Title
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Abstract
At least five million American homes have Internet-connected thermostats. These devices improve comfort and reduce energy consumption using cloud-based algorithms. Every five minutes, they collect and transmit detailed operating information, including thermostat setpoints, actual indoor temperatures, occupancy, and HVAC operation. One thermostat provider established a program that enables customers to anonymously "donate" their data to researchers and more than 50,000 customers have opted in. This dataset represents the most comprehensive public data on home temperature preferences for North America and provides far more detail than any previous method based on surveys or monitoring programs. The data show in detail preferred temperatures while occupants are home, sleeping, and away. On average, these households lower their thermostats about 1 °C when they are asleep compared to when awake, though this average conceals both widespread constant operation and deeper setbacks. The peak usage of air conditioners in Texas was shown to precisely match the grid's systemwide peak. The connected thermostats also raise a survey research question: when should policymakers rely on a small sample of rigorously selected buildings instead of a huge, unrepresentative sample with detailed data? Many fruitful applications of this dataset will be constrained by privacy protections and reluctance of firms to share information.

Introduction
In North America and Europe, space heating and cooling is responsible for about half of all residential energy use (U.S. Energy Information Administration 2018). It is therefore a target for energy-saving actions, both in new and existing homes. Many technologies are available to reduce a home's heating and cooling use, though most are directed towards reducing envelope losses, raising the efficiency of the heating, cooling, and ventilation (HVAC) systems, and more precisely controlling their operation. The thermostat is a key element of the control system. Thermostats play a more important role in North America than in Europe because homes rely primarily on forced-air heating and their wood construction gives them less thermal mass (Peffer et al. 2011). In these constructions, temperature setbacks (for nights and absences) can achieve significant energy savings. Temperature setbacks (or set-ups in summer) require vigilance by the occupants or a programmable thermostat. Consumers have long had difficulty operating thermostats and achieving the maximum energy savings potential, especially with programmable thermostats (Peffer et al. 2011). The problems were so common that, in 2009, ENERGY STAR – a U.S. government program that endorses high-efficiency products (U.S. Environmental Protection Agency 2019) – ceased endorsing programmable thermostats as a reliable energy-saving technology, primarily because there were insufficient documented savings.

The Internet-connected thermostat appeared in about 2011, most notably with the Nest Learning Thermostat. These thermostats learned the habits of the occupants with the aid of an occupancy sensor, and then applied various algorithms – usually in the cloud – to optimize heating and cooling. The Internet connection also allows occupants to control the thermostats remotely through a web portal or smartphone. ENERGY STAR

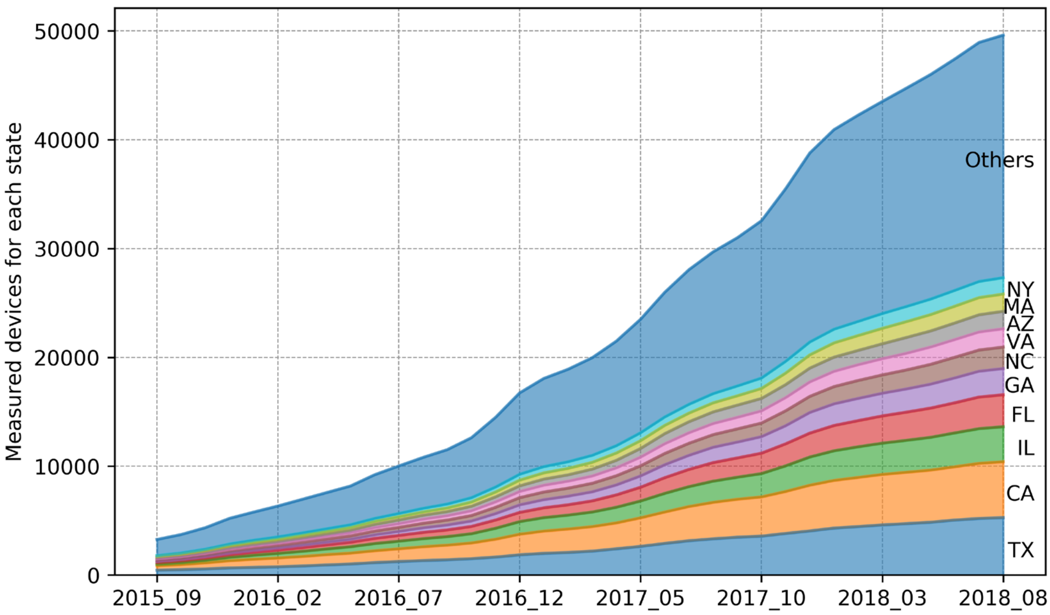

Figure 1. Monthly trend of participating thermostats by state (DYD data).

restarted its recognition program in 2017 but limited the program exclusively to Internet-connected thermostats. Based on discussions with manufacturers, 5–10 million homes appear to have Internet-connected thermostats. Major suppliers include Nest, ecobee, Honeywell, and Emerson.

