Comparative Analysis of Residential Occupants' Interactions with Centralized and Decentralized Heating Systems in Quebec

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Abstract

Occupant thermostat preferences and override behaviour are key sources of uncertainty when it comes to modelling and implementation of energy efficiency measures to improve building energy performance. This is particularly crucial in the residential sector, where accurate estimation of energy demand is important to optimize energy distribution. Therefore, a comprehensive understanding of how occupants engage with HVAC systems is essential to effectively address these uncertainties and minimize disparities between predicted and actual energy consumption. This study presents a comparative analysis of thermostat data from various residences across Quebec, Canada, focusing on centralized and decentralized heating systems. The primary objective of this research is to understand how occupants interact differently with these two types of heating systems to achieve their desired thermal comfort and the resulting impact on energy consumption patterns. This study uses two distinct datasets: one comprising information from 30 residences equipped with decentralized heating systems provided by Hydro-Quebec and the other consisting of data from 611 Quebec households with centralized heating systems. The analysis aims to discern differences in occupant behaviours and preferences and identify the advantages and disadvantages of central and decentralized HVAC systems in terms of optimizing occupant comfort and energy efficiency. Using the two datasets, models predicting the probability of a thermostat override are also developed to provide valuable insights into user behaviour when engaging with these two distinct HVAC systems. Such insights are vital for informed decision-making in designing and operating heating systems in residential buildings. Moreover, these findings are of great significance to utilities, as they rely on accurate estimations of residential energy demand to manage the grid more effectively.

Introduction

In Canada, space heating constitutes over 60% of the energy consumed in an average Canadian household (NRC, 2022). In the context of residential buildings, occupant interaction with building systems, particularly with heating, ventilation, and air conditioning (HVAC) systems, drives significant differences in building energy consumption (Kane and Sharma, 2020). Therefore, understanding how users engage with such systems is crucial for optimizing HVAC operations and achieving energy efficiency in residential buildings (Zhao and Shan, 2020). Over the past few years, a greater emphasis has been placed on the role of occupants in influencing building energy demand. Rather than solely focusing on designing high-performance buildings and energy-efficient technologies, current research has shifted toward gaining a deeper understanding of user behaviour and their interaction with the building (Laskari et al.,2022). Various parameters are known to influence the energy behaviour of users, including factors such as occupant presence, preferred comfort conditions, and their interactions with the building systems (Annex66, 2017). Wei et al. (2014) conducted an extensive literature review study emphasizing the intricacy of occupants' space-heating behaviour in residential buildings. They suggested 27 factors that play a role in shaping this behaviour. They concluded that while certain factors like outdoor temperature and dwelling type have undergone extensive evaluation in numerous studies, with their impact on space heating widely acknowledged, others, such as the type of HVAC system and social grade, have only been explored in a limited number of studies and require further investigation. In another study, it was indicated that distinct HVAC control strategies can directly impact both occupant comfort and adaptive behaviour within residential buildings (Ryu and Kim, 2021).

Existing studies highlight the significance of occupant behaviour in energy usage. However, there is a limited exploration of how distinct HVAC systems contribute to these dynamics. This paper contributes to this field by investigating the interplay between occupant behaviour and different types of heating systems.

The primary objective of this paper is to examine and compare occupant behaviour in residential houses equipped with centralized and decentralized heating systems. Centralized heating systems typically use a singular unit or source to generate heat, distributing air through a network of ducts. On the other hand, decentralized heating systems are distinguished by individual heating units, typically baseboards, in separate rooms or zones, offering localized control and potentially leading to diverse user experiences. The focus is to analyze real-world thermostat data and gain insights into the diverse ways occupants interact with these two types of heating systems and their preferences in setting temperatures for optimal comfort. Subsequently, predictive models are developed to estimate the likelihood of users

adjusting the heating setpoint's increase and decrease for that specific heating system.

