Unintended consequences of smart thermostats in the transition to electrified heating

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Abstract

As building space heating undergoes an increasingly rapid transition toward electrification, it is vital to understand the impacts of these new electrical loads on the grid for future energy resource planning. While current methods for estimating heating demand rely on building modeling and occupant behavioral assumptions, we provide a scalable, data-driven approach for estimating regional electrical demand using real-world data from thousands of homes in a new, publicly available smart thermostat dataset. We find that despite lowering overall energy consumption, smart thermostat control algorithms can severely increase the winter peak heating demand through load synchronization during the early morning hours, when solar energy is unavailable. These peaks present unintended system-level consequences of focusing purely on local energy efficient control and can hinder the integration of renewable energy and electric heating. As a resource for future energy system planning, we provide our methodology as an open-source toolkit that can be used to analyze other regions around the world.

Keywords: Electrification, Smart Thermostats, Energy System, Peak Demand, Heating Demand

1. Introduction

[1]While a vast majority of commercial and residential space heating systems still rely on fossil fuels [1], there is a rapidly growing trend toward building electrification. Advances in electric heat pump efficiency in cold climates [2, 3] combined with aggressive clean energy policy goals from federal, state, and even local governments [4] have recently made heat pumps more economically preferable to conventional fossil-fuel systems [5]. These influences are leading to a swift adoption of heat pumps, with the International Energy Association predicting that the global share of homes heated by heat pumps could quadruple by 2030 [6].

At the same time, renewable energy generation is also seeing rapid growth worldwide, and almost half of electricity is projected to be sourced from renewables by 2030 [7]. This universal transition away from fossil-fuels is already posing difficult new challenges for the electrical grid, as the weather now affects both the supply and demand of electricity. In places with high solar penetration like California, US, the net electrical demand forms a "duck curve" [8] that creates high ramping requirements in the morning and evening during the summer. However, some cold-climate regions such as Vermont, US, are also beginning to experience winter duck curves due to the rise in electric heating [9]. A winter duck curve can be much more pronounced than a summer curve: Heating loads are typically much higher than cooling loads, and the highest heating demand in the early morning hours does not coincide with solar energy availability like cooling demand does. Winter grid resiliency has struggled during recent extreme winter weather events, creating dangerously cold indoor environments for homes with electric heating sources [10]. This potential danger emphasizes the urgency of predicting future heating electrical demand and planning sufficient renewable energy and storage capacity that provides electricity when buildings need it the most.

Smart thermostats are a rapidly growing technology that are often looked to as powerful energy management tools that can conserve energy and provide grid interactivtiy. Smart thermostats are estimated to be in 40% of homes in 2021 [11], and utilities are heavily encouraging more widespread adoption for both energy efficiency and for participation in demand response programs [12]. The built-in controls use setbacks to lower heat loss when the occupant is away or asleep in an attempt to lower energy costs. Smart thermostat manufacturers [13], academic studies [14] and the US DOE [15], claim setpoint setbacks can provide significant energy savings of 10-15% on average and up to 23%.

But as smart thermostats become more common, their new, autonomous control behaviors have the power to dramatically change the heating demand profile. Despite being more energy efficient, smart thermostat control algorithms may introduce unintended consequences for the electrical grid: Smart thermostat controls tend to operate similarly across the population and can cause load synchronization during recovery from nightly setpoint setbacks, increasing the daily peak heating electrical demand. Since these schedules are automated, they can shift the setback recovery period earlier in the morning before sunrise, preventing solar energy from meeting the electrical demand.

However, the vast majority of studies predicting future heating electrical demand do not consider the effect of smart

[1]This paper has been published as Lee, Z.E. and Zhang, K. M. Unintended consequences of smart thermostats in the transition to electrified heating. Applied Energy 322, 119384. 2022.

thermostat controls because they lack widespread, real world data on smart thermostat control behavior. As a result, these studies rely on modeling and assumptions based on historical data. One common method is a top-down approach that fits heating demand models to weather data and then scales the result based on available total monthly or annually energy consumption data. Both Refs. [16] and [17] assume heating demand is linearly dependent on the hourly outdoor temperature and fit model parameters based on longer-term fossil-fuel consumption data (e.g. monthly or yearly total fuel consumption). They then derive electric demand based on models of various heat pump coefficients of performance (COP). However, these studies neglect occupant behavior and varying setpoint schedules, a key component in estimating the heat demand. In another study, Ruhnau et al. [18] improve the top-down approach using a method from German gas suppliers that fits a more complex, time-dependent model, implicitly estimating the effect of varying occupant behavior by using the time-of-day.