In 2015, ecobee established the Donate Your Data (DYD) program (Ecobee Inc. 2018). The DYD program enables users to anonymously donate their operation data for research use. User data is gathered in servers managed by ecobee. Every five minutes, the ecobee thermostat records the thermostat setpoints, the actual inside temperature, relative humidity, motion, and HVAC run-time. Some models record occupancy and temperatures in other rooms. These data are collected by the thermostat and then transmitted via WiFi and the Internet to an ecobee server. Note that energy consumption data are not collected through this system.

Ecobee shares limited metadata about each participating DYD home with researchers, including the home's location (city and state or province), floor area, number of stories, number of occupants, and age. Ecobee also supplies outside temperatures from nearby weather stations. This is a very large dataset – about 1 terabyte (TB) – which enables analyses that were heretofore inconceivable. For example, it is now possible to estimate with high confidence the average temperature in American homes at, say, 11 AM on February 14, 2018 (though it's not clear what value this information has).

The DYD program began in 2015 and the number of participants increased rapidly. Figure 1 shows the monthly trend of the total number of devices (some homes have more than one device) and the populations of those in the largest ten states. The dataset includes homes in Canada and Europe but these were not included in this analysis. By mid-2018, about 50,000 thermostats were in the DYD program and it was growing at a rate of ~1,700 per month. This study used only 8,575 homes because it was conducted relatively early in the program and many homes did not yet have 12 months of complete data.

The ecobee DYD research dataset provides insights into residential heating and cooling behaviors (and potentially, energy use) that were never before available. Researchers have only begun to explore the DYD dataset. For example, Huchuk et al. (2018) investigated how different climates, seasons, and utility tariffs affected the occupants' selection of indoor temperatures. Other studies are underway.

What can be learned from connected thermostat data? Can it inform energy policy or assist in evaluating energy-saving programs? Can it help understand people's behavior and thermal comfort preferences? In this paper, we explore insights that can be obtained from this extraordinary dataset. At the same time, this exploration shows its serious limitations.

Results

COMPARISON WITH THE RESIDENTIAL ENERGY CONSUMPTION SURVEY

Every four years the U.S. Energy Information Administration conducts the Residential Energy Consumption Survey (EIA 2015). The RECS gather information to help explain differences in energy use among households. The results are also used to better forecast future energy consumption. The 2015 survey asked about space heating, air conditioning, water heating, appliances, electronics, structural features and, importantly, thermostat practices. RECS also collect energy consumption data for each home. About 6,000 homes were surveyed, of which about 4,000 were single-family homes (which reflects the national proportions). Rigorous sampling methods were employed to ensure a representative group, and energy providers are required (by law) to provide billing data. The RECS results are widely considered to be the most reliable source of information for describing U.S. residential energy use. How do the DYD homes compare to the homes in RECS?

The DYD dataset differs from RECS in several fundamental ways. First, the RECS sample was designed to be representative of all homes in the United States, while the 8,575 DYD homes are self-selected. The DYD homes are mostly single-family. As early adopters of this technology, the participants probably have higher incomes and are more technically proficient (they must have a reliable broadband connection, for example) than the United States as a whole.

A variety of comparisons were undertaken to determine how different the DYD homes were from the whole stock of U.S. homes. These comparisons included: geographic distribution, floor area, number of occupants, type of heating system, and age of home. Three comparisons are presented graphically in Figures 2–4.

There are some differences between the groups but fewer than one might expect. The DYD homes are geographically distributed roughly the same as RECS. There are relatively fewer DYD homes in the Northeast (but not hugely). The DYD