The outcome of this research can lead to designs that improve heating system operation according to the user preferences. By discerning how occupants interact with centralized and decentralized heating systems, this knowledge can contribute to the development of energy-efficient HVAC control systems in residential buildings. The models predicting thermostat override probabilities offer insights into designing user-friendly heating systems that align with occupant preferences. Additionally, utilities can benefit from accurate estimations of residential energy demand based on the type of HVAC system, enabling more effective grid management and resource allocation.

The structure of this paper is as follows: The Methodology section provides a comprehensive overview of the study's approach, including the datasets and the development of user override behaviour prediction. In the Results section, we emphasize the data analysis outcomes and the results derived from prediction models. Subsequently, the Discussion and Implication section explores the potential implications of the study findings for residential buildings and utilities. Finally, the Conclusion section summarizes the main outcomes and suggests directions for future research.

Methodology

This section is comprised of two subsections. In the first subsection, the introduction of two different datasets used in this study is presented, along with the application of all necessary steps for preprocessing and data preparation. The second subsection explains the methodology used to develop predictive models for user thermostat override behaviour.

Analysis of two datasets: overview and data preparation procedures

Two datasets were used in this study. The first dataset includes information on thermostats from 30 houses in the province of Quebec, with these residential homes equipped with decentralized HVAC systems provided by Hydro-Quebec. This dataset is denoted as the HQ dataset in this paper. Additionally, the study used the Ecobee DYD (Donate your Data) dataset, which underwent filtering to include data specifically collected from households in Quebec, resulting in a total of 611 households featuring centralized HVAC systems (Ecobee DYD, 2018). It is worth noting that the Ecobee dataset used in this study is limited to homes with centralized HVAC systems, such as natural gas or electric furnaces, and central heat pumps as Ecobee thermostats are incompatible with decentralized HVAC systems like baseboards or mini-split heat pumps.

To narrow the study to the winter duration, both datasets were filtered to include data from November 1, 2017, to April 1, 2018. The HQ dataset includes data from 30 houses with decentralized HVAC systems across the province of Quebec. It features five main zones, specifically the living room, bedroom, bathroom, kitchen, and dining room. The time intervals in this dataset are random, and it captures three primary variables: indoor temperature, heating setpoint, and the energy consumption of the associated heater. Notably, each time the setpoint is adjusted, the corresponding value is consistently recorded for accuracy. Consequently, the data was aggregated on an hourly basis. In addition, since the dataset lacks outdoor temperature information, a weather API was utilized to extract and merge the hourly outdoor temperature. This process was conducted based on each house's location and the corresponding time period.

The thermostats used in these residential houses (HQ dataset) are programmable, but not all zones have been scheduled by the user. A pre-processing step was implemented as the data does not explicitly indicate whether the setpoint change is due to user intervention or a predefined schedule. This step helps differentiate between adjustments made based on a predefined program by occupants, referred to as "schedule," and adjustments made by the user, which are labelled as "override". To achieve this, the data for the entire period was organized on an hourly basis, ranging from 0 to 23, representing each hour across a 24-hour period from early morning to late night. The sum of setpoint adjustments (count) in each hour was then calculated. Subsequently, hours in which the count of setpoint adjustments exceeded a defined threshold (the mean of the count of setpoint adjustment for that specific thermostat) were designated as the scheduled timing for that thermostat. Consequently, any adjustment occurring within those specified hours was classified as part of the schedule, while adjustments outside the designated schedule timing were considered user overrides. For example, if the thermostat's setpoint was adjusted 90 times at 9 am during the 150-day data period, this time slot was considered part of the thermostat's programmed schedule. Any adjustments made at this time were presumed to be automatic, following the preset schedule, rather than initiated by the user (override).

The Ecobee dataset, on the other hand, comprises a 5-minute interval time series of information collected by smart thermostats. It includes attributes such as date-time, indoor temperature, cooling and heating setpoint temperatures, relative humidity, fan runtime, and motion detection. The Ecobee smart thermostat offers default schedules like ‘Home’, ‘Away’, and ‘Sleep’, allowing users to create their own schedules. Users can program their desired heating setpoint schedules through their smart thermostats. Additionally, they can manually override these schedules by selecting different setpoints either through the thermostat on the wall or the mobile application. These manual adjustments, commonly known as holds in the data, are referred to in this paper as user overrides for the sake of consistency. Both datasets underwent comprehensive data cleaning and preprocessing to ensure the quality and reliability of the information analyzed in this study.