Other studies use a bottom-up, building modeling approach that generates building models that are estimated to be representative of the larger building stock. For example, electricity demand forecasts in many US states rely on hourly heating demand schedules generated by the US Department of Energy that use synthetic occupancy schedules and building modeling [19, 20]. This bottom-up, building modeling style has also been applied in other countries like Germany, where Fischer, et al. proposed a stochastic modeling approach using thermodynamic parameters from representative buildings to account for various uncertainties [21]. Finally, Ref. [22] estimated the impact of electrification on the Texas energy grid using more detailed building stock data and the Resstock building simulation platform [23].

The main limitation of these approaches is that they heavily rely on region-specific assumptions on both the occupant behavior and the composition of building stock, making them difficult to generalize to new regions and susceptible to incorrect assumptions. For example, synthetically generated occupancy schedules may not reflect actual occupant control behaviors, particularly when affected by new smart thermostat controls. Occupancy schedules can be region specific (e.g., rural, suburban, and urban), and can significantly vary from reference occupancy schedules [24]. Since occupancy and thermostat control behaviors have a very strong effect on the heating demand, it is essential to have an accurate estimate of these behaviors for heating demand prediction.

In this paper, we use a publicly available Dataset containing smart thermostat operational data from hundreds of thousands of homes across the world [26] to estimate the impact that smart thermostats will have on future, region-specific heating demand. The Dataset contains anonymized temperature, setpoint, equipment runtime, and occupancy on a five-minute resolution across a wide range of residential building types and locations, allowing us to directly capture the field behavior of heating systems and occupants for any region in Dataset. The key improvement of our approach compared to prior heating demand prediction methods is that we make no assumptions on the relationship between heating demand and factors like weather and occupant behavior, but instead rely on smart thermostat data to directly provide the relationship. As a result, our approach not only shows the impact of smart thermostats on the heating demand profile, but also provides a new, scalable method for estimating heating demand that can capture regional differences in behavior, weather, and building thermodynamics from widespread, real-world data.

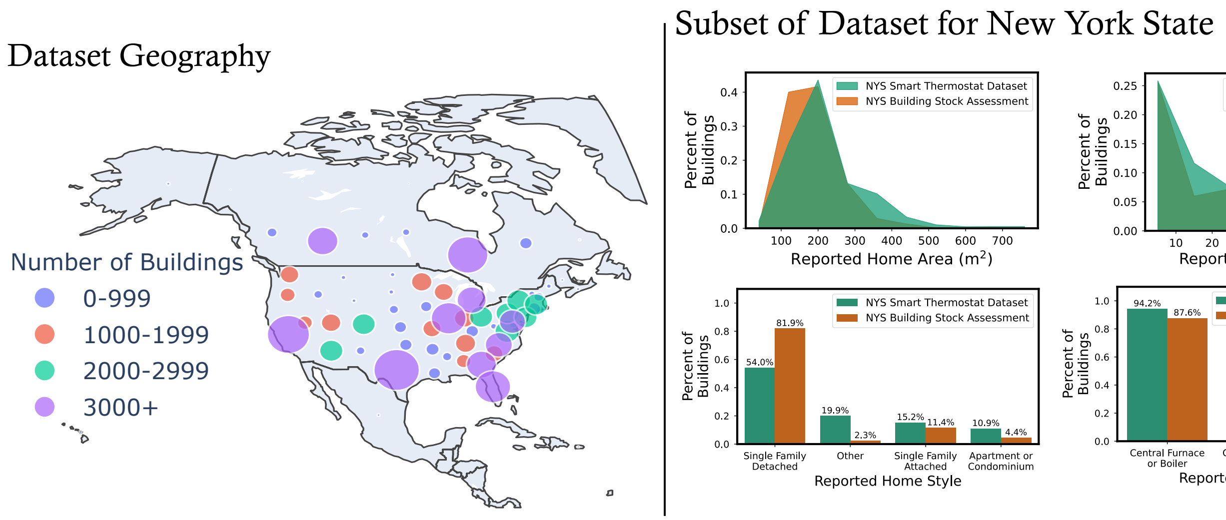
While many studies have explored the potential of smart thermostats as energy management tools, none have explored their affect on the aggregate heating demand on a large scale in this way. Ref. [27] explored the behavioral data of the Dataset to generate representative occupancy schedules, but did not explore how the occupancy affects heating demand. Other smart thermostat studies look at locally curated smart thermostat datasets for British homes [28] and university residence halls [29], but focus on total energy consumption, not the heating demand profile or load synchronization. In addition, these studies note a key limitation that their dataset is both small and relatively homogeneous, making their results difficult to generalize to a larger population. In contrast, our approach includes data from a far higher number of homes with increased diversity and thus scales and generalizes far better.