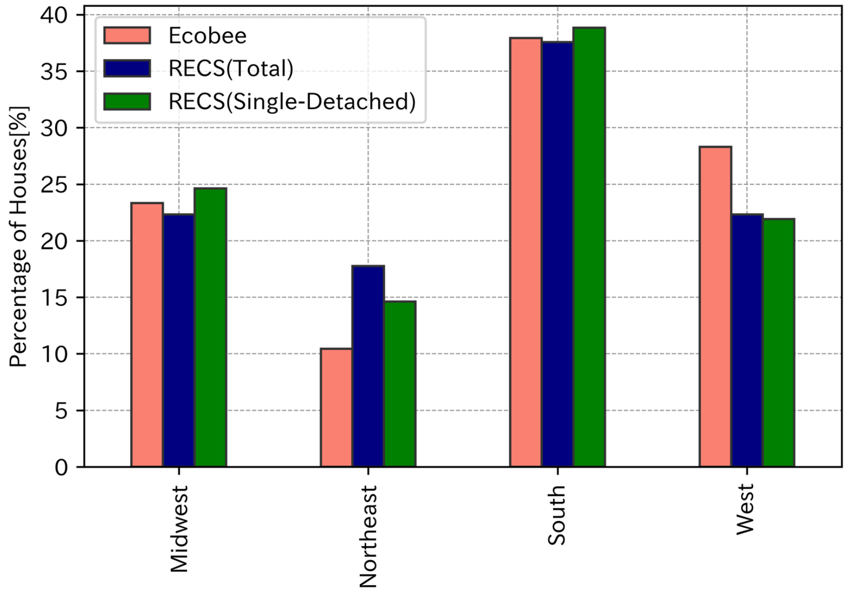

Figure 2. Geographical distribution of DYD participants compared to RECS.

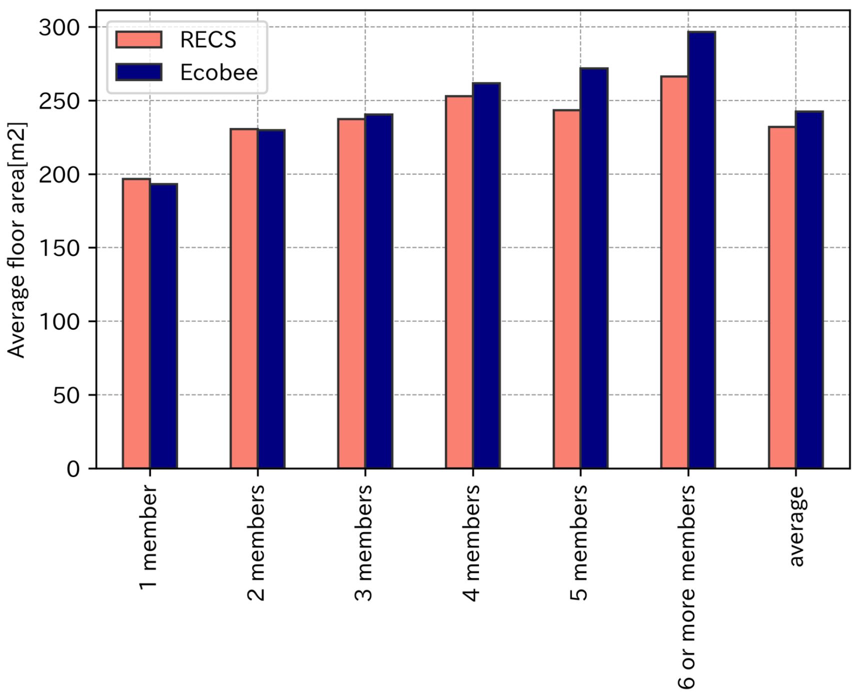

Figure 3. Distribution of floor areas with respect to number of occupants for DYD participants and RECS.