Prediction models for user thermostat override behaviour

The aim of this prediction model is to determine the probability of thermostat adjustment by the user (referred to as "user override") in the subsequent time step. Discrete-time Markov logistic regression thermostat usage models were developed utilizing the scikit-learn package in Python, as outlined by Pedregosa et al. (2011). The model equation is represented as Equation 1, where P(x) denotes the probability of an action taken by the occupant, either a setpoint increase or decrease. β_0 and β_1 are the coefficients of the logistic regression model, and x represents the predictor variable of the model. The predictor variable used in this modelling framework is indoor temperature, which is employed to compute the anticipated probability of observing thermostat override actions in the next time step. It is worth noting that this modelling structure has been extensively adopted in prior studies on occupant behaviour modelling, and as such, the fundamental principles of this approach are not restated within the scope of the present study, following the methodology by D'Oca et al. (2019).

$$P(x) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 x)}} \qquad \textit{Equation 1}$$

Results

This section is divided into two parts. The first part presents the analysis results of both datasets, focusing on the comparison of user thermal comfort preferences, scheduling behaviours, and interaction frequency between centralized and decentralized heating systems. The second section presents the results of the prediction model for thermostat override for centralized and decentralized heating systems.

Data analysis results

Figure 1 illustrates a line plot depicting the average setpoint temperature across various zones within all the houses over a 24-hour period throughout the entire duration of the data analysis. Each distinct zone is represented by a specific colourful line, while a dashed line denotes the average setpoint temperature of the centralized system. The graph provides insight into how temperature preferences fluctuate throughout the day and across different zones, catering to the diverse comfort levels of occupants. Notably, the kitchen and living room consistently exhibit higher average heating setpoints, which reflects their importance as central living spaces. In contrast, the bedroom and bathroom zones maintain lower average setpoint temperatures, which are aligned with their functions and typical comfort expectations. Interestingly, the average setpoint temperature of the centralized system closely mirrors the values observed in the living room and kitchen zones throughout various times of the day, which suggests synchronization with the comfort needs of the primary living areas. During the early morning hours (0 to 5 AM), the average heating setpoint for the centralized system tends to be 0.5 to 1 degree higher compared to both the coolest and hottest zones equipped with decentralized heating systems. As the morning peak period (5 to 9 AM) approaches, the setpoint temperatures in the living room and kitchen zones surpass those of the bathroom and bedroom by at least one degree. Notably, the centralized heating system maintains lower temperatures relative to the living room and kitchen during both the morning and evening peak periods. All in all, the centralized heating system aligns closely with the setpoint temperatures observed in the living room and kitchen. However, it exhibits smoother peaks and shallower valleys.

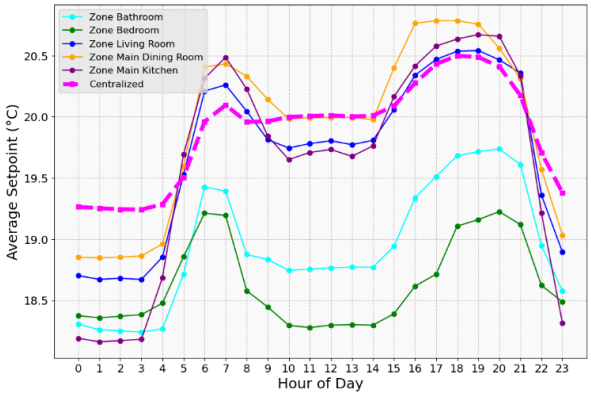


Figure 1: Average setpoint temperatures for the centralized heating system (dashed line) and various zones (colourful solid lines) across all houses over a 24-hour period during the data analysis.

