendix A: Examples of Tool Output

Introduction

Below are examples of outputs from the temperature-schedule tool. These data can be entered directly in simulation models for hourly parameters. The output is divided into two parts: setpoint temperatures and schedules. Typical setpoint temperature profiles for seasons, schedules, and climate zones are prepared for N = 5. In addition, typical schedules for days of week and number of occupants were prepared for N = 5 and N = 10. Three levels of occupancy are presented: single occupancy, four occupants, and all numbers of occupants.

More prototypes are available from the authors (and will be updated as new thermostat data are incorporated into the tool).

Setpoint Temperatures

Recommended Setpoint Temperature (°C) for 10 Typical Setpoint Temperatures:

Season: Summer

Schedule: Home

CLIMATE ZONE	1	2	3	4	5	6	7	8	9	10
HOT-HUMID	22.6	23.2	23.6	23.9	24.2	24.5	24.8	25.2	25.6	26.0
MIXED-HUMID	22.1	22.6	23.0	23.3	23.6	23.9	24.2	24.6	25.2	25.7
MIXED-DRY/HOT-DRY	23.3	23.9	24.4	24.8	25.1	25.4	25.7	26.0	26.5	27.5
MARINE	22.0	23.1	23.6	24.0	24.5	25.0	25.5	25.6	25.8	26.7
VERY-COLD/COLD	22.1	22.7	23.0	23.4	23.7	24.0	24.4	24.8	25.5	25.8

Schedule: Sleep

CLIMATE ZONE	1	2	3	4	5	6	7	8	9	10
HOT-HUMID	21.6	22.2	22.8	23.2	23.5	23.9	24.4	24.8	25.3	26.0

MIXED-HUMID	21.2	21.9	22.4	22.8	23.2	23.6	24.1	24.5	25.3	26.3
MIXED-DRY/HOT-DRY	22.6	23.4	24.0	24.5	25.0	25.4	25.7	26.3	26.7	27.7
MARINE	21.4	22.7	23.4	24.1	24.6	25.4	26.0	26.6	26.7	27.1
VERY-COLD/COLD	21.3	22.2	22.7	23.1	23.4	23.9	24.4	25.0	25.7	26.7

Schedule: Away

CLIMATE ZONE	1	2	3	4	5	6	7	8	9	10
HOT-HUMID	23.4	24.0	24.5	24.9	25.3	25.5	26.0	26.4	26.8	27.6
MIXED-HUMID	23.0	23.5	24.0	24.4	24.8	25.3	25.8	26.3	26.9	27.7
MIXED-DRY/HOT-DRY	23.9	24.7	25.5	25.9	26.3	26.7	27.3	27.7	28.3	29.4
MARINE	23.3	24.2	25.0	25.6	26.2	26.7	27.3	27.7	27.8	29.4
VERY-COLD/COLD	22.9	23.7	24.2	24.6	25.2	25.6	26.2	26.7	27.4	27.8

Season: Winter

Schedule: Home

CLIMATE ZONE	1	2	3	4	5	6	7	8	9	10
HOT-HUMID	18.2	19.1	19.5	19.9	20.1	20.5	20.8	21.1	21.6	22.2
MIXED-HUMID	18.2	18.9	19.4	19.7	19.9	20.2	20.5	20.8	21.2	21.7
MIXED-DRY/HOT-DRY	18.2	18.9	19.4	19.8	20.1	20.4	20.8	21.1	21.5	22.1
MARINE	17.9	18.6	19.2	19.5	19.8	20.0	20.3	20.6	21.0	21.6
VERY-COLD/COLD	18.0	18.7	19.3	19.7	19.9	20.2	20.4	20.7	21.1	21.6

Schedule: Sleep

CLIMATE ZONE	1	2	3	4	5	6	7	8	9	10
HOT-HUMID	17.1	18.2	18.6	19.1	19.5	19.9	20.2	20.6	21.1	22.1
MIXED-HUMID	16.4	17.5	18.1	18.6	18.9	19.4	19.6	20.0	20.5	21.4
MIXED-DRY/HOT-DRY	16.4	17.4	18.1	18.6	19.1	19.6	20.0	20.5	21.1	21.9
MARINE	15.3	16.3	17.1	17.8	18.3	18.7	19.3	19.6	20.2	21.0
VERY-COLD/COLD	15.6	16.7	17.5	18.1	18.5	19.0	19.4	19.8	20.3	20.9