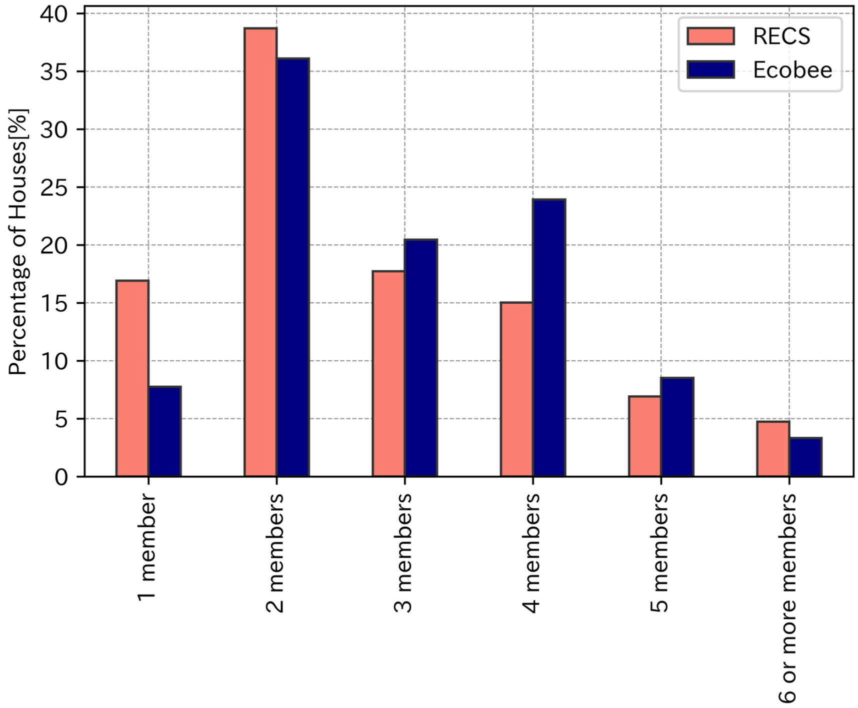

Figure 4. Distribution of number of occupants in homes for DYD participants and single-family detached homes in the RECS sample.

and RECS homes are nearly the same size – DYD average floor area is only 4 % larger. The relationship between the number of occupants and floor area is very close. With the exception of 1-person homes, DYD and RECS have a similar occupancy distribution. For example, 35 %–40 % 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). Overall, the DYD homes are not perfectly representative of the U.S. housing stock of single-family homes but are surprisingly good given their different origins.

Which data are more accurate? The RECS survey asks households only a few questions about their thermostat settings, such as what temperature they maintain while away. In contrast, the ecobee thermostat reports the thermostat setpoint and the actual temperature every five minutes. An increasing number of ecobee thermostats have additional temperature sensors in other rooms – these are also reported. So which source is closer to "ground truth"? Are self-reported average values from a small, but rigorously representative, group of homes more credible than exact values collected every five minutes from many more homes that are self-selected? This dilemma will be a central analytical issue for many future applications of big data. Ultimately, combining the two different sources of data will provide results with the greatest confidence. However, these data fusion techniques still need development.

HOURLY LOAD SHAPES FOR HEATING AND COOLING

Obtaining representative hourly load shapes for major end uses is important for energy forecasting but expensive to obtain. The DYD data offers a simple means of obtaining hourly load shapes for air conditioning and heating because the run-times of HVAC units are collected every five minutes. The fraction of HVAC run-time (per hour) at each hour will have the shape of an hourly load curve. This load shape – technically, a "run-time curve" – can be generated for a specific day (such as the system peak day) or for a specific home, or it can be aggregated for all homes in a utility region.

The run-time of each HVAC system must still be converted into power before it becomes a load curve. This conversion requires the rated power consumption of the HVAC system. Unfortunately, ecobee does not know this value, and the DYD participants do not provide it, so it must be estimated with external data. A survey of actual HVAC capacities would of course be more accurate. The shape of the average run-time curve (constructed by assuming each HVAC system has the same power consumption whenever it runs) can nevertheless provide insights even without the conversion from run-time to power.

The state of Texas, which is also its own grid authority (ERCOT – The Electric Reliability Council of Texas) experienced its system peak electrical demand for 2017 on 28 July at 16:00–17:00. This peak is driven by hot weather and because nearly every Texas home has air conditioning (and needs it). Figure 5 shows the average air conditioning run-time load shape for 2,131 DYD homes in Texas on 28 July. The run-time – a proxy for power – is expressed in seconds of run-time per five-minute metering interval. The DYD homes and the ERCOT system peaked at almost exactly the same time.

Separate analysis revealed that the DYD Texas homes also experienced their summer peak demand on 28 July. Thus, the DYD homes and the Texas grid experienced their peaks on the same day and one hour apart. This coincidence demonstrates the potential value of thermostat data in understanding the components of electrical demand and, ultimately, strategies to reduce it.

Figure 5 also shows that, at the peak, the average air conditioner run-time is about 210 seconds/5 minutes or about 70 % of the time. Texas is larger than France and covers several climate zones; nevertheless, this heat wave engulfed the entire state. These results suggest that Texan's homes may have spare cooling capacity to accommodate the extreme events of near-term climate change or expanding heat islands.

The situation for space heating is very different. Figure 6 shows the average load shape for all 417 DYD homes in the state of Massachusetts – a cold region – on the system peak winter day when the minimum temperature was about -12 °C. All of these homes controlled by ecobee thermostats have gas or oil furnaces, so the heating run-time shape has less immediate impact on electrical load than air conditioning does. However, the winter load shape may become more important as climate change policies are implemented. Many regions have de-carbonization plans which will, ultimately, require homes to switch from fuel heating to electric heating (Williams et al. 2018).