Figure 2 shows the box plot of the number of weekly overrides by households for both decentralized and centralized heating systems. The decentralized heating system seems to have more engagement from the users, as they can adjust the temperature in different zones according to their preferences. This leads to a higher frequency of overrides, especially in zones where activities may cause temperature fluctuations, such as the kitchen and living room. On the other hand, the centralized heating system shows much less frequent overrides, suggesting that users may be setting a "one-size-fits-all" temperature that is satisfactory for all zones in the house or are less inclined to make adjustments when they cannot target specific zones. These findings suggest that decentralized heating systems may offer control and customization over their indoor comfort levels, potentially leading to improved satisfaction with their heating environment. However, this increased autonomy may also come with trade-offs, as more frequent overrides could result in higher energy consumption.

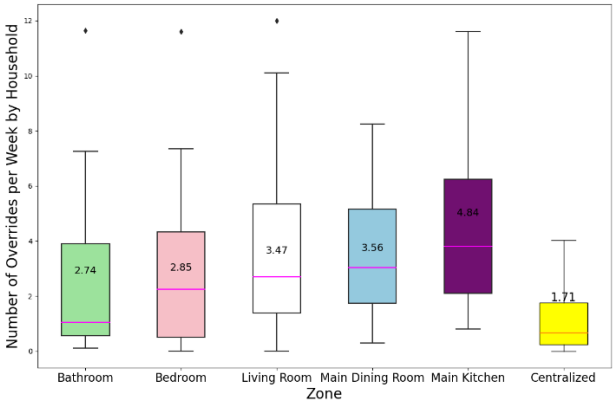
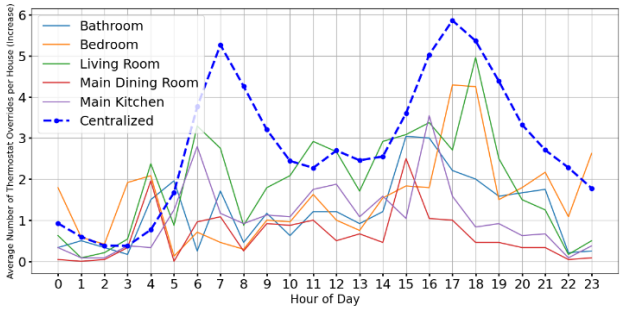


Figure 2: Box plots of the number of weekly overrides by households.

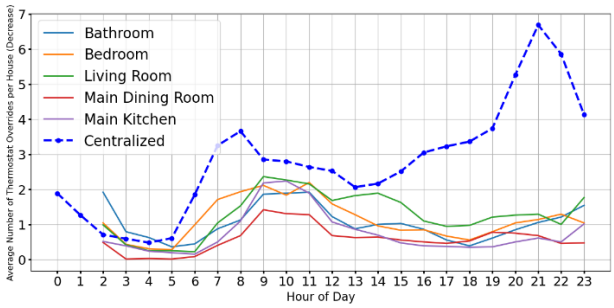
Figure 3 shows the hourly average number of thermostat overrides per house. The data is separated into two categories: Setpoint Increase and Setpoint Decrease. The plot vividly demonstrates how thermostat adjustments contribute to peak load occurrences, particularly during morning and evening hours. Notably, specific zones play more pivotal roles during these peak periods. For instance, the bedroom exhibits minimal involvement in the morning peak. However, it experiences a notable increase in thermostat overrides, up to four times per week, during the evening peak. Another example is observed in the bathroom. Although this zone displays peak activity during both morning and evening hours, the evening peak appears to be more pronounced.

Regarding timing, each zone shows distinct patterns of thermostat adjustments that correlate with their expected use times and functions. In other words, increases happen in the living room during evening relaxation times, in the kitchen during meal preparation, and in the bedroom during typical sleeping hours. For instance, the evening peak for increased thermostat adjustments occurs at 18:00 for the living room and bedroom, while it transpires at 16:00 for the kitchen and bathroom.