We show the potential and impact of this scalable methodology by analyzing the heating behavior for thousands of residences across New York State. The methodology consists of three parts. First, in Sec. 3 the setpoint and occupant control behaviors are explored to better understand both the behavior of smart thermostat controls as well as their potential energy efficiency benefit. Second, in Sec. 4, we analyze the effect that these controls have on the aggregate heating demand profile. Third, in Sec. 4.1 we use the detailed time-series data to analyze the region-specific relationship between periods of high heating demand and local renewable energy availability. We find that while smart thermostat controls are designed to save energy on a local level, they can introduce unintended consequences on the electrical grid at the system-level by creating new, higher peaks in times of low renewable resource availability.

2. Dataset Overview

The overall Dataset participants consist of Ecobee smart thermostat owners that opt-in to the Donate-Your-Data program. Locations of these participants are shown in Fig. 1a, and are mainly located in the US and Canada, the primary market for the thermostat manufacturer. However, over 2000 participants can be found in various other countries around the world. While opt-in participation can introduce some selection bias, Ref. [27] found that the participant demographics are relatively similar to that of other large energy consumption surveys like the US Residential Energy Consumption Survey [1].

At a five-minute resolution, the smart thermostats collect a large amount of various data, including indoor and outdoor temperatures; calls for heating or cooling for the heat pump or auxiliary heat; occupant setpoint; estimated occupancy captured through motion sensors; and operational mode such as home, sleep, demand response, or time-of-use rate. In addition, participants self-report metadata about their home such as age, home type, floor area, and location. The smart thermostats are installed in residential spaces served by their own



(a) Locations of buildings in the overall dataset. Buildings are primarily located throughout the US and Canada, but also contain around 2000 buildings dispersed in various other countries

(b) Self-reported metadata statistics for New York State (NYS), the focus of the Case Study. The data contain a wide range of home types, sizes, and ages that aligns closely with a previous building stock assessment for NYS [25]

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Figure 1: Metadata for **(a)** the overall dataset and **(b)** the subset of the dataset consisting of homes in New York State.

heating and cooling systems. The types of systems include single- and dual-stage heat pumps and up to three stages of auxiliary heat. Since the Dataset does not specify the auxiliary heating source, we assume auxiliary heat is either electric resistance heating or a fossil-fuel furnace.

While our methodology can be applied to any region contained in the Dataset, we focus the analysis of this paper on New York State (NYS). In many ways, New York is a microcosm of many cold-climate regions: It is a high-population state with a mix of urban, suburban, and rural communities and can have large variations in climate across the state. Fig. 1 shows various metadata statistics about homes in NYS.

There are 2244 homes represented in the NYS dataset and are predominately heated by non-heat pump heating sources, such as an electric or fossil-fuel furnace or boiler. This distribution aligns closely with New York's own survey [25], with a slight skew toward a higher proportion of heat pumps. Fig. 1b also shows a minor limitation common in survey-based datasets: Since the metadata is self-reported, there is likely some amount of incorrect metadata, implied by the high proportion of 0 m^2 buildings. However, since the majority of data used in this study is automatically reported by the thermostat, this incorrect metadata should not affect our results.

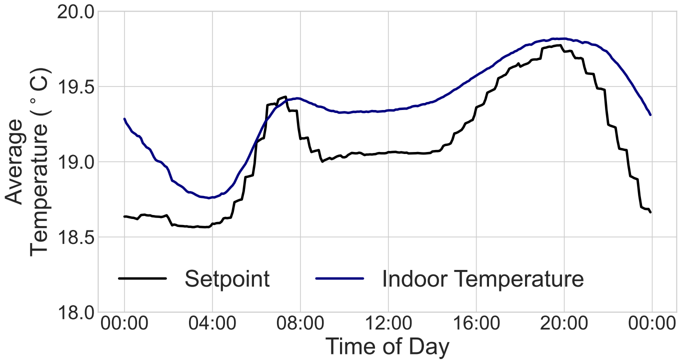
3. Setpoint Behavior

We first look at the setpoint behavior to get a direct measurement for how residents and smart thermostat control algorithms control the heating systems. They can use occupancy sensors to further reduce energy consumption through automatic setbacks when no occupancy is detected. Setpoint behavior for the Dataset was also extensively explored in Ref. [27] for a range of various factors in order to generate individual heating and cooling setpoint schedules. We analyze the data from a different perspective based on how the setpoint behavior affects the heating demand.