Figure 6 shows how conversion to electric heating will affect the systemwide load shape. The grid operator for Massachusetts experienced its peak demand at 18:00–19:00 (Babula 2018). Thus, electrification of space heating in Massachusetts will initially not add to the system peak. The magnitude of the homes' contribution to peak load cannot be directly estimated, however, until the HVAC run-time is converted into electrical demand. This requires knowledge of current fuel-based furnace

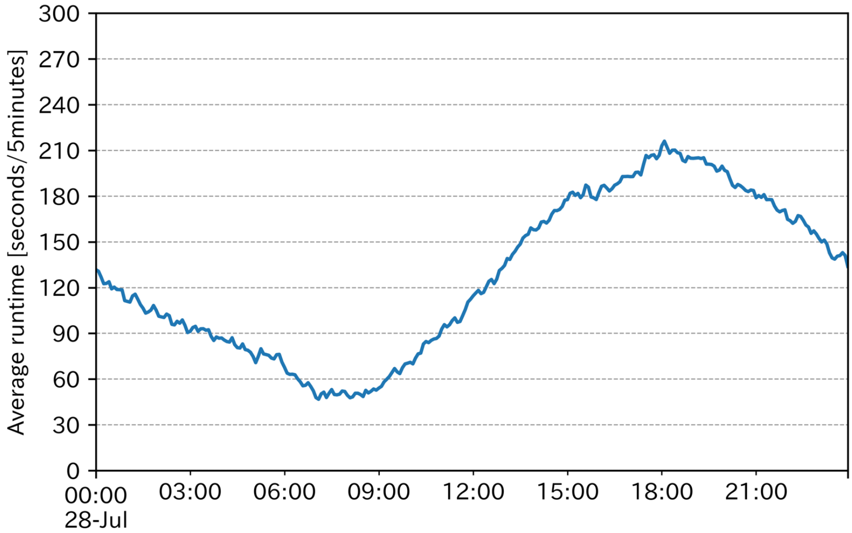

Figure 5. Run-time load shape of DYD homes in Texas (N = 2131) on 28 July 2017, the same day as ERCOT's system peak.

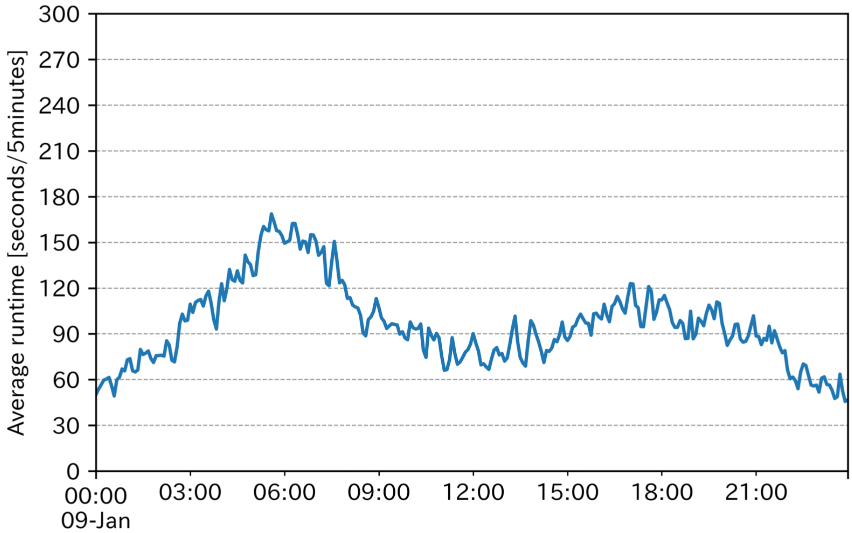

Figure 6. Run-time load shape of DYD homes in Massachusetts (N = 417) on 9 January 2017, the winter system peak day for the New England grid.

capacities and efficiencies of the heat pumps that will replace them (which are not known). Note that the DYD homes are operating at only a little above 50 % of maximum capacity during the coldest hours. This suggests that they have considerable spare capacity, possibly as a consequence of oversizing or years of adding insulation and air-sealing.

Estimating the load impacts from fuel-switching as described above would be difficult because few utilities or researchers collect hourly natural gas usage at the customer level. Instead, most researchers rely on building energy simulations of prototype homes to estimate future electrical loads. These simulations include grossly uncertain thermostat setpoint assumptions. So, the DYD dataset offers a new approach to this question.