Schedule: Away

CLIMATE ZONE	1	2	3	4	5	6	7	8	9	10

HOT-HUMID	16.1	17.5	18.0	18.3	18.7	19.0	19.3	19.8	20.1	21.0
MIXED-HUMID	15.8	16.8	17.6	18.0	18.3	18.6	18.9	19.3	19.7	20.3
MIXED-DRY/HOT-DRY	15.3	16.8	17.3	17.8	18.3	18.7	19.2	19.8	20.3	20.9
MARINE	14.6	16.5	17.1	17.4	18.0	18.3	18.9	19.3	19.7	20.1
VERY-COLD/COLD	15.8	16.8	17.3	17.9	18.2	18.6	18.9	19.3	19.7	20.4

Schedules

Number of Typical Prototypes: 5

S: Sleep, H: Home, A: Away

Day of Week: Weekday

Number of Occupants: 1

[HOUR]	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1 (26.5%)	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H
2 (26.2%)	S	S	S	S	S	S	H	A	A	A	A	A	A	A	A	A	A	H	H	H	H	H	S	S
3 (24.8%)	S	S	S	S	S	S	S	H	A	A	A	A	A	A	A	A	A	A	H	H	H	H	H	S
4 (17.0%)	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S	S
5 (5.5%)	A	A	S	S	S	S	S	S	S	S	S	S	S	S	A	A	H	H	A	A	A	A	A	A

Number of Occupants: 4

[HOUR]	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1 (28.8%)	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S
2 (26.1%)	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S	S	S
3 (16.8%)	S	S	S	S	S	S	H	H	A	A	A	A	A	A	A	A	A	H	H	H	H	H	H	S
4 (15.3%)	S	S	S	S	S	S	H	H	A	A	A	A	A	A	A	H	H	H	H	H	H	H	S	S
5 (13.0%)	S	S	S	S	S	S	S	H	A	A	A	A	A	A	A	A	A	H	H	H	S	S	S	S

Number of Occupants: All

[HOUR]	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1 (34.2%)	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S
2 (23.9%)	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S	S	S
3 (21.7%)	S	S	S	S	S	S	S	H	A	A	A	A	A	A	A	A	A	A	H	H	H	H	S	S

4 (18.1%)	S	S	S	S	S	S	H	H	A	A	A	A	A	A	A	A	H	H	H	H	H	H	S	S
5 (2.0%)	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	H	H	H	H	H	S	S

Day of Week: Holiday

Number of Occupants: 1

[HOUR]	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1 (35.7%)	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S
2 (25.1%)	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S	S
3 (22.5%)	S	S	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S
4 (13.3%)	S	S	S	S	S	S	S	H	A	A	A	A	A	A	A	A	A	A	H	H	H	H	H	S
5 (3.5%)	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S

Number of Occupants: 4

[HOUR]	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1 (30.0%)	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S
2 (28.8%)	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S	S
3 (19.2%)	S	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S	S
4 (12.2%)	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	S	S	S	S
5 (9.7%)	S	S	S	S	S	S	S	H	H	A	A	A	A	A	A	A	A	H	H	H	H	H	S	S

Number of Occupants: All

[HOUR]	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1 (40.6%)	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S
2 (26.2%)	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S	S	S
3 (22.1%)	S	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S	S
4 (9.3%)	S	S	S	S	S	S	S	H	H	A	A	A	A	A	A	A	A	A	H	H	H	H	S	S
5 (1.8%)	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S

Number of Typical Prototypes: 10

Day of Week: Weekday

Number of Occupants: 1

[HOUR]	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1 (21.3%)	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S
2 (16.4%)	S	S	S	S	S	S	S	A	A	A	A	A	A	A	A	A	A	H	H	H	H	H	S	S
3 (16.1%)	S	S	S	S	S	S	H	H	A	A	A	A	A	A	A	A	A	A	H	H	H	H	H	S
4 (15.9%)	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S	S
5 (8.6%)	S	S	S	S	S	S	S	A	A	A	A	A	A	A	A	A	H	H	H	H	H	H	S	S
6 (6.1%)	S	S	S	S	S	S	H	H	A	A	A	A	A	A	A	A	A	A	A	A	H	H	S	S
7 (6.1%)	S	S	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H
8 (5.5%)	S	S	S	S	S	S	S	S	H	H	A	A	A	A	A	A	A	H	H	H	H	H	H	H
9 (2.9%)	A	A	A	A	A	A	A	A	A	S	A	A	A	A	A	A	A	A	A	A	A	A	A	A
10 (1.2%)	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	H	H	H	S	S	S	S