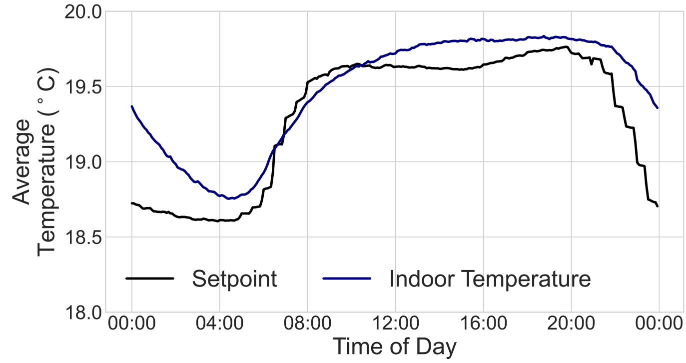
To see how resident behavior affects the overall time-dependent heating demand, it is important to analyze the setpoint behavior in aggregate. We average together the setpoints and indoor temperatures of all the homes in the focus region to get profiles that show average resident and smart thermostat control behavior. Fig. 2 shows the average daily heating setpoint and indoor temperature profiles for weekends and weekdays for NYS. Somewhat counterintuitively, the indoor temperature steadily increases during weekdays despite the setpoint being lowered, likely due to effects from solar irradiation.

Fig. 2 shows that on average, smart thermostats tend to use setbacks at night and during the workday, likely in an attempt to save energy. Whether or not these setbacks actually reduce energy consumption is a historically contested question. From a thermodynamics perspective, setbacks can only reduce energy consumption to the extent that they can reduce the average indoor temperature, and thus the building's heat loss, assuming the heat pump efficiency remains constant. While setbacks can certainly reduce the instantaneous energy consumption in the short term, recovering to original indoor temperature requires an almost equivalent amount of additional energy consumption, with the only total energy savings being from the reduced heat loss from the temporary reduction in indoor temperature. Therefore, depending on the manner in which the setbacks are configured, there is often a performance gap between potential and actual energy savings.

Field evidence has shown that residents are often unable to program their thermostats in a manner to achieve the potential energy savings [30], and as a result setbacks were historically discouraged, with the US EPA even revoking the ability for programmable thermostats to receive an EnergyStar rating in 2009 [31]. While the EPA has since reinstated this certification for connected, or smart, thermostats, more recent studies on smart thermostats in British homes [28] and university residence halls [29] have found that residents remain confused on how to efficiently program their thermostat and report energy savings of only 5-8% compared to to the



(a) Weekday



(b) Weekend

Figure 2: Average daily winter setpoints and indoor temperatures. On average, users tend to use setbacks to reduce the setpoint when they are away or asleep.

modeled potential of 25-30%.

One limitation noted in these studies is the lack of sample size and lack of building diversity. Therefore we explore the benefit of smart thermostats using the NYS Dataset (2244 homes). Fig. 3 shows the effect that the indoor and outdoor temperature difference has on the required daily heating hours for each building in the NYS Dataset. For each of the buildings, we fit a linear least squares model to predict the required daily heating hours as a function of the difference in daily indoor and outdoor temperatures. This model is given as

$$Q_k^i = a^i(\overline{T}^i_{\text{in},k} - \overline{T}^i_{\text{out},k}) + b^i \quad (1)$$

where Q_k^i is the daily heating hours, $\overline{T}^i_{\text{in},k} - \overline{T}^i_{\text{out},k}$ is the daily mean indoor and outdoor temperature difference, and a_i and b_i are the linear coefficients for each building. The terms are indexed by the building i and the day k. Thus, a_i provides each building's change in heating hours per degree change in the daily mean indoor and outdoor temperature difference. To obtain the percent change shown in Fig. 3, we divide a_i by the building's winter average daily heating hours.