INFORMATION FOR BUILDING ENERGY SIMULATION

When simulating a building's energy use, the researcher must make assumptions regarding the indoor temperature settings and schedules. RECS or similar surveys are often used as a source for this information. More often than not, the results are average temperatures for a few situations, e.g., "home" and "away" for summer and winter seasons. The duration of these settings is rarely collected. The building scientist must then convert this single-point information to thermostat schedules for 24 hours/day and 365 days per year.

The DYD dataset permits much more precise characterizations of temperatures and schedules. Figures 7 and 8 illustrate average hourly setpoint temperatures during the heating and cooling seasons for each day of the week. Even at this very high level of aggregation, the schedules are obvious. It is also clear that weekends have different schedules than weekdays.

Note that the changes in temperatures (when the setpoint is adjusted) are less than 2 °F (1 °C). This set-up/setback is smaller than typically recommended setbacks or set-ups. ENERGY STAR, for example, recommends setbacks and set-ups in the range of 8 °F (~5 °C). Some people appear to adopt "round numbers" for setbacks, that is, 5 °F.

The small absolute changes in setpoints observed here probably reflect the fact that the curves are composites of thousands of different schedules and represent very few actual homes. A better approach is to segment users into temperature schedule clusters, simulate several combinations of temperatures and schedules, and weight the results to reflect the fraction of homes in those bins. For now, only simple averages are available. On average in the winter, the DYD households lower their thermostats about 1 °C when they are asleep compared to when awake, though this conceals both constant operation and deeper setbacks.

Note also the cool temperature settings – under 20 °C – for space heating, even when people are home. This suggests that a significant fraction of the homes is continuously maintained at rather low temperatures, thus lowering the average. This phenomenon is reversed for cooling, that is, the average temperature setting is relatively high (from a comfort standpoint), suggesting that a significant fraction of households maintains quite warm indoor conditions.

The methods described above show how the energy impacts of building code changes and new technologies can be more realistically estimated because they capture the diversity of behaviors and usage patterns.

INFLUENCE OF DEFAULT THERMOSTAT SETTINGS

Behavioral "nudges" have been shown to be an effective strategy to save energy (Sunstein and Thaler 2008) and with thermostats in particular (Brown et al. 2013; Ge and Ho 2018). Having default settings is one type of nudge because many users will simply adopt them, believing that these settings must be the recommended values (or they are not able to program it themselves). The extent to which users retain the default settings was explored.

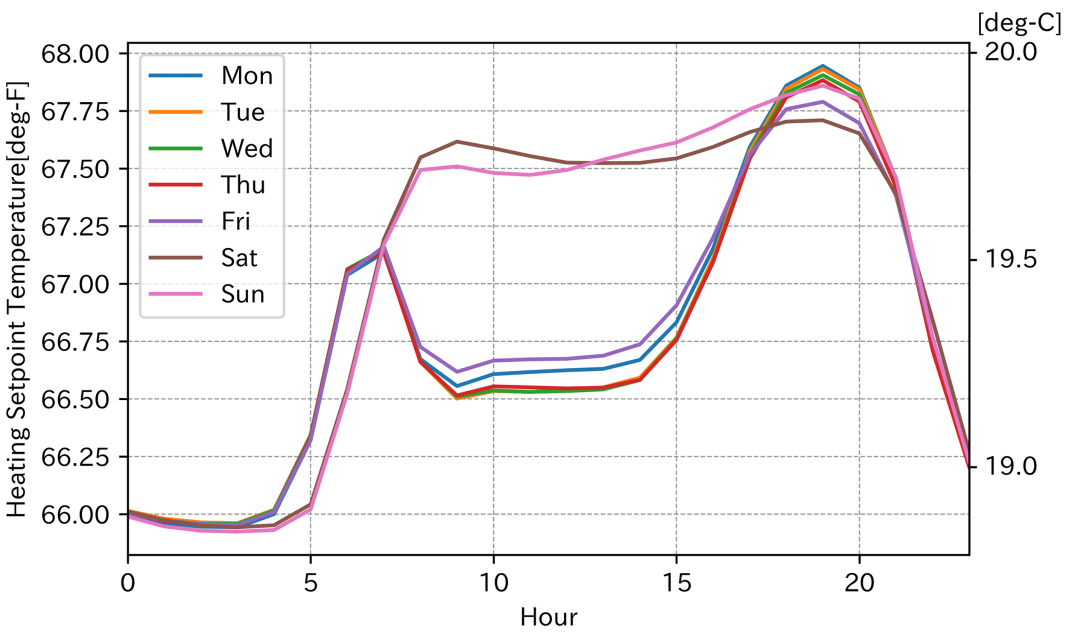

Figure 7. Average hourly setpoint temperatures for DYD homes for each day of the week for days when the heating system operated.