The graph for the home with a centralized heating system shows a different pattern. It demonstrates a more uniform distribution of setpoint changes throughout the day, implying distinct usage patterns compared to decentralized systems, where adjustments tend to be more localized and room specific. This suggests a more dynamic use of heating throughout the entire home.



(a) Setpoint increase



(b) Setpoint decrease

Figure 3: Hourly average number of setpoint overrides per house: a) Setpoint increase, b) Setpoint decrease.

Predicting User Override Behaviour in Centralized and Decentralized HVAC Systems

Figure 4 shows the probability of setpoint override by the user with colourful dashed lines representing the corresponding probabilities for individual zones. The solid line shows the corresponding probability for houses with centralized heating systems.

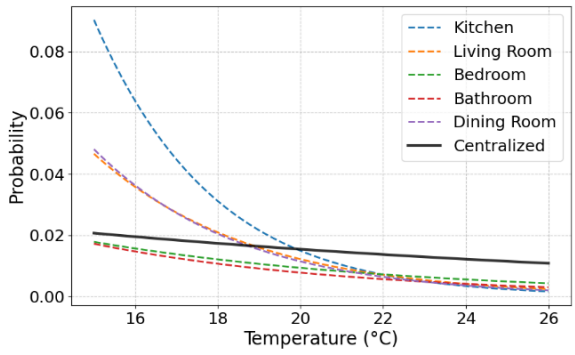
The kitchen zone has the highest probability of a setpoint increase at lower temperatures among other zones, but this probability decreases at the fastest rate as temperature increases, crossing below other rooms as the temperature reaches around 22°C. On the other hand, the centralized system demonstrates a more gradual decline in setpoint increase probability, which indicates a lower likelihood of adjustments as temperatures fluctuate compared to individual zones equipped with decentralized heating systems.

Regarding setpoint decrease probability, overall, the probabilities remain relatively low for both centralized and decentralized until the temperature is up to about 24°C. It means there is little likelihood of the setpoint being decreased by the users when temperatures are in this range. However, past approximately 24°C, the probability of setpoint decrease increases sharply, especially for the centralized system, indicating a higher sensitivity of centralized heating system users to rising temperatures compared to decentralized heating systems. It is worth noting that, unlike the other zones, the bathroom zone demonstrates a sharp increase in the probability of setpoint

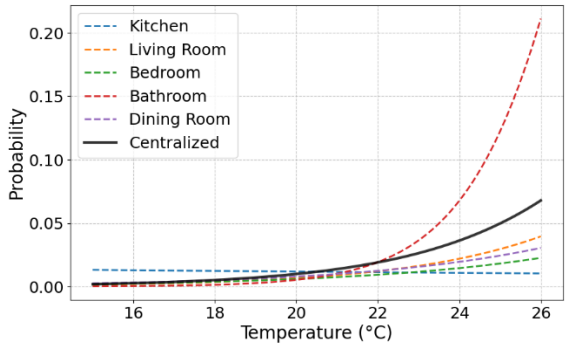
decrease after 24°C. This could be attributed to the functional nature of bathrooms, characterized by confined spaces and rapid heat retention, especially during activities such as showering or bathing, which contribute to the perceived warmth. Additionally, the intermittent usage pattern of bathrooms and the desire for a cooldown after using hot water further incentivize occupants to lower the setpoint in response to rising temperatures.

In summary, these plots indicate that individual zone thermostats have a higher likelihood to be adjusted more frequently at lower temperatures, potentially for comfort reasons, while a centralized system is less likely to be adjusted until temperatures surpass a higher threshold. From the graph, these thresholds are observed to be approximately 20°C and 22°C for setpoint increase and decrease probabilities, respectively.

Table 1 displays the mean, standard deviation, median and interquartile of the magnitude of setpoint changes resulting from user overrides. Overall, it is evident that users of centralized heating tend to make smaller changes in terms of the magnitude of setpoints compared to decentralized systems. Another noteworthy finding in user behaviour difference between decentralized and centralized systems: users of decentralized systems typically select a higher magnitude of setpoint change for setpoint increases than decreases. Conversely, users of centralized systems exhibit the opposite tendency.