Results show that for every degree decrease in the average daily indoor and outdoor temperature difference, the required heating hours decreases by between 3.5 and 14% for nearly 90% of homes with a strong correlation of $R^2 = 0.75$. This result aligns with the DOE's estimate of 10-15% [15] and heavily depends on how effective the smart thermostats are at lowering the daily average indoor temperature.

However, the data do not suggest that smart thermostat controls are in practice able to reduce the average daily indoor temperature or required heating hours. If smart thermostat controls are a significant contributor toward reducing the required heating hours or indoor temperature, one would expect that days where controls were used more extensively (e.g. large setbacks or longer times in "away" mode) would require less heating hours than days when the setpoint remained higher or more constant (e.g. when the occupant was home). Correlation analyses were run for each of the buildings to determine whether days with increased use of smart thermostat controls correlated with lower required daily heating hours or lower daily indoor temperature.

Fig. 4 shows the average Spearman correlation coefficients

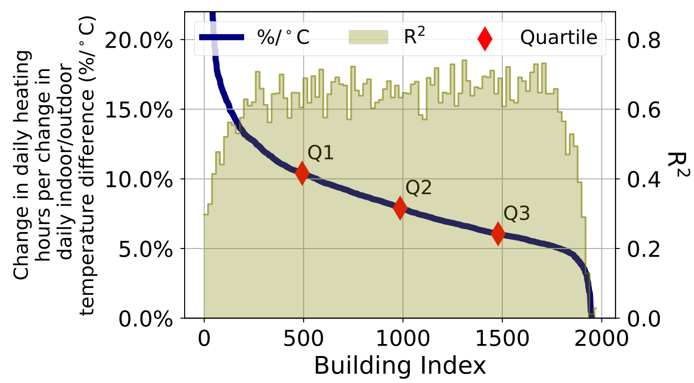


Figure 3: Percent Change in average daily heating hours per °C change in the average daily indoor and outdoor temperature difference for each of the buildings in the NYS Dataset. Almost 90% of homes could potentially save between 3.5 and 14% of energy consumption by lowering their average daily indoor temperature by 1 °C.

between smart thermostat control metrics and energy consumption metrics for all of the buildings in the NYS Dataset. For each building, the metrics were calculated over a single day, and the correlation analysis contains each day of winter 2019.

As expected from Fig. 3, the difference between the setpoint and the outdoor temperature has a large correlation with the daily heating hours. In contrast, other control metrics had much less correlation with either the indoor temperature or the required heating hours. The setpoint standard deviation, or a measure of the severity and frequency of setpoint setbacks, had virtually no correlation with reduced average indoor temperature, heating hours, or the mean setpoint, implying that residents were unable to significantly lower their heat loss or energy consumption through varying their setpoint. Likewise, time spent in "Home" and "Away" modes also had very little correlation with reduced daily average indoor temperature, heating hours, or mean setpoint. This result suggests that the performance gap between predicted and realized efficiency gains remains a widespread issue in current smart thermostat controls.

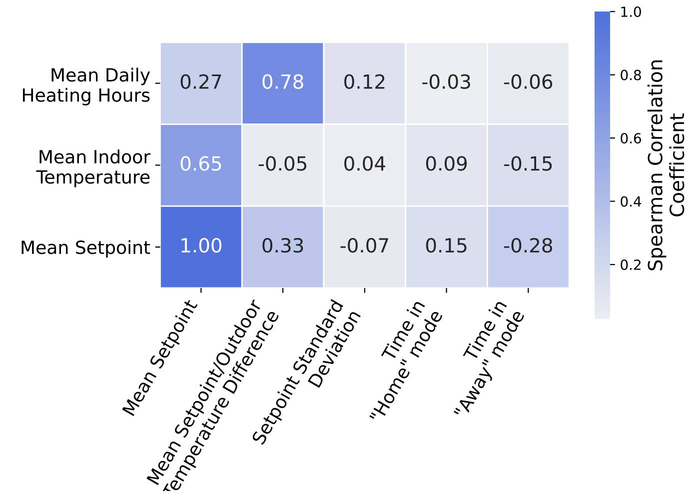


Figure 4: Spearman correlation coefficients between smart thermostat daily average control metrics and energy consumption metrics. Only the setpoint mean shows correlation with either reduced daily heating hours and reduced daily average indoor temperature, and other control metrics like setbacks and occupancy modes have relatively little effect.