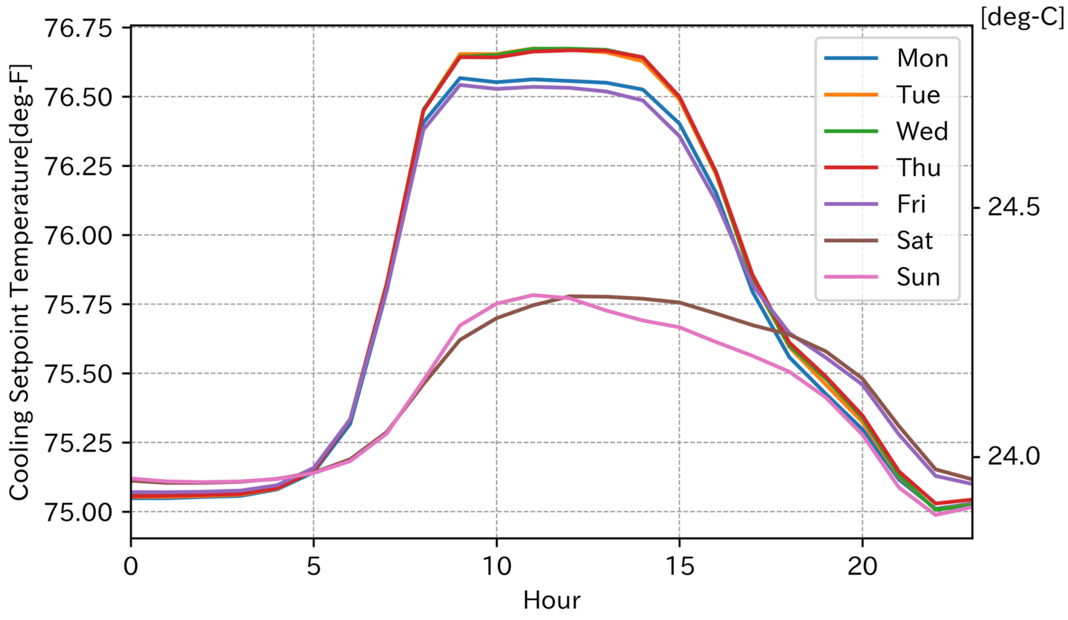

Figure 8. Average hourly setpoint temperatures for DYD homes for each day of the week for days when the cooling system operated.

If a person buys an ecobee thermostat and rushes through the set-up procedure, the default setpoints shown in Table 1 will be adopted (Huchuk 2019). Furthermore, the "Home" option is scheduled to begin at 06:30 and continues to 23:30, when "sleep" is resumed.

During the winter (see Figure 7) the sleep and at-home setpoints adopted by DYD homes are considerably lower (colder) than the defaults. Put another way, the households have adopted more energy-conserving temperatures than the defaults. The summer situation (Figure 8) is reversed. In the summer, the actual sleep and at-home setpoints are lower (cooler) than the defaults. These settings translate into lower indoor temperatures and greater air conditioning energy use compared to the default.

This preliminary analysis suggests that DYD homes found the ecobee defaults uncomfortably warm in the winter and not cool enough during the summer. This interpretation is only tentative, however, until the distributions of users are examined. In any event, the DYD households are clearly not accepting the default temperatures. They may still be accepting the default schedules (or at least for weekdays). These nudges – if they were indeed deliberate – were probably unsuccessful.

EQUIPMENT SIZING

Climate change and heat islands are contributing to ever-higher summer temperatures in cities. Are current air conditioning systems capable of handling rising thermal loads? The DYD dataset can give insights into future comfort and peak electricity demand problems. Specifically, to what extent are today's air conditioning systems already unable to supply adequate cooling during peak temperatures?

Homes with undersized cooling systems can be identified by continuous operation during multiple high-temperature events. (Multiple events must be identified because a system will not be sized for the maximum event.) However, not all periods of continuous operation will be caused by undersizing. Continuous operation may occur when the setpoint is lowered on a hot afternoon; the air conditioner may require longer time than usual to reach the lower target temperature. Each home's operating data must be carefully screened to remove these kinds of events.

Table 1. Default temperature setpoints for ecobee thermostats.