(a)



(b)

Figure 4: The probability of thermostat override by the user: a) probability of setpoint increase, b) probability of setpoint decrease.

Table 1: Mean, standard deviation (SD), median, and interquartile (IQ) of the setpoint increase and setpoint decrease magnitude.

	Setpoint increase				Setpoint decrease			
	Mean	SD	Med	IQ	Mean	SD	Med	IQ
Centralized	1.53	1.78	0.9	1.29	1.67	1.83	1	1.69
Living room	3.3	1.75	3	3	3.12	1.81	3	3
Bedroom	2.74	1.67	3	3	2.85	1.78	3	3
Bathroom	3.41	2.01	3	3.5	2.91	1.87	3	3
Kitchen	3.68	1.80	4	2.5	3.54	1.79	3	3
Dining room	2.81	1.40	2.75	2	2.67	1.33	2.75	2

Discussion on Findings and Implications

Previous research underscores the significance of integrating occupant behaviour into building energy reduction strategies, recognizing occupants' critical role in influencing energy consumption patterns. This study seeks to contribute to our understanding of occupant behaviour and the differences in their interactions with centralized and decentralized heating systems. The observed disparities in user behaviour between these systems suggest distinct perceptions and approaches to comfort control. A decentralized system allows for localized control, evident from the room-specific peaks, whereas the centralized system seems to be regulated on a whole-house basis, reflected in the more even distribution of adjustments. Decentralized system adjustments tend to align with specific activities, whereas centralized systems reflect a broader comfort strategy, potentially constrained by the inability to control individual zones separately.

The crucial takeaway from these results lies in the potential implications for energy management strategies. By understanding the user behaviour dynamics with decentralized and centralized heating systems, grid operators can develop targeted approaches to optimize energy usage, mitigate peak loads, and enhance grid resilience, considering the distinct ways users interact with each heating system and accounting for their unique preferences, habits, and needs. For decentralized heating systems, strategies may focus on leveraging localized control capabilities to optimize energy usage and enhance user comfort during specific activities or times of the day. In contrast, centralized heating systems may benefit from strategies that promote holistic comfort control while ensuring efficient energy utilization across the entire household.

Integrating the findings of logistic regression prediction models for user thermostat adjustments from this study into building simulations could lead to more informed decision-making in energy management strategies. Accounting for

the behavioural nuances that influence energy usage in residential homes equipped with either centralized or decentralized heating systems would enhance the accuracy of energy demand estimations for buildings and grids.

Conclusion

The primary objective of this paper is to investigate and compare occupant behaviour in residential houses equipped with centralized and decentralized heating systems. The focus is on analysing thermostat data to understand how occupants interact with these systems, set temperature preferences, and experience thermal comfort. We found that zone-level control in the decentralized systems led to higher peaks and valleys of the average setpoint profiles, while the setpoint profiles of centralized buildings tended to be more flat throughout the day. Next, we saw that the probability of a setpoint override was highest in certain areas of the house for those with decentralized systems, notably the kitchen and bathroom, and in general, the magnitude of the setpoint overrides tended to be higher for houses with decentralized systems compared with those with centralized systems. It is important to note that our sample size for the decentralized systems is just 30 houses, and thus additional data would be required to corroborate these findings. Likewise, all houses considered in this study were obtained using smart thermostat data, and thus there is potential bias in the houses analyzed with respect to the total building stock of Quebec. The findings of this research are intended to contribute valuable insights for improving the design, operation, and user experience of residential HVAC systems, ultimately fostering energy-efficient and occupant-friendly living environments.

Moving forward, future research could explore additional factors influencing user behaviour and further refine predictive modelling. By continuing to advance our understanding of how occupants interact with different heating systems, we can develop more sophisticated energy management strategies and contribute to a more sustainable built environment.

Acknowledgement

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