4. Aggregate Heating Demand

We estimate the aggregate heating demand for smart thermostat heated homes by averaging together the heating system runtime at each five-minute timestep reported by each thermostat. For this profile, we only include the non-heat pump heated homes, since furnaces typically provide the same amount of heat input regardless of external conditions and prevents the need for additional assumptions. While the Dataset does not provide actual system capacity information, we can obtain a normalized profile that represents the shape of the heating demand curve that can be scaled based on the estimated monthly or annual energy consumption for a given region.

Fig. 5 gives the average daily profile of heating demand compared to the profiles generated by several other highly cited approaches given in literature. NREL [20] is a bottom-up approach developed by the US National Renewable Energy Laboratory and is widely used in the US for planning future energy policies [19]. SynPRO [21] is a stochastic bottom-up building modeling based approach and validated against historical German gas consumption data. When2Heat [18] is a top-down, statistical modeling-based approach also derived from German historical gas consumption data. Since each of the studies compare different region sizes and climates, the heating demand profiles were normalized by dividing by the mean winter heating demand, allowing the shape of the profiles to be directly compared. Thus, a normalized value of 1.5 represents a heating demand 1.5 times the average winter heating demand.

Fig. 6 shows the distribution of the daily peak demand for the smart thermostat, NREL, and When2heat data [2]. The smart thermostat data shows both an increase in frequency of high daily peak heating demand, as well as an increase in the magnitude of the overall peak demand.

[2]SynPRO was not included in this figure since they do not provide their raw data.

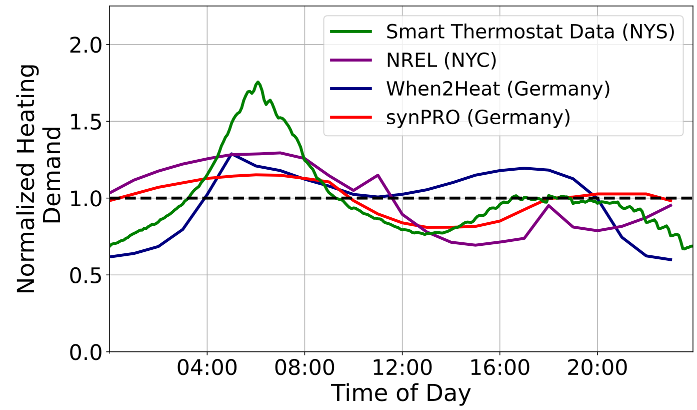


Figure 5: Daily average normalized heating demand profiles generated by the smart thermostat data compared to prior approaches in literature. Steep peaks in the morning are due to recovering from automatic nightly setbacks not accounted for in other studies.

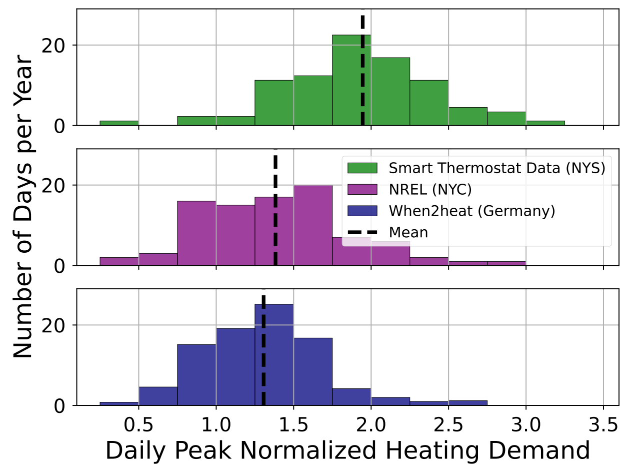


Figure 6: Distribution of the daily peak loads per year for the New York State (NYS) smart thermostat data compared to prior literature approaches. Both the average, as well as the overall daily peak heating demand are much higher under smart thermostat control methods.

While previous heating demand estimates align fairly closely across methodologies and geographical regions, the smart thermostat data stands out due to it's 40% increase in the daily average morning peak. This morning peak is caused by heating systems recovering from automated nightly setbacks that were not accounted for in prior studies and can be particularly difficult when combined with renewable energy integration. The peak occurs at 6:05 AM, around an hour before daylight for NYS. Without proper energy storage, solar energy may be unable to supply this peak demand, and fossil fuel generators may be required to satisfy the electrical load, offsetting the greenhouse gas emissions benefit of electrification.