Number of Occupants: 4

[HOUR]	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1 (24.3%)	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S
2 (20.4%)	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S	S
3 (10.9%)	S	S	S	S	S	S	H	H	A	A	A	A	A	A	A	A	A	H	H	H	H	H	S	S
4 (8.4%)	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	S	S	S	S
5 (8.1%)	S	S	S	S	S	S	S	H	H	A	A	A	A	A	A	H	H	H	H	H	H	H	H	S
6 (7.8%)	S	S	S	S	S	S	H	H	A	A	A	A	A	A	A	H	H	H	H	H	H	H	S	S
7 (7.0%)	S	S	S	S	S	S	S	H	A	A	A	A	A	A	A	A	H	H	H	H	S	S	S	S
8 (6.6%)	S	S	S	S	S	S	H	H	A	A	A	A	A	A	A	A	A	H	H	H	H	H	H	S
9 (4.7%)	S	S	S	S	S	S	S	H	A	A	A	A	A	A	A	A	A	A	H	H	H	S	S	S
10 (1.7%)	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H

Number of Occupants: All

[HOUR]	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1 (27.7%)	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S
2 (16.3%)	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S	S
3 (14.0%)	S	S	S	S	S	S	S	H	A	A	A	A	A	A	A	A	A	A	H	H	H	H	H	S

4 (10.4%)	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S	S	S
5 (8.9%)	S	S	S	S	S	S	H	H	A	A	A	A	A	A	A	A	H	H	H	H	H	H	S	S
6 (8.7%)	S	S	S	S	S	S	H	A	A	A	A	A	A	A	A	A	A	H	H	H	H	S	S	S
7 (6.9%)	S	S	S	S	S	S	H	H	H	H	A	A	A	A	A	H	H	H	H	H	H	H	S	S
8 (3.5%)	S	S	S	S	S	S	S	H	A	A	A	A	A	A	A	A	A	A	A	A	A	A	S	S
9 (1.8%)	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	H	H	H	H	H	S	S
10 (1.8%)	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H

Day of Week: Holiday

Number of Occupants: 1

[HOUR]	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1 (30.3%)	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S
2 (16.7%)	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S	S
3 (13.8%)	S	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S	S
4 (12.7%)	S	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S
5 (8.4%)	S	S	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S
6 (8.1%)	S	S	S	S	S	S	S	H	A	A	A	A	A	A	A	A	A	H	H	H	H	H	H	S
7 (3.7%)	S	S	S	S	S	S	S	S	H	H	A	A	A	A	A	A	A	A	A	A	H	H	S	S
8 (2.3%)	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S
9 (2.3%)	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A	A
10 (1.7%)	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H

Number of Occupants: 4

[HOUR]	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1 (23.6%)	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S
2 (17.7%)	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S	S
3 (14.0%)	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S	S	S
4 (11.3%)	S	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S
5 (10.0%)	S	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S	S
6 (9.2%)	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	S	S	S	S
7 (6.5%)	S	S	S	S	S	S	S	H	H	A	A	A	A	A	A	A	A	A	H	H	H	S	S	S
8 (4.9%)	S	S	S	S	S	S	S	H	H	H	A	A	A	A	H	H	H	H	H	H	H	H	S	S
9 (1.9%)	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H

10 (1.0%)	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S

Number of Occupants: All

[HOUR]	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1 (27.7%)	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S
2 (16.3%)	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S	S
3 (14.0%)	S	S	S	S	S	S	S	H	A	A	A	A	A	A	A	A	A	A	H	H	H	H	H	S
4 (10.4%)	S	S	S	S	S	S	S	H	H	H	H	H	H	H	H	H	H	H	H	H	H	S	S	S
5 (8.9%)	S	S	S	S	S	S	H	H	A	A	A	A	A	A	A	A	H	H	H	H	H	H	S	S
6 (8.7%)	S	S	S	S	S	S	H	A	A	A	A	A	A	A	A	A	A	H	H	H	H	S	S	S
7 (6.9%)	S	S	S	S	S	S	H	H	H	H	A	A	A	A	A	H	H	H	H	H	H	H	S	S
8 (3.5%)	S	S	S	S	S	S	S	H	A	A	A	A	A	A	A	A	A	A	A	A	A	A	S	S
9 (1.8%)	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	S	H	H	H	H	H	S	S
10 (1.8%)	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H	H