	Heating (°F/°C)	Cooling (°F/°C)
Home	69/20.6	78/25.6
Sleep	67/19.4	80/26.7
Away	64/17.8	82/27.8

We have not yet performed a sizing analysis beyond inspection of small samples of homes. The first large-scale analyses will target smaller regions that experience exceptional heat waves because they may reveal other trends, such as health impacts.

What the DYD dataset cannot tell us

The DYD dataset is tantalizing: five-minute data about thousands of homes distributed across North America makes possible dozens of promising avenues of research. The discussions above demonstrate that much can be learned from the DYD homes, often at lower cost or with greater confidence than with other methods. These data also give insights into topics not directly related to temperatures and HVAC use. For example, occupancy patterns revealed by the motion sensors in the thermostats may be more accurate than diaries and self-reporting. When a home's thermostat stops reporting data to ecobee's server, a likely explanation is a power failure. It is possible to exploit these interruptions to track power outages with a high degree of geospatial precision, and nearly as quickly as the electricity utilities (Ueno, Pritoni, and Meier 2018). At the same time, many avenues of inquiry are blocked by technical and legal reasons. Some of these constraints are described below.

Combining thermostat and energy data would make possible detailed evaluations of thermal performance. Such evaluations could identify energy-conservation opportunities, broken equipment, or perhaps even an open window. These could be performed retrospectively or in real-time when smart meters are available. (Some energy enthusiasts have actually done this.) A smartphone app (doing most of the computation in the Cloud) could perform these functions. The constraints to merging thermostat and utility data are both legal and commercial. The thermostat companies are legally obliged to protect their customers' privacy. (Most thermostat companies have extended European Union [EU] privacy regulations to North America because they sell some units in the EU.) The thermostat companies also resist sharing their data because it has commercial value.

The utilities have similar privacy requirements. In the United States, these rules are established by state regulatory commissions, so each utility has unique data privacy standards. The patchwork nature of these regulations prevents "scaling up" data sharing solutions. At the same time, utilities are also beginning to recognize the value of consumption data, so they are less eager to share. To date, no legal pathway exists to routinely merge the data, either for an individual customer or an entire utility service area.

A home's energy consumption for heating and cooling can be estimated if the HVAC system's input rating – electricity or fuel – is known. This is a simple calculation of the unit's rating (in kW) times the run-time (hours/year). As noted earlier, the DYD participants do not report the input ratings of their HVAC systems, so this conversion and calculation cannot be performed. This data gap could probably be solved with a survey of homes' HVAC ratings. A survey of several thousand homes could potentially populate a model that would reliably predict HVAC input rating based on floor area, age of home, and other independent variables.

The lack of detailed demographic and economic information about the DYD occupants' limits exploration of behaviors related to thermostat settings, technology, and innovations. While some simple investigations are possible, such as the relationship between number of occupants and run-time, it's not possible to investigate the impact of children (and especially babies and the elderly). Is there, for example, a relationship between a household's income and levels of thermal comfort? Parallel surveys of homes connected thermostats might answer some of these questions.

Conclusions

To answer the question posed in this paper's title, connected thermostats can give insights into the way households in a region keep thermally comfortable. The DYD dataset could give immediate insight into nationwide setpoints, actual temperatures, and schedules, which were not available in such detail before now. This information is useful for policymaking, including establishing guidelines and simulating building energy use. The HVAC run-times showed how residential air conditioning contributed to a grid's systemwide peak. It was a surprise that the DYD homes' peak demand exactly coincided with Texas' systemwide peak because commercial buildings and industry also contribute to the peak. These results show the extent to which residential air conditioning practices drive total electricity demand in Texas and where load-reduction policies should be directed.

The data from connected thermostats raise new questions for building science. The concept of "indoor temperature" will need more careful definition. Connected thermostats measure indoor temperature every five minutes and those with multiple sensors may be recording conditions in several rooms. What do occupants prefer? How can these conditions be provided in an energy-efficient manner? Finally, this level of building temperature modeling exceeds the capabilities of most simulation models.

The DYD dataset raises a survey research question, too. When should policymakers rely on a small sample of rigorously selected buildings – RECS in the United States – versus a huge, unrepresentative sample with high-fidelity data? Put another way, when does the value of a statistically representative sample selection outweigh its poor data quality? One part of the answer is to find research techniques in which the two approaches can complement each other and provide greater insights.

Connected thermostats, combined with energy, social, and economic data, could provide even greater insights. Many of those insights will not happen because legal, commercial, and technical barriers exist. Nevertheless, data from connected thermostats can provide actionable and valuable information.

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