4.1. Heating Demand and Renewable Resource Availability

By combining the thermostat data with nearby local weather data, we can explore the real-world relationship between the heating demand and local renewable resource availability. Previous methods for heating demand estimation cannot fully explore this relationship due to one main limitation:

Since heating demand estimates are often modeled as a function of weather, the assumed model structure implicitly defines the relationship between heating demand and weather-dependent renewable resources. For example, Refs. [32], [33], and [34] assume heating demand as a some linear function of outdoor temperature or heating degree days, meaning that their model assumption would assert an assumed prior on the relationship between renewable resources and outdoor temperature. Similarly, bottom-up approaches such as Refs. [35] and [22] rely on assumed building models intended to represent the specific region's building stock, which again impose the assumed building model and building stock information in the renewable resource and heating demand relationship. For example, the buildings' assumed solar heat gain implicitly defines the relationship to solar availability.

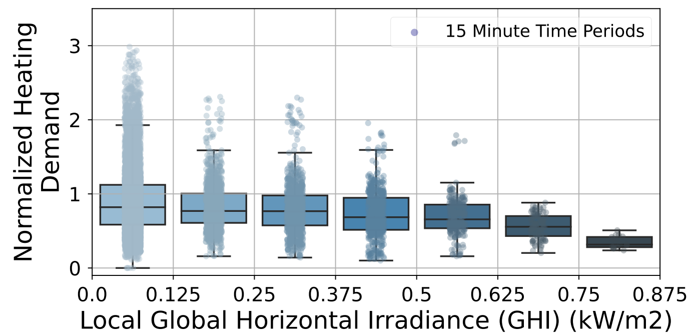
By using real-data, we remove the risk of inaccurate assumptions on behavior and the heating demand model and directly capture the local relationship between heating demand and renewable resources. In this way, any region in the Dataset can be mapped to a nearby weather file to find the relationship without building stock modeling or behavioral assumptions. Fig. 7 shows New York State's relationship between heating demand and local renewable resources. We aggregated the heating demand for each of the buildings into 16 location-based clusters, which each contain a weather file obtained from the National Solar Radiation Database [36]. Each dot represents a 15-minute time interval for one of the clusters, providing the extent to which local renewable resources can provide electricity during times of high heating demand.

Fig. 7a shows an inverse relationship between solar irradiation and normalized heating demand, suggesting that solar power may not be an effective method for providing electricity for space heating, particularly when it is controlled by smart thermostats. The relationship is particularly strong for high heating loads: Nearly all of the high heating demand time steps occur when there is between 0 and .125 kW/m^2 of solar irradiation. These high heating demand peaks most often occur in the early morning hours during the setpoint setback recovery period before the sun rises. In contrast, Fig. 7b indicates a positive relationship between wind speed and heating demand, with higher wind speeds corresponding to times of higher heating demand.

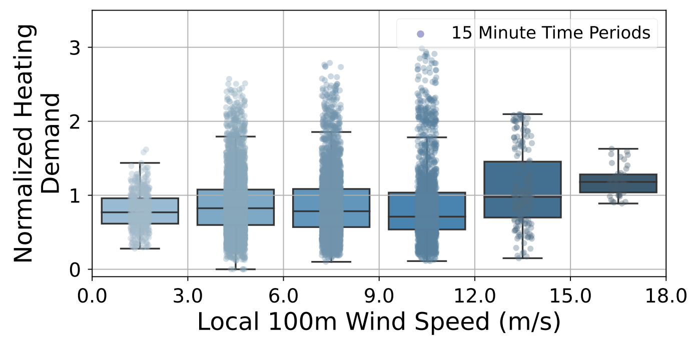
In fact, Fig. 7c shows that the highest heating demand periods also have the highest average 100 meter wind speed, suggesting that wind generation could be very effective at supplying renewable electricity during high heating demand times. Fig. 7c gives the mean local 100 meter wind speed and mean local GHI compared to the normalized heating demand. There is also a strong inverse relationship between wind and solar resource availability, where solar generation is at its highest when heating demand is lowest. As a result, there may be much lower demand for online solar generation as heating electrification continues and smart thermostat controls increasingly shift heating electricity consumption toward the early morning hours.

4.2. Discussion on Smart Thermostat Control Effects

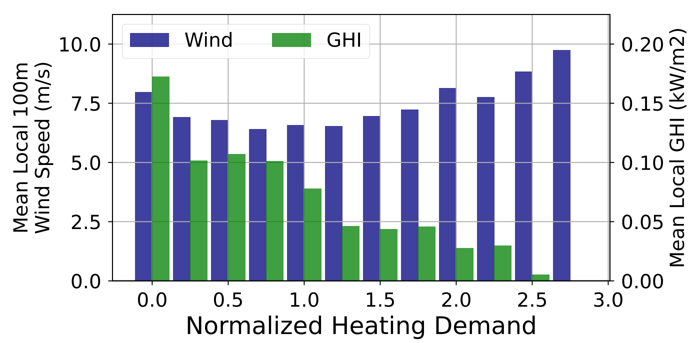
These three sets of results suggest that implementation of smart thermostat control schedules can have unintended



(a) Solar Resources



(b) Wind Resources



(c) Resource Correlation

Figure 7: Relationship of heating demand to local renewable energy resources. While a majority of high heating demand time periods occur where there is little to no solar irradiation, there is often plentiful wind resources available during those times. This inverse correlation suggests that wind generation is preferable to solar generation for providing renewable electricity for peak heating demands.

system-level consequences despite their objective to promote energy efficiency. While Fig. 3 suggests that the theoretical potential energy savings for reducing the indoor temperature is between 5-10% per °C, the setpoint schedules designed to achieve this benefit raise the peak heating demand by nearly 50%. These peak demands are concentrated primarily during times of low renewable resource availability, as shown in Fig. 7, meaning that incorporation of supporting technologies like energy storage and demand flexibility are vital to reducing space heating greenhouse gas emissions.

Moreover, Fig. 4 suggests that building owners and smart thermostat energy-saving mechanisms like occupancy mode and automated setpoint setbacks are not as effective in practice at lowering energy consumption compared to their predicted benefit. The data supports the large performance gap between modeled and real-world smart thermostat energy savings reported in smaller studies [29, 30], and shows that this gap extends to a large, diverse sample size. While these smart thermostat control mechanisms in theory should lower the indoor temperature (and thus the heat loss), the confusion reported by smart thermostat owners on the correct implementation [28] can prevent buildings from capturing the true potential benefit without more advanced control algorithms or sacrificing some thermal comfort.

More advanced building control algorithms must be carefully introduced due to the risk of high peaks in aggregate demand due to load synchronization and recovery from nightly setbacks. Model-based control methods that focus only on the building level have been shown to create similarly high peaks in aggregate demand despite lowering the overall energy consumption [37]. Therefore, controlling aggregations of heating systems as flexible loads that can provide grid services with a system level perspective [38] are vital for maintaining a reliable energy grid and utilizing renewable energy resources for space heating demand.

Finally, the composition of renewable energy generation must be carefully planned for future electrical demand profiles and must consider heating electrification under the effect of smart thermostats controls. Without energy storage, wind generation may be much more effective than solar generation since its highest output coincides with times of the highest heating demand. Future energy system planning must consider the interaction of weather, generation capacity, and demand controls *together* in order to build an efficient and reliable grid.

5. Conclusion

We have presented an analysis on the heating behavior of New York State as the basis for a scalable methodology for estimating heating demand in the context of building electrification. Our methodology uses a publicly available smart thermostat dataset containing years of operational data from tens of thousands of thermostats around the world, and shows the potential for using smart thermostats to estimate the impacts of building electrification. Our methodology is designed to be applicable to other regions contained in the smart thermostat dataset, so that the same analysis can be done for other regions around the world.

Our findings show very different estimates for heating demand than prior studies have due to the effects of new, expanding energy technologies. Smart thermostats, considered powerful potential energy management tools, show a large performance gap between potential energy savings and actual energy savings, and even present new challenges to the grid in the form of load synchronization and high demand peaks. As a result, new technologies like these that focus only on local energy efficiency have the potential to introduce unintended negative consequences on the grid at a system level. Widespread energy management initiatives must also look at the effects at a system level, and not only pursue energy efficiency. In addition, estimates of future heating demand must consider the effects of widespread changes in the way homes are heated as technology changes, since smart thermostat controls have the potential to radically change the shape of the heating demand curve.

Acknowledgement

The authors acknowledge the support from the National Science Foundation (NSF) under grant 1711546, the NSF Graduate Research Fellowships Program (to ZEL).

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